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# Postsecondary STEM Paths of High-Achieving Students in Math and Science: A Longitudinal Multilevel Investigation of Their Selection and Persistence

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# POSTSECONDARY STEM PATHS OF HIGH-ACHIEVING STUDENTS IN MATH AND SCIENCE: A LONGITUDINAL MULTILEVEL INVESTIGATION OF THEIR SELECTION AND PERSISTENCE

by

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*My dearest Juan and Arin,*

*the bright light and the clear water for the world*

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# ABSTRACT

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This study used a quantitative approach to investigate high-school students' talent-development pathways in STEM from 10th through 12th grades and for 8 years thereafter. The purpose of this study was to longitudinally investigate three important choices and accomplishments on the STEM talent development trajectory: a) selecting a STEM major in college; b) persisting with the STEM major until graduation; and c) selecting a career in STEM after college graduation. Given that students with gifts and talents are more likely to persist and succeed in STEM fields than average achievers, and understanding their unique needs may be the first important task to promote their talent and career development, this study concentrated on college bound high school students who achieve at high levels in math and science. I operationally defined students identified as high-achieving in math and science as those who scored in the 95th percentile or above in math or science in college entrance exams. Through an investigation, I used the longitudinal data of the Education Longitudinal Study of 2002 (ELS:2002) of a nationally-representative cohort of U.S. students. Two inferential analytic methods were used to estimate the probabilities associated with each binary outcome variable: multilevel logistic regression model and discrete-time hazard model.

Students identified as high-achieving by the criteria of this study were more likely than students who did not meet the criteria to enter postsecondary STEM education and to persist in STEM after college graduation. However, there were severe disproportions in the numbers of students identified as college bound high-achievers. Female, Black, Hispanic, Native American,

and other-race students, students from families of lower-quartile SES, and students who attended schools with higher levels of academic pressure were less likely to be identified as high-achievers than students in the corresponding reference groups. Mathematics self-efficacy and advanced courses in math and science, as moderators, increased the probabilities of STEM entrance, regardless of the identification as high-achieving. In terms of STEM persistence and graduation, fewer Black, Hispanic, Native American, and other race students graduated from college with a STEM major compared to White and Asian students. The disparities in the probabilities of further persistence also existed by student- and school-level covariates.

Unlike prior studies in STEM education, I controlled for the effects of high achievement in college entrance exams, thus, the results revealed the effects of some covariates were unique for students identified as high-achieving. Based on the baseline estimates of probabilities provided by this study, more research needs to be conducted to investigate reasons for the significant effects promoting or preventing desirable outcomes on STEM pathways.

# CHAPTER 1 INTRODUCTION

Given that Science, Technology, Engineering, and Mathematics (STEM) have been well recognized as the foundation of the U.S. economy and innovation, attracting and retaining prospective students in these fields is a serious national task. Recent national reports highlighted the necessity of motivating talented high school students to pursue math and science through quality STEM education (e.g., Committee on Prospering in the Global Economy of the 21st Century, 2007; Katehi, Pearson, & Feder, 2009; National Academy of Engineering, 2010; National Governors Association, 2007; The National Academies, 2007).

In *Preparing the Next Generation of STEM Innovators: Identifying and Developing Our Nation's Human Capital*, the National Science Board (NSB; 2010) diagnosed the current state of STEM education: "The U.S. education system too frequently fails to identify and develop our most talented and motivated students who will become the next generation of innovators" (p. 5). The board went on to argue that "elevating the ceiling" is not mutually exclusive with "raising the floor of base-level performance," and both should be pursued in the U.S. education system (p. 10). Nevertheless, unknown variables still exist regarding the talent pool of high-achieving students in math and science, particularly the educational experiences and psychosocial developmental milestones during high school that promote entrance, persistence, and achievement in postsecondary STEM fields.

Although a number of researchers have attempted to investigate student persistence within STEM pathways, studies concentrating on the pathways of talented high school students in math and science are scarce. In particular, it is unknown why high-achieving students in math and science, despite their high achievement in these fields, do not select, persist in, and succeed in postsecondary STEM pathways. To establish pertinent strategies and policies to recruit competent high school students in these areas, more emphasis needs to be placed on understanding their characteristics and experiences, as well as the contextual variables influencing students' decisions to pursue STEM pathways.

**Rationales for "All STEM for Some"**

Atkinson and Mayo (2010, p. 9) argued that the prevailing "Some STEM for All" approach, which focuses on expanding STEM education to all students, was neither effective nor economic. Instead, they suggested an "All STEM for Some" framework, which focuses on providing the best educational pipeline to those students who are interested in and capable of achieving in STEM (p. 9). They also suggested establishing a national STEM talent recruiting system in high schools to concentrate national endeavors promoting STEM education.

Despite the national negligence towards talented students in secondary schools, the rationales for "All STEM for Some" are laudable. First, students with gifts and talents deserve the opportunity to reach their highest potential (NSB, 2010; Wyner, Bridgeland, & Diiulio, 2007). Subotnik, Olszewski-Kubilius, and Worrell (2015) argued that the lack of support for talented students relates to prevalent myths that those talented students already have advantageous backgrounds, and will be able to independently achieve their accomplishments. However, approximately 3.4 million students achieving in the top quartile in the U.S. come from low-income families, and these talented students, if they lack educational resources, often fall behind their peers from affluent backgrounds (Giancola & Kahlenberg, 2016).

Second, the secondary school age is a critical period for realizing and developing talents in math and science (Lee, 2012; Subotnik, Olszewski-Kubilius, & Worrell, 2011). Math and science are areas that have domain-specific developmental trajectories, starting at an early age, and the development of these talents mostly relies on the schooling system (Feldhusen, 2005;

Subotnik et al., 2011). Therefore, if educational systems neglect to identify and appropriately educate talented students during their secondary education, it is likely that they may lose the opportunity to develop these talents throughout their lives. Furthermore, schooling from a talent development perspective is even more important for underrepresented students (e.g., female students, Black and Hispanic students, students from low-income families) given that those students rely more on their high schools to explore their future academic career pathways, as well as to develop their talents.

Third, from an economic standpoint, it is frequently argued that motivated and talented people in STEM undertake leading roles for national prosperity (Atkinson & Mayo, 2010; National Academy of Sciences, National Academy of Engineering, & Institution of Medicine, 2007; NSB, 2010). This perspective often undergirds and drives leading countries in STEM to concentrate their national endeavors to deliver a quality education for talented students (Atkinson & Mayo, 2010). The "All STEM for Some" approach, which focuses on students who are interested in and capable of achieving in STEM, is more cost-effective in achieving this than the "Some STEM for All" approach (Atkinson & Mayo, 2010).

## Significance of the Study

Given the critical need to understand the STEM paths of high school students, researchers have examined the effects of high school GPA and other achievement indices in math and science (e.g., SAT scores) that influence these pathways. They found that math and science achievement were consistent predictors for entrance, persistence, and achievement in postsecondary STEM fields (e.g., Astin, 1993; Smyth & McArdle, 2004; Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpkiattaworn, 2007). In addition to high school achievement indices, a number of variables were found to influence students' decisions for and persistence in

STEM paths. In terms of student-level variables, sex, race, first language, parents' STEM profession, and self-efficacy were critical determinants for STEM persistence (Besterfield-Sacre, Moreno, Shuman, & Atman, 2001; Chimka, Reed-Rohads, & Barker, 2008; Leslie, McClure, & Oaxaca, 1998). Characteristics of high schools and postsecondary institutions (e.g., type, size) were also found to influence student STEM persistence (e.g., French, Immekus, & Oakes, 2005, Maple & Stage, 1991; Tyson, Lee, Borman, & Hanson, 2007, Wang, 2013). However, despite the need to concentrate on the talented students who are most likely to be motivated and to achieve in STEM fields, researchers have not investigated the unique needs of those students. Furthermore, although motivational factors and learning experiences in high school matter for talent and career development in academic domains, their moderating roles, alleviating risk-factors or promoting catalysts in STEM paths, have not been studied with respect to developmental trajectories.

A noteworthy trend in recent studies regarding STEM education and policy is the increased use of advanced longitudinal analytic techniques with large national datasets. To examine the longitudinal patterns of students' persistence, achievement, and graduation rates in postsecondary education and their associations with predictors, survival analysis and logistic regression analysis have frequently been used. Survival analysis enables estimation of the hazard probability of an event occurrence (e.g., persistence/graduation in college with a STEM major) and estimation of when the event is likely to occur, as well as insight into whether event occurrences increase, decrease, or remain constant over time. (Singer & Willet, 2003). Min, Zhang, Long, Anderson, and Ohland (2011), using a nonparametric survival analysis, found that engineering students were most likely to leave an engineering major during their third semester, and these students tended to be female, White, and have SAT math scores lower than 550.

Chimka et al. (2008) and Zwick and Sklar (2005) also used survival analysis with STEM college students to investigate student graduation and its predictors. Logistic and probit modeling have been also used to estimate the probability of attaining dichotomous outcomes (e.g., graduation in STEM) and their predictors (Chen & Soldner, 2013; Nicholls et al. 2010; Zhang et al. 2004).

Given the need to extend understanding concerning high school high-achieving students in math and science, this study concentrated on this group of students. I applied multiple longitudinal analytic techniques to investigate when and why those students select, persist in, achieve well in, and depart from STEM paths. Using the national longitudinal panel data, it was possible to investigate these longitudinal patterns and their underlying factors by following cohorts from their early teenage years to their postsecondary years. Several features distinguish this study from previous research. In particular, this study:

- Follows up with college bound high school students identified as high-achieving in math and science to examine their entrance, persistence, and achievement in postsecondary STEM education, as well as further persistence in STEM fields;
- Focuses on the STEM paths after controlling for the effects of high school achievement to examine whether or not the developmental and career decision patterns of high achievers are the same as for average-achieving students;
- Highlights failures (e.g., failing to graduate from college in eight years), obstacles, and the needs of young talented students in postsecondary STEM education by examining the factors influencing failure and success;
- Uses multilevel modeling including school-level variables as well as student-level variables to examine the impact of school characteristics on students' decisions and performance in STEM;

- Investigates the moderating roles of motivational factors and advanced learning experiences in high schools to extend understanding of how these factors are differently influenced by student demographic backgrounds.

## Purpose of the Study

The purpose of this study was to longitudinally investigate three important choices and accomplishments on the STEM talent development trajectory: (a) selecting a STEM major in college; (b) persisting with the STEM major until graduation; and (c) selecting a career in STEM after college graduation. The research questions are as follows:

*Research Question 1.* Are secondary school students identified as high-achieving in math and science more likely to select their postsecondary education paths in STEM compared to non-identified students included in the ELS:2002?

*Research Question 2.* After entering postsecondary STEM paths, when are students identified as high-achieving most likely to complete an undergraduate program in a STEM field? Which variables most significantly influence completion rates in postsecondary studies?

*Research Question 3.* Are STEM undergraduate students who were identified as high-achieving in high school more likely to select graduate programs or occupations in STEM after college graduation compared with other STEM undergraduate students?

## Definition of Key Terms

### Students identified as high-achieving in math and science

This study concentrates on high-achieving students in high school math and science. For a high school student, a variety of achievement indices are available, such as high school grade point averages (GPA), college entrance exams (e.g., SAT, ACT, SAT subject exams, AP exams), state achievement tests (e.g., Iowa Tests of Educational Development, Indiana Statewide Testing for Educational Progress-Plus), and national-level achievement tests (National Assessment of Educational Progress). Of the indices, this study used college entrance exams as the only criterion for identifying high-achieving students, because the other indices were not standardized across schools and states, and/or the opportunities to take certain tests were not equivalent for all students of interest in this study. I operationally defined students identified as high-achieving in math and science as students who scored at or above the 95th percentile in one or more of the following: SAT math, ACT math, and SAT subject exams in math and science. I also included students who scored 5 (extremely well qualified) on AP exams in math and science. I use the term “non-identified students” to refer to students not identified by the criteria.

**STEM fields**

In this study, following the Classification of Instructional Programs (CIP), STEM fields include: mathematics, physical sciences, biological/life sciences (including agriculture and related sciences, natural resources and conservation, biological and biomedical sciences), computer and information sciences, and engineering and technologies (including engineering, engineering technologies, and science technology).

**Secondary education**

Secondary education indicates the education level between primary/elementary education and higher education. Specific grade-levels included in secondary education differ by countries and schools. This study, following the definition of the International Standard Classification of Education (ISCED: United Nations Educational, Scientific and Cultural Organization, 2011), considers secondary education in two stages: lower secondary education and upper secondary education. Lower secondary education includes a curriculum designed to give a basic education to students after 6 years of primary/elementary education, and its standard duration is 3 years.

Upper secondary education is designed to prepare students for higher level academic or vocational studies, and its standard duration is 3 years. In line with the U.S. education system, this study uses the term “secondary education” to indicate a schooling system for Grades 7-12. This range includes junior high schools/middle schools, as well as (senior) high schools. The phrase “high school education” always refers to the senior high school level, rather than to junior high schools.

# CHAPTER 2 LITERATURE REVIEW

## Conceptual Models of Talent Development in STEM

The paradigm of talent development provides a conceptual framework explaining how talented high school students in math and science could successfully identify and develop their talents on the developmental trajectory. As an alternative to the traditional gifted education paradigm, which failed to explain how individuals transform potential in youth to outstanding accomplishment in adulthood, the talent development paradigm has emerged, using the concept of talent development pathways to link childhood potential with adulthood accomplishment (Dai & Chen, 2013). Distinct features included in talent development theories are summarized as follows:

- Giftedness/talent is demonstrated in a specific domain;
- Giftedness/talent is malleable along the continuum of the developmental process;
- Giftedness/talent developmental trajectories vary within, and between, domains;
- Creativity, productivity, and psychosocial variables matter for the successful development of talent;
- Expertise, eminence, and contribution to society in adulthood are the desirable outcomes of talent development.

Since the paradigm highlights the developmental process of talent in a specific domain, it is particularly fit for explaining why and how those who have academic potential in math and science could or could not develop their talents. Furthermore, this conceptual framework is concerned with career development beyond academic success in high school, and therefore provides an extended framework of talent development comparable with the career development process over a whole lifetime. In this section, I briefly introduce three key theories regarding talent and career development that are appropriate for explaining the talent trajectories of high-achieving high school students in math and science, and I suggest an integrated conceptual framework that was used in this study.

**Differentiated Model of Giftedness and Talent**

Gagné (1985; 2005; 2015) developed the Differentiated Model of Giftedness and Talent (DMGT) and has revised it over the years. A key concept in the DMGT is the differentiation between giftedness and talent; according to the theory, giftedness is closely linked to a person's natural abilities, demonstrated in at least one domain, and talent refers to systematically developed abilities (giftedness) in at least one field. The DMGT is a model explaining how giftedness transforms into talent. Gagné (2015) defined talent development as "the systematic pursuit by talentees, over a significant period of time, of a structured program of activities leading to a specific excellence goal" (p. 20). Learning and practice, in the talent development process, are important mechanisms that enable the transformation of giftedness into competence or expertise in a domain. Two catalytic factors (intrapersonal catalysts, environmental catalysts) and a chance factor determine the success or the failure of talent development. Intrapersonal catalysts include physical and mental traits, motivation, volition, and awareness of self and others; environmental catalysts include macro- and micro-level factors to do with the surroundings or milieu, and resources. Chance influences all the precedent factors for transforming talent that individuals cannot tightly control. The index of successful talent development is individual accomplishment above the 90th percentile among peers with a similar investment in the same field.

**Mega-Model of Talent Development**

The recently proposed mega-model of talent development (Subotnik et al., 2011) integrates compelling components of existing talent development theories. The model contains five key principles explaining talent development: (a) abilities are important and malleable; (b) developmental trajectories vary by domain; (c) opportunities should be offered to young talented individuals; (d) psychosocial factors determine the success of talent development; and (e) eminence is the desirable outcome of talent development. Providing multi-dimensional factors determining and influencing talent development, the basic framework of the mega-model is similar to the DMGT, but it extended the previous model by addressing the disconnect between childhood giftedness and adult eminence. In the model, the talent development process involves several transitions; potential in childhood transforms into competencies, competencies into expertise, and expertise into eminence in (late) adulthood. In the trajectories of specific domains, creativity has a crucial role in producing outcomes of excellence.

When applied to mathematical talent, the model provides important insights into secondary education from talent development perspectives. First, mathematical talents can be recognized early, and be demonstrated clearly by consistent achievement in adolescence. Second, those talents are developed by training and education in line with the schooling system. And third, psychosocial factors are important at every stage to make outstanding accomplishments.

**Social Cognitive Career Theory**

The Social Cognitive Career Theory (SCCT; Lent, Hackett, & Brown, 1994; 1996) explains how individuals form their career interests, perform, and make decisions on a career path. Although the model is not a talent development theory, given the fact that talent is a developmental concept, which transforms into adulthood achievement and expertise in a domain, this career development model provides an important insight to elaborate on the missing pieces when explaining talent development beyond adolescence. In fact, the SCCT framework can be appropriately applied in cases regarding academic interest, choices, and performance. Lent and his colleagues (2004) explained the reasons for the conceptual overlap between academic and career development, as well as the continuum for the school-to-work transition of students. Due to the strength of their reasoning, the SCCT has been widely used as a conceptual foundation in studies regarding the transition into postsecondary education, and persistence in a career domain after high school graduation, particularly in STEM fields.

The model was designed to integrate, in a parsimonious manner, numerous psychological and social variables used in a variety of career development models (Lent, Brown, & Hackett, 2004). Principally inspired by Bandura's social cognitive theory (1986), this model emphasizes the role of the interplay between cognitive processes and social processes in influencing an individual's behavior in career development. Like other talent development models, a key concept of the SCCT is the interaction between person and environment, determining overt actions, which influence situations, and in turn influence thoughts and behaviors relevant to career development.

Three central variables are incorporated in the SCCT: (a) self-efficacy, (b) outcome expectations, and (c) personal goals. The concept of self-efficacy is derived from Bandura's theory, and refers to an individual's beliefs about their capabilities "to organize and execute course of action required to attain designated types of performances" (Bandura, 1986, p. 391). Self-efficacy is acquired and continuously modified through personal performance, vicarious learning, social persuasion, and physiological and affective states. Of these four sources, personal performance is the most influential. Outcome expectations are the beliefs "about the consequences or outcomes of performing particular behaviors" (Lent et al., 2004). Like self-efficacy, outcome expectations can be acquired through learning experiences. A goal is defined as "the determination to engage in a particular activity or to affect a particular future outcome" (Lent et al., 2004).

Those three key variables come into play in three interlocking models concerning career interest, choice, and performance: (a) the interest development model, (b) the career choice model, and (c) the performance model. Interest is an important determinant for career choice and performance. Individual environment, experiences, self-efficacy, and outcome expectations crucially influence the formation of career interests. The career choice model incorporates the developmental process of career interest, which influences career choice actions and performance. In the performance model, the level of accomplishment and persistence in a career is defined by the outcome of the interaction between previous performance/ability, self-efficacy, outcome expectations, and performance goals.

Another important facet of the SCCT is that it offers an explanation for the roles of sex, race, and other socioeconomic factors in career development. Lent and his colleagues viewed these factors from a social constructivist perspective, in which individuals internalize the social influence of the factors. These socially constructed factors influence learning experiences and contextual influences, and moderate career interests, goals, choices, and career choice actions.

**Theoretical model of the study**

Integrating the three promising conceptual models that explain talent and career development, this study offered a hypothetical model for talent and career development specifically in math and science during adolescence and early adulthood including both secondary and postsecondary education. In this study, I concentrated on college bound students who achieved well in math and science during high school, and I identified those students by their scores on standardized college entrance exams. Good achievement in college entrance exams, particularly in math- and science-related subjects, is mostly required to be admitted into colleges in STEM fields. Not only that, but achievement in such subjects is important for providing fundamental background knowledge for continued studies in STEM fields. Therefore, I hypothesized that students who were interested in STEM fields beyond secondary education were likely to prepare for, take, and achieve highly on those exams. Furthermore, given that explicit achievement in an academic domain should be demonstrated on a talent development trajectory by late adolescence (Feldhusen, 2005), college entrance exams in math and science can be used as appropriate indices to identify talented students who are likely to enter, persist in, and achieve well on STEM pathways.

Within the scope of talent development theories (e.g., Gagne, 2005; Feldhusen, 2005; Subotnik, Olszewski-Kubilius, & Worrell, 2011), three milestones should be achieved during adolescence and early adulthood for talent development in academic domains such as mathematics and science. These are as follows: (a) the identification of personal potential within a domain, (b) the development of potential into competence and early expertise through training and education, and (c) the explicit demonstration of career decisions within the domain. Since developing talents in math and science mostly relies on schooling systems, the roles of secondary and postsecondary education are especially important because achievements, psychosocial attitudes, commitment, and career goals become more evident during this period (Feldhusen, 1998; 2005).

Figure 1 represents the theoretical model of this study. This study restricted the sample to college bound high-achieving students in math and science, identified through twelfth-grade standardized achievement college admissions test scores in math and science. In accordance with research purposes, the theoretical model shows controlled effects: how and why talented students in math and science, after achieving well in high school, develop or don't develop their talents. I assumed that environmental factors, experiences of advanced learning in the domain, and psychosocial development during secondary education crucially influenced those talented adolescents' career decisions and achievements in college. Environmental factors included student-level factors (sex, race, SES) and school-level factors (school average SES, and school climate, particularly regarding academic pressure) that a student cannot control. These factors interplay with controllable factors: motivation (mathematics self-efficacy), the math and science learning experience in high school (influenced by taking advanced courses in math and science), and the learning experience in postsecondary institutions (including STEM course-taking, high-impact activities). To limit the effects of variations between the advanced courses that secondary school students can take for their talent development, this study restricted consideration of advanced courses to AP and IB courses, given that those programs were relatively standardized. I also hypothesized that motivation and learning experiences not only influenced desirable outcomes in postsecondary education in STEM fields, but also moderated the risk factors and impetus of environmental factors in the pursuit of STEM studies. Three important outcome variables were measured in the lives of those who had been on postsecondary STEM paths: first, entrance into STEM fields; second, graduation from postsecondary institutions with a STEM major; and third, further persistence, such as having a job in STEM fields and/or continuing STEM studies in graduate schools. The years in the timeline in Figure 1 represent the time at which students were likely to experience each event or the time at which the psychological variables were measured.

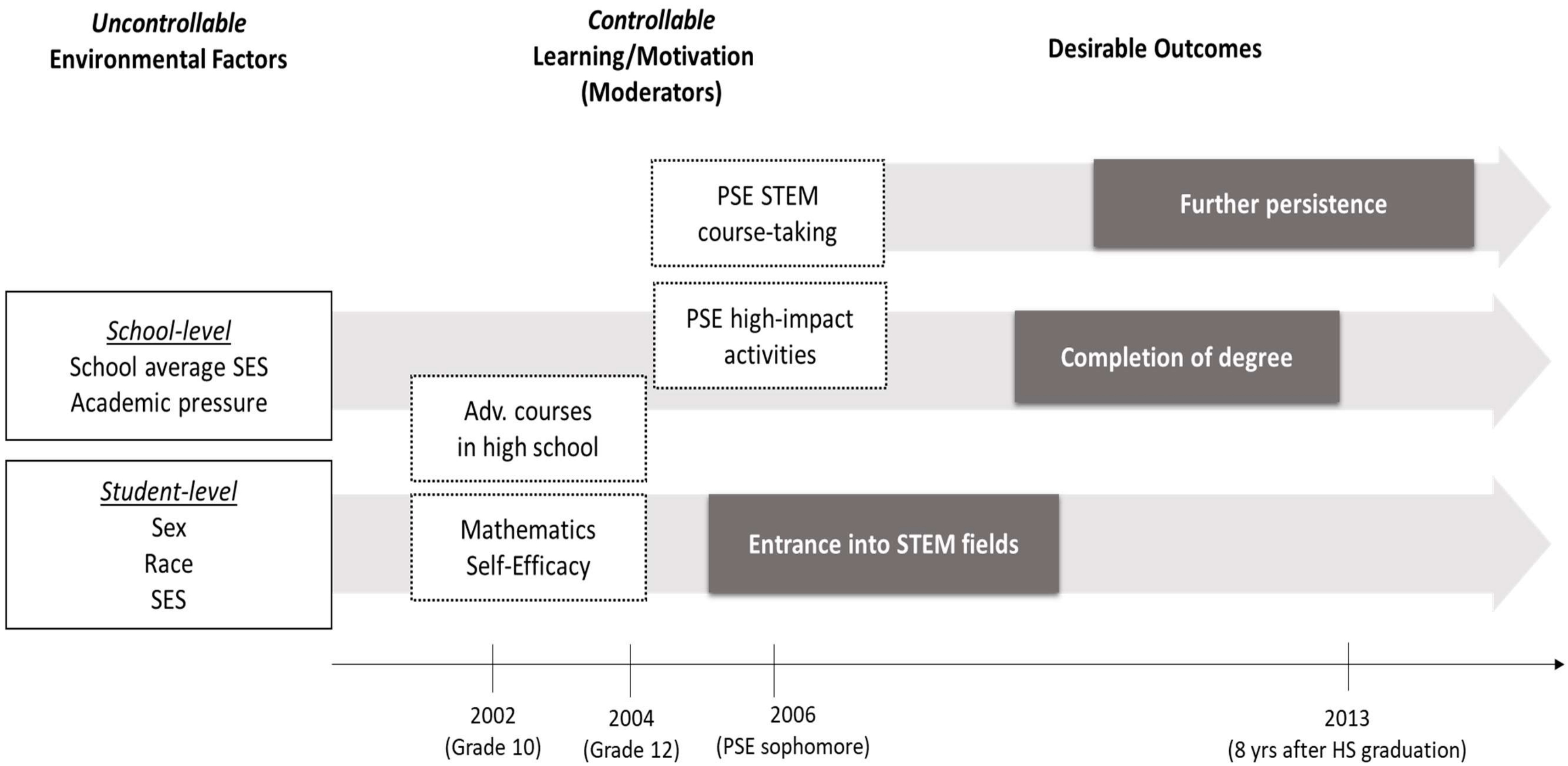


*Figure 1.* *Theoretical Model of the Study: A Talent Development Path in STEM. "Adv. Courses in high school" is college-preparatory courses in math and science such as AP and IB. PSE= postsecondary education.*

## STEM Pathways

The metaphors of “pathway” and “path” are commonly used in the STEM education literature. Both terms indicate “a trail that one (a student) constructs along contours of the terrain” (Adelman, 1999, p. 10); in other words, they indicate academic and career paths that are created by students. Since the fields of STEM usually require postsecondary education for talent development, success in postsecondary paths has been the major concern of the literature. Entrance, persistence, and performance are three key outcome variables in research on postsecondary STEM pathways. Those three outcome variables are also in line with the literature of talent and career development; talented high school students in math and science are expected to get into postsecondary institutions to continue their studies; they are expected to build strong competencies in postsecondary institutions; they are expected to complete a degree while demonstrating early expertise in STEM, and eventually to successfully proceed onto expert-level paths (graduate schools or the workplace).

Given the calls for research investigating the reasons why the STEM pipeline is leaking in the U.S. (e.g., NSB, 2010), many researchers have investigated how and why U.S. students enter or do not enter, persist or give up, and achieve or underachieve in postsecondary STEM education. The “why” questions were particularly well discussed within the literature. Researchers studying STEM pathways have investigated the positive and negative factors surrounding students that influence their entrance into, and performance on STEM paths. In this section, I summarize the findings and research models of empirical studies regarding those three key outcome variables in postsecondary STEM paths. The literature that took these key outcomes as dependent variables and explored the factors that influence them is reviewed in Table 1.

**Entrance**

Despite the abundance of literature regarding college students' persistence in and completion of postsecondary STEM education, academic choices and students' entrances into STEM paths have received less focus (Wang, 2013). Although the number of studies is limited, high school achievement and the study of math and science curricula have been found to be consistent predictors of student choice regarding entrance into STEM studies at colleges and universities (e.g., Adelman, 1999; Nicholls et al., 2007; Seymour & Hewitt, 1997; Wang, 2013). In particular, curricula emphasizing math and science were positively associated with entrance into STEM fields (Adelman, 1999). Wang (2013) used a structural equation model based on the SCCT, and found that student achievement in math in grades 10 and 12 positively influenced a student's intent to major in a STEM field, finally leading to the student entering a STEM field during postsecondary education. He also found that a positive interplay between high school math achievement and mathematics self-efficacy increased the chances of entrance into STEM. In terms of student background, male students, students financially dependent on family, students whose parents received higher education, White and Asian students, and students who didn't need to work were more likely to enter a STEM major (e.g., Chen & Weko, 2009; Gruca, Ethington, & Pascarella, 1988; Wang, 2013). These findings are consistent with the talent and career development theories, and are particularly in line with the SCCT; learning experiences and motivation facilitate talented students choosing STEM majors in college.

**Persistence**

It has been a national problem that more than half of the college students who at one point declared a STEM major later withdrew their academic choice during their postsecondary education (e.g., Chen, 2009; Higher Education Research Institution, 2010; Lowell, Salzman, Bernstein, Henderson, 2009; National Science Board, 2012). In the literature, persistence in a STEM field after declaring a STEM major during postsecondary education is usually referred to as enrollment status in a STEM major. In studies, the periods of observation were usually 4 to 6 years of undergraduate programs. Given this time span, persistence status is a variable that can change with time; it indicates enrollment status in a STEM major between the declaration of a study major and the end of the study (college graduation in the field). It is usually presented as a dichotomous variable (e.g., 1 = enrolled in a STEM major or graduated, 0 = dropped out of school or switched to another major).

The underlying factors of STEM persistence in postsecondary education can be categorized into two groups: high school factors and postsecondary education factors. In terms of high school factors, achievement and a rigorous math and science curriculum were consistently associated with STEM persistence (e.g., Chang, Sharkness, Hurtado, & Newman, 2014; Chen & Soldner, 2013; French, Immekus, & Oakes, 2005; Mendez, Buskirk, Lohr, & Haag, 2008; Watkins, 2013). Affective and motivational factors also played important roles towards student persistence. Eris, Chachra, Chen, Sheppard, Ludlow, Rosca, Bailey, and Toye (2010) found that the students who persisted in an engineering major had greater confidence in their math and science skills, and had experienced mentoring during high school. Intrinsic motivation in academic domains was also significantly associated with persistence in STEM fields (French et al., 2005).

In terms of postsecondary education, students who had fewer credit hours and performed poorly in STEM majors were more likely to switch to other majors (Chen & Soldner, 2013). In contrast, research project experience and an intensive STEM major curriculum were positively associated with persistence. Like other educational outcomes, individual variables that students could not control were also found to negatively influence STEM persistence. After declaring their major in STEM, students were more likely to drop out from their STEM paths if they were female, had a father whose education level was lower, or were Black and Hispanic students (Chimka et al., 2008; Min, Zhang, Long, Anderson, and Ohland, 2011; Zwick & Sklar, 2005).

**Performance and future career choice**

More desirable outcomes are achieved when students have high academic performance in college, and make career choices in STEM beyond a bachelor's degree, than from mere entrance and persistence in the fields while attending college. Given that talents should be explicitly and consistently demonstrated in different forms of achievement and accomplishment from early adulthood (Subotnik et al., 2011), college performance is a crucial index for predicting a successful path in a STEM field. French, Immekus, and Oakes (2005) used a hierarchical linear model to examine the effects of cognitive and non-cognitive factors on college GPA in STEM fields. Adopting a stepwise procedure, they found that SAT scores, high school rank, and sex (female) were the best predictors for college achievement. Motivation and integration were less important than those variables. Tyson (2011) examined the factors influencing high or low achievement in college-level physics and calculus, using multinomial logistic regression models, and found that the taking of calculus courses in high school was the strongest predictor.

As is the case concerning college entrance and achievement, further career choices in STEM fields after college graduation are critical on the continuum of talent development for math and science talents. The Study of Mathematically Precocious Youth (SMPY) provided empirical evidence regarding the career choices of high-ability students in mathematics who were identified and educated in their youth. Benbow and Arjmand (1990) categorized these high-ability students by their academic and career performance. High-achieving groups contained individuals who attended graduate school for mathematics or sciences, or who attended medical schools. Low-achieving groups contained individuals who majored in science but finished with a low GPA, or who dropped out of college, or who did not complete high school. Using stepwise linear discriminant function analysis, they found that great performance during college preparation (AP math and science courses, college courses in math and science taken during high school, college-level exams), being encouraged to attend college, and having positive attitudes toward mathematics played important roles in high achievement beyond college graduation.

Lubinski, Webb, Morelock, and Benbow (2001) sampled 320 exceptionally high-ability students who scored over 700 in SAT math and over 630 in verbal before the age of 13, and tracked them for ten years after the base-year study. They found that the participants were likely to pursue doctoral degrees (at a rate more than 50 times the base rate expectation in the U.S.), and were more likely than their peers to achieve scientific, technical, or occupational accomplishments by their early 20s (e.g., scientific publications, software development, inventions). Among precocious SMPY cohorts, students who scored higher on SAT math were more likely to achieve occupational accomplishments in STEM fields than other students of the cohort (Park, Lubinski, & Benbow, 2007; 2008). Ability patterns were also important for determining academic and career choices. Lubinski et al. (2001) compared three ability patterns using SAT math and verbal scores (i.e., high-math, high-verbal, and high-flat groups), and found that a high ability in math before the age of 13 was associated with the pursuit of science and technology in course preferences at high school, and choice of major at college.

The subsequent SMPY studies highlighted the important roles played by preferences, motivational factors, and educational experiences during adolescence in advancing occupational accomplishment in adulthood. Achter, Lubinski, Benbow, and Eftekhari-Sanjani (1999), using discriminant function analysis, found that a study of value, such as the value placed in theoretical, aesthetic, social, religious, or economic studies, in conjunction with SAT scores obtained at the age of 13, could predict college majors. They grouped participants into three categories based on their college major: humanities, math or science, or something else. The results showed that students who scored higher on SAT math and considered theoretical and economic studies to be important were more likely to study college majors related to math or science than other students. Robertson, Smeets, Lubinski, and Benbow (2010) also argued that a study of vocational interests refined the prediction of academic and career choices and lifestyle preferences were a likely indicator of career persistence. Regarding Advanced Placement (AP) programs, Bleske-Rechek, Lubinski, and Benbow (2004) found that more than 70% of participants who had taken one or more AP courses or exams had later completed a graduate program, as opposed to 43% for students who had not taken those courses.

**The scope of the study**

In summary, high school achievement in math and science, as indicated by either high school GPA or standardized test scores (e.g., SAT math), is known to be the best predictor of entrance, persistence, and performance in postsecondary STEM education (e.g., Adelman, 1988; Astin, 1993; Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpkiattaworn, 2007; Zhang, Anderson, Ohland, & Thorndike, 2004). This means that high achievers in high school math and science are most likely to select, persist in, and achieve well on STEM pathways. However, little is known about the pathways after controlling for the effects of high school achievement; in other words, it is unknown whether or not the developmental and career decision patterns of high achievers are the same as for average-achieving students. It is important to fill in the missing pieces because talented students are more likely to persist and succeed in STEM fields than average achievers, and understanding their unique needs may be the first important task to promote their talent and career development.

Table 1

*A Review of the Factors Influencing Postsecondary STEM Paths*

| Study | Data | DV/Grouping | Analytic Method | Significant IV |
|---|---|---|---|---|
| *Entrance* | | | | |
| Adelman (1999) | High School & Beyond/Sophomore (HSBS) | Entrance into STEM fields | Correlation | High school math and science curriculum |
| Nicholls et al. (2007) | Cooperative Institutional Research Program | The time students first registered in STEM/students who would be pursuing a non-STEM degree | Independent t-test | SAT math score<br>High school GPA<br>Self-ratings of mathematical ability, computer skills, academic ability |
| Wang (2013) | Educational Longitudinal Study:2002 (ELS:2002) | Entrance into STEM fields of study within 2-years of high school graduation | SEM | 12th-grade math achievement<br>Exposure to math and science courses<br>Math self-efficacy beliefs<br>College readiness in math and science<br>Financial aid<br>Enrollment intensity<br>Academic interaction<br>Having children<br>Work hours |
| *Persistence/Attrition* | | | | |
| Burtner (2005) | Pittsburgh Freshman Engineering Attitudes Survey | Enrollment status in engineering school | Discriminant function analysis | Expectations and perception of the engineering profession<br>Confidence |

(Continued)

Table 1 Continued

| Study | Data | DV/Grouping | Analytic Method | Significant IV |
|---|---|---|---|---|
| Chen & Soldner (2013) | Beginning Postsecondary Students Longitudinal Study & Postsecondary Education Transcript Study | Leaving a STEM major | Multinomial probit model | Precollege preparation<br>Institution first enrolled<br>STEM courses<br>STEM performance |
| Chen & Soldner (2013) | Beginning Postsecondary Students Longitudinal Study, Postsecondary Education Transcript Study | Switching to another major | Multinomial probit model | Fewer credit hours in STEM<br>Poor performance in STEM |
| Chimka, et al. (2008) | Collected by study | Declaring and persisting with a STEM major until graduation | Hazard/Survivor model | SAT math scores<br>ACT science scores<br>Gender |
| Eris et al. (2010) | Persistence in Engineering (PIE) | Persistence status: those who either graduated or are still working toward graduation in an engineering degree | Repeated measure ANOVA | High school mentor<br>Confidence in math and science skills<br>Confidence in professional and interpersonal skills<br>Confidence in solving open-ended problems<br>Perceived importance of math and science skills<br>Exposure to project based learning |
| French et al. (2005) | Collected by study | University enrollment & enrollment in an engineering major | | GPA<br>SAT math scores<br>High school rank<br>Intrinsic motivation |

(Continued)

Table 1 Continued

| Study | Data | DV/Grouping | Analytic Method | Significant IV |
|---|---|---|---|---|
| Min et al. (2011) | Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFEILD) | The hazard of leaving engineering fields | Hazard/Survivor model | SAT math scores<br>Gender<br>Ethnicity |
| Mendez et al. (2008) | Collected by study | Declared and graduated with a STEM major | Logistic regression | High school GPA<br>Freshman year GPA<br>Number of science and engineering courses taken |
| Nicholls et al. (2010) | National Educational Longitudinal Study of 1988 (NELS:88) | STEM path departure and time of leaving/Graduation | Logistic regression & hazard/survivor model | Standardized test scores (ACT, SAT)<br>Measures of skill and performance in math and science classes<br>Family composition<br>Native language<br>Type of high school<br>Father's highest education level<br>Student expectation for educational attainment<br>Ethnicity<br>Gender |
| Tyson et al. (2007) | Florida Longitudinal Education and Employment Dataset | Graduated with a STEM major | Logistic regression | Mathematics course-taking<br>Science course-taking variables |
| Watkins et al. (2013) | Collected by study | Retention for 6 years | Logistic regression | SAT math scores<br>ACT composite scores<br>Average load aid<br>Average gift aid<br>Cumulative GPA |

(Continued)

Table 1 Continued

| Study | Data | DV/Grouping | Analytic Method | Significant IV |
|---|---|---|---|---|
| Zhang et al. (2004) | Southeastern University and College Coalition for Engineering Education | Graduation in engineering | Logistic regression | High school GPA<br>SAT math scores<br>SAT verbal scores<br>Citizenship |
| *Performance and Further Career* | | | | |
| French et al. (2005) | Collected by study | College GPA of engineering students | HLM | SAT verbal scores<br>SAT math scores<br>High school rank<br>Gender |
| Tyson (2011) | Florida Department of Education PK-20 Education Data Warehouse | Achievement in college physics and calculus | Multinomial logistic regression analysis | High school calculus achievement |
| Benbow & Arjmand (1990) | Study of Mathematically Precocious Youth (SMPY) Cohort 1 | High achiever group: attending graduate school in math and science, or attending medical school<br>Comparison group: having low college GPA, dropping out of college, or failing to complete high school | Discriminant function analysis | AP math and science courses<br>College courses in math and science taken as a high school student<br>College-level exams<br>Encouragement to attend college<br>Parental education levels<br>Attitude toward mathematics |
| Achter et al. (1999) | SMPY | Math and science college major | Discriminant function analysis | Study of values – theoretical, analytic<br>SAT math scores |

## Achievement as an Index for Identifying Talents

Under the No Child Left Behind (NCLB, 2001) act and the Every Student Success Act (ESSA, 2015), achievement tests have been used in schools across the U.S. more than ever before. These tests are used not only to compare the scores of students within a grade and across different grades, but also to make diagnostic and high-stakes decisions concerning educational settings (Kubiszyn & Borich, 2010). In gifted and talented education, standardized achievement test scores have frequently been used, in addition to the use of IQ or aptitude tests, to identify students with high ability (Ziegler & Raul, 2000). The 2014-2015 State of the States Report (National Association for Gifted Children & The Council of State Directors of Programs for the Gifted, 2015) reported that achievement is the second most commonly used criterion in the states for the identification of gifted children after multiple criteria.

Unlike IQ and aptitude tests, which measure the extent to which a student is capable, achievement tests measure what students have learned. Pyryt (2004) found that the use of achievement test scores was an effective method for identifying gifted students. Pyryt, using discriminant function analysis, examined whether multiple criteria, including group-administered IQ scores, achievement test scores, honor roll status, teacher nomination, arithmetic ability, leadership ability, artistic ability, and musical ability, could correctly distinguish between those students already identified as gifted, and those of average ability. Use of the criteria could correctly classify 78.1% of the gifted students, and group-administered IQ tests as well as achievement test scores were the most effective predictors for identifying gifted students. The standardized discriminant function coefficient was .55 for group IQ scores and .52 for achievement test scores.

From the perspective of talent development in early adolescence, the Talent Search model, developed by Julian Stanley, used standardized achievement tests for above-grade-level testing to identify mathematically precocious youth. The SMPY adopted the identification model from the Talent Search, employing two steps in an identification procedure using standardized tests. In the first step, the study selected the students of grades 7-8 who scored in the top 3% on standardized achievement tests usually administered in schools. In the second step, those selected students took the SAT, an out-of-level test for which they had no preparation. The study then refined the selection to include only those students who scored 500 or higher on the SAT (Cohort 1), and 700 or higher (Cohort 2) (Lubinski & Benbow, 2006). Based on the above-grade-level scores, the SMPY provided these talented students with accelerated programs. In longitudinal studies lasting 20-years and 35-years (Benbow, 1990; Benbow, 1992; Lubinski & Benbow, 2006; Lubinski, Webb, Morelock, & Benbow, 2001; Robertson et al., 2010; Wai, Lubinski, & Benbow, 2005), the researchers found that these precocious youths were more likely to choose academic career paths and succeed in STEM fields compared with the base rate in the U.S. Furthermore, Cohort 2, consisting of those students who scored 700 or higher on the SAT, were more likely to earn a higher income and to have patents and tenure-track positions by the time they were middle aged, compared with the U.S. base rate.

In the gifted education literature, the cutoff scores for identifying high-achieving students are not fixed across studies; rather, the cutoff scores on achievement tests have ranged from the 90th percentile to the 97th percentile (Dai, 2013; Reis & McCoach, 2000; Ziegler & Raul, 2000). Although it is not explicitly mentioned in talent development theories, standardized achievement test scores are mainly appropriate for identifying talented students beginning in late adolescence, as by this point talented individuals can be expected to have attained a certain level of expertise and to be gaining explicit achievements, rather than just exhibiting potential.

## Factors Associated with Postsecondary STEM Pathways

A number of factors are associated with postsecondary STEM pathways as shown in Table 1. Among them, a rigorous high school curriculum and student motivation are the most frequently mentioned variables. In this section, I illustrate how the moderating and independent variables of this study were conceptualized using the literature, and how those variables were found to be associated with dependent variables on STEM pathways.

### College-level courses in math and science

Advanced Placement (AP) and International Baccalaureate (IB) diploma programs are college-preparatory courses offered to high school students. Both programs provide advanced level courses in line with high school curricula to facilitate students in preparing for college-level academics, but the foci of the two programs are somewhat different.

The AP program was developed in the United States in 1955, and has been administered in response to the issue that high schools did not provide enough quality, challenging courses to high-achieving students, and almost half of high school graduates who went to college did not graduate from there (Potter & Lena, 2000). The AP program offers 38 college-level courses, and exams in 20 subjects. Students choose the courses by consulting with their teachers or counselors, and take the courses in schools that have been audited by the College Board to ensure the quality of the AP curriculum. After taking the courses, students can also take AP exams, but taking the exams is not required. AP exams are intended to indicate readiness for placement in introductory college courses. Thus, the scores can be used not only for college admissions, but also for granting exemptions from introductory courses in colleges. A score above 3 (out of 5) is usually considered equivalent to the completion of a college-level course (College Board, 2016).

The International Baccalaureate Diploma Programme (IB or IBDP) was developed in Europe to provide an internationally standardized, rigorous college-preparation curriculum for high school students. The IB program provides a high-level curriculum that helps students to have a more holistic and in-depth mindset when entering academia. The program is composed of six subject groups, and students must take six subjects, three or four of which should be higher-level courses. Students must also meet three core requirements (Extended Essay, Theory of Knowledge, and Creativity, Activity, Service) and pass the subject exam to receive an IB diploma. Unlike students who usually take two or three AP courses a year in grades 11 and 12, IB candidates enroll in IB prep courses in grades 9 and 10, and in full courses in grades 11 and 12. Students who do not pursue the IB diploma can still take individual IB courses.

College-prep programs have been dramatically growing during the last sixty years. In 2016, approximately 2,600,000 students from grades 9 to 12, and across 21,953 schools, took AP exams. This number of students is almost double that of ten years ago, and triple that of fifteen years ago (College Board, 2016). Although the number of participating students in the U.S. is smaller than that of the AP program, the IB program has also been growing throughout the world as well as in the U.S. (International Baccalaureate, 2014). The growth in both programs is associated with several factors. First, the programs were systematically standardized across teachers and schools under the coordination of their respective agencies (e.g., College Board, IB), so that the quality of the curriculum is consistently maintained across schools. It signifies reciprocal benefits for students and schools; students, particularly those who are achieving above-grade-level and who are ready to study a college-level curriculum, can have advanced opportunities to learn through the readily available curriculum. At the same time, AP and IB courses are options that schools can provide to high-achieving students with fewer concerns about the personnel and resources needed to develop and implement quality advanced courses (Kyburg, Hertberg-Davis, & Callahan, 2007).

Second, the programs and exams have cumulative validity, particularly in terms of predictive validity. Although variations exist in the study findings, it is widely accepted that students who have taken AP courses and scored 3 or above on the AP exams are more likely to succeed in college and on their academic paths than students who have not taken those courses or exams. Taking courses in either program was associated with degree completion in college (Adelman, 1999; Mattern, Marini, & Shaw, 2013; Mathews, 2004) and with improved grades in similar college courses (Ewing & Howell, 2015; Keng & Dodd, 2008; Krista, Shaw, & Xiong, 2009; Murphy & Dodd, 2009; Patterson & Ewing, 2013). In addition, taking AP courses in biology, calculus, chemistry, and physics was associated with career choices in STEM fields after college graduation (Robinson, 2003). Based on the cumulative predictive significance, universities in the U.S. have recently allowed undergraduates who took AP programs and scored 3 or above on AP exams to be exempt from introductory courses in college (Lichten, 2007).

Another potential benefit of AP and IB courses is their relative accessibility to students, including those who have disadvantaged backgrounds (e.g., students from families in poverty, students attending schools with large proportions of low-achieving students). AP and IB courses are even available to students who do not attend high school but want to prepare for college entrance. Although students who are Black, Hispanic, and American Indian/Alaskan Native, and students who come from low-income families are still underrepresented on AP programs (College Board, 2014), some researchers in education have argued that participation in AP programs might be still beneficial for those students' academic growth (Burton, Whitman, Yepes-Baraya, Cline & Kim, 2002; Kyburg, Hertberg-Davis, & Callahan, 2007).

In terms of math- and science- related courses, the AP offers five courses in math and computer science, which include Calculus AB, Calculus BC, Computer Science A, Computer Science Principles, and Statistics, and seven courses in sciences, which include Biology, Chemistry, Environmental Science, Physics C: Electricity and Magnetism, Physics C: Mechanics, Physics 1: Algebra-Based, and Physics 2: Algebra-Based (College Board, 2016). The IB program offers two subject groups related to mathematics and science: experimental sciences, which includes Chemistry, Biology, Physics, Design Technology, Computer Science, and Environmental Systems and Societies, and mathematics, which includes Mathematical Studies at Standard and Higher levels. High school course-taking experiences in AP and IB math and sciences have been associated with entrance, persistence, and performance on postsecondary paths in general academic fields (e.g., Ewing & Howell, 2015; Mattern, Marini, & Shaw, 2013; Murphy & Dodd, 2009; Patterson & Ewing, 2013), as well as in STEM fields (Andersen & Ward, 2012; Ackerman, Kanfer, & Calderwood, 2013; Shaw & Barbuti, 2010; Tyson et al., 2007; Robinson, 2003). Ackerman and his colleagues (2013) found that participation in AP STEM courses was positively associated with college GPA, STEM persistence, and graduation rates. Robinson (2003) found that students of underrepresented races who took AP calculus and/or science courses in high school were more likely to select engineering majors.

**Motivational factor: mathematics self-efficacy and the big-fish-little-pond effect**

***Mathematics Self-Efficacy***

Mathematics self-efficacy (MSE) is defined as "a situational or problem-specific assessment of an individual's confidence in her/his ability to successfully perform or accomplish a particular task or problem” (Heckett & Betz, 1989, p. 262). MSE, based on the framework of the Social Cognitive Career Theory (Lent et al., 1994), has received much attention in educational research because of its ability to predict desirable outcomes in education. In terms of student performance in mathematics, MSE has been found to predict not only achievement in mathematics, but also key components in learning processes, such as choosing to do math-related tasks, problem-solving in mathematics, persistence in solving difficult problems, and attitudes towards mathematics during secondary education (Betz & Hackett, 1983; Hackett & Betz, 1989; Hoffman & Schraw, 2009; Pajares & Miller, 1995; Randhawa, Beamer, & Lundberg, 1993). Furthermore, MSE has become known as a key factor influencing student performance and career/academic decisions beyond secondary education, particularly in STEM fields. MSE can also be good predictor of interests, goals, choice of major, persistence, and performance on postsecondary STEM paths (See the review of Lent, Sheu, Singley, Schmidt, Schmidt, & Gloster, 2008). Zeldin and Pajares (2000) identified MSE as a crucial factor in leading women to be successful in STEM careers, many of which are in male-dominated fields.

In addition to MSE’s ability to directly predict various desirable outcomes, MSE has also been extensively studied as a moderator when factored into relationships between other variables. In psychological and educational research, a moderator is referred to as a variable that “affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable” (Baron & Kenny, 1986, p. 1174). Baron and Kenny (1986) provided an example of a moderating variable in the controllability of life events, which affected the relation between life-event change and the severity of an illness. Brown, Lent, and Larkin (1989) found that efficacy beliefs moderated low-aptitude students’ persistence and performance across a variety of STEM majors. Specifically, students who had lower levels of aptitude but had high levels of self-efficacy received GPAs one standard deviation higher than students who had lower levels of aptitude and also had low levels of self-efficacy. Hackett (1985), using a path analysis model, found that a student's choice to enroll in an undergraduate major in a math or science related area could be mediated by MSE. In other words, MSE levels explained why there was a relation between high school math achievement (ACT math scores and high school math GPA) and choice of college major. After controlling for the effect of MSE, the relationship between high school math achievement and choice of college major became non-significant.

The sources of MSE and self-efficacy in academic settings in general have also been studied across a variety of age-groups and domains (See the review of Usher & Pajares, 2008). Theoretically, self-efficacy beliefs are formed and changed as a student interprets information from four sources, including mastery experience, vicarious experience, verbal and social persuasions, and emotional and physiological indexes (Bandura, 1986, 1977). Of the four sources, mastery experience is the most important source. As an example of mastery experience, a student can strengthen his/her beliefs that the effort put into completing a task is worth repeating on a similar task if the first task was a success. The vicarious experiences gained through observing others also influence the formation of self-efficacy by providing normative comparisons. The verbal and social persuasions from significant others (e.g., parents, teachers) as well as emotional and physiological states (e.g., stress, anxiety) are also sources of self-efficacy. In secondary education settings, school experiences incorporating these four factors are crucial in shaping student self-efficacy. To be specific, secondary school students are influenced by the classroom environment, the structure of instruction, their teacher's self-efficacy, and their peers in the development of their MSE (Schunk & Meece, 2005). For example, in a competitive classroom that uses more achievement comparisons, students are more likely to decrease in self-efficacy, especially if those students feel that their achievement is not satisfactory (Schunk & Meece, 2005). Usher and Pajares (2006) found that middle school girls tended to rely on social persuasions (information from others) in their formation of self-efficacy.

One important note concerning research into mathematics self-efficacy is that one should be cautious when selecting measures of MSE and outcome variables. Bandura (1986) cautioned, “ill-defined global measures of perceived self-efficacy or defective assessments of performance will yield discordances” (p. 397). Pajares and Miller (1995) elaborated the argument, suggesting “measures of self-efficacy should be specifically tailored to the criterial task being assessed and the domain of functioning being analyzed” (p. 190). Pajares and Miller showed that the specific details or examples given in the written context of MSE assessments (e.g., mathematics problems, tasks, courses) differently predicted the outcome variables. Efficacy beliefs specific to math-related courses were more strongly associated with choosing math-related majors than efficacy beliefs specific to other contexts (i.e., mathematics tasks, problems). But efficacy beliefs regarding solving mathematics problems were associated with performance in math problem solving. Schunk and Meece (2005) also argued that the inconsistency of findings in self-efficacy studies, particularly studies from developmental perspectives, may be due to variations in the specificity of MSE measurement across a range of domains and tasks.

### ***Big-Fish-Little-Pond Effect***

The big-fish-little-pond effect (BFLPE) refers to students’ lowered levels of academic self-concepts when exposed to learning environments with relatively higher-achieving students (Marsh, 1987). More recently, BFLPE has been investigated in terms of its stability over time, particularly focusing on transition from elementary to secondary school, and one from high school to postsecondary education. Prior studies found that the BFLPEs persisted for more than two years after secondary school graduation, which negatively influenced vocational training, postsecondary education, educational achievement, and occupational aspirations (Marsh & O'Mara, 2010; Marsh, Trautwein, Lüdtke, Baumert, & Köller, 2007). The BFLPE has not yet been studied regarding postsecondary STEM paths. However, since this study concentrated on postsecondary paths of high-achieving students, it is assumed that high-achieving students' academic self-concept might be influenced by more homogeneous environments in postsecondary STEM paths after transition from secondary education to postsecondary education, and which is also assumed to influence those students' persistence and achievement in STEM paths.

### Coursework and high-impact activities in postsecondary education

As summarized in Table 1 with regard to a student's postsecondary education experience, taking courses in STEM fields is another important factor influencing student persistence and achievement in college STEM majors. Chen and Soldner (2013) found that the intensity of STEM course-taking and the type of math courses taken in the first year of an undergraduate program were associated with persistence in STEM fields during postsecondary education. They also found that taking fewer courses, taking less challenging courses, and withdrawing from or failing courses in STEM majors were associated with switching to non-STEM majors. However, research project experience and an intensive STEM major curriculum were positively associated with persistence.

### Individual backgrounds

#### *Sex*

Gender differences within STEM pathways have been studied, and it is widely accepted that female students are less likely than male students to begin, persist, and complete STEM-related degrees in postsecondary education (e.g., Astin & Astin, 1993; Besterfield-Sacre et al., 2001; Cassell & Slaughter, 2006; Tyson et al., 2007; Zhang et al., 2004). Although a few researchers have argued that the gaps between male and female students have been narrowing in STEM education (e.g., Hill, 2007; Huang et al, 2000; Davenport, Davison, Kuang, Ding, Kim, & Kwak, 1998), most the studies with a large data set still show an underrepresentation of females in the fields.

Some researchers investigated the reasons why female students were less likely to enroll, persist in, and complete STEM paths. A number of qualitative researchers found that psychosocial factors, rather than cognition or ability, significantly influenced sex differences. Erwin and Maurutto (1998), in their qualitative study, found that traditional attitudes towards sex roles, low self-esteem, and a male-dominated learning environment influenced low college enrollment and low persistence among female students in STEM fields. Wang (2011) found that the mathematics self-efficacy of female students was lower than among male students, despite comparable achievements. Davenport and his colleagues (1998) argued that the rigor and contents of the coursework affected the sex, rather than the number, of students; specifically, female students were less likely to take physics but more likely to take biology and chemistry.

Longitudinal studies from the SMPY provided several findings regarding the distinctive paths of female students identified as high-achieving in math and science. Lubinski and Benbow (2006) found that, compared to their male counterparts, high-ability female students less frequently entered STEM careers requiring higher degrees and expertise, but the entry rates were much closer for careers and advanced degrees in non-STEM fields that require multidimensional abilities and preferences (e.g., law, medicine, social sciences). The SMPY research team argued that changes in lifestyle preferences played an important role in these decisions; female participants became more holistic and community- and family-oriented as they aged, as opposed to men who became more career-focused and agentic after the completion of their graduate degrees.

***Race***

Black, American Indians/Alaska Natives, and Hispanics have historically been underrepresented in STEM fields (National Action Council for Minorities in Engineering; NACME, N.D.). The groups are not only underrepresented in high school advanced courses (Barnard-brak, McGaha-Garnett, & Burley, 2011), but also in academic and career paths in STEM fields. In high schools, students of these races are less likely to have opportunities to be on the most rigorous academic tracks or to take the most rigorous courses, such as higher-level math courses and Advanced Placement (AP) or International Baccalaureate (IB) courses (Bell, Rowan-Kenyon, & Perna, 2009; College Board, 2012; Oakes, 1992; Roderick, Coca, & Nagaoka, 2011; Roderick, Nagaoka, & Allensworth, 2006).

According to NACME, Black, American Indian/Alaska Native, and Hispanic students who earned bachelor's degrees in their postsecondary education were almost three times greater in 2011 than in 1977. Even so, most researchers have still found students of these races underrepresented in postsecondary STEM education (e.g., Bailyn, 2003; Kulis & Sicotte, 2002; Wang, 2011). Wang (2011) argued that ethnic disparities in STEM fields are detrimental because these disparities influence long-term social mobility and contribute to socioeconomic inequality for those underrepresented groups, particularly given that graduates from STEM fields are likely to earn high incomes and gain social status associated with occupations in their fields. Lewis and Connell (2005) found that African American students were likely to select math- and science-related courses based on their interests and the courses' utility values. Anderson and Ward

(2013), using nationally representative data, found that a higher course utility value and student mathematics achievement were associated with STEM persistence for Hispanic and African American students. However, mathematics and science self-efficacy were not associated with their persistence. Cooper (2011) identified the lack of same-race role models as a possible reason for the small number of students of underrepresented races in STEM fields. Wang (2011) found that exposure to math and science did not affect enrollment in STEM colleges for Hispanic and Black students, whereas it did significantly affect White students' enrollment. On the other hand, mathematics self-efficacy mattered for the persistence of students of underrepresented races on STEM pathways, just as it mattered in the persistence of other ethnicities (White and Asian American students).

***Socioeconomic status***

Socioeconomic status (SES)[1] refers to the relative status of an individual in access to and control over wealth, prestige, and power (Mueller & Parcel, 1981). A student's SES reflects his/her family income, prestige, and power, and is known as an important variable that influences overall student outcomes in educational settings. However, researchers have given much less attention to the effect of SES on college students' STEM pathways, compared to the effects of sex and race. Rather, SES has been studied in postsecondary education in general, particularly regarding its effect on entrance and completion. Most researchers found that gaps in SES could be related to levels of attendance and graduation from postsecondary institutions; students with a lower SES were less likely to enter and complete postsecondary paths than those with a higher SES (Carneiro & Heckman, 2002; Heckman, 2000), and were also less likely to enter and graduate from highly selective universities (Hill & Gordon, 2008; Hill & Winston, 2006). The

[1] I recognize the bias in the language of socioeconomic status (SES), but use the variable because ELS defines a composite variable as described as SES.

disparity also existed when the sample was restricted to high-ability students. Cardak and Ryan (2006) found that SES did not influence university attendance, but it did affect later performance at university. Wyner, Bridgeland, & Dilulio (2007) investigated achievement gaps among students identified as high-achieving, using K-12 and postsecondary data. They found that lower-income students were less likely to achieve in Grades K-12, were less likely to graduate from college, and were even less likely to graduate from the most selective colleges than students from higher-income families.

**School factors**

Talent developmental theorists (Gagne, 2004; Feldhusen, 2005) have viewed schools as an important environmental catalyst for student talent development. Eccles and Roeser (2011), in a review paper concerning *schools as developmental contexts during adolescence*, explained the significance of schools in adolescence as “the place where adolescents are exposed to the culture’s fount of knowledge, hang out with their friends, engage in extracurricular activities that can shape their identities, and prepare for their future” (p. 255). Therefore, experiences at school influence students’ whole lives, and especially their adolescence, in areas “ranging from the breadth and depth of their intellectual capital to their psychological well-being to the nature of peer influences on their development” (p. 225). The researchers conceptualized a framework of school-factors taking an ecological approach, which incorporates factors from the macro-level of society and culture to the micro-level of individual classrooms within a school.

The micro-level includes teacher qualifications and characteristics, the curriculum and academic work, teacher-student relationships, and the emotional atmosphere of the classroom. In particular, the curriculum delivered and academic work done in classrooms are important, because the content and structure of the curriculum directly influences students, not only by cultivating their intellectual learning, but also by providing interest, meaningfulness, and challenge in the broad context of learning. A student's needs and capacities should be matched by the curriculum taught to help students avoid boredom and low interest, which lead to diminished engagement and learning in the classroom.

Eccles and Roeser also listed broader, school-wide factors that influence talent development, such as school culture, safety, the student body, and peer influences. On the macro-level, schooling systems (e.g., grade configuration, school transitions, school size), extracurricular activities, and service learning were included. The school context is especially important for students who have talents in math and science, as most of them develop these talents within the school system and context. In the following sections, I discuss these school factors in terms of their influence on student achievement and motivation, particularly regarding the development of talents in math and science.

***School poverty rate***

The influence of school-level socioeconomic status on student achievement has received attention in recent literature. Researchers have consistently found that a large proportion of students from low SES families in schools strongly correlates with low achievement (e.g., Crosnoe, 2009; Everson & Millsap, 2004; Lee & Burkham, 2002; Rumberger & Palardy, 2005). Poverty has been investigated not only at the student-level, but also at the school-level. Vanderharr, Muñoz, and Rodosky (2006) argued that school poverty rate is a stronger predictor of academic failure than student-level poverty. To be specific, the percentage of students who received federal meal subsides (free or reduced-price school meals) within a school was associated with the number of students who were under the state standards of achievement. Furthermore, despite a relatively small number of studies, school poverty has been found to be negatively associated with student academic attitudes and motivation (Battistish, Solomon, Kim, Watson, & Schaps, 1995). Less qualified teachers and a lack of available school resources for use in educating students were found as possible reasons for the negative effects of impoverished schools on student achievement (Clotfelter, Ladd, Vigdor, & Wheeler, 2006; Myers, Kim, & Mandala, 2004).

School-level poverty has received little attention from researchers in gifted research or from studies concentrating on students identified as high-achieving. Hébert and his colleagues found that a lack of resources, peer cultures, and low expectations for academic achievement in schools with high proportions of students from disadvantaged backgrounds negatively influenced high-ability students' achievement and academic growth (Hébert, 1998; Hébert, 2001; Hébert & Reis, 1999). However, Burney (2010) found no significant effect of school poverty on the success of students on AP exams. She found that the percentage of students receiving free or reduced-price lunches in a school was not associated with the percentage of students passing AP exams within the school.

#### ***School climate: academic pressure***

School climate has been conceptualized and investigated as an important variable that influences student achievement and psychosocial development. Although more recent studies have focused on how positive social atmospheres within schools affect psychosocial development during adolescence (e.g., Preble, 2011; Dewitt & Slade, 2014), academic values and the serious pursuit of learning in schools are also important to explain student school life and achievement (Sinclair, 1970; McDill, Rigsby, & Meyers, 1969). "Academic pressure" refers to a school climate that emphasizes academic excellence and conformity to specific academic standards (McDill, Natriello, & Pallas, 1986). Lee and Smith (1999) revealed that academic pressure in schools positively predicted student achievement, not only in terms of academic performance, but also in terms of the time and effort students spent on academic work. Shouse (1996) argued that academic pressure could be a strong mediator, particularly in low-SES schools, if schools were organized communally. Andrade (2014), using two waves of longitudinal data, investigated whether academic pressure at school was associated with student academic performance and substance use. He found that higher levels of academic pressure at school were particularly associated with improvements in student academic performance. Most of the studies are outdated and did not investigate the relationship between academic pressure and student decisions to enter postsecondary education, however academic pressure is certainly worth studying, particularly because of its ability to be controlled by school members.

# CHAPTER 3 METHODS

The main purpose of this study was to investigate three important student choices and accomplishments on STEM pathways during late adolescence and into early adulthood: (a) choosing a STEM major in college, (b) persisting in the STEM major until graduation, and (c) selecting a career in STEM after college graduation. In this investigation, I used the Educational Longitudinal Study of 2002 (ELS:2002; Ingels, Pratt, Alexander, Jewell, Lauff, Mattox, Wilson, & Christopher, 2014), which followed students from the 10th grade (in the base year) up until eight years after high-school graduation. An important aspect of the current study was that it concentrated on students who achieved highly in secondary school math and science. In this chapter, I describe how I identified those students using multiple standardized test scores that demonstrated student achievement in math and science.

I adopted two inferential analytic methods in answering the research questions. First, I used a set of logistic regression models to estimate the probabilities associated with each binary outcome variable (e.g., the probability that students selected a STEM major in college). I considered using a multilevel model to nest students within their schools. Second, I used a discrete-time hazard model to investigate the longitudinal patterns of student persistence in STEM majors at college. Compared to the logistic regression model, a discrete-time hazard model allowed me to estimate when students were most likely to experience a target event (e.g., college graduation with a STEM major) and to assess whether students persisted in their college STEM paths over the observed period.

## Research Questions

The following research questions guided this study:

*Research Question 1.* Are secondary school students identified as high-achieving in math and science more likely to select postsecondary education paths in STEM compared with their peers?

*a.* What is the probability that students identified as high-achieving select postsecondary education paths in STEM colleges?

*b.* Are there any disparities in STEM entrance rates due to student-level (e.g., sex, SES, Race) or school-level variables (school-average SES, academic pressure)?

*c.* Do mathematics self-efficacy and advanced courses in math and science during high school moderate the positive or negative effects of significant covariates?

*Research Question 2.* After entering postsecondary STEM paths, when are students identified as high-achieving most likely to complete an undergraduate program in a STEM field? Which variables most significantly influence completion rates in postsecondary studies?

*a.* What are the hazard probabilities that students identified as high-achieving graduate with a STEM major from a college or university? When are those students most likely to complete their undergraduate programs?

*b.* Do any disparities in the student-level covariates result in different hazard probability functions?

*c.* Do mathematics self-efficacy and advanced courses in math and science during high school moderate the positive or negative effects of significant covariates?

*Research Question 3.* Are STEM undergraduate students who were identified as high-achieving in high school more likely to select graduate programs or occupations in STEM after college graduation compared with other STEM undergraduate students?

*a.* What is the probability that students identified as high-achieving select graduate programs or occupations in STEM after college graduation?

*b.* Are there any disparities in the rates of the further persistence in STEM paths due to student-level or school-level variables?

*c.* Do educational experiences during undergraduate programs (e.g., number of STEM courses taken, internship, research project) moderate the positive or negative effects of significant covariates?

## Data Set

I used data from the Education Longitudinal Study of 2002 (ELS:2002), which includes data about a nationally representative cohort of U.S. students. The ELS:2002 was designed to investigate the transition of a national sample of 10th grade students through high school and into postsecondary education and the workplace (Ingels et al., 2014). The ELS:2002 dataset contains multiple variables collected from students, their parents, high school teachers, schools, and postsecondary institutions, as well as longitudinal data following the students through high school and their postsecondary education. Compared to other nationally representative longitudinal studies (e.g., National Longitudinal Study of the High School Class of 1972, High School and Beyond, National Educational Longitudinal Study of 1988, High School Longitudinal Study of 2009), the ELS:2002 is relatively recent, considering that the final follow-up survey was completed in 2012, and it includes eight years of follow-up data after the students' high school graduation. To address the research questions, I used the data files of *ELS:2002/12 Base Year to Third Follow-up Restricted data files with Postsecondary Transcripts*.

**Data collection**

The target population of the ELS:2002 was "spring-term sophomores in 2002 (excluding foreign exchange students) enrolled in schools" (Ingels et al., 2014, p. 20). The ELS:2002 selected a sample using stratified cluster random sampling. Initially, 1,270 schools were selected, taking school characteristics into account to facilitate a nationally representative sample. Of 1,220 eligible schools, 750 schools responded to the study request, with a weighted response rate of 68 percent. Weighted response rates were calculated using the ratio of the weighted number of completed surveys to the weighted number of in-scope sample cases (Ingels, Pratt, Rogers, Siegle, Stutts, & Owings, 2004). Twenty-six students per responding school were selected as sample students, but only 17,590 students were eligible given the definition of the target population. Of the eligible students, 15,360 students participated in the study, with an unweighted response rate 87.3 percent. The base year study of 2002 surveyed the students' demographic information, achievements, and psychological states. Contextual data were also collected from the students' parents, teachers, and school administrators using a survey.

In the first follow-up study (2004), the sample was freshened, including eligible students from the base year sophomore cohort (*n*=16,530), as well as an additional cohort of seniors in 2004 (*n*=240). The ELS:2002 senior cohort is overlapping but conceptually different from the sophomore cohort; the sophomore cohort consists of students who were enrolled in 10th grade in 2002 and the senior cohort consists of 12th grade students who were enrolled in 2004. The sophomore cohort includes students who dropped out of school between 2002 and 2004, students who graduated early, and students who repeated a grade during the period (Ingels et al., 2005). However, since both cohorts are appropriate to address the research questions, and the variables of interest to this study were all collected after the first follow-up study (2004), I included the senior cohort as well as the sophomore cohort so as to include as many students as possible. Of the eligible sample students, 14,930 students completed the survey and the unweighted response rate was 90.4 percent. High school transcripts of the participating students were collected in 2004.

The second follow-up survey in 2006 was administered to the eligible 15,890 students focusing on their postsecondary education and employment, and 14,150 students participated in the study. The final follow-up survey was conducted in 2012, six years after the second follow-up survey (2006), and eight years after high school graduation (2004). Information was collected regarding the participants' current status, postsecondary education, and employment. Of 15,720 eligible members, 13,250 members participated in the final study. The unweighted response rate was 84.3 percent. Panel attrition rate in the final year study was 13.7 percent. Table 2 summarizes sample response rates and panel attritions in the ELS:2002.

Table 2

*Sample Responses and Panel Attritions in the ELS:2002*

| | BY | F1 | High school transcript | F2 | F3 |
|---|---|---|---|---|---|
| (Year of data collection) | (2002) | (2004) | (2004) | (2006) | (2012) |
| *N* of eligible students | 17,590 | 16,520 | 16,370 | 15,890 | 15,720 |
| *N* of participating students | 15,360 | 14,930 | 14,920 | 14,150 | 13,250 |
| Response rate | 87.3% | 90.4% | 91.1% | 89.0% | 84.3% |
| Attrition rate | | 2.8% | | 7.9% | 13.7% |

*Note*. BY = base year; F = follow-up year. Attrition rate was calculated by the proportion of non-participating students in total students participating in the base year. All unweighted sample size numbers were rounded to the nearest ten.

### Weights

Due to the design of multi-stage probability sampling, I used a series of student-level and school-level weights to compensate for unequal selection probabilities and nonresponse. From a set of weights provided by the ELS:2002, I selected a student-level weight that was intended for analyses based on third-round follow-up data in combination with first-round and second-round follow-up data (see Table 7 for the list of variables in this study). The estimates, using the weight, represent approximations of the population of students enrolled in 10th grade in the spring of 2002 and the population of students enrolled in 12th grade in the spring of 2004 (Ingels et al., 2014). I also used a school-level weight for the estimation of multilevel logistic modeling. To incorporate the SAS command, PROC GLIMMIX, which I used for *RQ 1* and *RQ 3*, a student-level scaled weight and a school-level weight needed to be specified. The scaled weight is the inverse of the conditional probability of selection, given that a school-level cluster was sampled. I calculated the scaled weights by the method suggested by Asparouhov (2006), which involves the following equation, where $w_{ij}$ represents the unscaled weight:

$$w_{ij}^{*} = w_{ij}\left(\frac{n_j}{\sum_i w_{ij}}\right).$$

A variable list of weights is presented in Table 5.

## Sample

### Identification

Out of a total of 13,250 students who completed their final surveys, students who achieved well in math and science during high school were identified using scores from standardized college entrance exams. I operationally defined a student identified as high-achieving in math and science as one who scored in the 95th percentile or above in math or science (or both) in a college entrance exam or advanced level of 5 on the AP subject exam (math/science). By definition, students identified as high-achieving were restricted to college-bound students, but I simply use the term “students identified as high-achieving” to refer to them in this study. The rationales for using college entrance exam scores are as follows: (a) college entrance exams are standardized across the national cohort, (b) the exams are accessible to all students who intend to enter postsecondary education, as long as there is no equity issue concerning access, (c) scores from the exams reveal the college-readiness of students as well as their achievement and progress during secondary education. The latter, (c), is a desirable factor for identifying students as high-achieving from the perspective of talent development. Multiple test scores were used to identify high-achieving students, and those who met any one of the criteria were selected. The criteria for identifying high-achieving students were as follows:

- An SAT math component score above the 95th percentile;
- An ACT math component score above the 95th percentile;
- SAT subject test scores in math (Mathematics 1, Mathematics 2) above the 95th percentile;
- SAT subject test scores in science (Physics, Biology, Chemistry) above the 95th percentile;
- An AP exam score of 5 (extremely well qualified) in math (Calculus, Statistics);
- An AP exam score of 5 (extremely well qualified) in general science and computer science (Biology, Chemistry, Computer science, Environmental Science, Physics).

Table 3 presents unweighted and weighted descriptive statistics of college entrance exam scores. It is noteworthy that 4,950 students did not have a score on college entrance exams; therefore, these students were excluded from identification. The unweighted statistics represent the estimates for sample students, and the numbers of students who took each exam are presented in the first column of unweighted statistics. In terms of math component scores for SAT and ACT, the reported scores in the data set were scaled using the concordance method (Ingels et al., 2014); thus, the scores may be higher or lower than the students' actual SAT or ACT scores to compensate for the level of difficulty of these exams. The 95th-percentile scores in Table 3 indicate the cut-off scores for identifying high-achieving students in math and science. The weighted estimates of the 95th-percentile scores were slightly lower than the unweighted estimates. Since the estimates using weights adjusted for disproportions in the sampling, I used the weighted estimates as the criteria scores for identifying high-achieving students in math and science.

Table 3

*Descriptive Statistics of College Entrance Exam Scores and Cutoff Scores for Identifying High-Achieving Students in Math and Science*

| Test | Subject | Unweighted | | | | Weighted | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | *N* | *M* | *SD* | P95 | *M* | *SE* | P95 | |
| | | | | | | | | *Estimate* | *SE* |
| SAT | Math | 8,260 | 509.28 | 112.96 | 700 | 500.48 | 1.51 | 681.09 | 4.27 |
| ACT | Math | 8,260 | 21.57 | 5.28 | 31 | 21.17 | 0.07 | 29.85 | 0.14 |
| AP exam | Biology | 400 | 3.07 | 1.36 | 5 | 3.04 | 0.06 | 4.77 | 0.12 |
| | Chemistry | 260 | 2.73 | 1.33 | 5 | 2.74 | 0.08 | 4.53 | 0.17 |
| | CS A | 50 | 2.94 | 1.61 | 5 | 2.78 | 0.19 | 4.79 | 0.41 |
| | CS B | 20 | 2.68 | 1.53 | 5 | 2.78 | 0.17 | 4.32 | NA |
| | Calculus AB | 720 | 3.05 | 1.45 | 5 | 3.05 | 0.06 | 4.77 | 0.09 |
| | Calculus BC | 190 | 3.53 | 1.48 | 5 | 3.46 | 0.11 | 4.87 | 0.19 |
| | PHY | 120 | 2.70 | 1.38 | 5 | 2.62 | 0.07 | 4.36 | 0.10 |
| | PHY CEM | 40 | 2.86 | 1.59 | 5 | 2.56 | 0.09 | 4.65 | 0.13 |
| | PHY ME | 90 | 2.86 | 1.46 | 5 | 2.84 | 0.11 | 4.69 | 0.15 |
| | Environmental | 130 | 2.70 | 1.27 | 5 | 2.71 | 0.12 | 4.33 | 0.25 |
| | Statistics | 200 | 2.87 | 1.27 | 5 | 2.88 | 0.10 | 4.54 | 0.16 |
| SAT subject | Mathematics 1 | 650 | 583.77 | 95.01 | 730 | 571.38 | 4.17 | 715.50 | 4.49 |
| | Mathematics 2 | 400 | 659.53 | 91.97 | 800 | 652.28 | 4.83 | 791.70 | 3.67 |
| | Physics | 90 | 633.91 | 86.20 | 790 | 620.96 | 4.49 | 747.76 | 4.20 |
| | Chemistry | 90 | 608.54 | 105.41 | 770 | 587.45 | 8.12 | 760.08 | 13.66 |
| | Biology | 20 | 591.82 | 89.74 | 690 | 560.65 | 4.86 | 668.12 | NA |

*Note*. P95 = 95th percentile score. CS = computer science, PHY = Physics, PHY CEM = Physics Electricity and Magnetism, PHY ME = Physics Mechanics. Note that 4,950 students did not have a score of college entrance exams in the dataset, weighted *N* = 1,362,031. All unweighted sample size numbers were rounded to the nearest ten.

Table 4 shows the unweighted and weighted numbers of students identified as high-achieving by the criteria above. The numbers in Table 4, the students identified by each exam, include duplicates because some of the students took multiple exams for college entrance, and, among those students, some satisfied two or more of the identification criteria. The unweighted total number of students identified as high-achieving was 720, which represented 5.44% of the sample students. The weighted total number of students identified as high-achieving was 143,631 (SD = 6,967), which was 4.37% of the population of students.

Since none of the tests listed above were required for every high-school student, and equivalency does not exist between the tests, the equivalency of the different exam scores used for identification was uncertain. Furthermore, some students were identified by more than one of the criteria. To understand invariance among the exam scores, I calculated the mean ELS:2002 mathematics assessment score for the group of students identified by each college entrance exam. The use of the ELS:2002 mathematics assessment was appropriate as the assessment was intended to be administered to all participating students in the ELS:2002, including non-college-bound students. The exam aimed to measure student growth in mathematics achievement while minimizing ceiling effects (Ingels et al., 2014). Its components were constructed using previous assessments such as NELS:88, NAEP, and PISA. The assessment in the first follow-up year was administered to 87% of the student questionnaire sample (Ingels et al., 2005). The ELS:2002 provided imputed data for student mathematics ability by model estimation using demographic variables (e.g., student sex, school type, parental education levels) as well as previous student abilities and aspirations. Figure 2 shows weighted estimates of the means and 95% confidence intervals of the ELS:2002 mathematics assessment scores corresponding to each college entrance exam score of students identified as high-achieving. The average score of all students identified as high-achieving was 67.04, *SE* = .42, which was obviously higher than for non-identified students, *M* = 42.67, *SE* = .26. As seen in Figure 2, variances in the ELS:2002 assessment scores existed based on the college-exam groupings. But the figures show that the average math achievement scores of students, grouped by exam, were all high enough for the students to be regarded as high-achieving. Therefore, I kept using the identification criteria for students identified as high-achieving for the operational definitions.

Table 4

*Unweighted and Weighted Frequencies of the Identification by College Exam Score*

| | | Unweighted | | Weighted | | |
|---|---|---|---|---|---|---|
| Test | Subject | *N* | Percent | *N* | Percent | *SE* |
| SAT | Math | 510 | 3.81 | 96,797 | 2.95 | 0.17 |
| ACT | Math | 630 | 4.78 | 123,596 | 3.76 | 0.20 |
| AP exam | Biology | 30 | 0.22 | 5,052 | 0.15 | 0.04 |
| | Chemistry | 90 | 0.65 | 15,935 | 0.48 | 0.07 |
| | CS A | 10 | 0.09 | 2,448 | 0.07 | 0.03 |
| | CS B | less than 10 | 0.02 | 248 | 0.01 | 0.01 |
| | Calculus AB | 160 | 1.20 | 32,671 | 0.99 | 0.10 |
| | Calculus BC | 70 | 0.56 | 15,021 | 0.46 | 0.07 |
| | PHY | 20 | 0.13 | 1,830 | 0.06 | 0.02 |
| | PHY CEM | 10 | 0.07 | 857 | 0.03 | 0.01 |
| | PHY ME | 120 | 0.13 | 2,400 | 0.07 | 0.02 |
| | Environmental | less than 10 | 0.07 | 1,888 | 0.06 | 0.02 |
| | Statistics | 20 | 0.17 | 4,766 | 0.15 | 0.04 |
| SAT subject | Mathematics 1 | 50 | 0.40 | 6,893 | 0.21 | 0.04 |
| | Mathematics 2 | 30 | 0.24 | 4,345 | 0.13 | 0.03 |
| | Physics | 10 | 0.08 | 1,110 | 0.03 | 0.01 |
| | Chemistry | less than 10 | 0.05 | 733 | 0.02 | 0.01 |
| | Biology | less than 10 | 0.02 | 258 | 0.01 | 0.00 |
| | Total (no duplicate) | 720 | 5.44 | 143,631 | 4.37 | 0.21 |

*Note.* The number of students in each cell, except the total numbers, is duplicated because some of the students were identified by more than two different test scores. CS = computer science, PHY = Physics, PHY CEM = Physics Electricity and Magnetism, PHY ME = Physics Mechanics. All unweighted sample size numbers were rounded to the nearest ten.

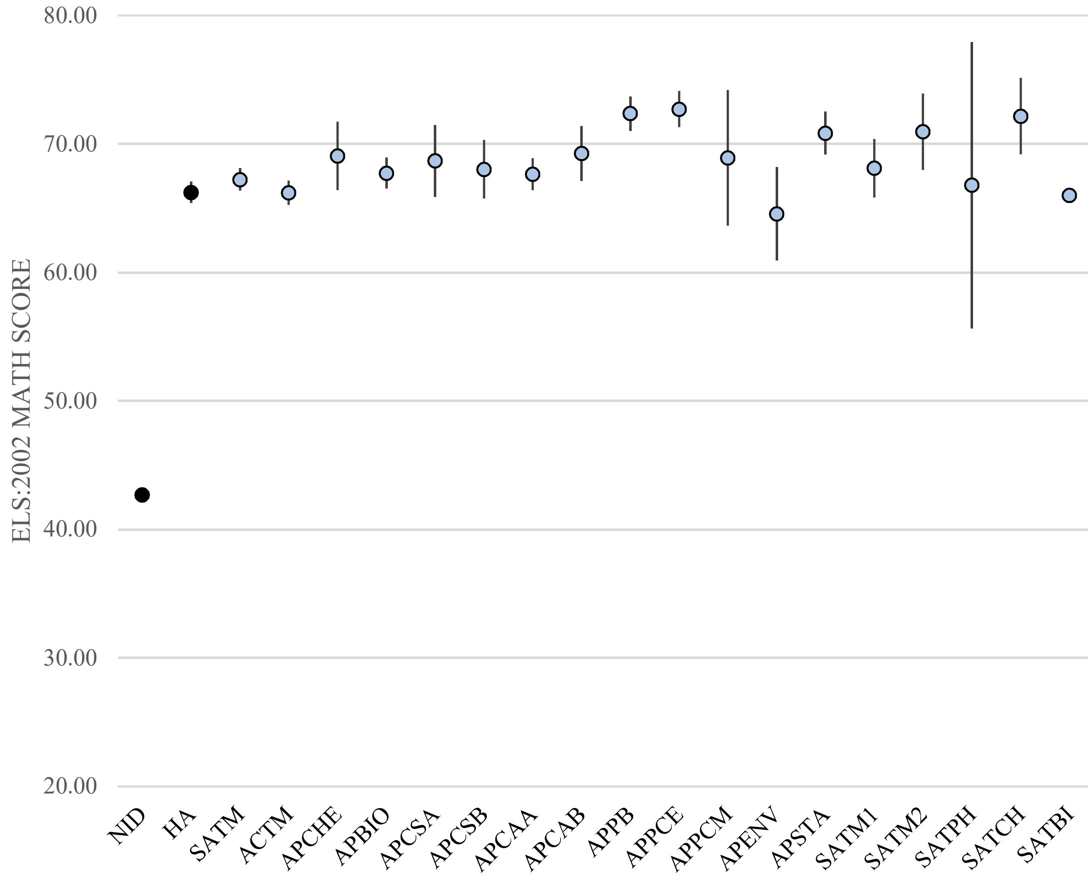


*Figure 2.* *Point Estimates and Confidence Intervals for the Average ESL:2002 Math Assessment Scores Corresponding to Each College Entrance Exam Score of Students Identified as High-Achieving. The estimation was weighted. Error bars represent 95% confidence intervals. The point estimate for "NID" is the average math achievement score of non-identified students, and the point estimate for "HA" is the average math achievement score of students identified as high-achieving.*

**Sample composition**

Table 5 and Table 6 show the demographic information of students identified as high-achieving and other students. Overall, the compositions were severely disproportionate in terms of student sex, race, and SES, particularly for the students identified as high-achieving. More male students were identified than female students (Figure 3); by weighted estimates, 5.59% of male students were identified, whereas 3.19% of female students were identified. The representation index (RI; Kitano & DiJiosia, 2002; Yoon & Gentry, 2009) was calculated to quantify the severity of underrepresentation (Figure 4). The RI is the ratio of the proportion of students identified as high-achieving from a given category (e.g., race, SES) to the proportion of students from that given category in total population. Given that female students comprised 50.83 of total population but only 37.13% of female students were identified as high-achieving, the RI for female students is 0.73. An RI of less than 1.0 indicates underrepresentation, and an RI of greater than 1.0 indicates overrepresentation given an assumption that the proportion of a group of identified students in any categories should be equal to the proportion of the group in total population. The RI for male students was 1.28.

In terms of race, it was obvious that students who were not White or Asian were underrepresented (Figure 5). Of the weighted number of students identified as high-achieving (*N* = 143,631 out of a total of 3,286,511), 0.88% were Black, 5.16% were Hispanic, and 2.2% were multiple races; in terms of proportions within each race, only 0.27% of Black, 1.39% of Hispanic, and 2.39% of multiple-race students were identified as high-achievers. The RIs also implied a severe underrepresentation by race, 0.06 for Black, 0.32 for Hispanic, 0.55 for multiple-race students whereas 3.54 for Asian and 1.28 for White students (Figure 6). The weighted number was not estimated for Native American students because of too small number of identified students as high-achieving in the data set; Less than 10 students were identified as high-achieving out of 110 Native American students. From the results of the unweighted estimations, less than 10 students were identified out of 1,700 Black students. The numbers of identified Hispanic and multiple-race students were also small (approximately *n* = 30 and 20 respectively, when rounded the unweighted numbers to the nearest ten). These numbers were too small to estimate the probabilities of dependent variables occurring by each race. However, this result was not surprising given the literature's review that Black, Native American, and Hispanic students are traditionally underrepresented in STEM fields (Bailyn, 2003; Kulis & Sicotte,2002; NACME, N.D.; Wang, 2011). Based on prior studies (Bailyn, 2003; Kulis & Sicotte,2002; NACME, N.D.; Wang, 2011), I decided to merge these four races, Black, Hispanic, Native American, and mixed race, to perform the analyses for the main research questions. In contrast to these four racial groups, Asian and White students were identified as high-achievers by the criteria in much higher proportions. By weighted estimation, 15.44% of Asian students were identified as high achievers, and the proportion of Asian students out of the total number of students identified as high-achieving was 14.85%. Given that Asian students only composed 4.2% of the population, this proportion was large. For White students, 5.58% were identified as high-achieving, and White students composed 76.92% of the population of students identified as high-achieving.

The proportions based on the socioeconomic status of the students' families were also imbalanced (Figure 7). Of the students identified as high-achieving, 67.57% were students with families in the first quartile of SES. In terms of proportions within each group, only 1.11% of students whose families were in the fourth quartile of SES were identified as high-achievers; 1.58% of second-quartile students and 4.37% of third-quartile students were identified as high-achievers; whereas, 12.63% of the highest quartile students were identified as high achievers by the criteria of college entrance exams. The RI for students from families in the first quartile of SES was 0.15, but the RI for students from families in the fourth quartile of SES was 2.71 (Figure 8).

Table 5

*Unweighted Frequencies and Proportions of the Sample by Sex, Race, and SES*

| | | Identified as high-achieving | | | Non-identified | | | Total | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *N* | Row% | Col% | *N* | Row% | Col% | *N* | Row% | Col% |
| Sex | Female | 290 | 4.13 | 39.94 | 6,690 | 95.87 | 53.40 | 6,980 | 100.00 | 52.67 |
| | Male | 430 | 6.90 | 60.06 | 5,840 | 93.10 | 46.60 | 6,270 | 100.00 | 47.33 |
| Race | Asian | 190 | 14.73 | 26.77 | 1,120 | 85.27 | 8.92 | 1,310 | 100.00 | 9.89 |
| | Black | 10 | 0.53 | 1.25 | 1,690 | 99.47 | 13.51 | 1,700 | 100.00 | 12.85 |
| | Hispanic | 30 | 1.54 | 4.02 | 1,860 | 98.46 | 14.81 | 1,890 | 100.00 | 14.23 |
| | Multiple | 20 | 3.56 | 3.05 | 600 | 96.44 | 4.76 | 620 | 100.00 | 4.66 |
| | Native | < 10 | 0.93 | 0.14 | 110 | 99.07 | 0.85 | 110 | 100.00 | 0.82 |
| | White | 470 | 6.12 | 64.77 | 7,160 | 93.88 | 57.15 | 7,630 | 100.00 | 57.56 |
| SES | First | 30 | 1.11 | 4.58 | 2,950 | 98.89 | 23.51 | 2,980 | 100.00 | 22.48 |
| | Second | 50 | 1.58 | 6.80 | 3,060 | 98.42 | 24.41 | 3,110 | 100.00 | 23.45 |
| | Third | 140 | 4.37 | 19.56 | 3,080 | 95.63 | 24.60 | 3,220 | 100.00 | 24.32 |
| | Fourth | 500 | 12.63 | 69.07 | 3,440 | 87.37 | 27.49 | 3,940 | 100.00 | 29.75 |
| Total | | 720 | 5.44 | | 12,530 | 94.56 | | 13,250 | 100.00 | |

*Note.* Row % indicates a proportion within sex, race, or SES. Col % indicates a proportion within an achievement group (i.e., high-achieving or non-identified students). All unweighted sample size numbers were rounded to the nearest ten.

Table 6

*Weighted Frequencies and Proportions of the Sample by Sex, Race, and SES*

| | | Identified as High-achieving | | | | Non-identified | | | | Total | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *N* | *SD* | Row% | Col% | *N* | *SD* | Row% | Col% | *N* | *SD* | Row% | Col% |
| Sex | Female | 53,328 | 4,072 | 3.19 | 37.13 | 1,617,242 | 19,807 | 96.81 | 51.46 | 1,670,570 | 19,803 | 100 | 50.83 |
| | Male | 90,304 | 5,766 | 5.59 | 62.87 | 1,525,638 | 21,430 | 94.41 | 48.54 | 1,615,941 | 21,550 | 100 | 49.17 |
| Race | Asian | 21,326 | 1,701 | 15.44 | 14.85 | 116,778 | 4,170 | 84.56 | 3.72 | 138,104 | 4,345 | 100 | 4.20 |
| | Black | 1,258 | 524 | 0.27 | 0.88 | 468,635 | 13,168 | 99.73 | 14.91 | 469,893 | 13,178 | 100 | 14.30 |
| | Hispanic | 7,415 | 1,749 | 1.39 | 5.16 | 527,937 | 13,543 | 98.61 | 16.80 | 535,352 | 13,612 | 100 | 16.29 |
| | Multiple | 3,156 | 959 | 2.39 | 2.20 | 129,014 | 7,394 | 97.61 | 4.11 | 132,170 | 7,447 | 100 | 4.02 |
| | Native | NA | NA | NA | NA | 31,706 | 3,716 | 100.00 | 1.01 | 31,706 | 3,716 | 100 | 0.96 |
| | White | 110,475 | 6,508 | 5.58 | 76.92 | 1,868,811 | 19,082 | 94.42 | 59.46 | 1,979,286 | 18,897 | 100 | 60.22 |
| SES | First | 5,678 | 1,287 | 0.70 | 3.95 | 809,739 | 16,595 | 99.30 | 25.76 | 815,417 | 16,615 | 100 | 24.81 |
| | Second | 11,553 | 2,132 | 1.38 | 8.04 | 823,285 | 17,357 | 98.62 | 26.20 | 834,839 | 17,429 | 100 | 25.40 |
| | Third | 29,346 | 3,221 | 3.59 | 20.43 | 788,428 | 16,997 | 96.41 | 25.09 | 817,774 | 17,152 | 100 | 24.88 |
| | Fourth | 97,054 | 5,783 | 11.86 | 67.57 | 721,427 | 14,714 | 88.14 | 22.95 | 818,481 | 15,189 | 100 | 24.90 |
| Total | | 143,631 | 6,967 | 4.37 | | 3,142,880 | 17,966 | 95.63 | | 3,286,511 | 16,817 | 100 | |

*Note.* Row % indicates a proportion within sex, race, or SES. Col % indicates a proportion within an achievement group (i.e., high achievers or non-identified students). The weighted number of Native American students was not estimated because of too small number of Native American students identified as high-achieving in the data set.

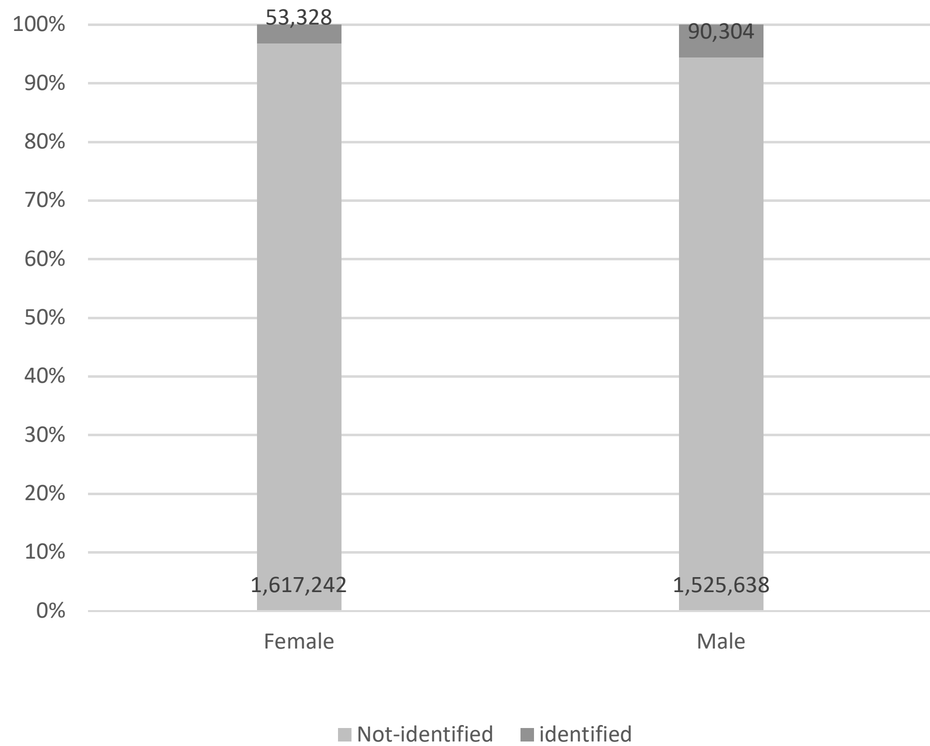


*Figure 3.* *Proportions of Students Identified as High-Achieving by Sex. The numbers represent the weighted frequencies of students for each category. Note that the total number of students is different by category: female = 1,670,570; male = 1,615,941.*

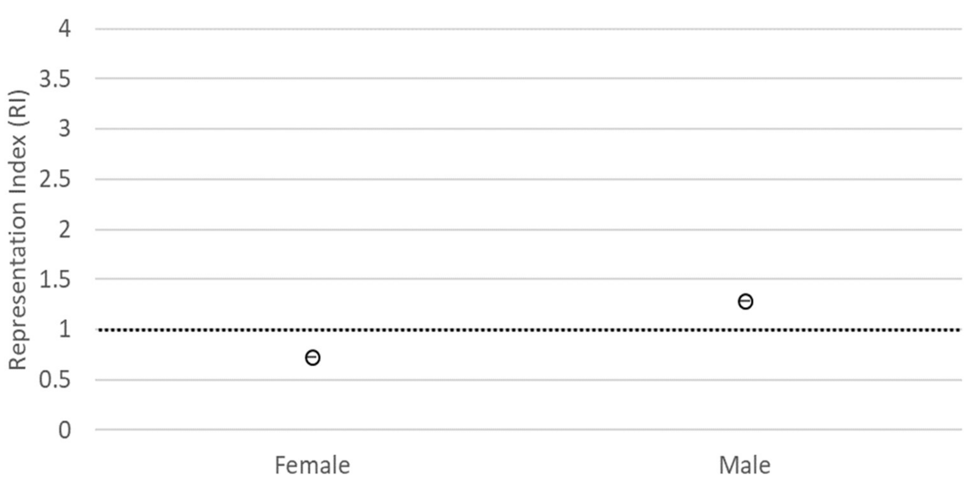


*Figure 4.* *Representation Indices by Sex. The dotted line indicates a perfect proportion of representation. Error bars expanded to 95% confidence intervals.*

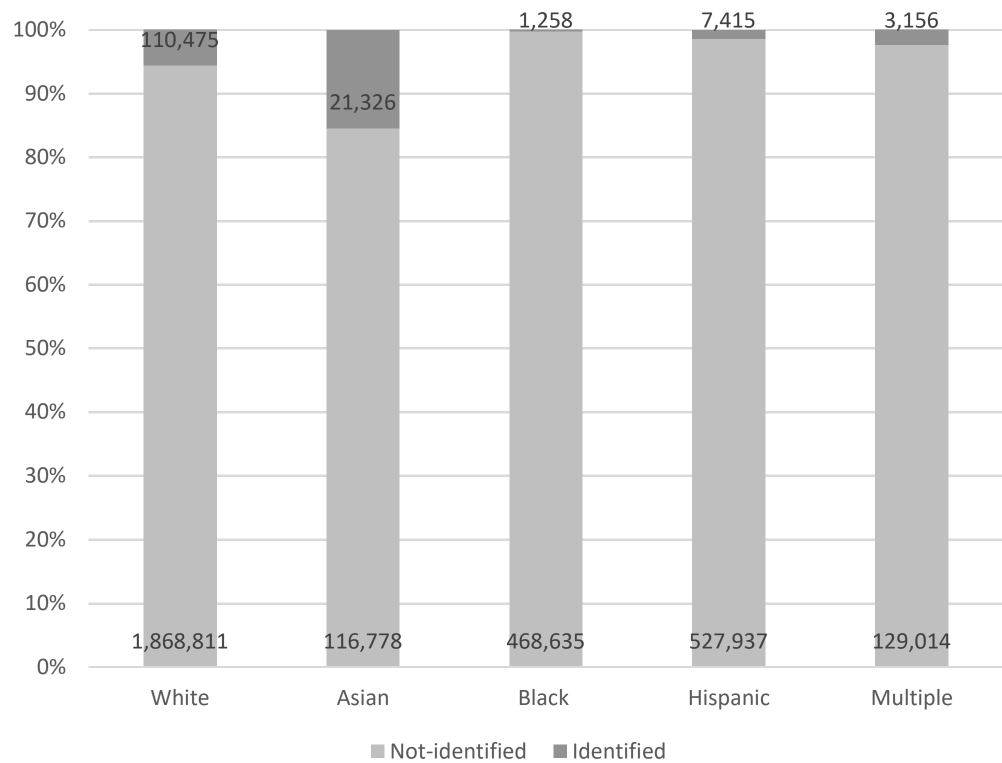


*Figure 5. Proportions of Students Identified as High-Achieving by Race. The numbers represent the weighted frequencies of students in each category. Note that the total number of students is different by category: White = 1,979,286; Asian = 138,104; Black = 469,893; Hispanic = 535,352; Multiple = 132,170. The weighted number of Native American students was not estimated because of too small number of Native American students identified as high-achieving in the data set.*

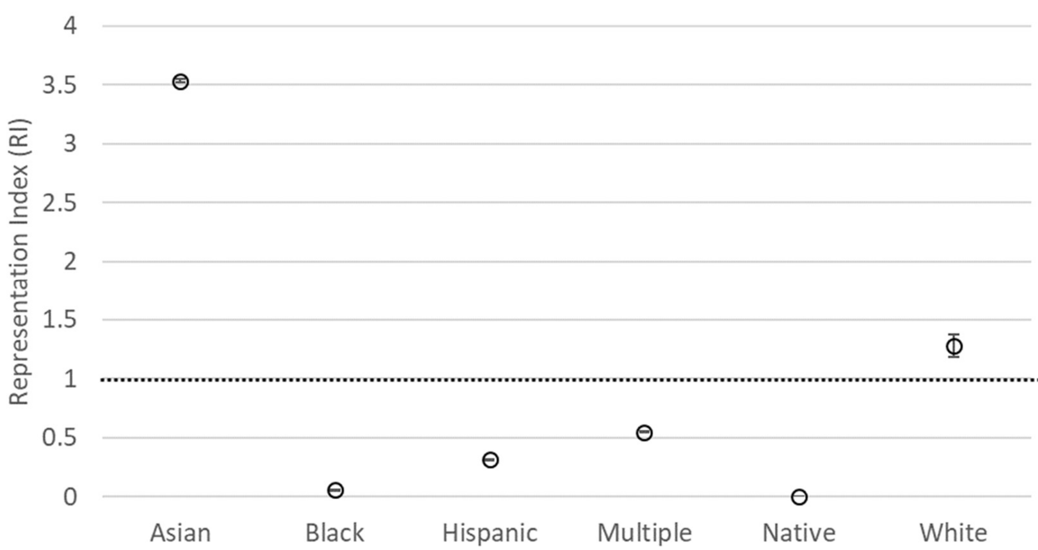


*Figure 6. Representation Indices by Race. The dotted line indicates a perfect proportion of representation. Error bars expanded to 95% confidence intervals.*

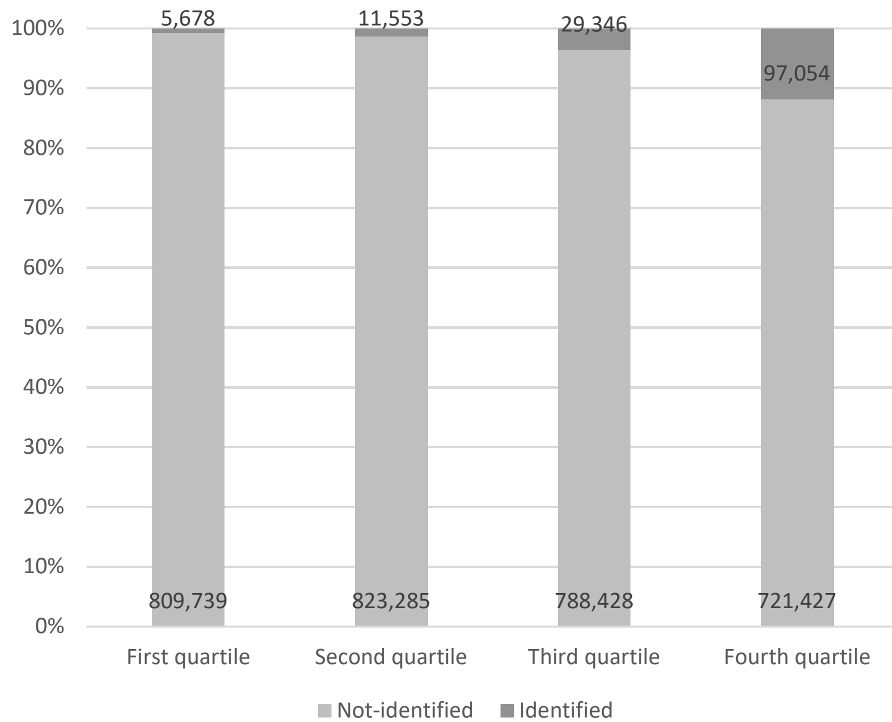


*Figure 7.* *Proportions of Students Identified as High-Achieving by SES. The numbers represent the weighted frequencies of students for each category. Note that the total number of students is different by category: first quartile = 815,417; second quartile = 834,839; third quartile =817,774; fourth quartile = 818,481.*

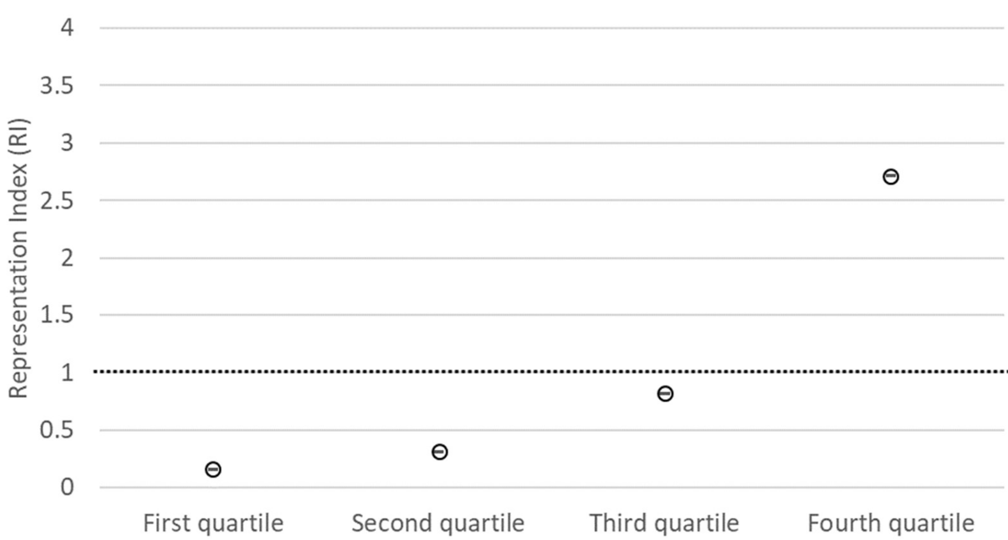


*Figure 8.* *Representation Indices by SES. The dotted line indicates a perfect proportion of representation. Error bars expanded to 95% confidence intervals.*

## Variables

### Student-level covariate variables

This section describes how I defined and used student-level covariates for the analyses. Frequencies and proportions of students by student-level covariates are presented in a later section, *Sample Composition.*

#### *Female (Sex)*

A binary variable was used, taking “0” for male students and “1” for female students.

#### *Socioeconomic status (SES)*

The ELS:2002 data set contained a composite variable of socioeconomic status, constructed through a combination of mother’s education level, father’s education level, mother’s occupation, father’s occupation, and family income or income proxy. In other words, five components, mainly from parent data, were equally weighted and combined to indicate SES. If parent data were missing, student data were used to impute this information. I used a variable of quartile-coded SES that was available in the ELS:2002, where “1” indicated the lowest quartile and “4” indicated the highest quartile.

#### *Race*

I used a set of dummy variables of race included in the ELS:2002. In the data set, there were six categories of race: Asian, Black, Hispanic, Native American, White, and multiple races. I used the categories to understand the baseline frequencies. But, based on the results for the baseline frequencies, which revealed severe underrepresentation in Black, Hispanic, Native American, and other races (BHNO), I had to merge those underrepresented races. I present the baseline frequencies by race in the next chapter, Results. Therefore, I used three categories of race for the main analyses for the research questions: White, Asian, and BHNO.

**School-level covariate variables**

***School rate of the federal meal subsidy (SCMS)***

I used a variable (school percentage of students who received the federal meal subsidy: SCMS) showing the percentage of students in each school that receive the federal meal subsidy (free or reduced-price meals) to represent school-level poverty. A greater value indicates a larger proportion of students who received federal meal subsides in a school. For the participating 750 schools, the average percentage of SCMS was 28.74. But it is noteworthy the variation was large ($SD$ = 26.07) and the distribution was positively skewed (skewness = 0.79). The 25th percentile was 5, meaning that 25% of schools had 5 or less percent of students who received the federal meal subsidy. And the 75th percentile was 45, meaning that the other side of 25% of schools had 45 or greater percent of students who received the federal meal subsidy.

***School climate: academic pressure (SCCL)***

I used five items to measure the climate of competitiveness at school: *"teachers press students to achieve," "learning is a high priority for students," "students are encouraged to compete for grades," "students are expected to do homework," and "counselors/teachers encourage students to enroll in academic classes.* The ELS:2002 asked school administrators to answer these questions using a 5-point Likert scale. Since no study had reported evidence of validity for the construct of school academic pressure using these items included in the ELS:2002, I investigated psychometric properties and the relation of academic pressure to overall achievement in mathematics before using the items in the study. The results for the psychometric properties are presented in the *Results* section.

## Dependent variables

### *Entrance into STEM fields*

This primary dependent variable of the study was coded using two criteria: (a) whether students had enrolled in a 4-year postsecondary institution (i.e., a college or university), and (b) whether students had selected a major in STEM. As stated, I used the CIP definition of STEM fields: mathematics, physical sciences, biological/life sciences (including agriculture and related sciences, natural resources and conservation, biological and biomedical sciences), computer and information sciences, and engineering and technologies (including engineering, engineering technologies, and science technology). I created two categories as follows: 0 = student has never selected a major in STEM or has never attended a postsecondary institution within eight years of high-school graduation; 1 = student has entered a college and has selected a major in STEM within eight years of high-school graduation. These categories were coded based on the postsecondary survey and postsecondary transcript data. A total of 1,030 students selected a major in STEM at a 4-year postsecondary institution, representing 7.77% of the participating students. From the weighted estimate, 34.98% of students identified as high-achieving and 5.84% of non-identified students selected to enter in STEM. Detailed descriptive statistics of this variable are presented in Chapter 4.

### *Persistence/graduation in STEM fields.*

To incorporate a discrete hazard model for persistence in STEM fields, three kinds of variables were needed: (a) a binary indicator of event, showing whether or not a student graduated in a STEM field, (b) a set of dummy variables covering the period from the initial time to the time of the graduation event, and (c) a binary indicator of censoring, showing whether students experienced the event during the observed period (i.e., right censored). In terms of the binary indicator of event, “1” indicates graduation with a STEM major, and “0” includes a variety of drop-out cases from STEM majors: (a) college graduation with a non-STEM major, which implies one or more switches in major, (b) transferring to another college, and switching to a non-STEM major, and (c) dropping out from college completely. I restricted the sample only for students who had declared a STEM major as of 2006, in order to standardize the time metric, which is a requisite for incorporating hazard/survival modeling. A total of 600 students graduated from a 4-year postsecondary institution with a major in STEM at, representing 4.56% of the participating students. Based on the binary variable of STEM graduation, I created a dummy variable for each year in which a student received a bachelor’s degree with a STEM major: January 2006 through to January 2013. Consequently, a total of seven dummy variables was created.

***Further STEM persistence beyond undergraduate STEM programs***

I used two variables to identify whether students earned a graduate school degree or had an occupation in a STEM field after college graduation. Using a variable, “ever earned a postsecondary credential in a STEM field as of June 2013,” I considered the following answer suggestive of completion of a graduate school degree in STEM: “graduate credentials in a STEM field.” I also used a variable of “STEM occupation flag for student’s known current occupation as of F3” to determine further STEM persistence. By the operational definition of STEM in this study, I considered life and physical sciences, engineering, mathematics, and information technology to be STEM fields, but excluded social science, architecture, and health occupations. Of 13,250 respondents, approximately 2,820 skipped or missed the former question, and 2,320 did the same with the later question. From weighted estimation, 0.39% of non-identified students and 6.08% of students identified as high-achieving had a graduate school degree in a STEM field within eight years of graduating high school. In terms of occupations, 4.69% of non-identified students and 21.42% of students identified as high-achieving had a job in a STEM field after college graduation.

**Moderating variables**

***Mathematics self-efficacy (MSE)***

The ELS:2002 contained five items measuring mathematics self-efficacy, which were measured in the base-year (Grade 10) and the first follow-up year (Grade 12). The items of the ELS:2002 were based on the PISA self-efficacy items (Ingels, Pratt, Rogers, Siegel, & Stutts, 2004). The PISA study originally developed three items to assess self-efficacy, based around classroom activities in the general domain, but the ELS:2002 modified the original items and added further two. The ELS:2002 items were specific to a set of classroom tasks in mathematics, including mathematics text comprehension, comprehension of teacher instructions, completion of assignments, achievement in tests, and mastery of skills. A sample item is *"I'm certain I can understand the most complex material presented by my math teacher."* (See Table 5 for all items).

However, there is no study that provides validity evidence for this application of the general domain self-efficacy scale. Therefore, as a preliminary study, the factor structure, psychometric properties, and ability of the scale to predict math achievement scores were examined regarding validity evidence. After addressing the validity issue of the scale, I used the average scores from the reliable items measuring MSE in 12th grade.

***Advanced courses in mathematics and science (ADC)***

A variable was used representing the number of AP and IB courses related to math and science taken by students during high school. In the data set, students reported the number of AP and/or IB courses in calculus, math, science, and computer science that they took while in high school. As I mentioned in the literature review, I selected AP and IB courses to represent advanced courses in high schools. Because these two programs provide the equivalent curriculum across schools, variations across programs are minimized (Burton et al., 2002; Kyburg, et al., 2007).

***STEM course credits in undergraduate programs (STCR)***

A variable representing the course credits in STEM taken in undergraduate programs was used.

***High-impact activities in undergraduate programs (HIGHIMP)***

I created a binary variable using two variables: (a) experience in the field, through an internship, co-op, field placement, student teaching position, or clinical assignment, and (b) experience working on a research project with a faculty member outside of the course/program requirements.

Table 7

*List of Variables in the Study*

| Construct | Description | Measure | Variable Name |
|---|---|---|---|
| *Dependent variable* | | | |
| Entrance | Declared a STEM major as of 2006 | Major declared/undeclared | F2B22 |
| | | Major as of 2006 | F2B23A |
| Graduation | Attained a bachelor's degree in a STEM major, having declared a STEM major as of 2006 | Date of bachelor's degree | F3TZBACHLTDT |
| | | STEM major/field-of-study indicator | F3TDSTEM1FLG |
| Further persistence | Entrance into a STEM graduate school | Type of credential pursued when last attending PS school | F3A13B |
| | Entrance into work related to a STEM major | Ever had a job closely related to field of study | F3B32 |
| *Moderating variable* | | | |
| HS mathematics self-efficacy | Average score of five items measuring mathematics self-efficacy | Can do an excellent job on math tests | F1S18A |
| | | Can understand difficult math texts | F1S18B |
| | | Can understand difficult math classes | F1S18C |
| | | Can do an excellent job on math assignments | F1S18D |
| | | Can master skills in math class | F1S18E |

(Continued)

Table 7 Continued

| Construct | Description | Measure | Variable Name |
|---|---|---|---|
| HS advanced courses in math and science | *n* of AP/IB courses taken in math and science | Total AP/IB calculus | F1RAPCA |
| | | Total AP/IB math courses | F1RAPMA |
| | | Total AP/IB science courses | F1RAPSC |
| | | Total AP/IB computer science courses | F1RAPCS |
| PSE STEM courses | *N* of courses | *N* of known STEM credits earned | F3TZSTEM1ERN |
| PSE high-impact activities | | Internship/co-op/field experience/student teaching/clinical assignment | F3A14A |
| | | Research project with faculty member outside of course/program requirements | F3A14B |
| <u>*Student-level covariates*</u> | | | |
| Sex | Sex reported by student | | F1SEX |
| Socioeconomic status | A quartile coding of the composite score constructed from parental education, family income, and parental occupations | | F1SES1QR |
| Race | Black, Native Pacific Islander/Indian/Alaska, Hispanic | | F1RACE |
| PS first year GPA | GPA in first year of known attendance | | F3TZYR1GPA |
| <u>*School-level covariates*</u> | | | |
| School-level Federal Meal Subsidy | % of student body receiving the federal meal subsidy (free/reduced-price lunch) | | F1A22A |

(Continued)

Table 7 Continued

| Construct | Description | Measure | Variable Name |
|---|---|---|---|
| School climate: academic pressure | Teachers press students to achieve | | F1A38B |
| | Learning is a high priority for students | | F1A38D |
| | Students are expected to do homework | | F1A38E |
| | Students are encouraged to compete for grades | | F1A38K |
| | Counselors/teachers encourage S to enroll in academic classes | | F1A38L |
| *Weight* | Panel weight, F1 and F3 HS transcript | | F3F1TSCWT |
| | School weight | | BYSCHWT |

## Analytic Techniques

To address *RQ 1*, "*Are secondary school students identified as high-achieving in math and science more likely to select postsecondary education paths in STEM compared with their peers?",* I estimated a multilevel logistic model to investigate the probabilities of attaining the desired dependent variables. *RQ 2*, "*After entering postsecondary STEM paths, when are students identified as high-achieving most likely to complete an undergraduate program in a STEM field? Which variables most significantly influence completion rates in postsecondary studies?",* was analyzed using a discrete-time hazard model to estimate the probabilities of a hazard occurrence (graduation from an undergraduate program in a STEM field) on the discrete-time trajectory defined by seven time points between January 2006 and January 2013, evenly spaced a year apart. *RQ 3, "Are STEM undergraduate students who were identified as high-achieving in high school more likely to select graduate programs or occupations in STEM after college graduation compared with other STEM undergraduate students?",* was analyzed using a multilevel logistic model.

Because all participating students were nested in schools, I considered using multilevel modeling. However, since *RQ 2* restricted the data to those students who entered a STEM undergraduate program by the second follow-up year (unweighted $N$ = 1,030, 7.8%) to standardize the time metric, the number of students per school was reduced to an average of 2.04, which made multilevel modeling ineligible (McNeish & Stapleton, 2016; Snijders & Bosker, 2012). Therefore, I used student-level models to address *RQ* 2. For the baseline models for *RQ 1* and *RQ 3*, I estimated intraclass correlation coefficients (*ICC*) to examine school-level effects on each dependent variable. The estimated variances of school means on outcome variables were statistically examined to determine if they were significantly greater than zero

(Raudenbush & Bryk, 2002). If the ICCs and the estimated variances implied significant school-level effects, I adopted multilevel modeling, nesting each student in a school.

**Preliminary analysis**

Understanding the baseline characteristics of the scales and the sampled students was essential in reliably interpreting the results of further analyses regarding the main research questions. Before I estimated models to address the main research questions, I investigated the psychometric properties of the scales to be used in the main analyses in terms of their validity evidence. In addition, I examined the baseline probabilities of individuals being identified as high-achieving students. I also presented, as preliminary analyses, the unweighted and weighted frequencies at which the dependent variables occurred, as well as unweighted estimates of descriptive statistics of moderating variables.

***Scale validation***

Psychometrically sound scales are prerequisite for conducting a statistical analysis. Among the variables of interest, mathematics self-efficacy (MSE) and school climate of academic pressure (SCCL) needed to be examined regarding their factor structure and psychometric properties. Therefore, I analyzed the two constructs and suggested evidence of validity regarding them. Given that both constructs already had theoretical backgrounds, I performed confirmatory factor analysis (CFA) to examine their factor structures. For both constructs, a one-factor model was specified and estimated. I evaluated goodness-of-fit indices for the model using multiple criteria (Vandenberg & Lance, 2000): .90 or above for the Tucker-Lewis index (TLI; Tucker & Lewis, 1973), .06 or less for the root mean square error of approximation (RMSEA; Steiger, 1990), and .08 or less for the standardized root mean square residual (SRMR; Bentler, 1995). I also evaluated item properties using factor loadings and by looking at internal consistency.

In addition to factor analysis, I also examined whether the factor structure of MSE was equivalent between students identified as high-achieving and other students not identified as high-achieving sampled in the ELS:2002. This measurement invariance analysis investigated whether students identified as high-achieving had unique perceptions of MSE compared to their peers. Since SCCL was not rated by students, but by school administrators, I did not examine measurement invariance in terms of a school climate scale. I employed five sequences of the measurement invariance tests, as recommend by Brown (2015): (1) comparing the CFA models of each group, (2) testing equal form, (3) testing equal factor loadings, (4) testing equal indicator intercepts, and (5) testing equal factor variances. Since the chi-square test is sensitive, especially for invariance tests with large sample sizes (Kline, 2010; Sass, 2011), I used model fit difference tests to evaluate whether significant invariance existed between two nested models. A change of $< -.010$ in Comparative Fit Index (CFI) and $>.015$ in Root Mean Square Error of Approximation (RMSEA) indicated non-invariance between the groups (Chen, 2007).

Finally, as evidence of the validity based on relations to other variables, I performed discriminant function analysis to investigate whether each item measuring mathematics self-efficacy and the academic pressure of school climate predicted student achievement in math and science. In the model for MSE, the dependent variable was identification as a high-achiever in math and science. In the model for school climate, the binary dependent variable was school math achievement, which was defined using the school average of ELS:2002 mathematics assessment scores. The high-achieving group of schools included the top quartile of schools ($N$ = 120), and the other group included the other three quartiles of schools ($N$ = 320).

***Descriptive statistics of dependent and moderating variables***

Since the dependent variables in this study were all binary variables, I estimated the unweighted and weighted frequencies of achieving the three main dependent variables: entry into a STEM field, graduation, and further persistence in a STEM occupation or graduate school degree. The weighted estimates enabled me to gauge the proportions of the student population who experienced the dependent variables of interest. The weighted frequencies were also estimated for student-level covariates (sex, race, and SES), and I graphically presented the disproportions according to these covariates. For moderating variables, which were measured with ordinal or interval scales, means and standard deviations were estimated.

***Probabilities of students being identified as high-achievers***

In addition to descriptive statistics for dependent and moderating variables, I also examined the probabilities of students being identified as high-achievers in math and science, as a baseline investigation. The binary variable of identification was neither a dependent nor a moderating variable; thus, the main research questions did not address the probability of being identified as a high-achiever and did not address potential disproportionate representations of covariates. However, it could be hypothesized that achieving the 95th percentile in college entrance exams was disproportionate to student- and school-level covariates (e.g., sex, race, SES, SCFL), and that most high-school students were not able to control against any potential negative effects of those covariates on their STEM pathways. It was important to understand these baseline disparities among students identified as high-achieving so as to best interpret the results of the main research questions.

To achieve this purpose, I performed a set of multilevel logistic analyses to estimate odds ratios indicating the extent to which students in each demographic category (e.g., female, Asian) were likely to be identified as high-achievers rather than non-high-achievers. Since school-level covariates were also considered, I first estimated the ICC with a null (baseline) model of a two-level logistic model.

**Multilevel logistic regression model**

A logistic regression model estimates the probability that a binary dependent variable occurred ($y_{ij} = 1$). Given that the dependent variable is coded with 0 and 1, the group-dependent probability is

$$\hat{P} = \frac{1}{S}\sum_{j=1}^{N}\sum_{i=1}^{n} Y_{ij}$$

where *S* is the total sample size, *N* is the number of groups, and *n* is the number of individuals in group *j* (Snijders & Bosker, 2013). Since *research questions 1* and *3* concern comparing probabilities in terms of covariates and identification, I estimated the odds ratios using the estimated log-odds. The odds represent the ratio of the probability of success to the probability of failure:

Odds = $P / (1 - P)$.

For example, if the probability of a female student's entrance into a STEM field is 0.2, the odds are 0.2/0.8 = 0.25, which means that the ratio of the probability of entrance to the probability of non-entrance for female students is 1/4. The odds ratio is the ratio between odds of this kind. If the probability of a female student's entrance is compared to the probability of a male student's, the odds ratio is

Odds ratio = $\frac{Odds_{female}}{Odds_{male}} = \frac{P_{female}/(1-P_{female})}{P_{male}/(1-P_{male})}$.

Using logistic regression modeling, I first estimated the log-odds of student entrance into postsecondary STEM paths as a function of predictors. The log-odds are the transformed probabilities using logarithms, defined by:

$$\text{logit}(P) = \ln(\frac{P}{1-P}).$$

The odds ratio can also be computed using the exponentiated log-odds of the predictors:

$$\text{Odds ratio} = \exp\{\text{logit}(\gamma)\}$$

where logit(γ) is the log-odds of the predictor. For example, if the log-odds of the variable of sex for STEM entrance are 1, the odds ratio for the variable is exp(1) = 2.72, which implies that the odds of female students are 2.72 times the odds of male students entering into STEM fields. Using the estimated log-odds, I estimated odds ratios to enable comparisons between groups.

In a baseline model (Model A), only a random intercept was included, and the odds probability was estimated:

$$logit(y_{ij} = 1|x_{ij}) = logit\left(\frac{\Pr(y_{ij}=1|x_{ij})}{1-\Pr(y_{ij}=1|x_{ij})}\right) = \beta_0 + u_j,$$

where *i* represents an individual, *j* represents a school, $\beta_0$ indicates the overall mean probability on a logistic scale, and $u_j$ is the school-level residual. The dependent variable was the binary variable of entrance into postsecondary STEM fields. Given that school-level residual variance was estimated on a logistic scale while individual-level residual variance was on a probability scale in the multilevel logistic modeling, the individual-level variance was corrected using the following equation,

$$\sigma_e{}^2 = \pi^2/3,$$

which gives the variance of standard logistic distribution. The corrected variance was used to calculate the intraclass correlation coefficient (ICC, Snijders & Bosker, 1999). In this study, the ICC for the baseline model was calculated by the formula

$$\text{ICC} = \frac{\tau_0^2}{\tau_0^2 + \pi^2/3}$$

where $\tau_0^2$ is the intercept variance and $\tau_0$ is the level-two standard deviation of $u_j$.

To address *RQ 1*, estimating the probabilities of high-achievers selecting postsecondary educational paths in STEM, compared with their peers, I added a variable to Model B that students identified as high-achieving (HA), which was defined as

$$logit\ (y_{ij}) = \beta_{0j} + \beta_1 HA_i$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_1 = \gamma_{10}.$$

A model adding student-level and school-level covariates was defined as Model C:

$$logit\ (y_{ij}) = \beta_{0j} + \beta_1 HA_i + \beta_2 Sex_i + \beta_3 Asian_i + \beta_4 BHNO_i + \beta_5 SES_i$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} SCMS_j + \gamma_{02} SCAT_j + u_{0j}$$

$\beta_k = \gamma_{k0}$ for the remaining k = 1 through 5.

The variable of race was input as a dummy variable. White was the reference group, and Black, Hispanic, Native American, and other races (BHNO) were categorized into a single group due to the small number of identified students in each one. Asian was the third group. In Model D, after examining the effects of the covariates, I added two-way interaction terms between identification and each covariate to examine whether the effects of the covariates differed for students identified as high-achieving and those not identified as such. Then, in Model E, I included moderating variables, MSE and advanced courses in math and science (ADC), and their two-way interaction effects with each covariate, in addition to the variables examined in Model D.

Model F was the final model. Based on the results of Model E, I added three-way interaction terms for identification, each covariate, and each moderator, and the significant variables remained in the final model. A possible full model is as follows:

$$logit\ (y_{ij}) = \beta_{0j} + \beta_1 HA_i + \beta_2 Sex_i + \beta_3 Asian_i + \beta_4 BHNO_i + \beta_5 SES_i + \beta_6 MSE_i + \beta_7 ADC_i + \beta_8 HA * Sex_i + \beta_9 HA * Asian_i + \beta_{10} HA * BHNO_i + \beta_{11} HA * SES_i + \beta_{12} HA * MSE_i + \beta_{13} HA * ADC_i + \beta_{14} MSE * Sex_i + \beta_{15} MSE * Asian_i + \beta_{16} MSE * BHNO_i + \beta_{17} MSE * SES_i + \beta_{18} ADC * Sex_i + \beta_{19} ADC * Asian_i + \beta_{20} ADC * BHNO_i + \beta_{21} ADC * SES_i + \beta_{22} HA * MSE * Sex_i + \beta_{23} HA * MSE * Asian_i + \beta_{24} HA * MSE * BHNO_i + \beta_{25} HA * MSE * SES_i + \beta_{26} HA * ADC * Sex_i + \beta_{27} HA * ADC * Asian_i + \beta_{28} HA * ADC * BHNO_i + \beta_{29} HA * ADC * SES_i + \beta_{kj}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} SCMS_j + \gamma_{02} SCAT_j + u_{0j}$$

$$\beta_{kj} = \gamma_{11} HA * SCMS_{ij} + \gamma_{12} HA * SCAT_{ij} + \gamma_{51} MSE * SCMS_{ij} + \gamma_{52} MSE * SCAT_{ij} + \gamma_{61} ADC * SCMS_{ij} + \gamma_{62} ADC * SCMS_{ij} + \gamma_{53} HA * MSE * SCMS_{ij} + \gamma_{54} HA * MSE * SCAT_{ij} + \gamma_{63} HA * ADC * SCMS_{ij} + \gamma_{64} HA * ADC * SCMS_{ij}$$

$\beta_k = \gamma_{k0}$ for the remaining k = 1 through 29.

All categorical and continuous variables were grand-mean centered for better interpretability. Each model was evaluated by a likelihood-ratio test and goodness-of-fit indices to determine which predictors would remain in the final model. I adopted the multiple imputation method to treat missing data. In doing so, I created five imputed datasets for the analyses and merged the estimated coefficients using PROC MIANALYZE in the SAS software. The estimated model fits (deviance tests) for each piece of imputed data had to be combined by the methods suggested by Little and Rubin (2002). The combined test statistic is as follows:

$$\tilde{C} = \frac{\frac{M\bar{C}}{q} - (M-1)V}{M + (M+1)V},$$

where *M* is the number of imputed data, $q$ is the degrees of freedom, and *V* is the sample variance of the square root, which was calculated by

$$V = \frac{1}{M-1}\sum_{m=1}^{M}(\sqrt{C_m} - \overline{\sqrt{C}})^2.$$

Each subsequent model was compared with a saturated model using deviance statistics; if the difference in the deviance statistics between the two nested models was significant, the subsequent model provided a better fit than the previous model (Snijders & Bosker, 1999). I also reported the average Bayesian Information Criterion (BIC) of the five pieces of imputed data to complement the deviance statistics. BIC is particularly useful when any two models are compared, even if they are not nested. If both model fits of a subsequent model decrease in comparison with the previous model, the subsequent model is supported.

A similar set of multilevel logistic models were estimated to address *RQ 3, "Are STEM undergraduate students who were identified as high-achieving in high school more likely to select graduate programs or occupations in STEM after college graduation compared with other STEM undergraduate students?"* In this case, the odds were defined according to the persistence of students in STEM, as shown through entrance into STEM occupations or graduate studies after college graduation. A further factor in this case was the addition of moderating variables from students' undergraduate programs (credits of STEM courses taken [STCR], high impact activities [HIMP]) instead of high-school experiences (MSE, ADC). The possible final full model was:

$$logit\ (y_{ij}) = \beta_1 HA_i + \beta_2 Sex_i + \beta_3 Asian_i + \beta_4 BHNO_i + \beta_5 SES_i + \beta_6 MSE_i + \beta_7 ADC_i + \beta_8 HA * Sex_i + \beta_9 HA * Asian_i + \beta_{10} HA * BHNO_i + \beta_{11} HA * SES_i + \beta_{12} HA * STCR_i + \beta_{13} HA * HIMP_i + \beta_{14} STCR * Sex_i + \beta_{15} STCR * Asian_i + \beta_{16} STCR * BHNO_i + \beta_{17} STCR * SES_i + \beta_{18} HIMP * Sex_i + \beta_{19} HIMP * Asian_i + \beta_{20} HIMP * BHNO_i + \beta_{21} HIMP * SES_i + \beta_{22} HA * STCR * Sex_i + \beta_{23} HA * STCR * Asian_i + \beta_{24} HA * STCR * BHNO_i + \beta_{25} HA * STCR * SES_i + \beta_{26} HA * HIMP * Sex_i + \beta_{27} HA * HIMP * Asian_i + \beta_{28} HA * HIMP * BHNO_i + \beta_{29} HA * HIMP * SES_i + \beta_{kj}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} SCMS_j + \gamma_{02} SCAT_j + u_{0j}$$

$$\beta_{kj} = \gamma_{11} HA * SCMS_{ij} + \gamma_{12} HA * SCAT_{ij} + \gamma_{51} STCR * SCMS_{ij} + \gamma_{52} STCR * SCAT_{ij} + \gamma_{61} HIMP * SCMS_{ij} + \gamma_{62} HIMP * SCMS_{ij} + \gamma_{53} HA * STCR * SCMS_{ij} + \gamma_{54} HA * STCR * SCAT_{ij} + \gamma_{63} HA * HIMP * SCMS_{ij} + \gamma_{64} HA * HIMP * SCMS_{ij}$$

$\beta_k = \gamma_{k0}$ for the remaining k = 1 through 29.

The same method as described above was used to evaluate each model to determine the predictors that would remain in the final model.

**Discrete-time hazard model**

A discrete-time hazard model enables estimation of the hazard probability of an event occurrence (e.g., graduation from postsecondary education with a STEM major) and investigation of when the event is particularly likely to occur, as well as whether those occurrences increase, decrease, or remain constant over time (Allison, 1982; Singer & Willett, 1993). Note that “hazard” in this study refers to a positive outcome, graduation from postsecondary education with a STEM major, and “survivor” refers to a negative outcome, not graduation from postsecondary education with a STEM major. To address *RQ 2,* I estimated a set of discrete-time hazard functions with a maximum likelihood method (Barber, Murphy, Axinn, & Maples, 2000; Singer & Willett, 2003). Note that I included in the sample only those who graduated high school on time and who had entered STEM fields as of 2006, in order to standardize the time metric, because it was a requisite for incorporating hazard modeling. In this model, the hazard probability is defined as the probability that a student graduated from a postsecondary education institution with a STEM major within eight years of high school graduation. The hazard function is as follows:

$$h(t_j) = \frac{n\ events\ j}{n\ at\ risk\ j}$$

where $n\ events\ j$ represents the number of students who experience the event in time period $j$, assuming that the event has not occurred before, and $n\ at\ risk\ j$ represents the number of students at risk during time period $j$. The survivor probability, $S(t_j)$, is the probability that an individual did not experience the hazard event (college graduation in STEM) during the observed period. In this case, “survivor” refers to a student who did not graduate during the observed period.

The time metric was a year, and I created binary event indicators during the observed period, *D*, using the data provided in terms of the month and year of college graduation. A total of seven event indicators were created, one for each year between January 2006 and January 2013.

Before estimating a set of hazard models for students identified as high-achieving (*RQ 2*), I estimated the baseline hazard probabilities for all the students, including non-identified students, who had entered STEM fields as of 2006, and I examined whether the hazard and survivor probabilities differed by identification.

To address the main research question, I restricted the sample only to college bound students identified as high-achieving. I estimated the log hazard odds of the event, based on logistic regression models. To begin with, a baseline model (Model A) was fitted with no covariate,

$$Logit\left[h\left(t_{ij}\right)\right] = log\left[\frac{h\left(t_{ij}\right)}{1-h\left(t_{ij}\right)}\right] = \alpha_1 D_{1ij} + \alpha_2 D_{2ij} + \cdots + \alpha_7 D_{7ij} = \beta_{0j}$$

where $\alpha$ is the intercept representing the log odds of the event occurrence, and $D$ is a dummy variable representing event occurrence at time $t$. Student-level covariates and moderators were added to the subsequent model. Model B included student-level covariates, and I added two moderators and their interactions with covariates in Model C. Only significant variables were remained in the final model, Model D. The possible full model is as follows:

$$Logit[h(t_i)] = \alpha_1 D_{1i} + \alpha_2 D_{2ij} + \cdots + \alpha_7 D_{7ij} + \beta_1 Sex_i + \beta_2 Race_i + \beta_3 SES +$$
$$\beta_4 MSE_i + \beta_5 ADC_{ij} + \beta_6 Sex * MSE_i + \beta_7 Race * MSE_i + \beta_8 SES * MSE_i +$$
$$\beta_9 Sex * ADC_i + \beta_{10} Race * ADC_i + \beta_{11} SES * ADC_i.$$

In this study, a plot for fitted survival functions provides the information about how many more and how much faster a group of students graduated with a STEM major than the other group of students, whereas a plot for fitted hazard functions is useful to understand when the graduation was most likely to happen. Therefore, for the baseline estimation, I presented both types of plots. For comparing between groups, I presented fitted survival functions only.

# CHAPTER 4 RESULTS

## Preliminary Analysis

In this section, I present preliminary results. I investigated the psychometric properties of the scales to be used in the main analyses in terms of their validity evidence and examined the baseline probabilities of individuals being identified as high-achieving students.

### Scale validation

#### *Mathematics self-efficacy questionnaire*

*Confirmatory factor analysis*

I examined the factor structure and internal consistency of the Mathematics Self-Efficacy Questionnaire (MSEQ; Ingels et al., 2004) to collect evidence of validity based on the internal structure. Since the MSE construct already had a theoretical background, I performed confirmatory factor analysis. A hypothetical one-factor model was specified and estimated using Mean- and Variance-Adjusted Maximum Likelihood (MLMV). Descriptive statistics, inter-item Pearson correlations, and covariance matrices that were used in the analyses are presented in Table 8.

Table 8

*Descriptive Statistics and Inter-Item Correlation/Covariance Matrix for Mathematics Self-Efficacy Questionnaire*

| | Response Percentage | | | | | | | | Correlation/Covariance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Item | 1 | 2 | 3 | 4 | *M* | *SD* | *Skew* | *Kurt* | MSE1 | MSE2 | MSE3 | MSE4 | MSE5 |
| MSE1 | 8.8 | 42.8 | 30.0 | 18.4 | 2.58 | 0.89 | -0.82 | 0.17 | -- | .55 | .54 | .52 | .56 |
| MSE2 | 15.4 | 43.7 | 28.2 | 12.8 | 2.38 | 0.89 | -0.68 | 0.24 | .70 | -- | .62 | .49 | .55 |
| MSE3 | 14.4 | 40.5 | 29.8 | 15.3 | 2.46 | 0.92 | -0.80 | 0.15 | .67 | .75 | -- | .51 | .57 |
| MSE4 | 5.3 | 29.3 | 39.1 | 26.4 | 2.86 | 0.87 | -0.80 | -0.23 | .68 | .63 | .64 | -- | .56 |
| MSE5 | 8.3 | 32.7 | 34.0 | 25.0 | 2.76 | 0.93 | -0.93 | -0.14 | .69 | .66 | .67 | .70 | -- |

*Note*. For the correlation/covariance matrix, the left side of the diagonal represents inter-item correlation coefficients and the right side represents covariance coefficients. MSE1= *can do excellent job on math tests*; MSE2 = *can do excellent job on math tests*; MSE3 = *can understand difficult math class*; MSE4 = *can do excellent job on math assignments*; MSE5 = *can master math class skills*. The anchors of the scale were: 1 = *almost never*; 2 = *sometimes*; 3 = *often*; 4 = *almost always*. Unweighted sample size was 10,230 when rounded to the nearest ten.

Model fit statistics for the one-factor model (Model 1) are presented in Table 9. The model fit statistics mostly indicated an acceptable fit (CFI = .980, TLI = .960, SRMR = .020, RMSEA = .111, 90% CI [.104, .118]), but RMSEA exceeded the recommended criterion for an adequate model fit: a value less than .80 (Vandenberg & Lance, 2000). Given that the justification of a model is not solely based on overall model fits, but has to also rely on localized areas of strain and the interpretability of the model (Brown, 2015), I also checked modification indices (MI) and factor loadings to evaluate the one-factor model (Model 1). The modification indices implied that an item, MSE2, had correlated errors with other items: MI = 534.10 with MSE3, MI = 202.43 with MSE4, and MI = 122.84 with MSE5. Factor loadings for the five items ranged from .69 to .77.

Based on the results, I modified the model in two ways; in Model 2, I specified a correlated error between MSE2 and MSE3, and in Model 3, I excluded MSE2 completely. Model 2 and Model 3 obviously showed better fits than Model 1 (Model 2, CFI = .996, TLI = .989, SRMR = .010, RMSEA = .058, 90% CI [.050, .067]; Model 3, CFI = .999, TLI = .996, SRMR = .005, RMSEA = .037, 90% CI [.026, .049]), which implied that MSE2 deteriorated the model fit of Model 1, due to correlated errors with other variables. Correlated errors usually exist between items that are similarly worded, reverse-worded, or differentially inclined to social desirability (Brown, 2015). In fact, the wording and the meaning of MSE2 (can understand difficult math texts) were similar to other items (e.g., can understand difficult math classes). Since correlated errors imply the interdependence of errors among items (Brown, 2015), a factor model with correlated errors might not be a preferred model, particularly if there is no theoretical background supporting the correlated errors. Therefore, I decided to exclude MSE2 from the scale, and Model 3 was the final model for MSE (CFI = .999, TLI = .996, SRMR = .037, RMSEA = .037, 90% CI [.026,

.049]). Factor loadings and the internal consistency coefficient for Model 3 (Cronbach's $\alpha$ = .89) are presented in

Table *10*.

Table 9

*Model Fit Statistics for the Factor Models of Mathematics Self-Efficacy*

| | $\chi^2$ | *df* | CFI | TLI | RMSEA | [90% CI] | SRMR |
|---|---|---|---|---|---|---|---|
| Model 1 | 631.984 | 5 | 0.980 | 0.960 | 0.111 | [.104, .118] | 0.020 |
| Model 2 | 143.633 | 4 | 0.996 | 0.989 | 0.058 | [.050, .067] | 0.010 |
| Model 3 | 29.698 | 2 | 0.999 | 0.996 | 0.037 | [.026, .049] | 0.005 |

*Note.* Model 1 is a 1-factor model specified with all five items; Model 2 is a 1-factor model specified with correlated errors between MSE2 and MSE3; Model 3 is a 1-factor model excluding MSE2.

Table 10

*Factor Loadings and Internal Consistency of the Final Model of Mathematics Self-Efficacy*

| | Factor loading | *SE* | Corrected item-total correlation | Cronbach's $\alpha$ if item deleted | Cronbach's $\alpha$ |
|---|---|---|---|---|---|
| MSE1 | 0.73 | 0.01 | 0.77 | 0.86 | 0.89 |
| MSE3 | 0.73 | 0.01 | 0.74 | 0.87 | |
| MSE4 | 0.71 | 0.01 | 0.76 | 0.86 | |
| MSE5 | 0.78 | 0.01 | 0.78 | 0.85 | |

*Measurement invariance*

In addition to factor analysis, I examined the measurement invariance of the MSEQ between students identified as high-achieving and non-identified students sampled in the ELS:2002. A factor model with four items was estimated for each of the two groups (RMSEA > .000, 90% CI [.000, .080], CFI = 1.000 for high-achievers, RMSEA = .036, 90% CI [.024, .048], CFI = .999 for non-identified students). Table 11 summarizes the results of a set of measurement invariance tests. The model fits from equal form testing, in which two separate models are simultaneously tested with two groups, were at acceptable levels (RMSEA = .032, 90% CI [.020, .044], CFI = .999). Based on the demonstrated equality of equal form, I tested the equality of factor loadings by restricting all factor loadings equally across the two groups. The model fit difference tests indicated acceptable levels of invariance (ΔRMSEA = .008, ΔCFI =.002), which implied that the overall factor loadings were equivalent across the two groups. Next, I examined the equality of indicator intercepts and found that constraining all indicator intercepts equally across the two groups did not significantly degrade the model fits (ΔRMSEA = .004, ΔCFI =.002). Based on the measurement invariance (i.e., equal factor loadings, equal indicator intercepts), I tested the population heterogeneity. Equal factor variance was confirmed (ΔRMSEA = .002, ΔCFI > .000); however, the test for equality of latent means was negative (ΔRMSEA = .038, ΔCFI > .016). The non-invariance of latent means implied that MSE of student identified as high-achieving, which was measured as a latent construct, was significantly greater than the MSE of other students. Given that the factor loadings and indicator intercepts were invariant between the two groups, the comparison of the latent means between the two groups was interpretable. The unstandardized parameter estimate for the latent mean of students identified as high-achieving was .94 (SE = .05), which indicated that students identified as high-achieving scored .94 units above non-identified students on the construct of mathematics self-efficacy.

Table 11

*Test Statistic of Measurement Invariance of the Mathematics Self-Efficacy Questionnaire*

| | *adj* $\chi^2$ | *df* | $\Delta$*adj* $\chi^2$ | $\Delta$*df* | RMSEA [90% CI] | $\Delta$ RMSEA | CFI | $\Delta$ CFI | TLI | $\Delta$ TLI |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | ***Single group solutions*** | | | | | |
| Full sample ($N$ = 10,230) | 29.70 | 2 | | | 0.037 [0.026, 0.049] | | 0.999 | | 0.996 | |
| High-achieving ($N$ = 520) | 1.52 | 2 | | | 0.000 [0.000, 0.080] | | 1.000 | | 1.001 | |
| Non-identified ($N$ = 9,710) | 26.55 | 2 | | | 0.036 [0.024, 0.048] | | 0.999 | | 0.997 | |
| | | | | | ***Multi-group comparisons*** | | | | | |
| Equal form | 24.64 | 4 | | | 0.032 [0.020, 0.044] | | 0.999 | | 0.997 | |
| Equal factor loading | 64.85 | 7 | 46.49*** | 3 | 0.040 [0.032, 0.049] | 0.008 | 0.997 | 0.002 | 0.995 | 0.002 |
| Equal indicator intercepts | 110.82 | 10 | 56.45*** | 3 | 0.044 [0.037, 0.052] | 0.004 | 0.995 | 0.002 | 0.993 | 0.002 |
| Equal factor variance | 111.77 | 11 | 3.98* | 1 | 0.042 [0.035, 0.050] | 0.002 | 0.995 | 0.000 | 0.994 | 0.001 |
| Equal latent mean | 405.68 | 12 | 384.13*** | 1 | 0.080 [0.074, 0.087] | 0.038 | 0.979 | 0.016 | 0.979 | 0.015 |

*Note.* Sample sizes were rounded to the nearest ten. *** $p$ < .001, * $p$ < .05

*Discriminant function analysis*

I performed discriminant function analysis (DFA) to examine how effectively the items of MSE predicted student achievement in math and science. Discriminant function analysis yielded a Wilks' Lambda of .96 ($df = 4$, $p < .001$), indicating that this set of MSE items significantly differentiated the two groups. However, only 4% of the variance in student achievement was explained by the discriminant function composed of the four items of MSE. The structure matrix is presented in Table 12. Burns and Burns (2008) suggested that .30 of the estimate ought to be the cut-off between important and less important variables. Based on this criterion, all the items were soundly loaded on the function. With the estimated function, 96.1% of students were correctly classified into the two groups.

Table 12

*Results of Discriminant Function Analysis for Mathematics Self-Efficacy*

| Variable | Structure Matrix |
|---|---|
| MSE 1 | .79 |
| MSE 3 | .94 |
| MSE 4 | .70 |
| MSE 5 | .87 |
| Eigenvalue | .04 |
| Wilks' Lambda | $.96^{***}$ |
| Canonical correlation | .20 |

$^{***}p < .001$

***School climate scale—academic pressure***

*Confirmatory factor analysis*

A hypothetical one-factor model for the academic pressure of school climate scale was specified with five items, and the model was estimated with Mean- and Variance-Adjusted Maximum Likelihood (MLMV). Descriptive statistics, inter-item correlations, and covariance matrices are presented in Table 13.

Model fit statistics indicated acceptable fit for the one-factor model with 5 items (CFI = .982, TLI = .963, SRMR = .025, RMSEA = .066, 90% CI [.028, .108]). However, the factor loading of SCCL4, “students are expected to do homework,” was low (standardized estimate = .188). An identical model excluding SCCL4 was estimated as Model 2, and this yielded better model fits (CFI = .992, TLI = .975, SRMR = .025, RMSEA = .018, 90% CI [.000, .133]). The factor loadings of the four items were all acceptable based on the criteria of .30 suggested by Burns and Burns (2008) (Table 15). Cronbach’s alpha was 0.81.

Table 13

*Descriptive Statistics and Correlation/Covariance Matrix for School Climate Scale – Academic Press (N = 440)*

| | Response Percentage | | | | | | | | | Correlation/Covariance | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Item | 1 | 2 | 3 | 4 | 5 | *M* | *SD* | *Skew* | *Kurt* | SCCL1 | SCCL2 | SCCL3 | SCCL4 | SCCL5 |
| SCCL1 | 0.0 | 2.3 | 19.1 | 37.3 | 41.2 | 4.18 | .82 | -.59 | -.57 | | .44 | .41 | .11 | .29 |
| SCCL2 | 1.1 | 10.3 | 41.6 | 34.2 | 12.8 | 3.47 | .88 | -.06 | -.27 | .60 | | .41 | .16 | .24 |
| SCCL3 | 0.7 | 3.7 | 16.7 | 32.9 | 46.1 | 4.20 | .89 | -.95 | .36 | .57 | .52 | | .09 | .30 |
| SCCL4 | 8.5 | 24.8 | 35.8 | 22.2 | 8.7 | 2.98 | 1.08 | .05 | -.59 | .13 | .17 | .01 | | .13 |
| SCCL5 | 0.0 | 0.7 | 10.7 | 35.5 | 53.2 | 4.41 | .71 | -.90 | -.03 | .51 | .39 | .48 | .18 | |

*Note*. For the correlation/covariance matrix, left side of the diagonal represents correlation coefficients and right side of it represents covariance coefficients. SCCL1 = *teachers press students to achieve*; SCCL2 = *learning is high priority for students*; SCCL3 = *students expected to do homework*; SCCL4 = *students are encouraged to compete for grades*; SCCL5 = *counselors/teachers encourage students to enroll in academic classes*. The anchors of the scale were: 1 = *not at all accurate*; 2 = *not at all accurate-somewhat accurate*; 3 = *somewhat accurate*; 4 = *somewhat accurate-very accurate*; 5 = *very accurate*.

Table 14

*Model Fit Statistic for the Factor Models of School Climate of Academic Pressure*

| | $\chi^2$ | *df* | CFI | TLI | RMSEA | [90% CI] | SRMR |
|---|---|---|---|---|---|---|---|
| Model 1 | 14.52 | 5 | .982 | .963 | .066 | [.028, .108] | .025 |
| Model 2 | 5.95 | 2 | .992 | .975 | .067 | [.000, .133] | .018 |

*Note.* Model 1 is a 1-factor model specified with all five items; Model 2 is a 1-factor model excluding SCCL4.

Table 15

*Factor Loadings and Internal Consistency of the Final Model of School Climate of Academic Pressure*

| | Factor loading | *SE* | Corrected item-total correlation | Cronbach's $\alpha$ if item deleted | Cronbach's $\alpha$ |
|---|---|---|---|---|---|
| SCCL1 | .66 | .03 | .70 | .72 | |
| SCCL2 | .63 | .04 | .61 | .76 | .81 |
| SCCL3 | .64 | .04 | .64 | .75 | |
| SCCL5 | .43 | .03 | .55 | .79 | |

*Note.* SCCL1 = *teachers press students to achieve*; SCCL2 = *learning is high priority for students*; SCCL3 = *students expected to do homework*; SCCL5 = *counselors/teachers encourage students to enroll in academic classes*.

*Discriminant function analysis*

I also examined how each item of academic press was associated with school math achievement. The discriminant function yielded a Wilks' Lambda of .81 ($df = 4$, $p < .001$), which indicated that the overall construct of the academic pressure of school climate significantly differentiated the two groups. However, approximately 19% of variance in the dependent variable was explained by the discriminant function of the four items of MSE (canonical correlation = .44). The structure matrix is presented in Table 16. By the criteria of Burns and Burns (2008) who suggested loadings equal or greater than 0.30, all the items soundly loaded on the function. With the estimated function, 77.9% of schools were correctly classified into the two groups.

Table 16

*Results of Discriminant Function Analysis for School Climate of Academic Pressure*

| Variable | Structure Matrix |
|---|---|
| SCCL1 | .95 |
| SCCL2 | .70 |
| SCCL3 | .65 |
| SCCL5 | .44 |
| Eigenvalue | .23 |
| Wilks' Lambda | .81$^{***}$ |
| Canonical correlation | .44 |

$^{***}p < .001$

**Descriptive statistics of dependent and moderating variables**

***Descriptive statistics of dependent variables***

*Entrance into STEM fields*

Table 17 shows the unweighted and weighted frequencies of student entrance into postsecondary STEM fields. The frequencies were estimated by sex, race, and SES. As with the results of a preliminary analysis, which purpose was to provide detailed representation of the descriptive statistic, I presented the results in terms of race according to six racial categories, as originally coded in the data set. A third of the students identified as high-achieving entered a 4-year undergraduate program in a STEM field, which was much higher than the percentage for non-identified students (6.31%). Male students and students whose families were in the highest quartile of SES were more likely to enter into STEM, both for and non-identified students. Asian students, out of the six categories, were the most likely to enter into a STEM field. However, considering that the research questions concern the probabilities of students identified as high-achieving entering into STEM fields, the numbers of identified Black, Hispanic, multiple race, and Native American students (*n* = less than 10, 10, 10, and 0, respectively) were too low to estimate models, particularly considering the moderating effects. Therefore, I confirmed my previous decision that merging these four racial categories into one group (Black, Hispanic, Native American, and other races [BHNO]) would be better for the probability estimations of the main research questions.

*College graduation in STEM fields*

Since the second research question concerned probabilities among students who had entered into postsecondary STEM paths as of 2006, I estimated unweighted and weighted descriptive statistics with data concerning 1,010 students who had entered the fields as of 2006 and had time variables indicating when they graduated from college (for the survival analyses). Table 19 shows the unweighted frequencies of student college graduation in STEM fields, and Table 20 gives the weighted frequencies. Overall, 55.25% of non-identified students graduated with a STEM major as of 2013, whereas 60.47% of students identified as high-achieving had done so. For the non-identified students, male (58.69%), Asian students (69.72%), and from families in the fourth quartile of SES (60.88%) graduated from colleges in STEM fields at a higher rate than other students; for example, female (48.90%), Black (26.65%), Hispanic (56.75%), Multiple (65.48%), students from families in the first quartile of SES (49.49%). But, for students identified as high-achieving, male (60.85%) and female (59.82%) graduated at the similar rates.

*Graduate degrees in STEM fields*

The dependent variable of *RQ 3* was a binary variable indicating further persistence in STEM, either through earning a graduate degree in a STEM field or having an occupation in the fields. I present descriptive statistics in separate tables for the sake of detail and clarity. Table 21 gives the unweighted frequencies of students who had earned graduate degrees in STEM fields as of 2013, eight years after high-school graduation. Only 0.49% of non-identified students had earned graduate degrees in STEM fields, but 6.24% of students identified as high-achieving had done so. Unlike the patterns for the other two dependent variables, the differences by covariate were not noticeable, particularly given the small number of students who fulfilled the dependent variable. Table 22 gives the results of weighted estimation.

*Having an occupation in STEM fields after college graduation*

Table 23 gives the unweighted frequencies of students who had occupations in STEM fields after college graduation. Approximately 5% of non-identified students had an occupation in STEM, whereas 20% of students identified as high-achieving had one. Discrepancies by sex existed for this dependent variable: for non-identified students, 2.51% female and 7.79% male had an occupation in STEM, and for students identified as high-achieving, 10.76% female and 26.79% male did so. It was also noteworthy that Asian students identified as high-achieving (20.21%) were no more likely to have an occupation in these fields than White (20.77%) and other-race students (13.64 – 22.22%, See Table 23) identified as high-achieving, which was not consistent with the proportions found with the other two dependent variables; Asian students identified as high-achieving were more likely to enter into postsecondary STEM fields and were more likely to graduate from college with a STEM major than students of other races. Students who had families in the fourth quartile of SES (22.29% of students identified as high-achieving and 7.26% of non-identified students) were more likely to have an occupation in a STEM field than students from families of the other three quartiles of SES (Table 23).

Table 17

*Unweighted Frequencies and Proportions of Students Who Entered Postsecondary STEM by Sex, Race, and SES*

| | | Identified as high-achieving (*N* = 720) | | Non-identified (*N* = 12,530) | |
|---|---|---|---|---|---|
| | | *N* | % within sub-group | *N* | % within sub-group |
| Sex | Female | 70 | 22.92 | 320 | 4.84 |
| | Male | 170 | 39.95 | 470 | 8.00 |
| Race | Asian | 80 | 39.38 | 120 | 10.83 |
| | Black | less than 10 | 33.33 | 120 | 6.91 |
| | Hispanic | less than 10 | 27.59 | 70 | 3.61 |
| | Multiple | less than 10 | 27.27 | 40 | 5.87 |
| | Native | 0 | NA | less than 10 | 1.87 |
| | White | 150 | 31.26 | 450 | 6.27 |
| SES | First | 10 | 30.30 | 90 | 3.02 |
| | Second | 20 | 32.65 | 140 | 4.68 |
| | Third | 40 | 30.50 | 210 | 6.68 |
| | Fourth | 170 | 34.14 | 350 | 10.25 |
| Total | | 240 | 33.15 | 790 | 6.31 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: “first” quartile represents students whose families are in the bottom 25% of SES; and “fourth” quartile represents students whose families are in the top 25% of SES. All unweighted sample size numbers were rounded to the nearest ten.

Table 18

*Weighted Frequencies and Proportions of Students Who Entered Postsecondary STEM by Sex, Race, and SES*

| | | Identified as high-achieving ($N$ = 143,631) | | | Non-identified ($N$ = 3,142,880) | | |
|---|---|---|---|---|---|---|---|
| | | Weighted $N$ | $SE$ | % within sub-group | Weighted $N$ | $SE$ | % within sub-group |
| Sex | Female | 13,250 | 1,970 | 24.85 | 68,817 | 4,926 | 4.26 |
| | Male | 36,994 | 3,026 | 40.97 | 114,685 | 6,811 | 7.52 |
| Race | Asian | 8,500 | 1,078 | 39.86 | 13,380 | 1,504 | 11.46 |
| | Black | 488 | 365 | 38.79 | 32,864 | 3,781 | 7.01 |
| | Hispanic | 1,514 | 668 | 20.42 | 16,778 | 2,484 | 3.18 |
| | Multiple | 601 | 199 | 19.05 | 7,646 | 1,801 | 5.93 |
| | Native | NA | NA | NA | 499 | 499 | 1.57 |
| | White | 39,140 | 3,153 | 35.43 | 112,337 | 6,651 | 6.01 |
| SES | First | 1,743 | 443 | 30.70 | 23,252 | 2,900 | 2.87 |
| | Second | 3,939 | 859 | 34.09 | 37,742 | 4,034 | 4.58 |
| | Third | 7,957 | 1,307 | 27.12 | 48,734 | 4,356 | 6.18 |
| | Fourth | 36,605 | 3,182 | 37.72 | 73,775 | 5,227 | 10.23 |
| Total | | 50,244 | 3,238 | 34.98 | 183,503 | 8,289 | 5.84 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES.

Table 19

*Unweighted Frequencies and Proportions of College Graduation in STEM by Sex, Race, and SES*

| | | Identified as high-achieving (*N* = 230) | | Non-identified (*N* = 770) | |
|---|---|---|---|---|---|
| | | *N* | % within sub-group | *N* | % within sub-group |
| Sex | Female | 50 | 62.35 | 160 | 54.30 |
| | Male | 90 | 62.59 | 300 | 62.63 |
| Race | Asian | 30 | 72.09 | 110 | 71.71 |
| | Black | 10 | 42.31 | 30 | 32.61 |
| | Hispanic | < 10 | 33.33 | 30 | 57.89 |
| | Multiple | < 10 | 54.55 | 20 | 56.67 |
| | Native | 0 | NA | 0 | NA |
| | White | 90 | 67.15 | 270 | 61.09 |
| SES | First | 10 | 44.44 | 40 | 51.47 |
| | Second | 20 | 51.43 | 60 | 46.34 |
| | Third | 30 | 58.93 | 110 | 57.14 |
| | Fourth | 80 | 71.93 | 260 | 65.90 |
| Total | | 150 | 62.50 | 460 | 59.38 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES. All unweighted sample size numbers were rounded to the nearest ten.

Table 20

*Weighted Frequencies and Proportions of College Graduation in STEM by Sex, Race, and SES*

| | | Identified as high-achieving (*N* = 51,048) | | | Non-identified (*N* = 183,503) | | |
|---|---|---|---|---|---|---|---|
| | | Weighted *N* | *SE* | % within sub-group | Weighted *N* | *SE* | % within sub-group |
| Sex | Female | 11,436 | 1,851 | 59.82 | 30,344 | 3,013 | 48.90 |
| | Male | 19,431 | 2,424 | 60.85 | 67,238 | 4,600 | 58.69 |
| Race | Asian | 3,265 | 679 | 76.56 | 12,131 | 1,379 | 69.72 |
| | Black | 2,220 | 936 | 30.93 | 6,761 | 1,477 | 26.65 |
| | Hispanic | 1,304 | 768 | 28.90 | 7,334 | 1,585 | 56.75 |
| | Multiple | 672 | 317 | 43.85 | 4,343 | 1,493 | 65.48 |
| | Native | NA | NA | NA | NA | NA | NA |
| | White | 23,405 | 2,648 | 69.74 | 67,014 | 4,730 | 58.63 |
| SES | First | 2,728 | 916 | 46.56 | 8,723 | 1,798 | 49.49 |
| | Second | 3,766 | 1,039 | 43.66 | 14,932 | 2,412 | 45.56 |
| | Third | 6,712 | 1,466 | 56.41 | 23,761 | 3,008 | 54.23 |
| | Fourth | 17,660 | 2,413 | 71.61 | 50,168 | 3,877 | 60.88 |
| Total | | 30,867 | 2,698 | 60.47 | 97,583 | 4,951 | 55.25 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES.

Table 21

*Unweighted Frequencies and Proportions of Students Who Earned Graduate Degrees in STEM by Sex, Race, and SES*

| | | Identified as high-achieving ($N$ = 720) | | Non-identified ($N$ = 12,530) | |
|---|---|---|---|---|---|
| | | Weighted $N$ | % within sub-group | Weighted $N$ | % within sub-group |
| Sex | Female | 20 | 6.25 | 30 | 0.60 |
| | Male | 30 | 6.24 | 40 | 0.40 |
| Race | Asian | 20 | 8.29 | <10 | 0.72 |
| | Black | 0 | NA | 10 | 0.59 |
| | Hispanic | <10 | 10.34 | <10 | 0.22 |
| | Multiple | <10 | 9.09 | <10 | 0.34 |
| | Native | 0 | NA | 0 | NA |
| | White | 20 | 5.14 | 40 | 0.53 |
| SES | First | 0 | NA | <10 | 0.20 |
| | Second | <10 | 6.12 | 10 | 0.39 |
| | Third | 10 | 7.09 | 10 | 0.42 |
| | Fourth | 30 | 6.43 | 30 | 0.90 |
| Total | | 50 | 6.24 | 60 | 0.49 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES. All unweighted sample size numbers were rounded to the nearest ten.

Table 22

*Weighted Frequencies and Proportions of Students Graduate School Degrees in STEM by Sex, Race, and SES*

| | | Identified as high-achieving (*N* = 143,631) | | | Non-identified (*N* = 3,142,880) | | |
|---|---|---|---|---|---|---|---|
| | | Weighted *N* | *SE* | % within sub-group | Weighted *N* | *SE* | % within sub-group |
| Sex | Female | 5,094 | 981 | 5.64 | 6,413 | 1,716 | 0.42 |
| | Male | 3,641 | 1,107 | 6.83 | 5,783 | 1,418 | 0.36 |
| Race | Asian | 1,584 | 475 | 7.43 | 764 | 355 | 0.65 |
| | Black | NA | NA | NA | 1,693 | 713 | 0.36 |
| | Hispanic | 609 | 361 | 8.21 | 669 | 390 | 0.13 |
| | Multiple | 156 | 117 | 4.93 | 1,146 | 870 | 0.89 |
| | Native | NA | NA | NA | NA | NA | NA |
| | White | 6,386 | 1,348 | 5.78 | 7,924 | 1,835 | 0.42 |
| SES | First | NA | NA | NA | 1,085 | 539 | 0.13 |
| | Second | 492 | 304 | 4.25 | 2,730 | 986 | 0.33 |
| | Third | 1,983 | 777 | 6.76 | 4,056 | 1,560 | 0.51 |
| | Fourth | 6,261 | 1,194 | 6.45 | 4,325 | 1,102 | 0.60 |
| Total | | 8,735 | 1,455 | 6.08 | 12,196 | 2,216 | 0.39 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: “first” quartile represents students whose families are in the bottom 25% of SES; and “fourth” quartile represents students whose families are in the top 25% of SES.

Table 23

*Unweighted Frequencies and Proportions of Students Who Had an Occupation in STEM by Sex, Race, and SES*

| | | Identified as high-achieving (*N* = 720) | | | Non-identified (*N* = 12,530) | | |
|---|---|---|---|---|---|---|---|
| | | Weighted *N* | *SE* | % within sub-group | Weighted *N* | *SE* | % within sub-group |
| Sex | Female | 30 | 0.76 | 10.76 | 170 | 0.10 | 2.51 |
| | Male | 120 | 1.37 | 26.79 | 460 | 0.17 | 7.79 |
| Race | Asian | 40 | 0.84 | 20.21 | 80 | 0.07 | 7.07 |
| | Black | <10 | 0.20 | 22.22 | 50 | 0.06 | 3.19 |
| | Hispanic | <10 | 0.34 | 20.69 | 50 | 0.06 | 2.69 |
| | Multiple | <10 | 0.24 | 13.64 | 30 | 0.04 | 4.36 |
| | Native | 0 | NA | NA | <10 | 0.01 | 2.80 |
| | White | 100 | 1.27 | 20.77 | 410 | 0.16 | 5.74 |
| SES | First | <10 | 0.31 | 15.15 | 80 | 0.07 | 2.82 |
| | Second | <10 | 0.37 | 14.29 | 100 | 0.08 | 3.37 |
| | Third | 20 | 0.67 | 17.02 | 190 | 0.11 | 6.07 |
| | Fourth | 110 | 1.35 | 22.29 | 250 | 0.12 | 7.26 |
| Total | | 150 | 1.50 | 20.39 | 620 | 0.19 | 4.97 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES. All unweighted sample size numbers were rounded to the nearest ten.

Table 24

*Weighted Frequency and Proportions of Students Who Had an Occupation in STEM by Sex, Race, and SES*

| | | Identified as high-achieving ($N$ = 143,631) | | | Non-identified ($N$ = 3,142,880) | | |
|---|---|---|---|---|---|---|---|
| | | Weighted $N$ | $SE$ | % within sub-group | Weighted $N$ | $SE$ | % within sub-group |
| Sex | Female | 25,264 | 2,548 | 27.98 | 108,898 | 6,670 | 7.14 |
| | Male | 5,505 | 1,036 | 10.32 | 38,478 | 3,851 | 2.38 |
| Race | Asian | 4,186 | 775 | 19.63 | 9,031 | 1,228 | 7.73 |
| | Black | 138 | 103 | 10.97 | 11,447 | 2,155 | 2.44 |
| | Hispanic | 1,159 | 545 | 15.63 | 11,756 | 2,065 | 2.23 |
| | Multiple | 247 | 158 | 7.84 | 5,719 | 1,467 | 4.43 |
| | Native | NA | NA | NA | 952 | 674 | 3.00 |
| | White | 25,038 | 2,742 | 22.66 | 108,470 | 6,792 | 5.80 |
| SES | First | 725 | 452 | 12.78 | 19,314 | 2,528 | 2.39 |
| | Second | 1,592 | 658 | 13.78 | 27,737 | 3,526 | 3.37 |
| | Third | 5,537 | 1,225 | 18.87 | 46,312 | 4,414 | 5.87 |
| | Fourth | 22,914 | 2,500 | 23.61 | 54,013 | 4,674 | 7.49 |
| Total | | 30,768 | 2,741 | 21.42 | 147,375 | 7,637 | 4.69 |

*Note.* Sub-group indicates a category in a covariate variable (e.g., female, Asian, second SES quartile). Percent within sub-group was estimated by a proportion of the number of sub-group within an identification group to a total number of the identification group. SES was quartile-coded: "first" quartile represents students whose families are in the bottom 25% of SES; and "fourth" quartile represents students whose families are in the top 25% of SES.

***Descriptive statistics of moderating variables***

*Mathematics self-efficacy (MSE)*

Table 25 shows the unweighted means and standard deviations of MSE according to identification, sex, race, and SES. The mean of students identified as high-achieving was higher than that of non-identified students (high-achieving $M = 3.29$, $SD = .72$; and non-identified $M = 2.63$, $SD = .77$). Male students and students from families of higher SES had higher levels of MSE.

Table 25

*Means and Standard Deviations of Mathematics Self-Efficacy by Covariates*

| | | Identified as high-achieving | | | Non-identified | | |
|---|---|---|---|---|---|---|---|
| | | *N* | *M* | *SD* | *N* | *M* | *SD* |
| Sex | Female | 240 | 3.09 | 0.77 | 4,340 | 2.58 | 0.77 |
| | Male | 360 | 3.41 | 0.65 | 3,670 | 2.70 | 0.76 |
| Race | Asian | 150 | 3.16 | 0.74 | 700 | 2.60 | 0.71 |
| | Black | 10 | 3.63 | 0.46 | 940 | 2.65 | 0.75 |
| | Hispanic | 20 | 3.30 | 0.80 | 1,010 | 2.58 | 0.76 |
| | Multiple | 20 | 3.02 | 0.79 | 350 | 2.59 | 0.77 |
| | Native | 0 | *NA* | *NA* | 60 | 2.50 | 0.74 |
| | White | 410 | 3.33 | 0.70 | 4,950 | 2.65 | 0.78 |
| SES | First quartile | 30 | 2.92 | 0.78 | 1,590 | 2.55 | 0.73 |
| | Second quartile | 40 | 3.26 | 0.67 | 1,890 | 2.58 | 0.76 |
| | Third quartile | 120 | 3.26 | 0.69 | 2,070 | 2.63 | 0.79 |
| | Fourth quartile | 410 | 3.32 | 0.72 | 2,470 | 2.73 | 0.77 |
| Total | | 600 | 3.29 | 0.72 | 8,010 | 2.63 | 0.77 |

*Note.* All unweighted sample size numbers were rounded to the nearest ten.

*Advanced courses in math and science*

Table 26 shows the unweighted means and standard deviations of the number of AP/IB courses that students took during high school. I present the statistics by identification, sex, race, and SES. The means were 2.64 for students identified as high-achieving (*SD* = 1.85) and 0.27 for non-identified students (*SD* = .82). Overall, male and Asian students, as well as students from families of higher SES took more AP/IB courses than female, other-race, and lower-SES students. But, the average number of courses for students identified as high-achieving from families of lowest-quartile SES (*M* = 3.33, *SD* = 2.15) exceeded the number for non-identified students from families of highest-quartile SES (*M* = 0.15*, SD* = 0.62).

Table 26

*Means and Standard Deviations of the Number of AP/IB in Math and Science by Covariates*

| | | Identified as high-achieving | | | Non-identified | | |
|---|---|---|---|---|---|---|---|
| | | *N* | *M* | *SD* | *N* | *M* | *SD* |
| Sex | Female | 270 | 2.55 | 1.78 | 6,150 | 0.26 | 0.81 |
| | Male | 420 | 2.70 | 1.89 | 5,330 | 0.28 | 0.82 |
| Race | Asian | 190 | 3.39 | 1.86 | 1,010 | 0.73 | 1.39 |
| | Black | 10 | 3.22 | 2.22 | 1,500 | 0.12 | 0.52 |
| | Hispanic | 30 | 3.17 | 1.72 | 1,680 | 0.16 | 0.61 |
| | Multiple | 20 | 3.03 | 2.06 | 550 | 0.29 | 0.89 |
| | Native | <10 | 4.00 | *NA* | 100 | 0.10 | 0.41 |
| | White | 440 | 2.25 | 1.72 | 6,650 | 0.26 | 0.77 |
| SES | First quartile | 30 | 3.33 | 2.15 | 2,690 | 0.15 | 0.62 |
| | Second quartile | 50 | 2.23 | 1.77 | 2,800 | 0.15 | 0.62 |
| | Third quartile | 140 | 2.35 | 1.81 | 2,810 | 0.26 | 0.76 |
| | Fourth quartile | 470 | 2.72 | 1.83 | 3,190 | 0.49 | 1.07 |
| Total | | 690 | 2.64 | 1.85 | 11,490 | 0.27 | 0.82 |

*Note.* All unweighted sample size numbers were rounded to the nearest ten.

*STEM course-taking in college*

Table 27 shows the unweighted means and standard deviations of the number of credits of STEM courses that students took in college. Students identified as high-achieving took an average of 49.41 credits of STEM courses (*SD* = 40.33), but non-identified students took an average of 21.62 credits (*SD* = 27.02). For students identified as high-achieving, male (*M* = 57.27), Asian (*M* = 56.04), Black (*M* = 55.90), and Hispanic (*M* = 60.40) students took more courses in STEM than female (*M* = 37.71), White (*M* = 45.91), and multiple-race students (*M* = 48.42), but no remarkable difference was observed for SES.

Table 27

*Means and Standard Deviations of STEM Credits Earned in College by Covariates*

| | | High-achieving | | | Non-identified | | |
|---|---|---|---|---|---|---|---|
| | | *N* | *M* | *SD* | *N* | *M* | *SD* |
| Sex | Female | 280 | 37.71 | 34.97 | 5,490 | 20.16 | 23.40 |
| | Male | 420 | 57.27 | 41.80 | 4,340 | 23.47 | 30.91 |
| Race | Asian | 190 | 56.04 | 42.35 | 950 | 32.31 | 35.63 |
| | Black | 10 | 55.90 | 51.15 | 1,250 | 17.99 | 24.60 |
| | Hispanic | 30 | 60.40 | 47.65 | 1,310 | 16.98 | 23.34 |
| | Multiple | 20 | 48.42 | 44.37 | 450 | 20.46 | 26.22 |
| | Native | <10 | 44.00 | *NA* | 60 | 16.56 | 22.93 |
| | White | 450 | 45.91 | 38.30 | 5,820 | 21.85 | 26.26 |
| SES | First quartile | 30 | 46.91 | 40.89 | 1,850 | 17.16 | 24.04 |
| | Second quartile | 50 | 47.43 | 35.64 | 2,240 | 18.76 | 24.68 |
| | Third quartile | 140 | 49.48 | 41.53 | 2,570 | 22.06 | 27.05 |
| | Fourth quartile | 480 | 49.76 | 40.50 | 3,170 | 25.89 | 29.45 |
| Total | | 700 | 49.41 | 40.33 | 9,830 | 21.62 | 27.02 |

*Note.* All unweighted sample size numbers were rounded to the nearest ten.

*High-impact activities in college*

Table 28 shows the unweighted frequencies for student participation in high-impact activities in college, which was a binary variable. Among students identified as high-achieving, 72.37% participated in at least one high-impact activity in college, whereas 45.89% of non-identified students did so. For both students identified as high-achieving those not identified, female students were more likely to participate in at least one high-impact activity in college than male students. For students identified as high-achieving, Asian, Black, Hispanic, and other-race students were more likely to participate than White students, but for non-identified students, White students were more likely to participate than were students of other races.

Table 28

*Unweighted Frequencies and Proportions of Students Who Participated in High Impact Activities in College by Covariates*

| | | Identified as high-achieving ($N$ = 600) | | | Non-identified ($N$ = 8,000) | | |
|---|---|---|---|---|---|---|---|
| | | *N* | Freq | % | *N* | Freq | % |
| Sex | Female | 280 | 210 | 76.17 | 5,490 | 2,770 | 56.39 |
| | Male | 420 | 290 | 69.86 | 4,240 | 1,690 | 39.93 |
| Race | Asian | 190 | 150 | 79.06 | 910 | 420 | 45.97 |
| | Black | 10 | <10 | 77.78 | 1,230 | 500 | 40.70 |
| | Hispanic | 30 | 20 | 71.43 | 1,300 | 490 | 37.28 |
| | Multiple | 20 | 20 | 80.00 | 430 | 190 | 44.01 |
| | Native | <10 | <10 | 100.00 | 60 | 30 | 39.06 |
| | White | 450 | 310 | 69.06 | 5,790 | 2,850 | 49.14 |
| SES | First quartile | 30 | 360 | 62.50 | 1,880 | 680 | 35.92 |
| | Second quartile | 50 | 90 | 72.34 | 2,220 | 890 | 39.87 |
| | Third quartile | 140 | 30 | 65.69 | 2,510 | 1,130 | 45.10 |
| | Fourth quartile | 480 | 20 | 74.95 | 3,120 | 1,770 | 56.83 |
| Total | | 700 | 500 | 72.37 | 9,730 | 4,460 | 45.89 |

*Note.* All unweighted sample size numbers were rounded to the nearest ten.

**Multilevel logistic models of identification as high-achievers**

To examine the variance among schools in terms of student identification, I estimated a baseline model without any covariates (Model A). The ICC was 0.36, which implied that 36% of the variance in identification was accounted for by the schools. The estimated variance of the school intercept was 1.82 ($SE$ = .05, $p$ < .001), indicating that there was a significant variability among schools in the log-odds of a student being identified as a high-achiever. The baseline log-odds of identification as a high-achiever in math and science was −3.99 ($SE$ = .02, $p$ < .001).

Given the variability among schools, I continued to estimate two-level random intercept models. For Model B, I added student-level covariates to Model A. The student-level covariates were all categorical variables; thus, male, White, and the highest quartile of SES were set as reference groups. Model C included school-level covariates, which were grand-mean centered. Table 29 is the results for Model A, B, and C. In Model C, the school-level and student-level covariates were all significant. I compared the deviance statistic between Model B and Model C, which implied that Model C was better fitted (Δ*deviance statistic* = 2121.8, $p$ < .001). In Model C, all student-level covariates were significant. Female students were less likely to be identified than male students ($\gamma$= −2.62, $SE$ = .02, $p$ < .001, odds ratio = .50, 95% CI [.48, .52]). In terms of race, Black, Hispanic, and other-race students were less likely to be identified than White students (Black $\gamma$ = −2.57, $SE$ = .13, $p$ < .001, odds ratio = .08, 95% CI [.06, .10]; Hispanic $\gamma$ = −.57, $SE$ = *.05,* $p$ < .001, odds ratio = .56, 95% CI [.51, .63]; other $\gamma$ = .28, $SE$ = *.07,* $p$ < .001, odds ratio = .28, 95% CI [.24, .32]). However, Asian students were more likely to be identified as high-achieving than White students ($\gamma$ = 1.20, $SE$ = .04, $p$ < .001, odds ratio = 3.32, 95% CI [3.07, 3.58]). Students of highest-quartile SES were more likely to be identified as high-achieving than students of lowest-quartile SES. School-level covariates were also significantly associated with the probabilities of students being identified as high achievers. School percentage of students receiving federal meal subsidy (SCMS) was negatively associated with identification ($\gamma = -.02$, $SE = .00$, $p < .001$), but the odds ratio was .98 (95% CI [.98, .98]), implying that a student in a school with higher SCMS rates was less likely to be identified as a high achiever, but that the disproportion was not severe. School academic pressure was positively associated with the dependent variable, implying that a student who attended a school that exerted more academic pressure was more likely to be identified as a high achiever ($\gamma = .47$, $SE = .02$, $p < .001$, $OR = 1.60$, 95% CI [1.52, 1.67]).

Table 29

*Estimates for Multilevel Logistic Models of Being Identified as High-Achievers*

| | | Model A | | Model B | | Model C | |
|---|---|---|---|---|---|---|---|
| | | *Estimate* | *SE* | *Estimate* | *SE* | *Estimate* | *SE* |
| <u>*Fixed effects*</u> | | | | | | | |
| Intercept | | -3.99*** | 0.02 | -2.41*** | 0.02 | -2.62*** | 0.02 |
| Sex | Female | | | -0.68*** | 0.02 | -0.69*** | 0.02 |
| Race | Asian | | | 1.30*** | 0.04 | 1.20*** | 0.04 |
| | Black | | | -2.80*** | 0.13 | -2.57*** | 0.13 |
| | Hispanic | | | -0.70*** | 0.05 | -0.57*** | 0.05 |
| | Other | | | -1.33*** | 0.07 | -1.27*** | 0.07 |
| SES | First quartile | | | -2.03*** | 0.04 | -1.61*** | 0.04 |
| | Second quartile | | | -1.93*** | 0.04 | -1.66*** | 0.04 |
| | Third quartile | | | -0.74*** | 0.02 | -0.63*** | 0.02 |
| SCCL | | | | | | 0.47*** | 0.02 |
| SCMS | | | | | | -0.02*** | 0.00 |
| <u>*Random effects*</u> | | | | | | | |
| Intercept | | 1.82*** | 0.05 | 1.00*** | 0.03 | 0.72*** | 0.03 |
| <u>*Fit statistics*</u> | | | | | | | |
| Deviance | | 99,245 | | 88,820 | | 86,699 | |
| Parameter | | 2 | | 10 | | 12 | |
| BIC | | 99,259 | | 88,887 | | 86,778 | |

*Note.* Reference groups are male, White, the fourth quartile ofSES, respectively. SCCL = school climate – academic pressure, SCMS = school rate of federal meal subsidy. *** $p < .001$

Table 30

*Estimated Odd Ratios for the Identification by Covariates*

| Covariate | Reference | | *Estimate* | [95% CI] |
|---|---|---|---|---|
| Sex | (Male) | Female | 0.50 | [0.48, 0.52] |
| Race | (White) | Asian | 3.32 | [3.07, 3.58] |
| | | Black | 0.08 | [0.06, 0.10] |
| | | Hispanic | 0.56 | [0.51, 0.63] |
| | | Other | 0.28 | [0.24, 0.32] |
| SES | (Fourth) | First quartile | 0.20 | [0.18, 0.22] |
| | | Second quartile | 0.19 | [0.18, 0.22] |
| | | Third quartile | 0.53 | [0.51, 0.56] |
| SCCL | (Lower) | Higher | 1.60 | [1.52, 1.67] |
| SCMS | (Lower) | Higher | 0.98 | [0.98, 0.98] |

**Multilevel Logistic Models of Entrance into Postsecondary STEM paths**

To examine whether entrance into STEM fields in postsecondary education differed between students identified as high-achieving and those not-identified as such, I estimated a set of logistic regression models with a binary dependent variable reflecting entrance into postsecondary STEM fields.

Model A was a baseline model. The estimated ICC from Model A was approximately 0.046, indicating that 4.6% of variance in the dependent variable was accounted for by variations between schools. The school-level variance was significant ($\tau_{00}$ = .16, *SE* = .01, *p* < .001); thus, I continued to estimate two-level models.

Model B contained a variable for identification as high-achieving in math and science (HA). The addition of the variable decreased the deviance statistic by 7,875 compared to the baseline model, which was significantly greater than the .05 critical value of 1 degree of freedom. Students identified as high-achieving in math and science were more likely to enter into postsecondary STEM paths than non-identified students ($\gamma$ = 2.06, *SE* = .02, *p* < .001). The corresponding odds ratio was 7.85, meaning that the odds of postsecondary STEM entrance for students identified as high-achieving were 7.85 times the odds for non-identified students.

Model C was a random intercept model that contained all the covariates (sex, race, SES, SCCL, SCMS). Deviance statistic decreased a statistically significant amount from the previous model ($\chi^2$ = 151,615 − 144,883 = 6,732, *p* < .05), which implied a significant improvement in the model. All the student-level and school-level covariates were significant in predicting entrance into postsecondary STEM fields. The log-odds of entering into postsecondary STEM fields were lower for female students than for male students ($\gamma$ = −.72, *SE* = .02, *p* < .001), which led to an odds ratio of 0.49. In other words, the odds of STEM entrance for female students were less than half of the odds for male students. The log-odds of STEM entrance were higher for Asian students than for White students ($\gamma = .62$, $SE = .03$, $p < .001$, OR = 1.86). However, students of BHNO were less likely to enter STEM paths than White students ($\gamma = -.22$, $SE = .02$, $p < .001$, OR = .55; $\gamma = -.27$, $SE = .04$, $p < .001$, OR = .80). It is noteworthy that the odds for Asian students entering the fields were 1.86 times the odds for White students; whereas, the odds for BHNO students were 0.80 times the odds for White students. Table 31 contains the results for Models A, B, and C.

Table 31

*Estimates for Multilevel Logistic Models of STEM Entrance: Models A—C*

| | | Model A | | | Model B | | | Model C | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| ***Fixed effects*** | | | | | | | | | | |
| Intercept | | -2.66 | 0.01 | *** | -2.80 | 0.01 | *** | -2.46 | 0.01 | *** |
| HA | | | | | 2.06 | 0.02 | *** | 1.59 | 0.02 | *** |
| Sex | Female | | | | | | | -0.72 | 0.02 | *** |
| Race | Asian | | | | | | | 0.62 | 0.03 | *** |
| | BHNO | | | | | | | -0.22 | 0.02 | *** |
| SES | | | | | | | | 0.39 | 0.01 | *** |
| SCCL | | | | | | | | 0.14 | 0.01 | *** |
| SCMS | | | | | | | | >.00 | >.00 | *** |
| ***Random effects*** | | | | | | | | | | |
| Intercept | | 0.16 | 0.01 | *** | 0.06 | 0.01 | *** | 0.04 | 0.01 | *** |
| ***Goodness-of-fit***$^{+}$ | | | | | | | | | | |
| Deviance statistic | | 159,490 | | | 151,615 | | | 144,883 | | |
| BIC | | 159,503 | | | 151,635 | | | 144,956 | | |

*Note.* $^{+}$ Goodness-of-fit indices were combined by the method as stated in previous chapter (Little & Rubin, 2002; Snijders & Bosker, 1999); Since I used multiple imputation, five pieces of model fits that were estimated from five different sets of imputed data should be combined. HA = high achiever in math and science; SCCL = school climate of academic pressure; SCMS = school rate of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Given the significance of all the covariates in Model C, I added interaction terms between high-achieving identification and each covariate to examine whether the effects of covariates on STEM entrance differed according to identification or non-identification as a high achiever. The results of the subsequent models, D, E, and F, are given in Table 32.

For Model D, the deviance statistic significantly decreased compared to the previous model ($\chi^2$ = 144,883 − 144,042 = 841, $p < .05$), which indicated an improvement in the model. The log-odds of entrance into postsecondary STEM fields were lower for female students than for male students ($\gamma = -.72$, $SE = .02$, $p < .001$), and this gender difference did not differ with identification ($\gamma = -.02$, $SE = .05$, $p = .69$). In other words, for both students identified as high-achieving and non-identified students, the odds of entrance into STEM fields for female students were less than half of the odds for male students (OR = .47 and OR= .49, respectively).

However, the interaction effects of race and identification were significant when White students were compared with students with other races (Asian, $\gamma = .14$, $SE = .07$, $p < .05$; BHNO, $\gamma = -.56$, $SE = .11$, $p < .001$). Figure 9 represents the interaction effects. The differences in STEM entrance were greater for students identified as high-achieving than for non-identified students; the predicted probabilities for non-identified students were 0.13 for Asian, 0.08 for White, and 0.07 for BHNO whereas those of high-achieving students were 0.61 for Asian, 0.42 for White, and 0.26 for BHNO students.

Student SES was significantly associated with entrance into postsecondary STEM fields. Students from families of higher SES were more likely to enter the fields than students from families of lower SES ($\gamma = .46$, $SE = .01$, $p < .001$, OR = 1.58). But, the interaction effect with identification was significant ($\gamma = -.62$, $SE = .03$, $p < .001$) (Figure 10). For non-identified students, the odds ratio was 0.25, meaning that the odds of students from families of first-quartile

SES entering the fields were 0.25 times the odds for students from families of fourth-quartile SES. However, for students identified as high-achieving, the odds ratio was 1.62, which means that the odds for students from families of first-quartile SES was 1.62 times the odds for students from families of fourth-quartile SES. In other words, high achievement in college entrance exams in math and science increased the predicted probability of entrance from 0.04 to 0.49 for students from the first-quartile of SES families, holding other covariates constant.

The two school-level variables and their interaction effects with identification were all significant (Table *32*). As the levels of SCCL increased, the students were more likely to enter into postsecondary STEM fields ($\gamma = .24$, $SE = .01$, $p < .001$, OR = 1.27). However, a significant interaction effect implied that the probabilities increased a lot more, with identification, for students who attended schools with lower levels of SCCL than for students who attended schools with higher levels of SCCL (Figure 11). For non-identified students who attended schools with SCCL two standard deviations lower than average, the predicted probability was 0.04, and the odds ratio was 0.32, meaning that the odds of entrance for those students were 0.32 times the odds for students who attended schools with SCCL two standard deviations higher than average. However, the probability of entrance for students identified as high-achieving from schools of lower levels of SCCL was 0.63, and the odds ratio was 5.55, which means that the odds of those students was 5.55 times the odds of students identified as high-achieving who attended schools with higher levels of SCCL.

SCMS was also significantly associated with entrance into postsecondary STEM fields, but the coefficient was nearly zero ($\gamma > .0.00$, $SE = .0004$, $p < .001$). The odds ratio was 1.00, which means that there is no actual difference between higher and lower percentages of SCMS. This significant result might result from large sample size. The interaction effect between SCMS and identification was also significant (Table 9). For non-identified students, students who attended schools with higher SCMS rates were more likely to enter postsecondary STEM fields than students who attended schools with smaller proportions (OR = 1.44 when comparing the 25th percentile and the 75th percentile of SCMS). However, for students identified as high-achieving, those who attended schools with higher SCMS rates were less likely to enter STEM paths than students who attended schools with smaller proportions (OR = .53 when comparing the 25th percentile and the 75th percentile of SCMS).

Table 32

*Estimates for Multilevel Logistic Models of STEM Entrance: Models D—F*

| | | Model D | | | Model E | | | Model F | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| ***Fixed effects*** | | | | | | | | | | |
| Intercept | | -2.49 | 0.01 | *** | -2.59 | 0.01 | *** | -2.59 | 0.01 | *** |
| HA | | 2.18 | 0.03 | *** | 1.63 | 0.04 | *** | 1.72 | 0.04 | *** |
| Sex | Female | -0.72 | 0.02 | *** | -0.83 | 0.02 | *** | -0.80 | 0.02 | *** |
| Race | Asian | 0.60 | 0.04 | *** | 0.58 | 0.05 | *** | 0.65 | 0.04 | *** |
| | BHNO | -0.16 | 0.02 | *** | 0.03 | 0.03 | 0.16 | 0.02 | 0.02 | 0.29 |
| SES | | 0.45 | 0.01 | *** | 0.40 | 0.01 | *** | 0.41 | 0.01 | *** |
| SCCL | | 0.24 | 0.01 | *** | 0.21 | 0.02 | *** | 0.19 | 0.02 | *** |
| SCMS | | >.00 | >.00 | *** | >0.00 | 0.00 | *** | 0.00 | 0.00 | *** |
| HA*Sex | Female | -0.02 | 0.05 | 0.69 | 0.18 | 0.05 | ** | 0.19 | 0.05 | *** |
| HA*Race | Asian | 0.14 | 0.08 | * | 0.73 | 0.09 | *** | -0.05 | 0.14 | 0.70 |
| | BHNO | -0.56 | 0.11 | *** | -1.10 | 0.32 | *** | -0.36 | 0.22 | 0.10 |
| HA*SES | | -0.62 | 0.03 | *** | -0.79 | 0.03 | *** | -0.89 | 0.03 | *** |
| HA*SCCL | | -0.61 | 0.04 | *** | -0.55 | 0.04 | *** | -0.66 | 0.05 | *** |
| HA*SCMS | | -0.01 | >0.00 | *** | -0.01 | 0.00 | *** | -0.01 | 0.00 | *** |
| MSE | | | | | 0.66 | 0.02 | *** | 0.68 | 0.02 | *** |
| ADC | | | | | 0.56 | 0.01 | *** | 0.59 | 0.01 | *** |
| HA*MSE | | | | | -0.03 | 0.03 | 0.42 | -0.07 | 0.05 | 0.11 |
| HA*ADC | | | | | -0.24 | 0.02 | *** | -0.42 | 0.02 | *** |
| Sex*MSE | Female | | | | 0.35 | 0.02 | *** | 0.32 | 0.02 | *** |
| Race*MSE | Asian | | | | -0.08 | 0.05 | 0.10 | -0.29 | 0.05 | *** |
| | BHNO | | | | -0.67 | 0.04 | *** | -0.70 | 0.03 | *** |
| SES*MSE | | | | | -0.13 | 0.01 | *** | -0.14 | 0.01 | *** |
| SCCL*MSE | | | | | -0.10 | 0.02 | *** | | | |
| SCMS*MSE | | | | | >0.00 | >0.00 | 0.08 | >0.00 | >0.00 | 0.41 |

*Note.* HA = high achiever in math and science; SCCL = school academic pressure; SCMS = school rate of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

(Continued)

Table 32 Continued

| | | Model D | | | Model E | | | Model F | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| Sex*ADC | Female | | | | -0.15 | 0.01 | *** | -0.15 | 0.01 | *** |
| Race*ADC | Asian | | | | -0.29 | 0.02 | *** | -0.38 | 0.03 | *** |
| | BHNO | | | | 0.16 | 0.02 | *** | 0.14 | 0.02 | *** |
| SES*ADC | | | | | 0.08 | 0.01 | *** | 0.04 | 0.01 | *** |
| SCCL*ADC | | | | | -0.08 | 0.01 | *** | -0.12 | 0.01 | *** |
| SCMS*ADC | | | | | 0.01 | >0.00 | *** | 0.01 | 0.00 | *** |
| HA*Race*MSE | Asian | | | | | | | 0.82 | 0.12 | *** |
| | BHNO | | | | | | | 0.61 | 0.16 | *** |
| HA*SCMS*MSE | | | | | | | | >0.00 | >0.00 | * |
| HA*Race*ADC | Asian | | | | | | | 0.22 | 0.05 | *** |
| | BHNO | | | | | | | -0.30 | 0.07 | *** |
| HA*SES*ADC | | | | | | | | 0.16 | 0.02 | *** |
| HA*SCCL*ADC | | | | | | | | 0.07 | 0.03 | ** |
| ***Random effects*** | | | | | | | | | | |
| Intercept | | 0.04 | 0.01 | *** | 0.10 | 0.01 | *** | 0.10 | 0.01 | *** |
| ***Goodness-of-fit***$^{+}$ | | | | | | | | | | |
| Deviance statistic | | 144,042 | | | 133,471 | | | 133,235 | | |
| BIC | | 144,142 | | | 133,676 | | | 133,480 | | |

Note. $^{+}$ Goodness-of-fit indices were combined by the method as stated in previous chapter (Little & Rubin, 2002; Snijders & Bosker, 1999); Since I used multiple imputation, five pieces of model fits that were estimated from five different sets of imputed data should be combined. HA = high achievers in math and science; SCCL = school academic pressure; SCMS = school rate of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

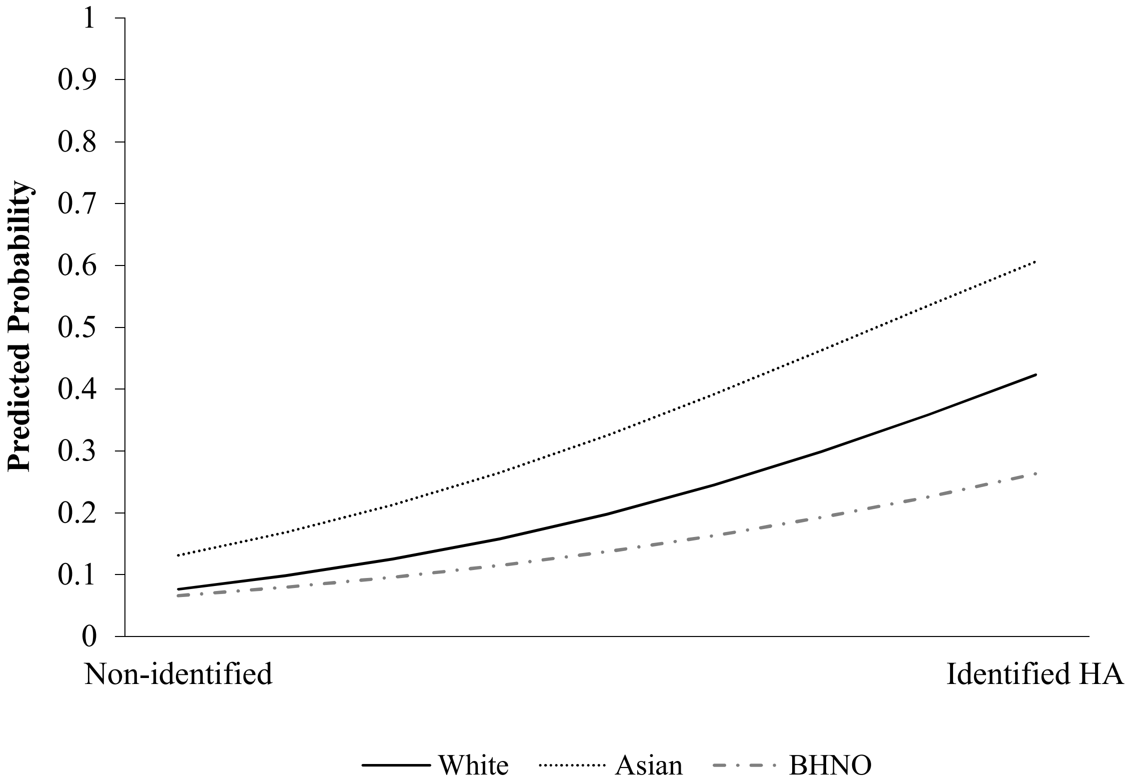


*Figure 9. Predicted Probabilities of STEM Entrance, the Interaction Effect by Identification and Race. HA = students identified as high-achieving. BNHO = Black, Hispanic, Native American, and other races.*

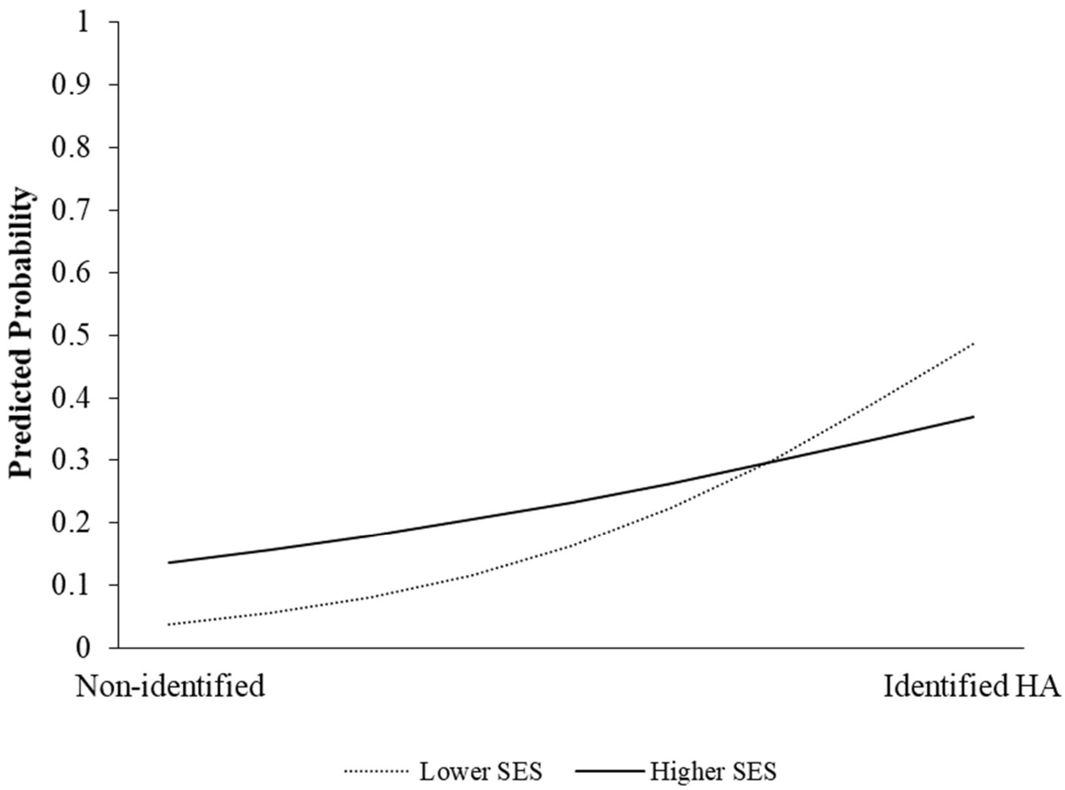


*Figure 10.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Identification and SES. The variable of SES was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES.*

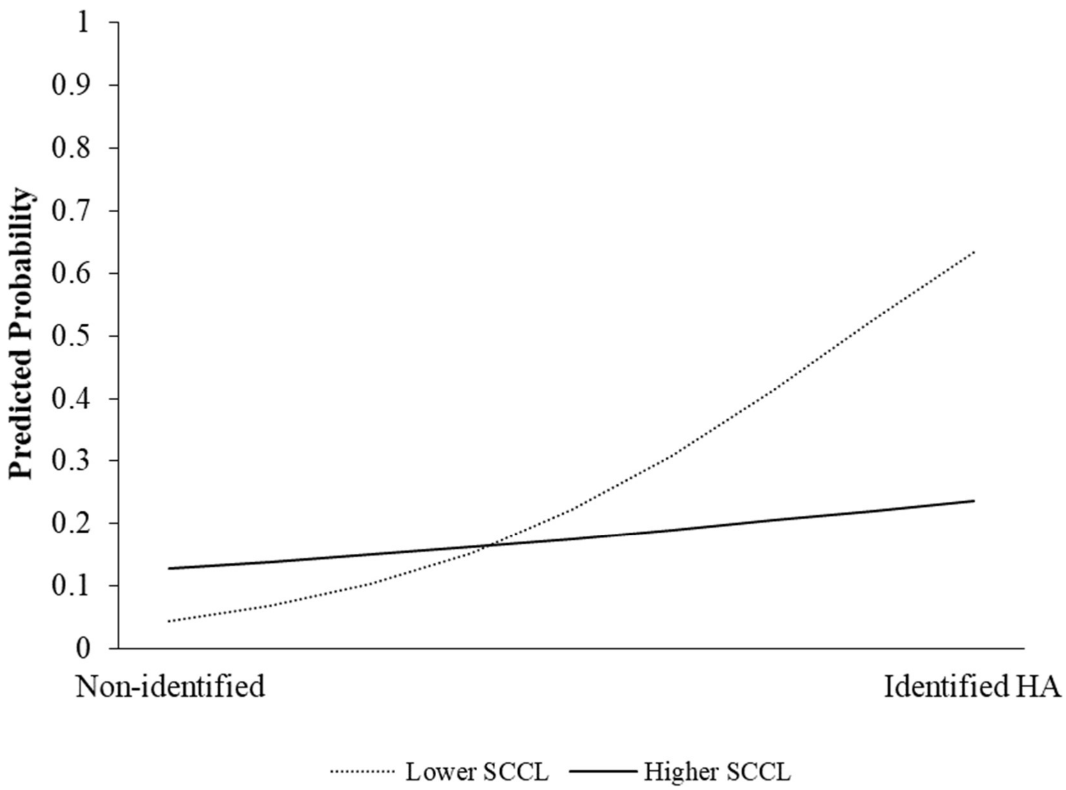


*Figure 11.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Identification and School Climate of Academic Pressure. SCCL = school climate of academic pressure. The variable of SCCL was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean, and "Higher SCCL" is 2 SD above the grand mean.*

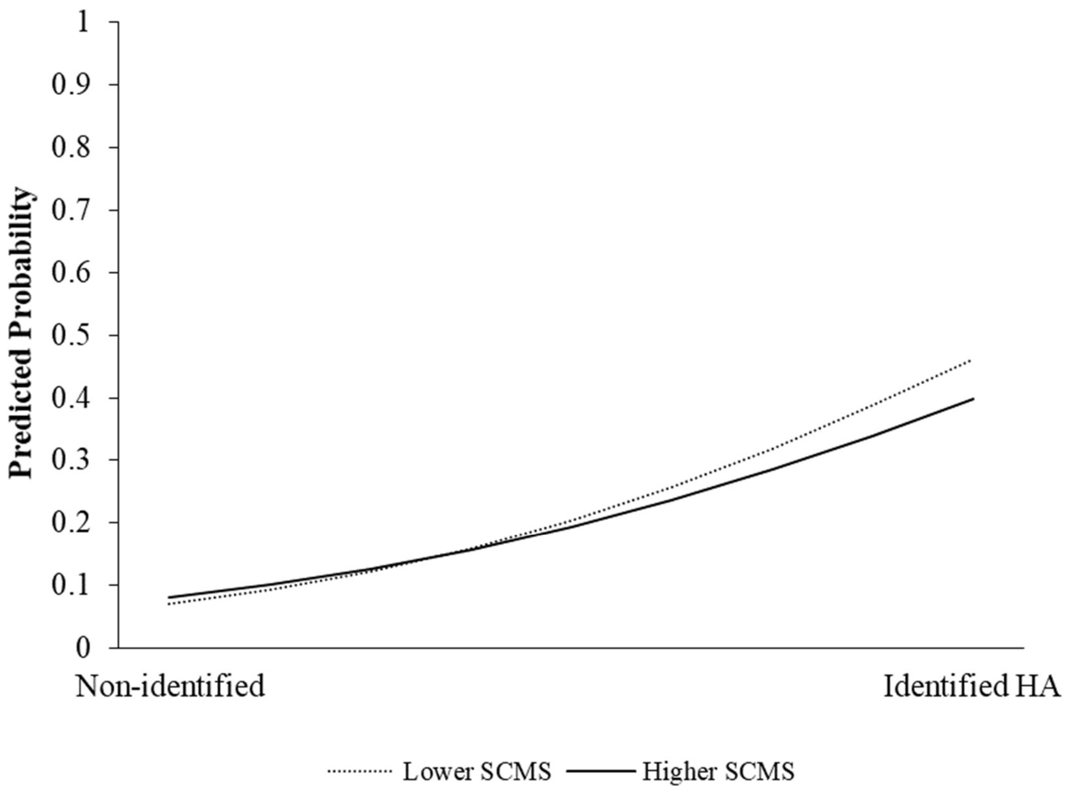


*Figure 12.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Identification and School Rate of the Federal Meal Subsidy. SCMS = School Meal Subsidy. The variable of SCMS was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCMS: "Lower SCMS" indicates the 25th percentile and "Higher SCMS" indicates the 75th percentile of SCMS.*

Model E contained the two moderators, mathematics self-efficacy (MSE) and number of advanced courses taken (ADC), and their interaction terms with the covariates. The BIC decreased from Model D to Model E ($\chi^2$ = 144,042 − 133,471 = 10,571, $p < .05$), implying that the addition of the moderators and the interaction terms made the model fit of Model E better (See Table 32).

The levels of MSE and ADC were positively associated with entrance into postsecondary STEM fields ($\gamma = .66$, $SE = .02$, $p < .001$ and $\gamma = .56$, $SE = .01$, $p < .001$, respectively). The interaction between MSE and identification as high-achieving was not significant ($\gamma = -.03$, $SE = .03$, $p = .42$), which meant that the effect of MSE on STEM entrance did not significantly differ with identification. In other words, MSE and entrance into STEM fields were positively associated for both groups ($\gamma = .66$, $SE = .02$, $p < .001$). However, the effect of the number of advanced courses taken on the probability of entrance did vary significantly according to identification ($\gamma = -.24$, $SE = .01$, $p < .001$). Figure 13 shows the interaction effects. For non-identified students, the probability of STEM entrance dramatically increased, compared to students identified as high-achieving, as students took more advanced courses. When comparing 1 *SD* above and below the average ADC, the odds ratio was 1.89, which means that the odds of entrance for more ADC were 1.89 times the odds for less ADC for students identified as high-achieving, but the odds ratio for non-identified students was 3.06.

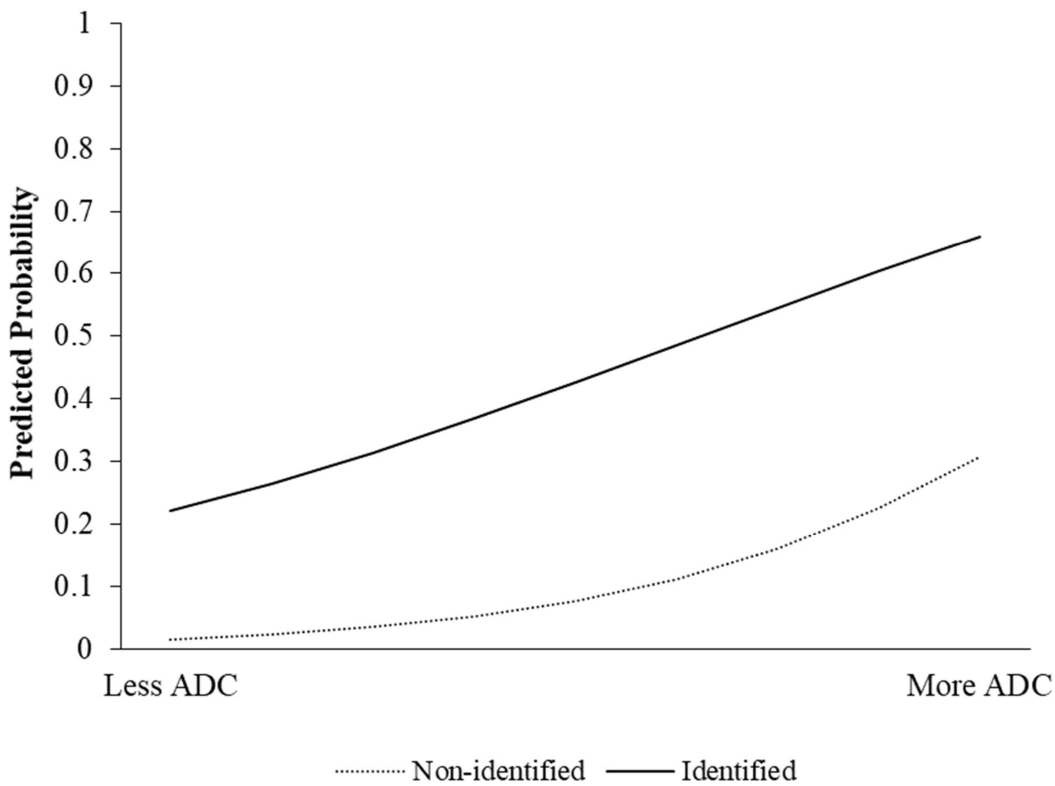


*Figure 13. Predicted Probabilities of STEM Entrance, the Interaction effect by Identification and Advanced Courses in Math and Science. ADC = advanced courses in math and science. The variable of ADC was grand-mean centered.*

In terms of sex and MSE, although female students were less likely to enter STEM fields than male students (main effect $\gamma$ = -0.83, *SE* = 0.02, $p < .001$), the probability of entrance more strikingly increased for female students than for male students as they had higher levels of MSE (interaction effect $\gamma$ = 0.35, *SE* = 0.02, $p < .001$; OR = 3.90 at −2 *SD* of MSE, and OR = 1.37 at +2 *SD* of MSE when comparing male and female students) (Figure 14). Figure 15 represents the interaction effects of MSE and race. Asian students were more likely to enter STEM fields than White students ($\gamma$ = .58, *SE* = .05, $p < .001$), and the difference was consistent regardless of MSE. For BHNO students, the main effect was not significant ($\gamma$ = .03, *SE* = .03, $p$ = .16) but the interaction effect was significant ($\gamma$ = −.67, *SE* = .04, $p < .001$). This means that the probabilities of entrance were not significantly different between White and BHNO students when controlling the other covariates contained in Model E. But, the probability of entrance for BHNO students decreased as MSE increased; in contrast, the probabilities of entrance for White and Asian students increased with MSE (comparing BHNO and White students, OR = 2.85 at −2 *SD* of the average MSE and OR = .38 at +2 *SD* of the average MSE).

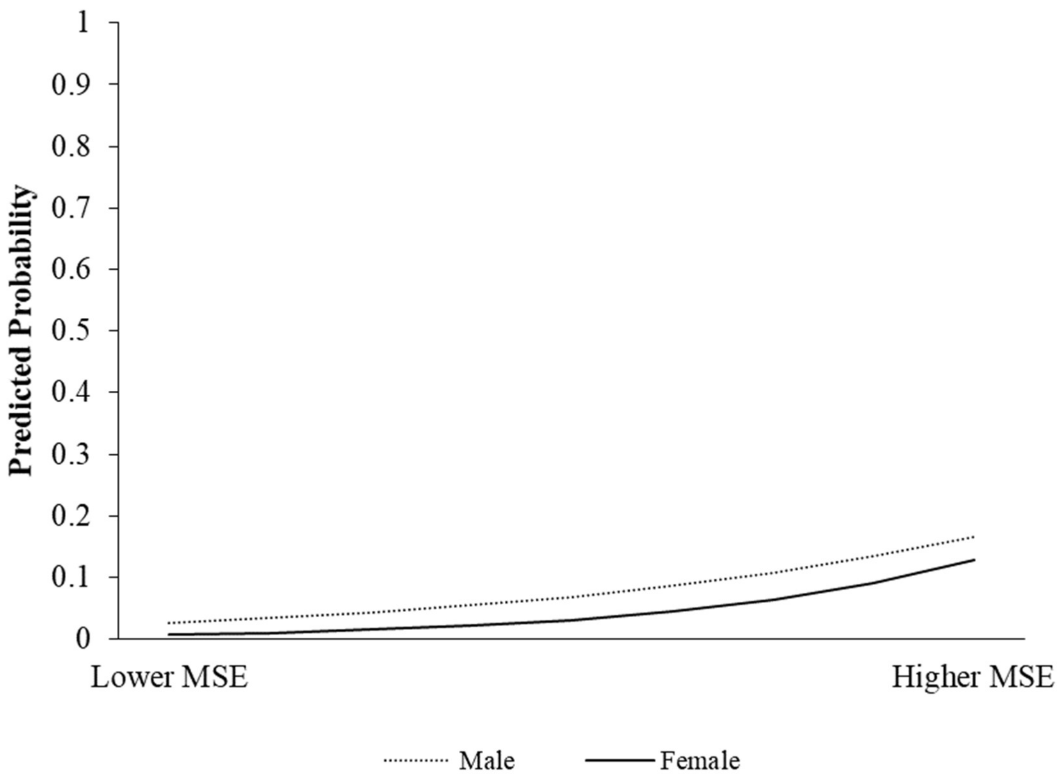


*Figure 14. Predicted Probabilities of STEM Entrance, the Interaction Effect by Mathematics Self-Efficacy and Sex. MSE = mathematics self-efficacy. The variable of MSE was grand-mean centered.*

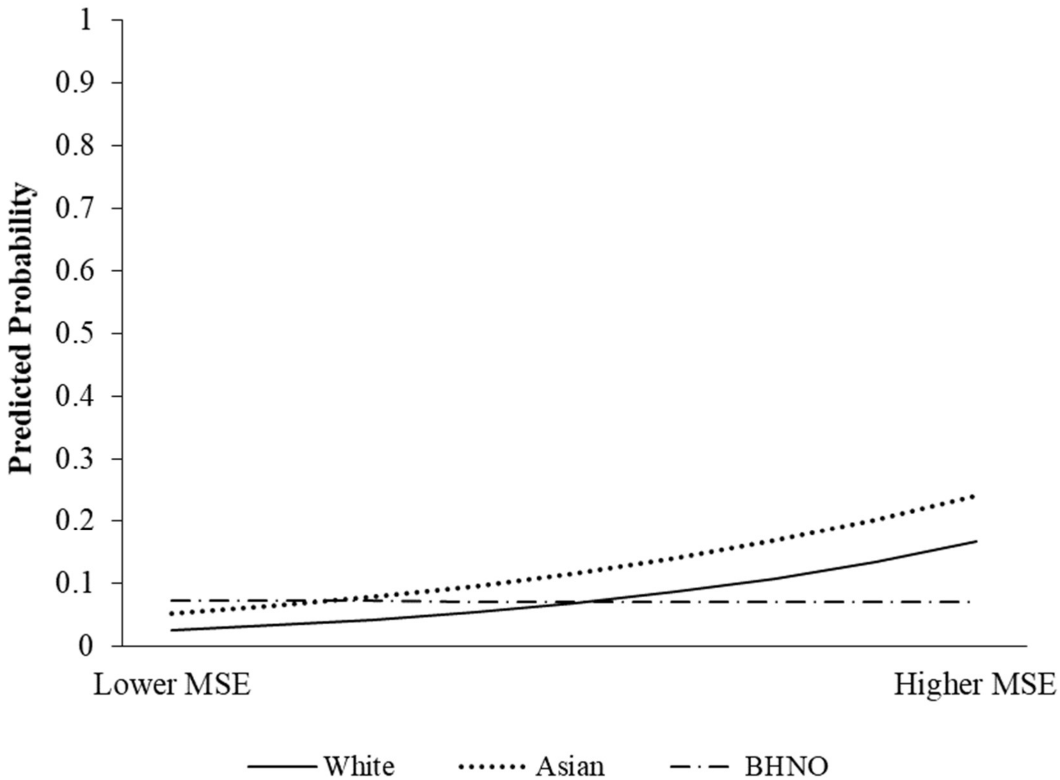


*Figure 15. Predicted Probabilities of STEM Entrance, the Interaction Effect by Mathematics Self-Efficacy and Race. The variable of MSE was grand-mean centered. BHNO = Black, Hispanic, Native American, and other races.*

To illustrate the interaction effects between MSE and categorical or continuous variables, I plotted graphs using the lower and upper values of the categorical and continuous variables. The interaction effect between MSE and SES was significant ($\gamma = -0.13$, $SE = 0.01$, $p < .001$). Figure 16 contrasts the predicted probabilities of STEM entrance for different levels of SES and MSE. “Lower SES” refers to the first quartile (bottom 25%) of SES and “higher SES” refers to the fourth quartile (top 25%). The odds of entrance for students from lower-SES families more steeply increased than the odds for students from higher-SES families as student MSE increased (OR = .17 at −2 *SD* of MSE and OR = .51 at +2 *SD* of MSE). The difference in STEM entrance probabilities between lower and higher levels of SCCL also decreased as the levels of MSE increased ($\gamma$ = -0.10, *SE* = 0.02, $p < .001$) (Figure 17). Students who attended schools with lower levels of SCCL were less likely to enter STEM fields than students who attended schools with higher levels of SCCL; but, the gap decreased as students had higher levels of MSE (OR = .25 at −2 *SD* of MSE and OR = .81 at +2 *SD* of MSE).

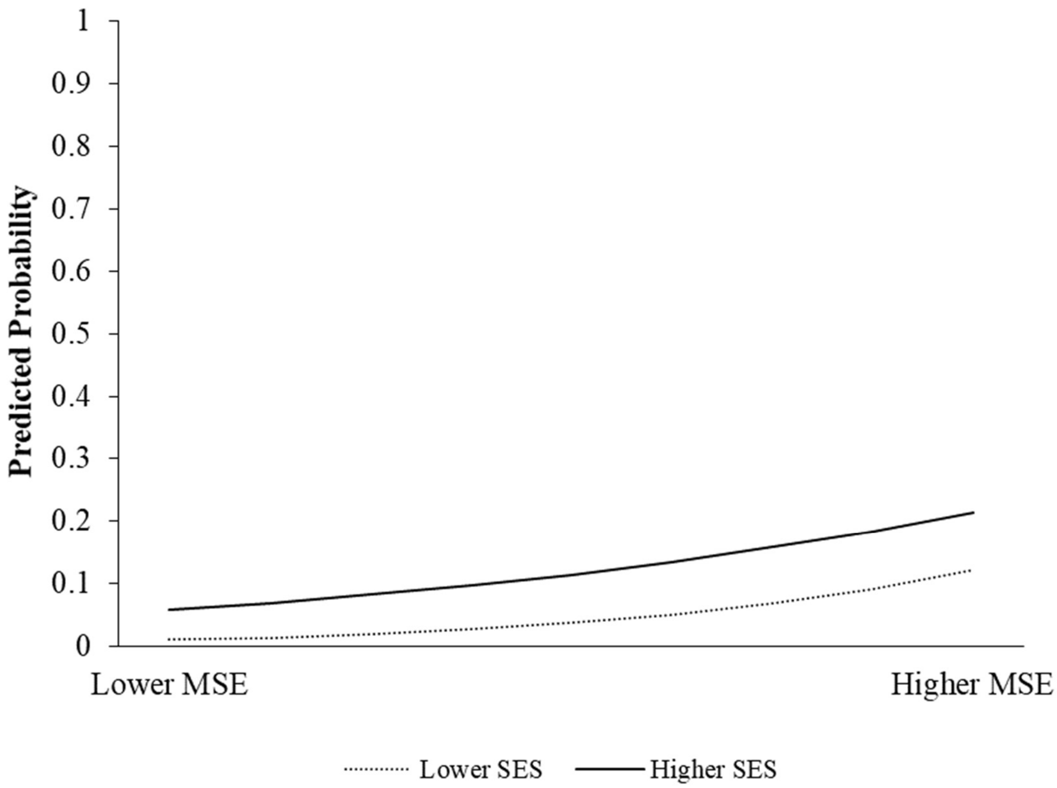


*Figure 16.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Mathematics Self-Efficacy and SES. The variable of MSE and SES was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES.*

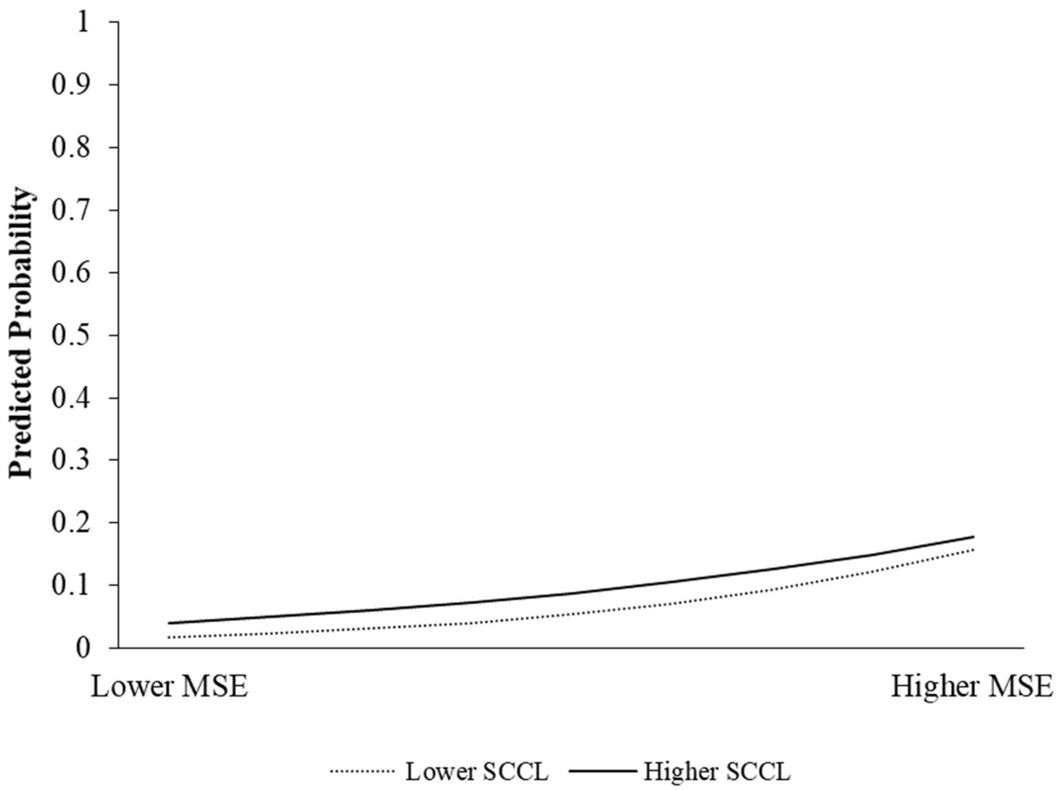


*Figure 17 Predicted Probabilities of STEM Entrance, the Interaction Effect by Mathematics Self-Efficacy and School Climate of Academic Pressure. SCCL = school climate of academic pressure. The variable of MSE and SCCL was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean of SCCL, and "Higher SCCL" is 2 SD above the grand mean of SCCL.*

The interaction effects between ADC and the covariates were also all significant. Female students were less likely to enter postsecondary STEM fields than male students ($\gamma = -.83$, *SE* = .02, $p < .001$), and if the students took advanced courses two or more standard deviations above the average number of advanced courses taken by the whole sample, the odds for male students increased by 2.81 times the odds for female students (Figure 18). Of the students who took advanced courses two standard deviations below the average number of advanced courses, Asian students were most likely to enter postsecondary STEM fields compared with White and BHNO students ($\gamma = -0.29$, *SE* = 0.02, $p < .001$; OR = 3.29 compared with White students) (Figure 19). But, if the students took more advanced courses, up to two standard deviations above the average, BHNO students were most likely to enter STEM fields out of all the races ($\gamma$ =0.16, *SE* = 0.02, $p < .001$; OR = 1.44 compared White students) (Figure 19).

The gaps in STEM entrance probabilities between students of higher and lower SES increased as students took more advanced courses (Figure 20). If students took advanced courses two standard deviations more than the average number of advanced courses, the odds for students from families of top quartile SES increased to 5.48 times the odds for students from families of bottom quartile SES ($\gamma = 0.08$, *SE* = 0.01, $p < .001$). However, taking advanced courses reduced the gaps between different levels of SCCL (Figure 21). The differences in probabilities of STEM entrance gradually decreased as students who attended schools with lower levels of academic pressure took more advanced courses (OR = .19 for −2 *SD* of ADC and OR = .77 for +2 *SD* of ADC). As for the SCMS variable, taking advanced courses increased the probability of entrance only for students who attended schools with higher rates of SCMS (Figure 22). The odds for students in these schools were 0.23 times the odds for students who were in schools with lower rates of SCMS at two standard deviations below the average number of advanced courses. However, the odds increased by 4.27 times when they took advanced courses two standard deviations above the average number of advanced courses.

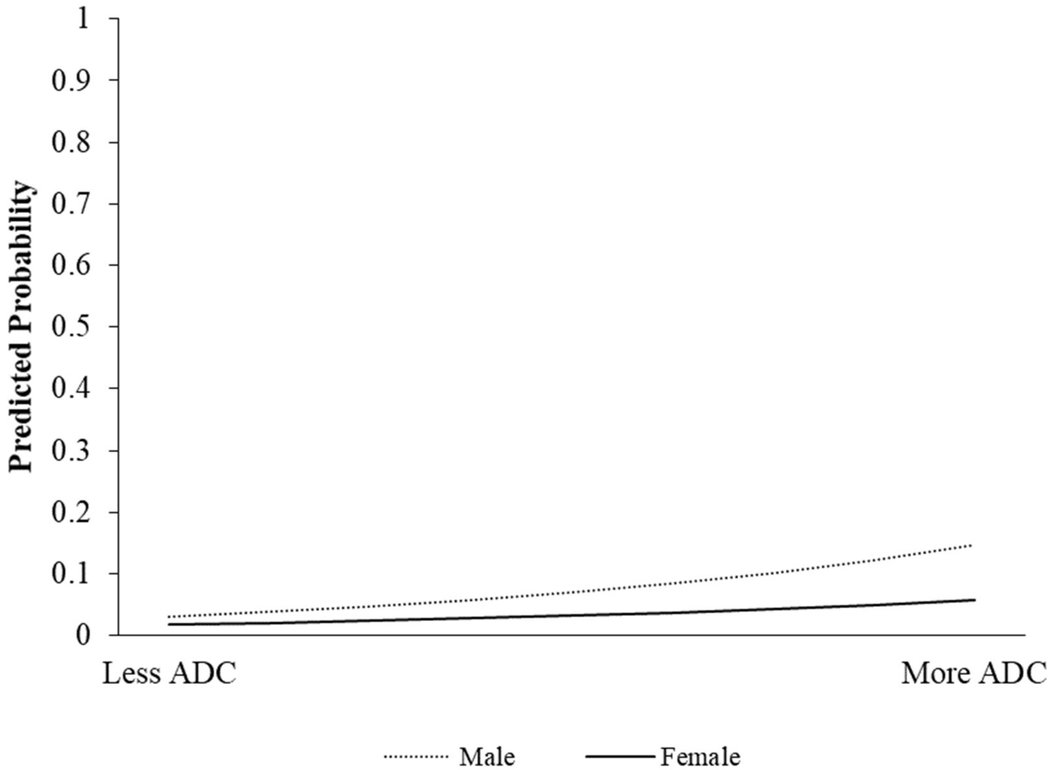


*Figure 18.* *Predicted Probabilities of STEM Entrance, the Interaction effect by Advanced Courses and Sex. ADC = number of advanced courses in math and science. The variable of ADC was grand-mean centered.*

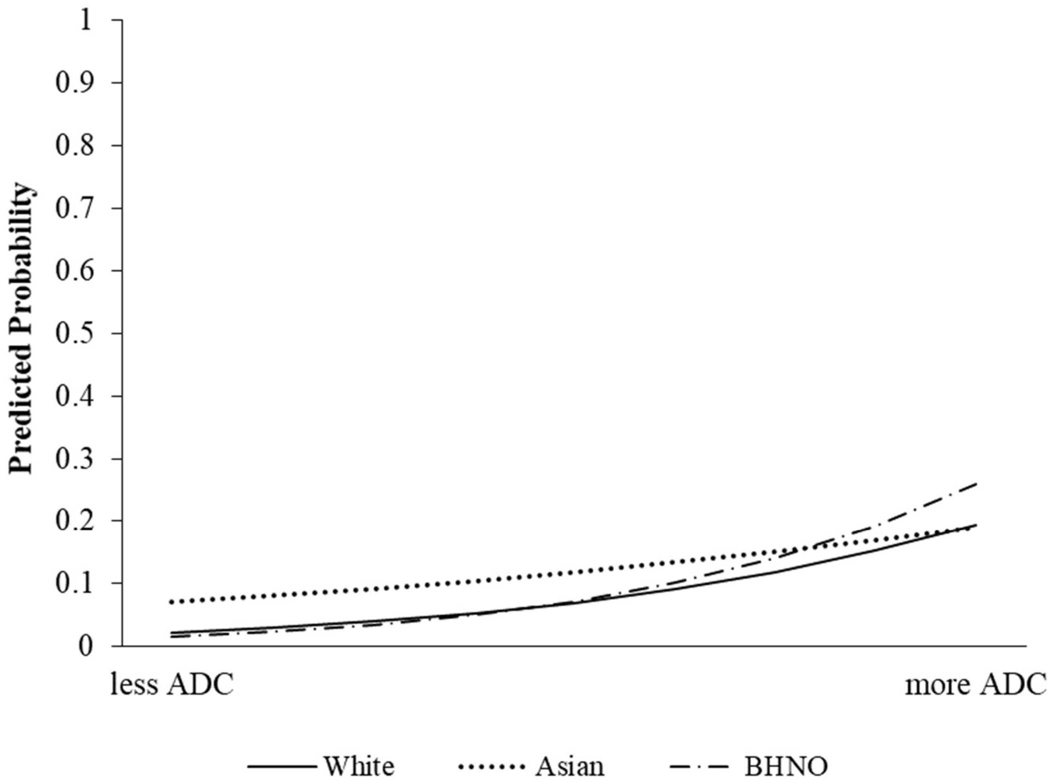


*Figure 19.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Advanced Courses and Race. The variable of ADC was grand-mean centered. ADC = number of advanced courses in math and science. BHNO = Black, Hispanic, Native American, and other races.*

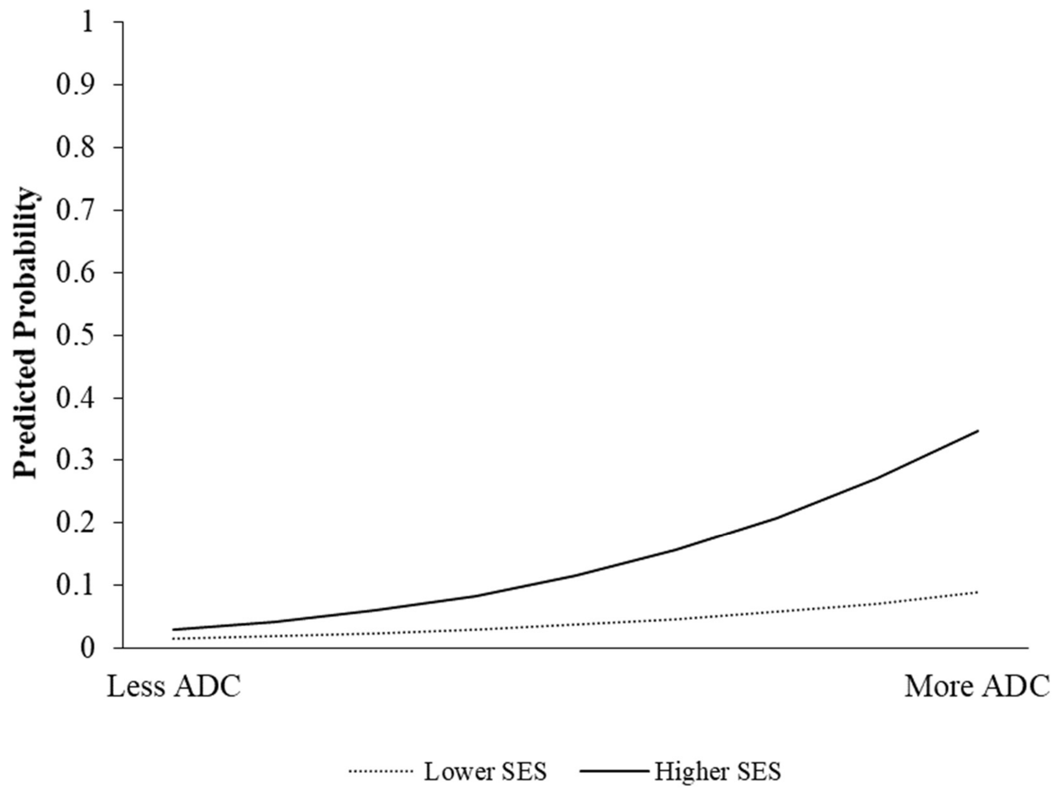


*Figure 20. Predicted Probabilities of STEM Entrance, the Interaction Effect by Advanced Courses and SES. The variables of ADC and SES were grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES. ADC = number of advanced courses in math and science.*

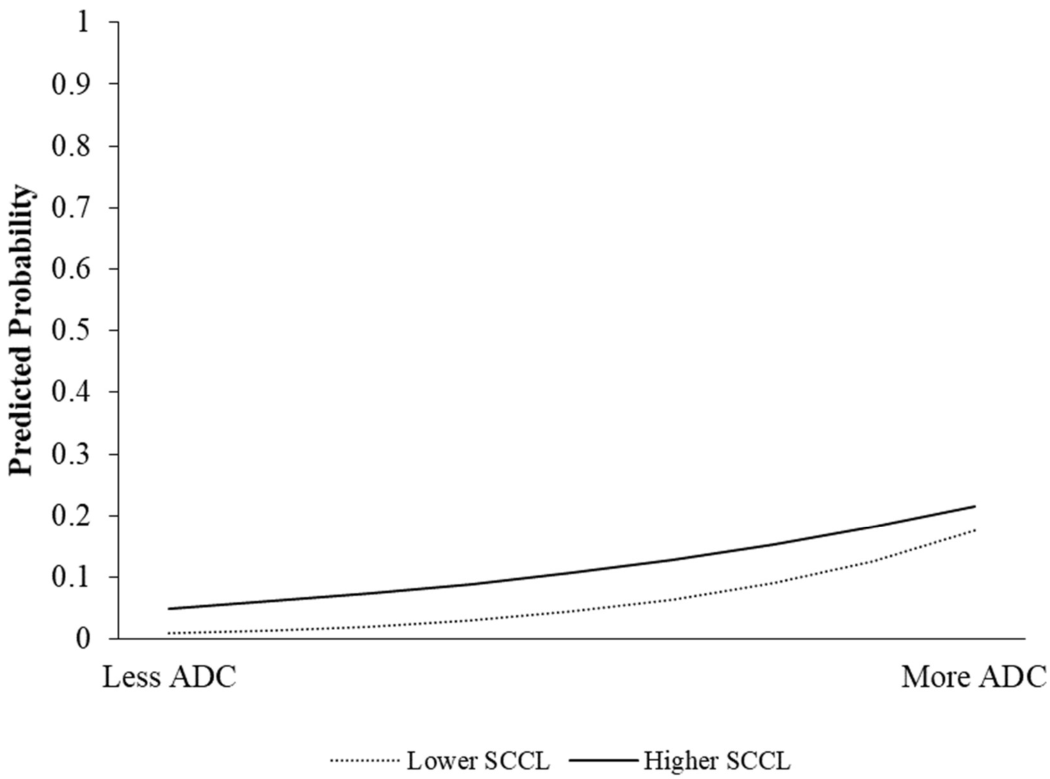


*Figure 21. Predicted Probabilities of STEM Entrance, the Interaction Effect by Advanced Courses and School Climate of Academic Pressure. The variable of ADC and SCCL was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean, and "Higher SCCL" is 2 SD above the grand mean of SCCL. ADC = number of advanced courses in math and science. SCCL = school climate of academic pressure.*

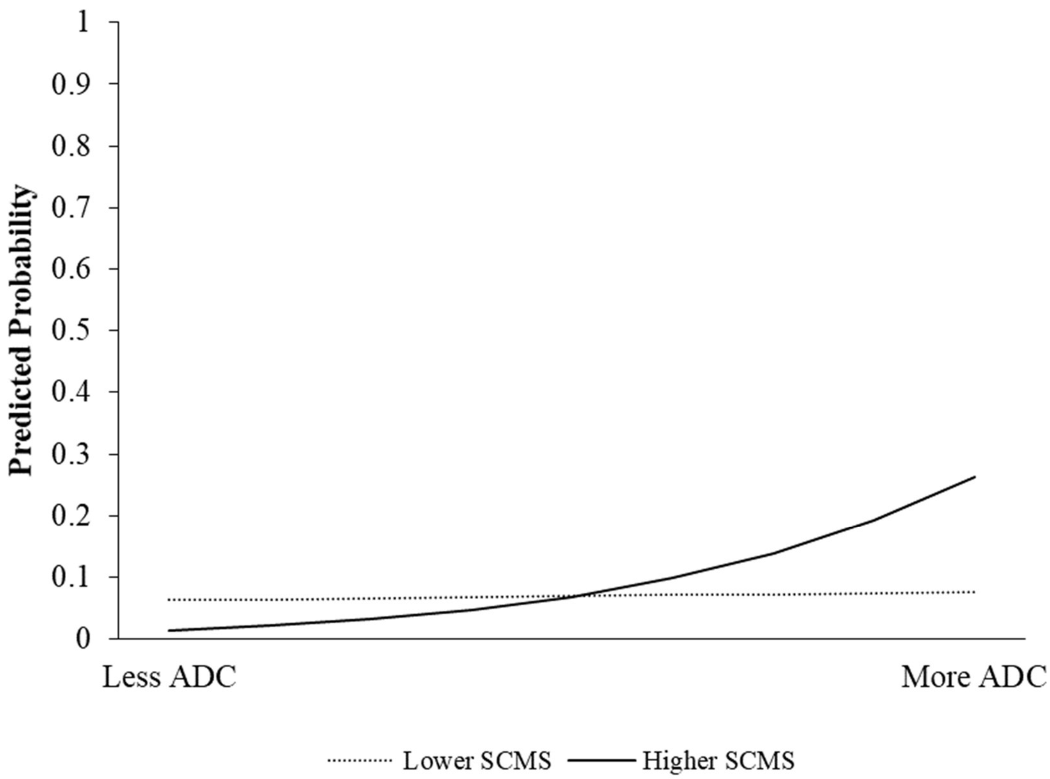


*Figure 22.* *Predicted Probabilities of STEM Entrance, the Interaction Effect by Advanced Courses and School Rate of the Federal Meal Subsidy. The variable of ADC and SCMS was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCMS: "Lower SCMS" is 2 SD below the grand mean, and "Higher SCMS" is 2 SD above the grand mean of SCMS. ADC = number of advanced courses in math and science. SCMS = school rate of the federal meal subsidy.*

Based on the results of Model E, I examined three-way interaction effects, in which I incorporated the moderating effects of MSE and ADC with identification and each covariate. Model F was the final model, which contained all the significant variables. Insignificant covariates (e.g., BHNO, $\gamma = .02$, $SE = .02$, $p = .29$) and two-way interaction terms (e.g., HA* BHNO, $\gamma = -.36$, $SE = .22$, $p = .10$) remained in the final model if they were parts of significant three-way interaction terms (e.g., HA*BHNO*MSE, $\gamma = .61$, $SE = .16$, $p < .001$), so that I could estimate predicted probabilities and odds ratios for the significant three-way interaction terms. The value of BIC decreased from the previous model (133,676 − 133,480 = 190, $p < .05$).

MSE had a significant moderating effect on the relation between identification and race, as well as the relation between identification and SCMS (Table 32). Figure 23 represents the interaction effect of identification, race, and MSE. Overall, the probabilities of STEM entrance increased as students had higher levels of MSE. However, the probabilities for non-identified BHNO students slightly decreased as levels of MSE increased. It is noteworthy that non-identified BHNO students were more likely to enter into postsecondary STEM fields than White students when they scored two standard deviations below the average on MSE (OR = 3.04). But, when they scored two standard deviations above the average on MSE, the odds for non-identified BHNO students decreased by 0.35 times the odds for White students (OR = 0.35). For students identified as high-achieving, the probabilities of STEM entrance increased with increased levels of MSE. Also, among students identified as high-achieving, the moderating effect of MSE was particularly strong for Asian students identified as high-achieving with two standard deviations below the average MSE, their predicted probability of STEM entrance was lower than the probability for White students (OR = .80); but, if their MSE increased to two standard deviations above the average, the odds for Asian students identified as high-achieving increased by 4.08 times the odds for White students.

Figure 24 represents the interaction effect of identification, SCMS, and MSE. Among students identified as high-achieving, those who attended schools with higher rates of SCMS were less likely to enter into postsecondary STEM fields, but the gap decreased as student MSE increased (OR = .20 at −2 *SD* MSE and OR = .58 at +2 *SD* MSE). However, for non-identified students, those who attended schools with higher rates of SCMS were slightly more likely to enter into postsecondary STEM fields than students who attended schools with lower rates of SCMS (OR = 1.57 at −2 *SD* MSE and OR = 1.39 at +2 *SD* MSE).

The interaction effect of identification, race, and advanced courses in math and science was also significant (Asian $\gamma = 0.82$, $SE = 0.12$, $p < .001$; BHNO $\gamma = 0.61$, $SE = 0.16$, $p < .001$) (Figure 25). The probabilities for White students, regardless of identification or non-identification as high achievers, increased as the students took more advanced courses in math and science (predicted probability ranged from .27 to .37 for students identified as high-achieving, and predicted probability ranged from .02 to .20 for non-identified students). In contrast, the probabilities for Asian and BHNO students identified as high-achieving, did not change much, despite the increased number of advanced courses taken. For students not identified, who took two standards deviations below the average number of advanced courses, Asian students were more likely to enter postsecondary STEM fields than White and BHNO students (OR = 4.27 compared with White students). But, as students took more advanced courses, BHNO students were most likely to enter into postsecondary STEM fields (OR = 1.37 compared with White students).

Increased numbers of advanced courses were usually associated with increased probabilities of entrance into postsecondary STEM fields, but this was not so for students identified as high-achieving who were from the first quartile of SES families; the probability decreased from 0.56 at 2 *SD* below the average ADC to 0.40 at 2 *SD* above the average ADC (Figure 26). Both students identified as high-achieving and non-identified students from families of the fourth quartile of SES were more likely to enter into postsecondary STEM paths as they took more advanced courses in math and science. When they took two standard deviations above the average number of advanced courses, the probabilities were 0.34 and 0.35, respectively;

when they took two standard deviations below the average number, the probabilities were 0.03 and 0.08.

In terms of the interaction effect of identification, ADC, and school climate of academic pressure, a significant difference existed in the extent to which the probabilities increased with ADC (Figure 27). The probability of STEM entrance for students identified as high-achieving, who attended schools with lower levels of academic pressure was the highest and increased the most among the four groups (predicted probability = .31 at −2 *SD* of ADC and predicted probability = .54 at +2 *SD* of ADC). From the results, students identified as high-achieving, who attended schools with higher levels of academic pressure were least affected by the number of advanced courses taken (predicted probability = .16 at −2 *SD* of ADC and predicted probability = .23 at +2 *SD* of ADC).

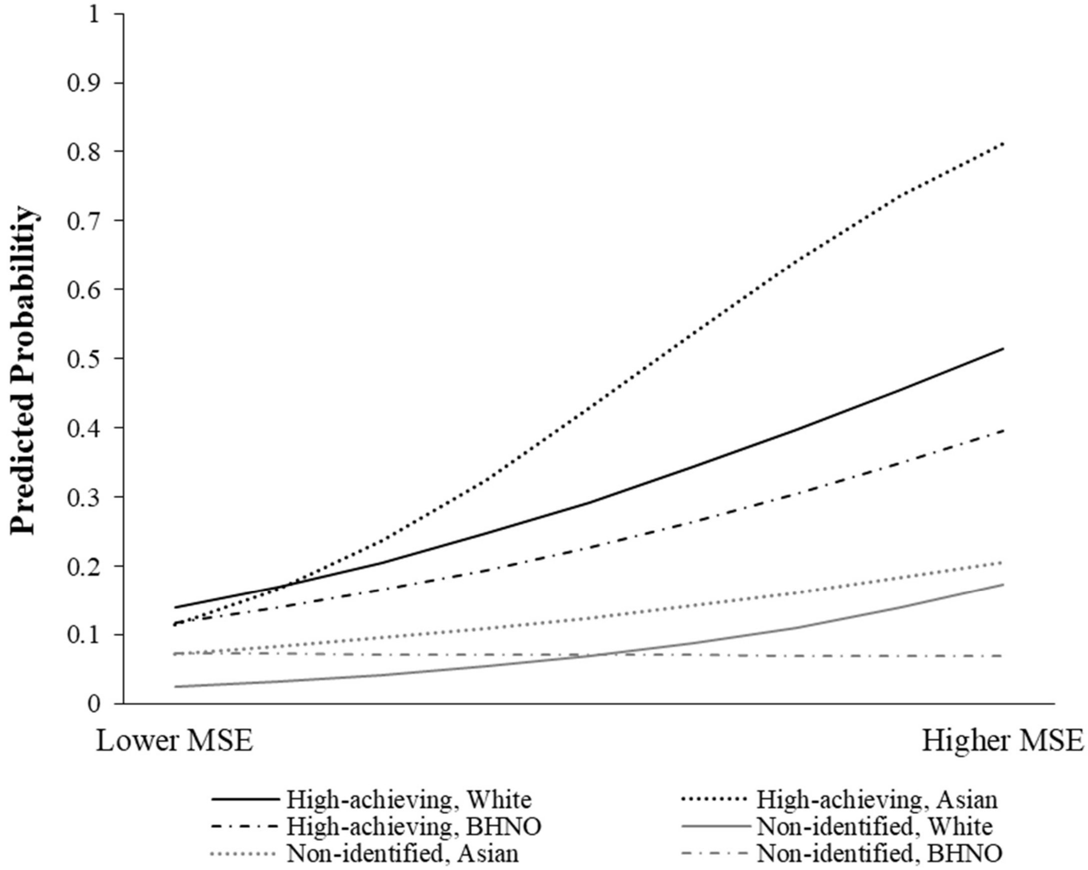


*Figure 23. Predicted Probabilities of STEM Entrance, the Three-Way Interaction Effect by Identification, Race, and Mathematics Self-Efficacy. The variable of MSE was grand-mean centered. BHNO = Black, Hispanic, Native American, and other races.*

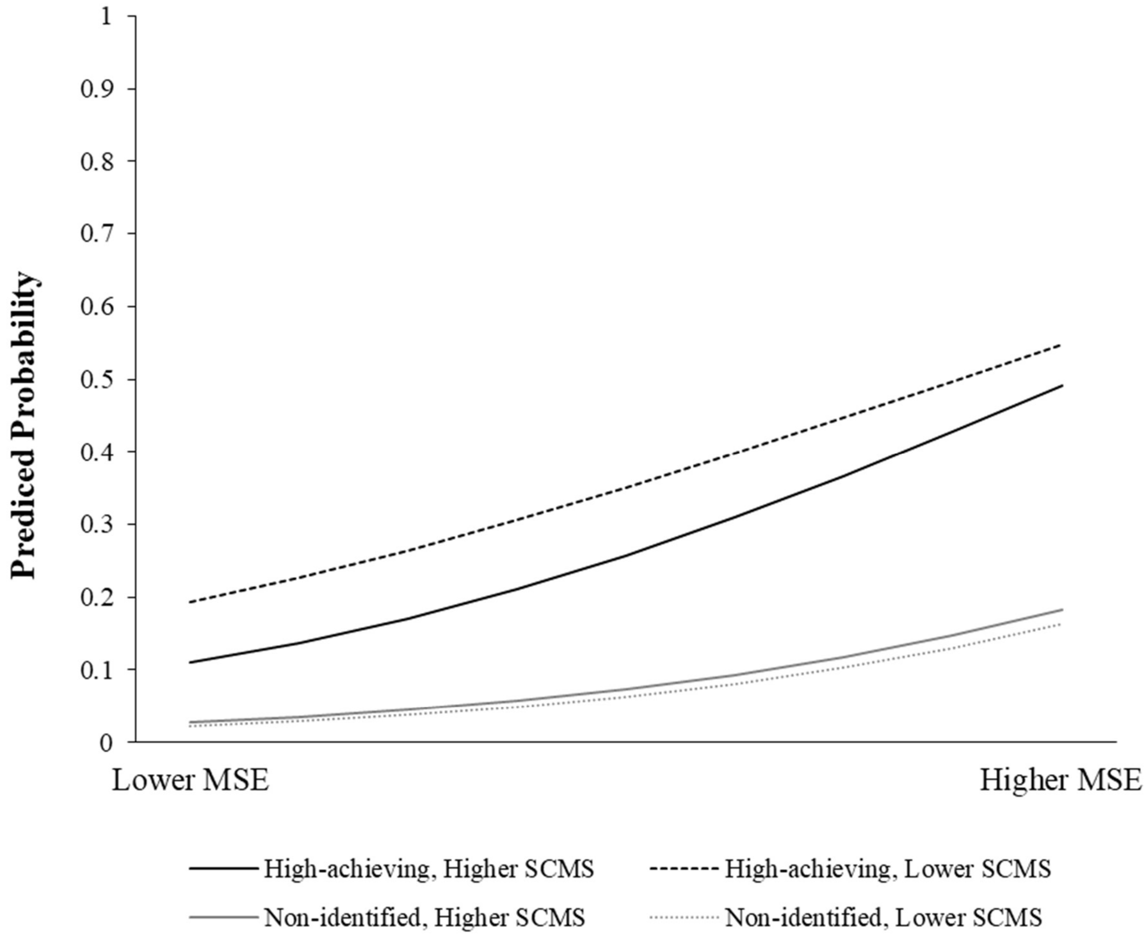


*Figure 24.* *Predicted Probabilities of STEM Entrance, the Three-Way Interaction Effect by Identification, School Rate of the Federal Meal Subsidy, and Mathematics Self-Efficacy. The variable of SCMS and MSE was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCMS: "Lower SCMS" indicates the 25th percentile and "Higher SCMS" indicates the 75th percentile. SCMS = school percentage of students who received the federal meal subsidy. MSE = mathematics self-efficacy.*

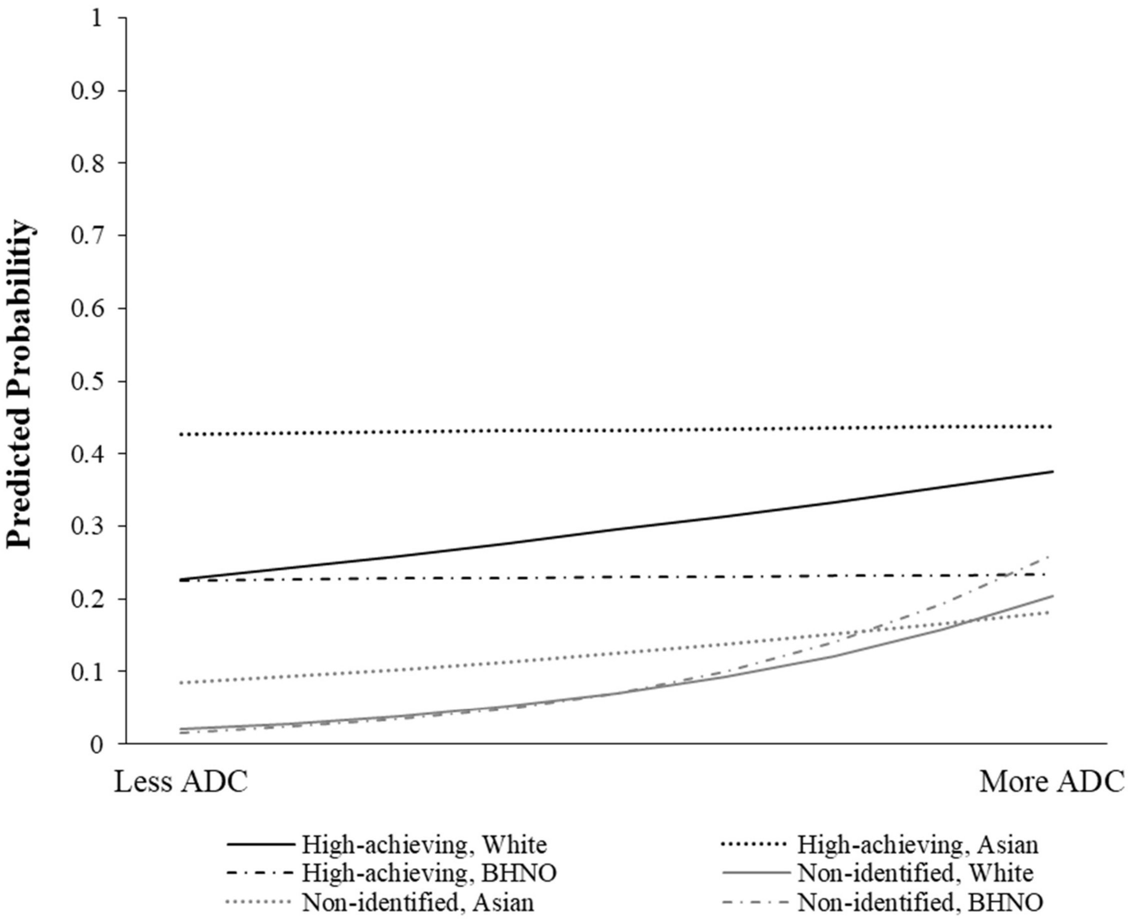


*Figure 25.* *Predicted Probabilities of STEM Entrance, the Three-Way Interaction Effect by Identification, Race, and Advanced Courses. The variable of ADC was grand-mean centered. ADC = advanced courses in math and science. BHNO = Black, Hispanic, Native American, and other races.*

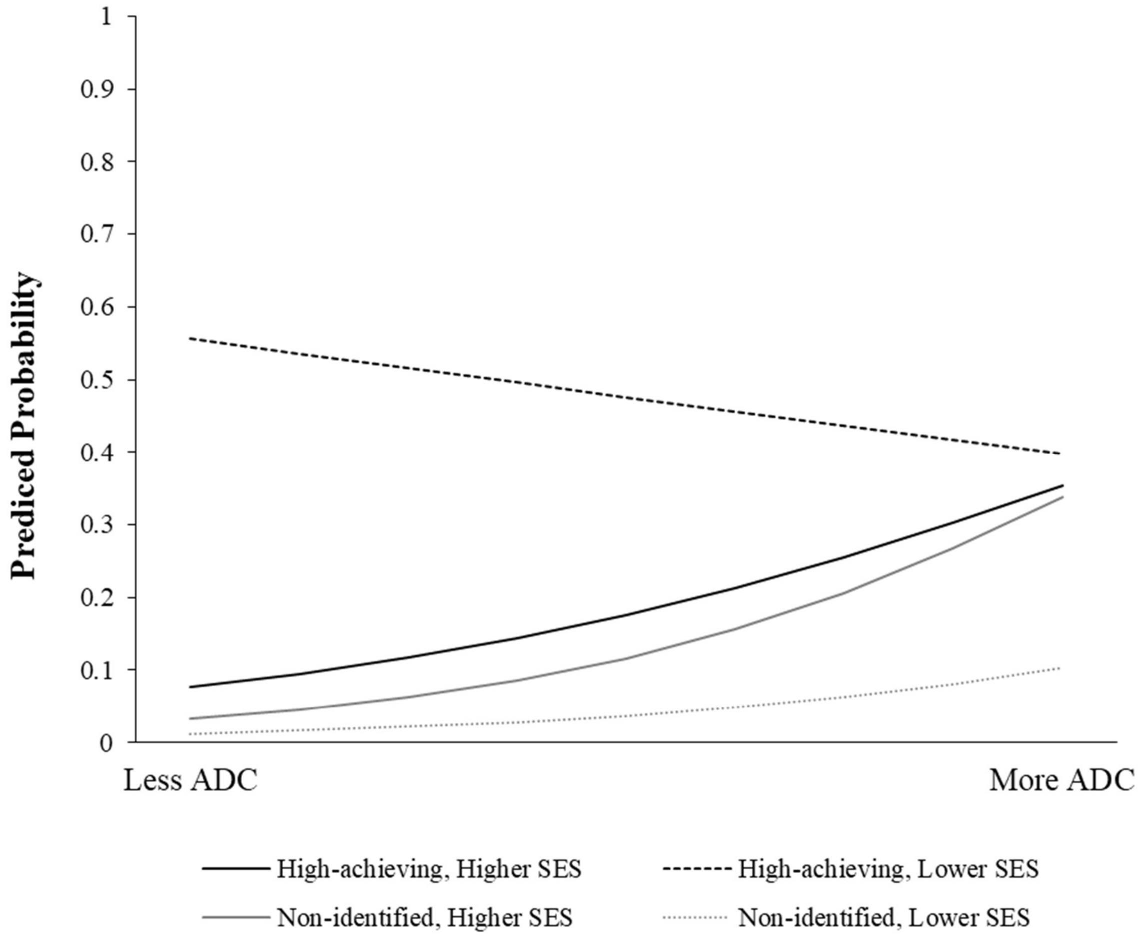


*Figure 26.* *Predicted Probabilities of STEM Entrance, the Three-Way Interaction Effect by Identification, SES and Advanced Courses. The variable of ADC was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES. ADC = advanced courses in math and science.*

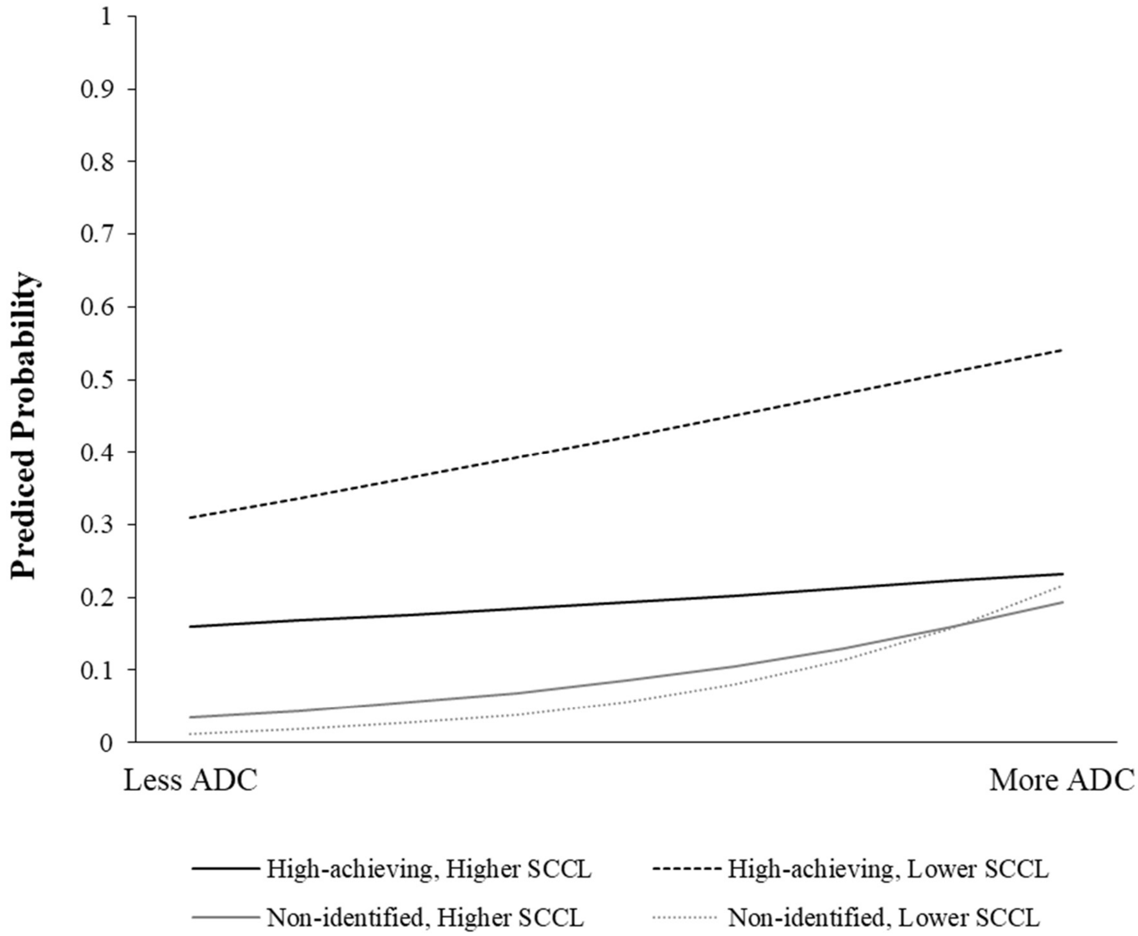


*Figure 27.* *Predicted Probabilities of STEM Entrance, the Three-Way Interaction Effect by Identification, School Climate of Academic Pressure and Advanced Courses. The variable of ADC was grand-mean centered. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean of SCCL, and "Higher SCCL" is 2 SD above the grand mean. SCCL = school climate of academic pressure.*

## Discrete-Time Hazard Models of Persistence in Postsecondary STEM paths

### Baseline comparisons

Before estimating a hazard model for students identified as high-achieving (*RQ 2. What are the hazard probabilities of high-achieving students graduating with a STEM major from a college or university? When are those students most likely to complete their undergraduate programs?*), I estimated hazard probabilities for all the students, including non-identified students, who had entered STEM fields as of 2006 (unweighted $N$ = 1,010), and I examined whether the hazard probabilities differed by identification. As stated, the hazard probability in this study is defined as the probability that a student graduated from a postsecondary education with a STEM major within eight years of high school graduation. Thus, the survival probability is the probability that a student did not graduate from a postsecondary education with a STEM major within the observed period.

Table 33 provides the estimated hazard and survival probabilities for all students. The table also includes the hazard and survival probabilities for students identified as high-achieving and non-identified students. Time was measured by the year that students graduated from college with a STEM major, and started in January 2006. As stated, hazard probability, $H(t)$, describes the conditional probability of students experiencing the event in each time period. The largest group of students graduated from college with a STEM major in the first two years, $H(t)$ = .27. However, considering that "year 1" indicates the third year after graduating from high school for the majority of the cohort, "year 2" actually means the fourth year after high-school graduation. The estimated probability for this time interval implied that more than a quarter of the students who started 4-year college programs with STEM majors after high-school graduation finished their college programs with STEM majors within four years. Within five years of high-school graduation, 47% of students had finished a bachelor's degree in STEM, and within seven years, 58% had done so. Within nine years of high-school graduation, at which point the ELS follow-up study ended, 60% of students who had started a STEM degree as of two years after high-school graduation had completed their college degree programs with STEM majors.

After estimating the baseline probabilities for all students, I estimated the hazard and survival probabilities in terms of identification (Table 33) and examined whether there were any differences. As seen in Figure 28 and Figure 29, students identified as high-achieving, were slightly more likely to complete their bachelor's degrees in STEM fields than non-identified students, particularly within the second year; approximately 62% of students identified as high-achieving, and 59% of non-identified students completed their STEM degrees by the end of the observed period. However, the difference was not statistically significant ($\beta = .05$, $SE = .11$, $p = .63$) when I fitted the discrete-time hazard model with the time dummy variables and a variable of identification. The result implied that among the students who had started college STEM majors as of 2006, the hazard probability of students identified as high-achieving, graduating college with a STEM major was not significantly different than the probability for non-identified students.

Table 33

*Estimated Hazard and Survival Probabilities for Postsecondary STEM Graduation*

| Time | All students | | High-achieving | | Non-identified | |
|---|---|---|---|---|---|---|
| | *H(t)* | *S(t)* | *H(t)* | *S(t)* | *H(t)* | *S(t)* |
| 1 | 0.01 | 0.99 | 0.00 | 1.00 | 0.01 | 0.99 |
| 2 | 0.27 | 0.72 | 0.29 | 0.70 | 0.26 | 0.73 |
| 3 | 0.27 | 0.53 | 0.19 | 0.51 | 0.20 | 0.53 |
| 4 | 0.15 | 0.45 | 0.08 | 0.43 | 0.08 | 0.45 |
| 5 | 0.06 | 0.42 | 0.03 | 0.39 | 0.03 | 0.43 |
| 6 | 0.04 | 0.40 | 0.01 | 0.38 | 0.02 | 0.41 |
| 7 | 0.01 | 0.40 | 0.00 | 0.38 | 0.00 | 0.41 |

*Note.* A hazard event is operationally defined as college graduation with a STEM major.

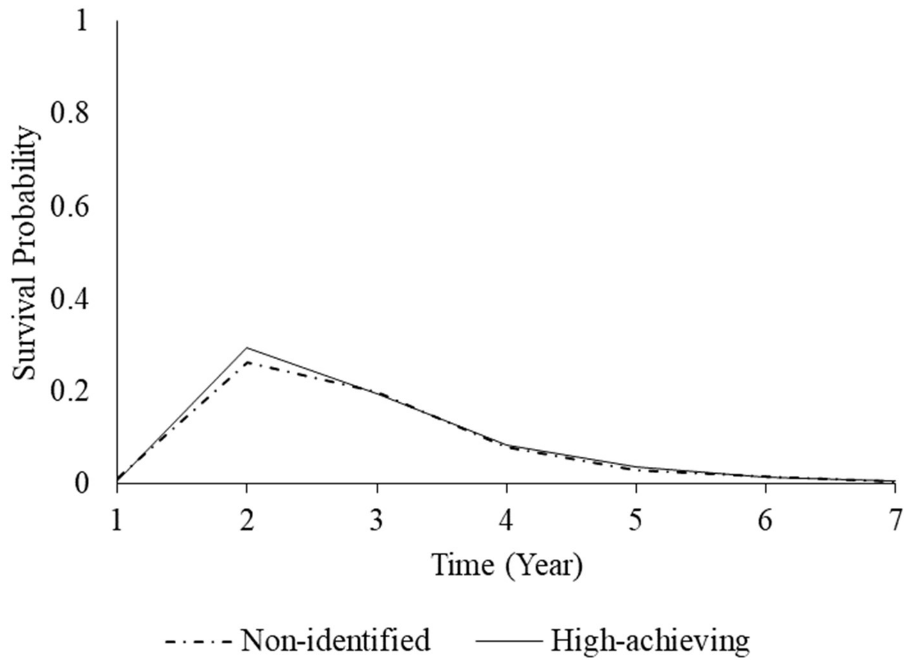


*Figure 28. Predicted Hazard Probabilities of College Graduation with a STEM Major.*

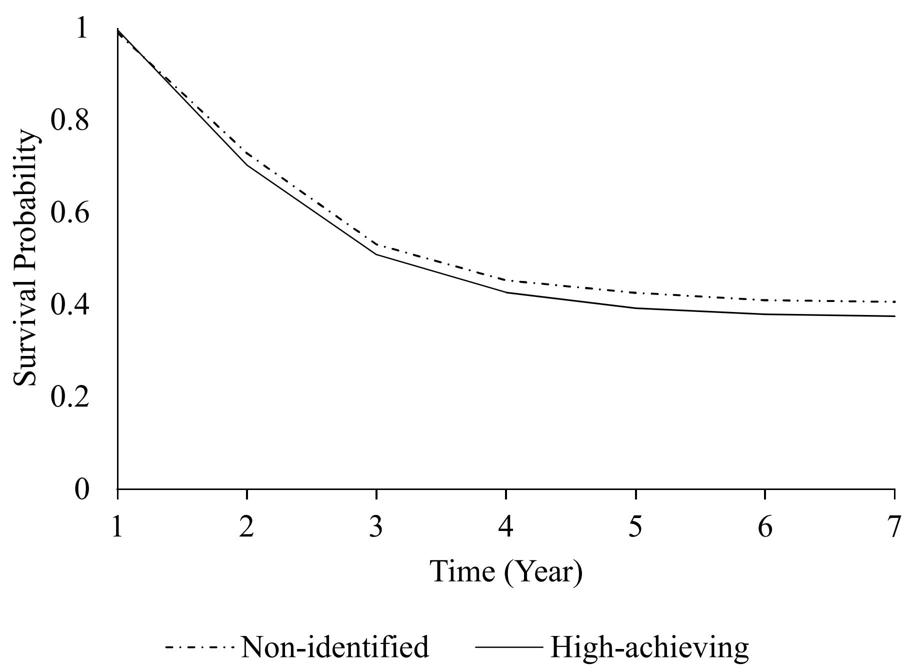


*Figure 29. Predicted Survival Probabilities of College Graduation with a STEM major.*

**Discrete hazard models for students identified as high-achieving**

To answer the main research question, I estimated a set of discrete-time hazard models with the data of students identified as high-achieving who entered into STEM fields as of 2006 (*unweighted N* = 240). Model A was the baseline model, in which dummy variables for the time periods (D1 to D7) were included but no covariates were contained. I added student-level covariates in Model B, and Model C contained moderators (MSE and ADC) and their interaction terms with the covariates. Model D was the final model, in which only significant variables remained.

Table 34 shows the results of the discrete-time hazard models. The model fit of Model B was an improvement on Model A ($\chi^2$ = 25). From the results of Model B, there were no significant differences in the graduation probabilities between male and female students and between White and Asian students. Comparing White and BHNO students, in every year from January 2006, BHNO students were less likely to experience the "event" of completing a bachelor's degree in a STEM field than White students ($\beta = -.67$, $SE = .27$, $p < .001$). Students from families of higher SES were more likely to experience the event than students from families of lower SES ($\beta = .34$, $SE = .10$, $p < .001$). The results of Model C showed that MSE and the interaction terms of MSE and the covariates were not significant.

Model D was the final model. Based on the results of Model C, only significant predictors remained in Model D; time variables, race, sex, and ADC were included. The deviance of Model D was lower than that of Model B ($\chi^2$ = 47), suggesting that Model D had better model fit than Model B. Figure 30 represents the contrasts in survivor functions by race, depicting the period-by-period differences in probabilities. BHNO students were less likely to graduate with a college degree in STEM than White and Asian students across all the observed time periods. By the end of the study, nine years after high-school graduation, 39% of BHNO students identified as high-achieving who had declared majors in STEM fields as of 2006 had completed their bachelor's degrees in STEM fields. This probability was remarkably low when compared to the other races; 70% of White students identified as high-achieving and 79% of Asian students identified as high-achieving who had declared majors in STEM as of 2006 completed their bachelor's degrees. The differences in the probabilities in terms of SES were also significant. Students from higher-SES families were more likely to graduate with STEM degrees than students from lower-SES families across all the time periods. Figure 27 shows the difference between students of two standard deviations above and below the average SES. By the end of the observed period, 64% of the students from lower-SES families had completed bachelor's degrees in STEM fields, whereas 77% of the students from higher-SES families had completed their STEM degrees. Figure 32 contrasts the probabilities of graduation for students who took two standard deviations above and below the average number of advanced courses. Students who took more advanced courses in math and science at high school were more likely to complete their bachelor's degrees in STEM than students who took fewer advanced courses. The final probabilities that students completed their college programs in STEM were 0.74 and 0.66, respectively.

Table 34

*Results of Discrete-Time Hazard Models for STEM Graduation*

| | | Model A | | | Model B | | | Model C | | | Model D | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *p* | *SE* | *Est.* | *p* | *SE* | *Est.* | *p* | *SE* | *Est.* | *p* | *SE* |
| D1 | | -5.44 | *** | 1.00 | -5.46 | *** | 1.01 | -5.46 | *** | 1.01 | -5.49 | *** | 1.01 |
| D2 | | -0.87 | *** | 0.14 | -0.83 | *** | 0.19 | -0.90 | * | 0.22 | -0.76 | *** | 0.18 |
| D3 | | -0.96 | *** | 0.18 | -0.83 | *** | 0.21 | -0.55 | *** | 0.25 | -0.70 | *** | 0.21 |
| D4 | | -1.65 | *** | 0.25 | -1.50 | *** | 0.28 | -1.44 | *** | 0.35 | -1.28 | *** | 0.28 |
| D5 | | -2.43 | *** | 0.37 | -2.28 | *** | 0.39 | -2.10 | *** | 0.46 | -2.03 | *** | 0.39 |
| D6 | | -3.38 | *** | 0.59 | -3.22 | *** | 0.60 | -3.21 | *** | 0.74 | -3.01 | *** | 0.60 |
| D7 | | -4.47 | *** | 1.01 | -4.30 | *** | 1.01 | -3.89 | *** | 1.02 | -4.09 | *** | 1.01 |
| Sex | | | | | >0.00 | 0.99 | 0.20 | 0.36 | 0.15 | 0.25 | | | |
| Race | Asian | | | | 0.37 | 0.17 | 0.27 | -0.04 | 0.92 | 0.36 | 0.26 | | 0.28 |
| | BHNO | | | | -0.67 | *** | 0.27 | -1.02 | ** | 0.33 | -0.79 | ** | 0.28 |
| SES | | | | | 0.34 | *** | 0.10 | 0.12 | 0.36 | 0.13 | 0.28 | ** | 0.11 |
| MSE | | | | | | | | 0.35 | 0.13 | 0.23 | | | |
| ADC | | | | | | | | 0.43 | *** | 0.11 | 0.28 | *** | 0.06 |
| Race*MSE | Asian | | | | | | | -0.36 | 0.54 | 0.28 | | | |
| | BHNO | | | | | | | -0.37 | 0.20 | 0.44 | | | |
| SES*MSE | | | | | | | | -0.20 | 0.27 | 0.19 | | | |
| Race*ADC | Asian | | | | | | | 0.03 | 0.90 | 0.22 | | | |
| | BHNO | | | | | | | -0.41 | 0.06 | 0.22 | | | |
| SES*ADC | | | | | | | | -0.10 | 0.26 | 0.08 | | | |
| ***Fit Statistic*** | | | | | | | | | | | | | |
| Deviance | | 682 | | | 657 | | | 458 | | | 610 | | |

*Note.* D1-7 are dummy variables for the time periods. $^{***}p < .001$, $^{**}p < .01$

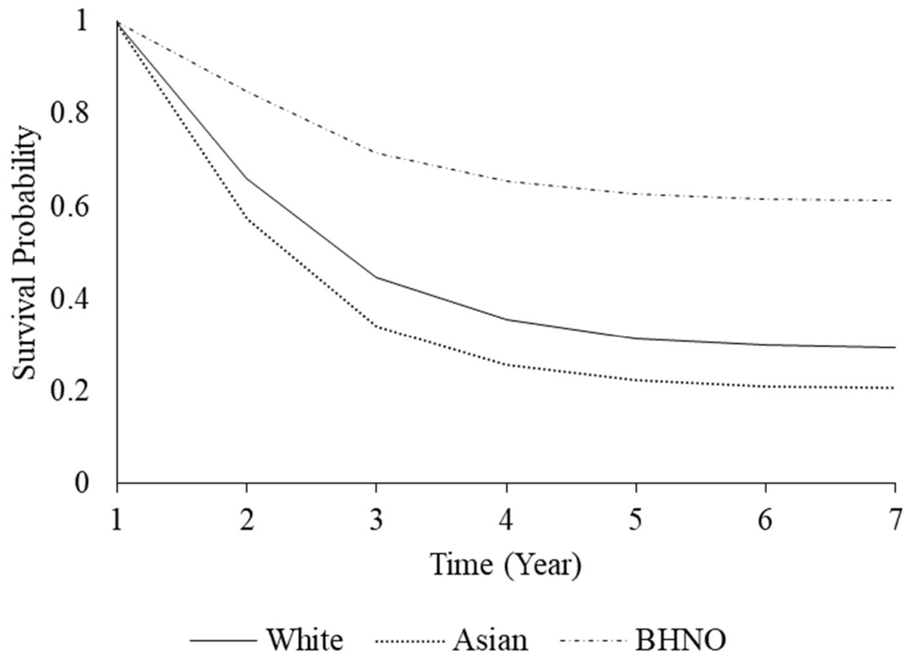


*Figure 30. Fitted Survival Functions by Race. BHNO = Black, Hispanic, Native American, and other races.*

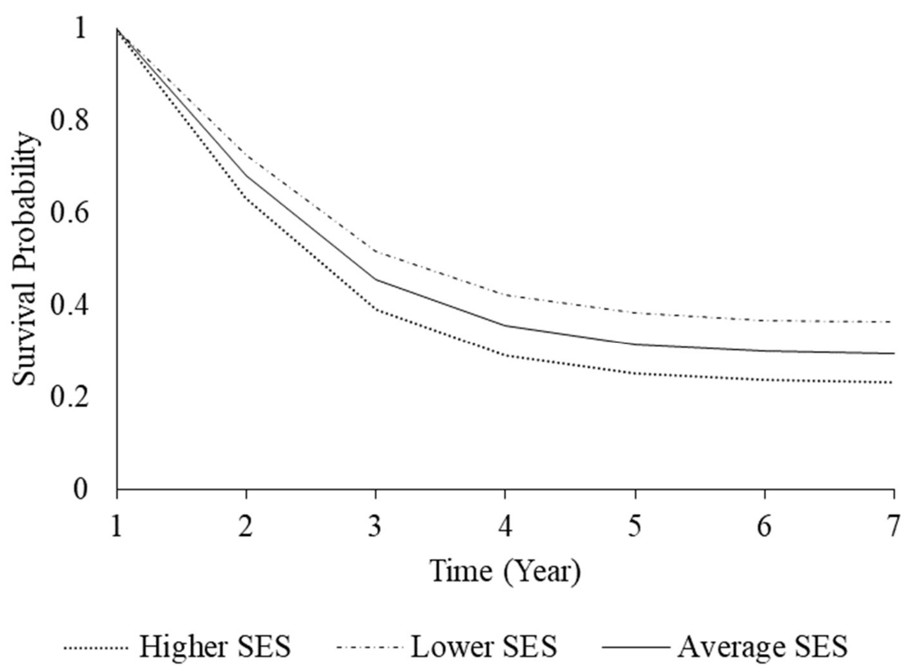


*Figure 31. Fitted Survival Functions by SES.*

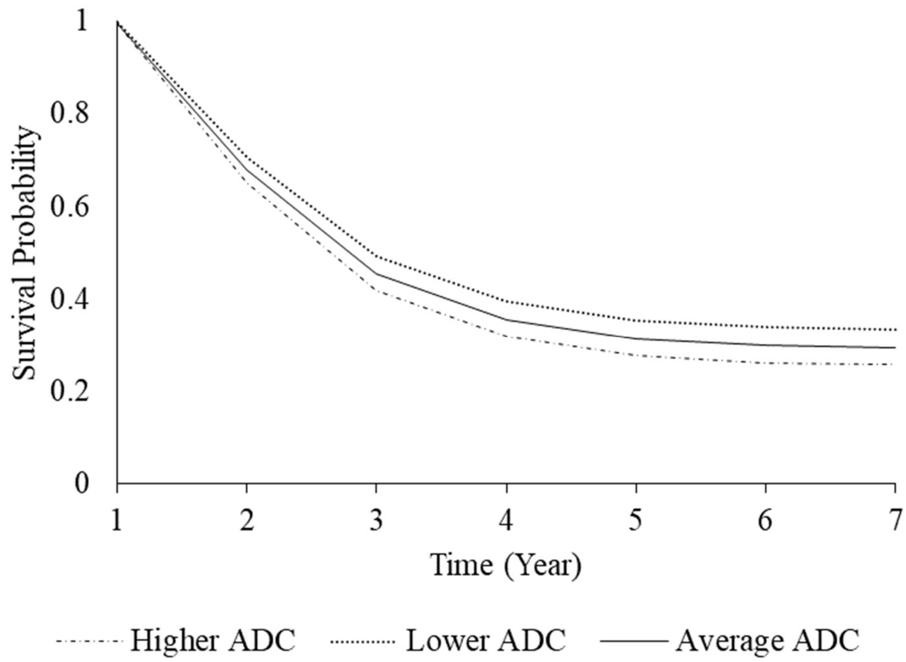


*Figure 32. Fitted Survival Functions by the Number of Advanced Courses Taken.*

**Multilevel Logistic Models of Further Persistence in STEM Fields**

To examine the third research question, concerning whether further persistence in STEM fields varied with identification, I estimated a set of multilevel logistic regression models with a binary dependent variable reflecting further persistence in STEM fields after college graduation.

Model A was a baseline model. The estimated ICC was approximately 0.011, indicating that approximately 1.1% of variance in the dependent variable was accounted for by variations among schools. The school-level variance was significant ($\tau_{00}$ = .19, *SE* = .01, $p < .001$) so I continued to estimate two-level models. Table 35 gives the results of Model A to Model C.

Model B contained the variable of identification as a high achiever in math and science, based on college entrance exams. The addition of the variable decreased the deviance statistic by 3,923 compared to the baseline model, which was significantly greater than the .05 critical value of 1 degree of freedom. Students identified as high-achieving in math and science were more likely to persist in STEM fields after college graduation than non-identified students ($\gamma$ = 1.61, *SE* = .02, $p < .001$). The corresponding odds ratio was 5.00, which means that the odds for students identified as high-achieving were five times the odds for non-identified students persisting in further careers in STEM fields after college graduation.

Model C contained all the covariates (sex, race, SES, academic pressure of school, school percentage of federal meal subsidy). The deviance statistic showed a statistically significant decrease compared to the previous model ($\chi^2$ = 7,833, $p < .05$). All the student-level and school-level covariates were significant in predicting further persistence in STEM fields after college graduation, except a dummy variable for Asian students. This meant that the probability of further persistence did not differ between Asian and White students. The log-odds for female students were lower than for male students ($\gamma = -1.13$, *SE* = .02, $p < .001$), which gave an odds ratio of 0.32. In other words, the odds of further persistence in STEM for female students were 0.32 times the odds for male students. BHNO students were less likely to work or study in STEM fields after college graduation than White students ($\gamma = -.49$, *SE* = .02, $p < .001$, OR = .61). Family SES was positively associated with further persistence in STEM fields after college graduation ($\gamma = .28$, *SE* = .01, $p < .001$). The odds of persistence for students from families in the fourth-quartile SES were 2.32 times the odds for students from families in first-quartile SES. However, school climate of academic pressure was negatively associated with further persistence ($\gamma = -.09$, *SE* = .01, $p < .001$). In other words, the log-odds of further persistence decreased by 0.09 of a unit when SCCL increased by a unit.

Table 35

*Estimates for Multilevel Logistic Models of Further Persistence: Models A—C*

| | | Model A | | | Model B | | | Model C | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| ***Fixed effects*** | | | | | | | | | | |
| Intercept | | -2.80 | 0.01 | *** | -2.91 | 0.01 | *** | -2.33 | 0.01 | *** |
| HA | | | | | 1.64 | 0.02 | *** | 1.19 | 0.02 | *** |
| Sex | Female | | | | | | | -1.13 | 0.02 | *** |
| Race | Asian | | | | | | | -0.01 | 0.04 | |
| | BHNO | | | | | | | -0.49 | 0.02 | *** |
| SES | | | | | | | | 0.28 | 0.01 | *** |
| SCCL | | | | | | | | -0.09 | 0.01 | *** |
| SCMS | | | | | | | | >.00 | >.00 | *** |
| ***Random effects*** | | | | | | | | | | |
| Intercept | | 0.19 | 0.01 | *** | 0.15 | 0.01 | *** | 0.11 | 0.01 | *** |
| ***Goodness-of-fit***+ | | | | | | | | | | |
| Deviance statistic | | 145,930 | | | 142,007 | | | 134,174 | | |
| BIC | | 145,943 | | | 142,027 | | | 134,233 | | |

Note. + Goodness-of-fit indices were combined by the method as stated in previous chapter (Little & Rubin, 2002; Snijders & Bosker, 1999); Since I used multiple imputation, five pieces of model fits that were estimated from five different sets of imputed data should be combined. HA = high achievers in math and science; SCCL = school academic pressure; SCMS = school percentage of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Model D contained two-way interaction terms of identification and each covariate, in addition to the variables in Model C. Table 36 shows the results for Model D, E, and F. The deviance statistic significantly decreased compared to the previous model ($\chi^2 = 798$, $p < .05$). The interaction effect of identification and BHNO was significant ($\gamma = .29$, $SE = .11$, $p < .01$). The gaps in the probabilities of persistence were greater for comparisons between non-identified students than comparisons between students identified as high-achieving. For example, the odds of persistence for White students identified as high-achieving were 1.20 times the odds for

BHNO students identified as high-achieving, but the odds for non-identified White students were 1.60 times the odds for non-identified BHNO students (Figure 33). The gaps in the probabilities of persistence in terms of SES were greater for students identified as high-achieving. When comparing students from the first and fourth quartiles of SES, the odds of persistence for students identified as high-achieving from lower-SES families were 0.58 times the odds for students identified as high-achieving from higher-SES families; but, the odds ratio by SES was slightly lower, 0.42 comparing between higher- and lower-SES, for non-identified students (Figure 34).

The interaction effects were remarkable for identification and school climate of academic pressure as well as identification and school percentage of federal meal subsidy (Figure 35 and Figure 36). For non-identified students, the probabilities of STEM persistence were equivalent regardless of the levels of school climate of academic pressure (OR = 1.00 when comparing 2 *SD* above and below the average SCCL). However, the odds ratio was 4.19 for students identified as high-achieving. This meant that the odds of persistence for students identified as high-achieving who attended schools with lower levels of academic pressure were almost 4 times the odds for students identified as high-achieving who attended schools with higher levels of academic pressure. In terms of SCMS rate (Figure 36), non-identified students who attended schools with lower rates of SCMS were more likely to persist in STEM after college graduation than non-identified students who attended schools with higher rates of SCMS. However, the effects were reversed for students identified as high-achieving. Students identified as high-achieving who attended schools with lower SCMS rates were less likely to persist in STEM after college graduation than students who attended schools with higher rates (OR = .24).

Table 36

*Estimates for Multilevel Logistic Models of Further Persistence: Models D—F*

| | | Model D | | | Model E | | | Model F | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| ***Fixed effects*** | | | | | | | | | | |
| Intercept | | -2.32 | 0.01 | *** | -2.75 | 0.02 | *** | -2.74 | 0.02 | *** |
| HA | | 1.65 | 0.04 | *** | 0.83 | 0.06 | *** | 0.95 | 0.07 | *** |
| Sex | Female | -1.14 | 0.02 | *** | -1.15 | 0.03 | *** | -1.12 | 0.03 | *** |
| Race | Asian | 0.08 | 0.05 | .10 | -0.29 | 0.09 | *** | -0.42 | 0.10 | *** |
| | BHNO | -0.47 | 0.02 | *** | -0.50 | 0.04 | *** | -0.46 | 0.04 | *** |
| SES | | 0.29 | 0.01 | *** | 0.06 | 0.01 | *** | 0.08 | 0.01 | *** |
| SCCL | | 0.00 | 0.01 | .96 | -0.12 | 0.02 | *** | -0.10 | 0.02 | *** |
| SCMS | | 0.00 | 0.00 | *** | 0.00 | 0.00 | .22 | 0.00 | 0.00 | .25 |
| HA*Sex | Female | -0.01 | 0.06 | .90 | 0.13 | 0.07 | * | -0.13 | 0.17 | .42 |
| HA*Race | Asian | -0.15 | 0.10 | .13 | -0.31 | 0.12 | ** | -0.15 | 0.30 | .63 |
| | BHNO | 0.29 | 0.11 | ** | -0.31 | 0.15 | * | -6.42 | 0.77 | *** |
| HA*SES | | -0.11 | 0.03 | *** | -0.02 | 0.03 | .55 | -0.40 | 0.07 | *** |
| HA*SCCL | | -0.60 | 0.04 | *** | -0.57 | 0.05 | *** | -0.03 | 0.13 | .82 |
| HA*SCMS | | 0.02 | 0.00 | *** | 0.03 | 0.00 | *** | 0.04 | 0.00 | *** |
| STCR | | | | | 0.03 | 0.00 | *** | 0.03 | 0.00 | *** |
| HIMP | | | | | 0.25 | 0.02 | *** | 0.23 | 0.02 | *** |
| HA*STCR | | | | | 0.00 | 0.00 | *** | -0.01 | 0.00 | *** |
| HA* HIMP | | | | | -0.04 | 0.07 | .53 | | | |
| Sex*STCR | Female | | | | 0.00 | 0.00 | * | | | |
| Race*STCR | Asian | | | | 0.00 | 0.00 | .30 | 0.00 | 0.00 | * |
| | BHNO | | | | 0.00 | 0.00 | *** | 0.00 | 0.00 | *** |
| SES*STCR | | | | | 0.00 | 0.00 | .88 | 0.00 | 0.00 | *** |
| SCCL*STCR | | | | | 0.00 | 0.00 | .56 | 0.00 | 0.00 | .66 |
| SCMS*STCR | | | | | 0.00 | 0.00 | | | | |

Note. HA = high achievers in math and science; SCCL = school climate of academic pressure; SCMS = school percentage of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

(Continued)

Table 36 Continued

| | | Model D | | | Model E | | | Model F | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* | *Est.* | *SE* | *p* |
| Sex*HIMP | Female | | | | 0.19 | 0.04 | *** | 0.18 | 0.04 | *** |
| Race*HIMP | Asian | | | | -0.05 | 0.10 | .64 | | | |
| | BHNO | | | | -0.05 | 0.05 | .35 | | | |
| SES*HIMP | | | | | 0.10 | 0.02 | *** | 0.12 | 0.02 | *** |
| SCCL*HIMP | | | | | 0.12 | 0.03 | *** | 0.07 | 0.03 | * |
| SCMS*HIMP | | | | | -0.01 | 0.00 | *** | -0.01 | 0.00 | *** |
| HA*Race*STCR | Asian | | | | | | | -0.01 | 0.00 | * |
| | BHNO | | | | | | | 0.02 | 0.00 | *** |
| HA*SES*STCR | | | | | | | | 0.02 | 0.00 | *** |
| HA*SCCL*STCR | | | | | | | | | | |
| HA*Sex*HIMP | | | | | | | | | | |
| HA*Race*HIMP | Asian | | | | | | | | | |
| | BHNO | | | | | | | | | |
| HA*SES*HIMP | | | | | | | | | | |
| HA*SCCL*HIMP | | | | | | | | | | |
| HA*SCMS*HIMP | | | | | | | | | | |
| ***Random effects*** | | | | | | | | | | |
| Intercept | | 0.08 | 0.01* | | >0.00 | >0.00 | *** | >0.00 | >0.00 | *** |
| ***Goodness-of-fit***+ | | | | | | | | | | |
| Deviance statistic | | 133,376 | | | 106,213 | | | 105,315 | | |
| BIC | | 133,475 | | | 106,330 | | | 105,573 | | |

*Note.* + Goodness-of-fit indices were combined by the method as stated in previous chapter (Little & Rubin, 2002; Snijders & Bosker, 1999); Since I used multiple imputation, five pieces of model fits that were estimated from five different sets of imputed data should be combined. HA = high achievers in math and science; SCCL = school academic pressure; SCMS = school percentage of federal meal subsidy, BHNO = Black, Hispanic, Native American, and other races. * $p < .05$, ** $p < .01$, *** $p < .001$

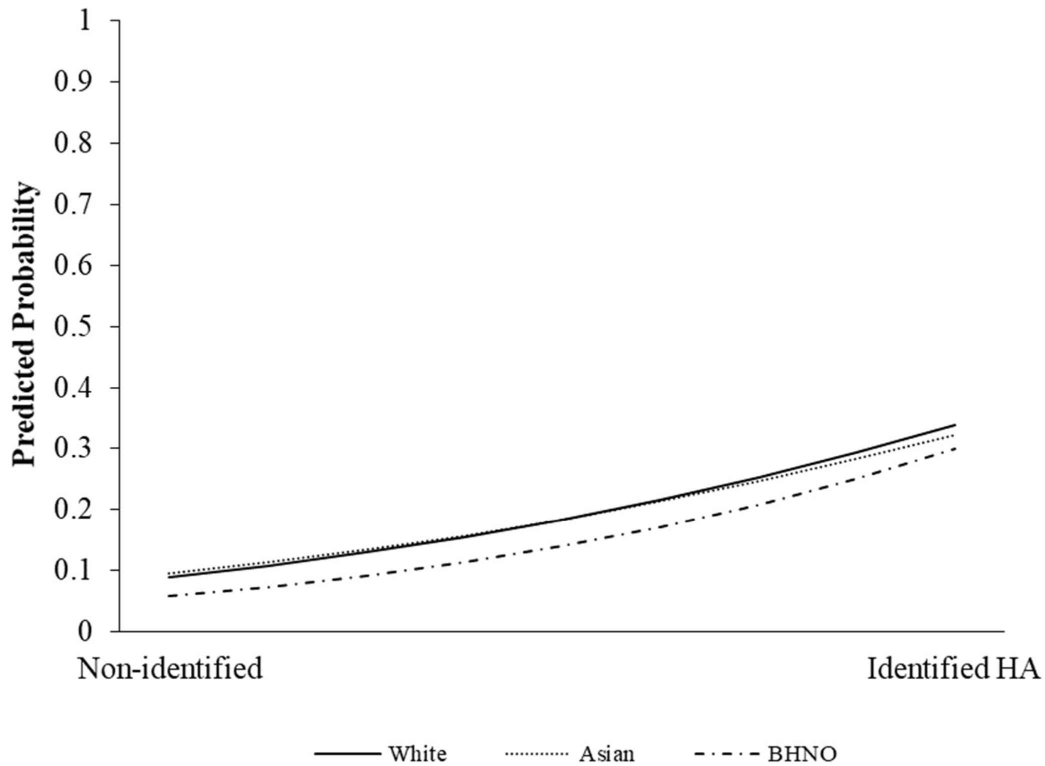


*Figure 33. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification and Race. BHNO = Black, Hispanic, Native American, and other races.*

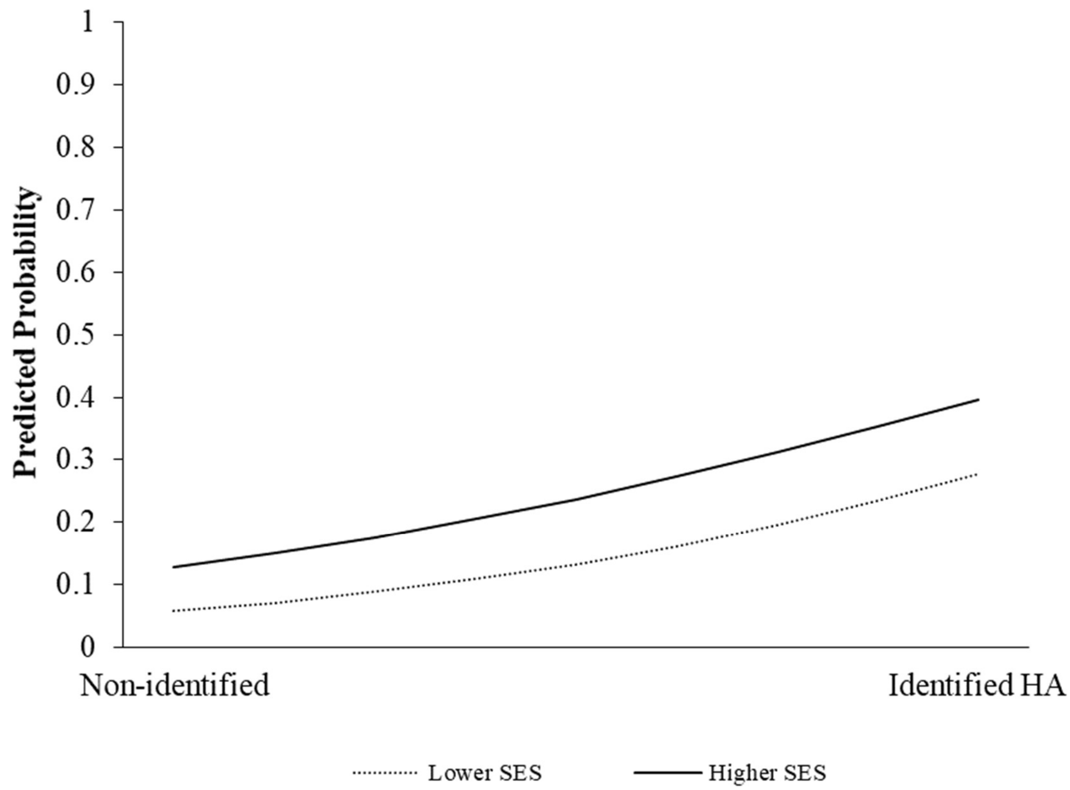


*Figure 34.* *Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification and SES. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES.*

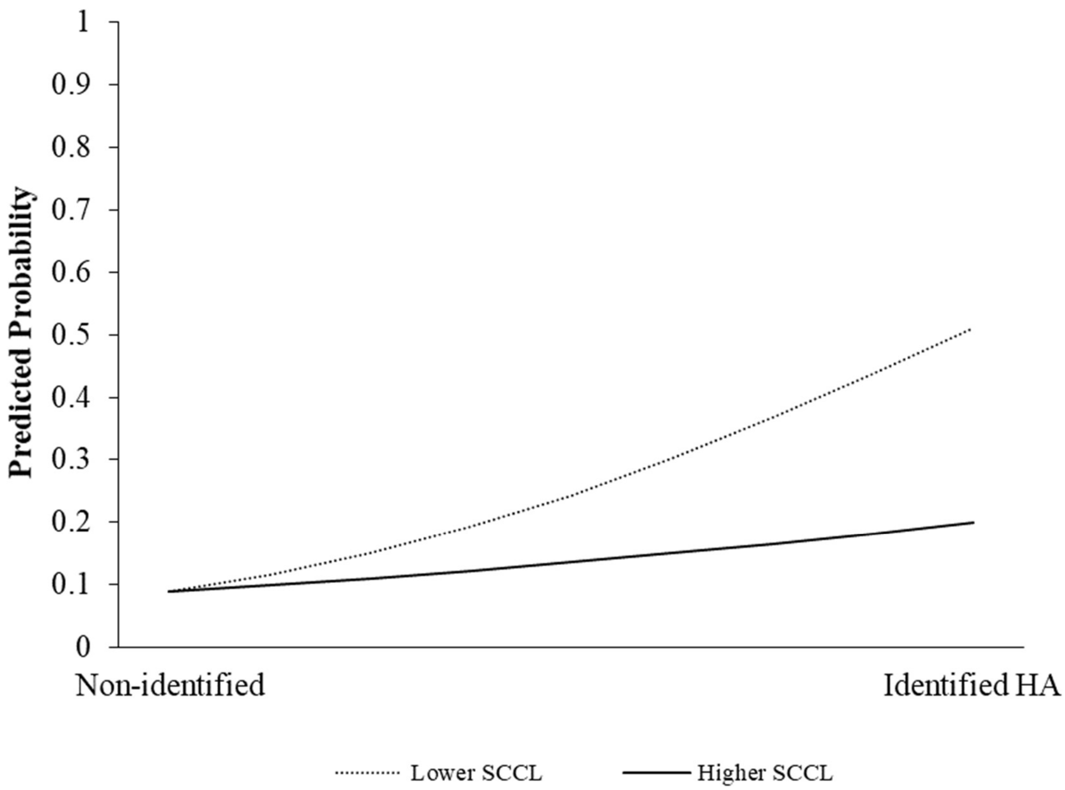


*Figure 35. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification and School Climate of Academic Pressure. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean of SCCL, and "Higher SCCL" is 2 SD above the grand mean. SCCL = school climate of academic pressure.*

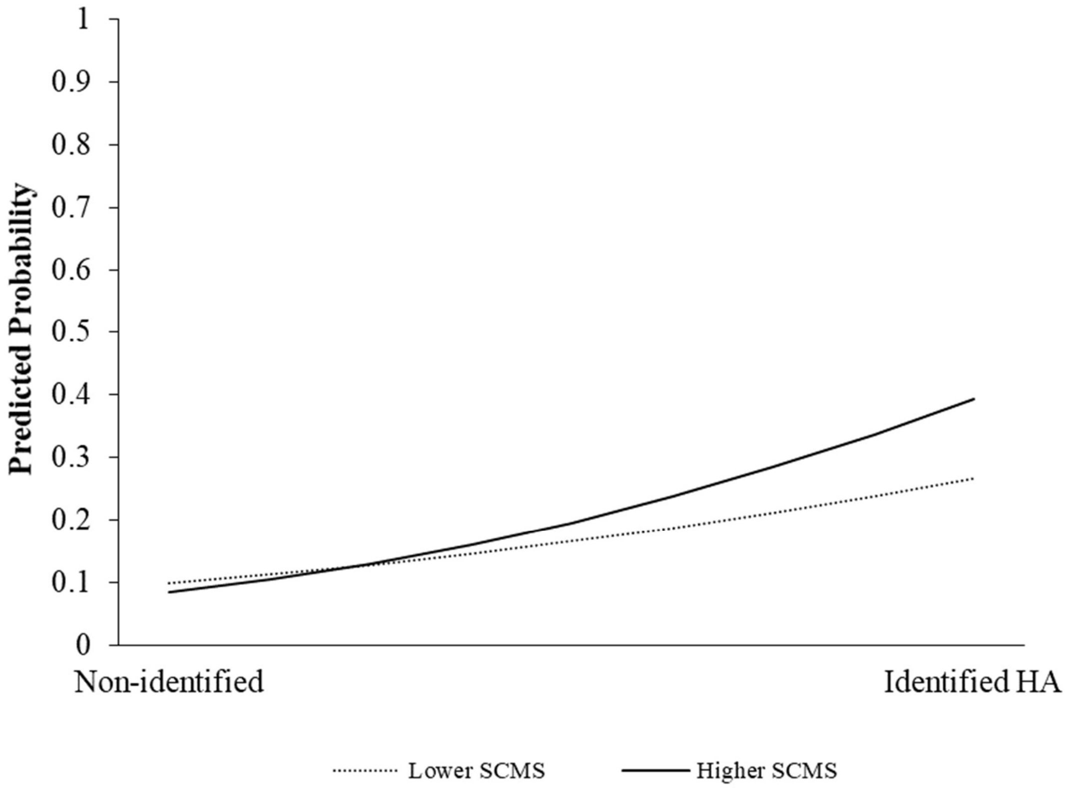


*Figure 36.* *Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification and School Rate of the Federal Meal Subsidy. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCMS: "Lower SCMS" indicates the 25th percentile, and "Higher SCMS" indicates the 75% percentile. SCMS = school rate of students who received the federal meal subsidy.*

In Model E, I added two moderators, number of STEM credits in college and high-impact activities, and their two-way interaction terms with each covariate. The main effects of the two moderators were significant (Table 36). Students who took more STEM credits or engaged in at least one high-impact activity were more likely to persist in STEM fields after college graduation ($\gamma = .03$, $SE > .00$, $p < .001$ and $\gamma = .25$, $SE = .02$, $p < .001$, respectively). In terms of college STEM credits, the interaction effect with identification was significant. The differences in probabilities by number of college STEM credits were greater for students identified as high-achieving than for non-identified students (Figure 37).

The interaction effect of sex and college STEM credits was significant. The probabilities notably increased for male students as they took more STEM credits in their undergraduate programs ($p = .03$ and $p = .13$ when students took $-2$ *SD* and $+2$ *SD* of the average number of STEM credits, respectively). However, the probabilities did not change much for female students ($p = .008$ to $p = .05$ for the same changes) (Figure 38). The interaction effect of race and number of college STEM credits was also significant, but the differences in terms of race were not large; the odds ratio for White and BHNO students at 2 *SD* below the average number of STEM credits was 1.38, but the odds ratio at 2 *SD* above the average was 1.30 (Figure 39).

The interaction effects were also significant for high-impact activities at college. High-impact activities slightly increased the probability of female student STEM persistence if female students did not participate in any high-impact activities, and if they participated in at least one high-impact activity but the activities did not change the probability for male students (Figure 40). The probability of persistence for students from the first-quartile of SES families increased as they experienced at least high-impact activity at college ($p = .06$ to $p = .09$), but the probability did not change for students from the fourth-quartile of SES families (Figure 41).

Students who attended schools with lower levels of academic pressure, if they did not participate in any high-impact activities at college, were more likely to persist in STEM after college graduation than students who attended schools with higher levels of school academic pressure (OR = 1.34, See Figure 42). However, if they did participate in at least one high-impact activity, the probabilities were almost equal regardless of school academic pressure (OR = 1.00). High-impact activities were also significantly associated with the gaps in the probabilities of persistence in terms of the rates of SCMS. But the effect size was small ($\gamma = -0.01$, $SE > 0.00$, $p < .001$, OR = 0.99), and as seen in Figure 43, no meaningful interaction effect was found.

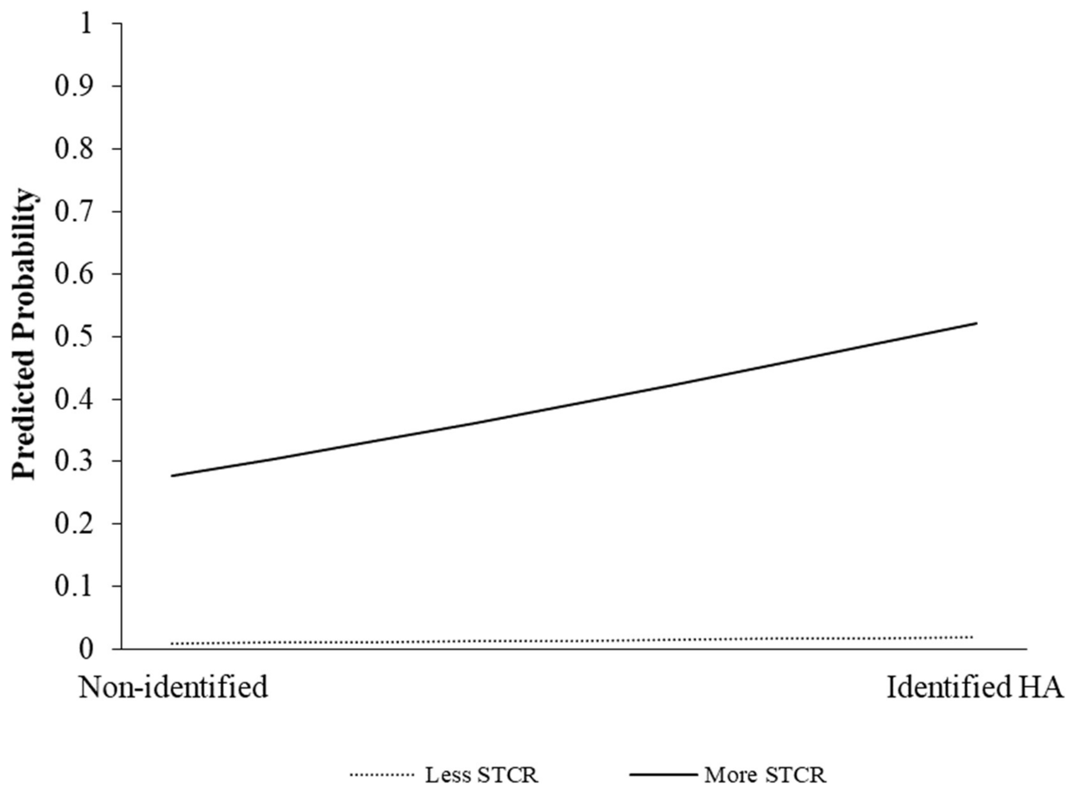


*Figure 37.* *Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification and College STEM Credits. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of STCR: "Lower STCR" is 2 SD below the grand mean of SCCL, and "Higher STCR" is 2 SD above the grand mean. STCR = STEM course credits earned in undergraduate programs.*

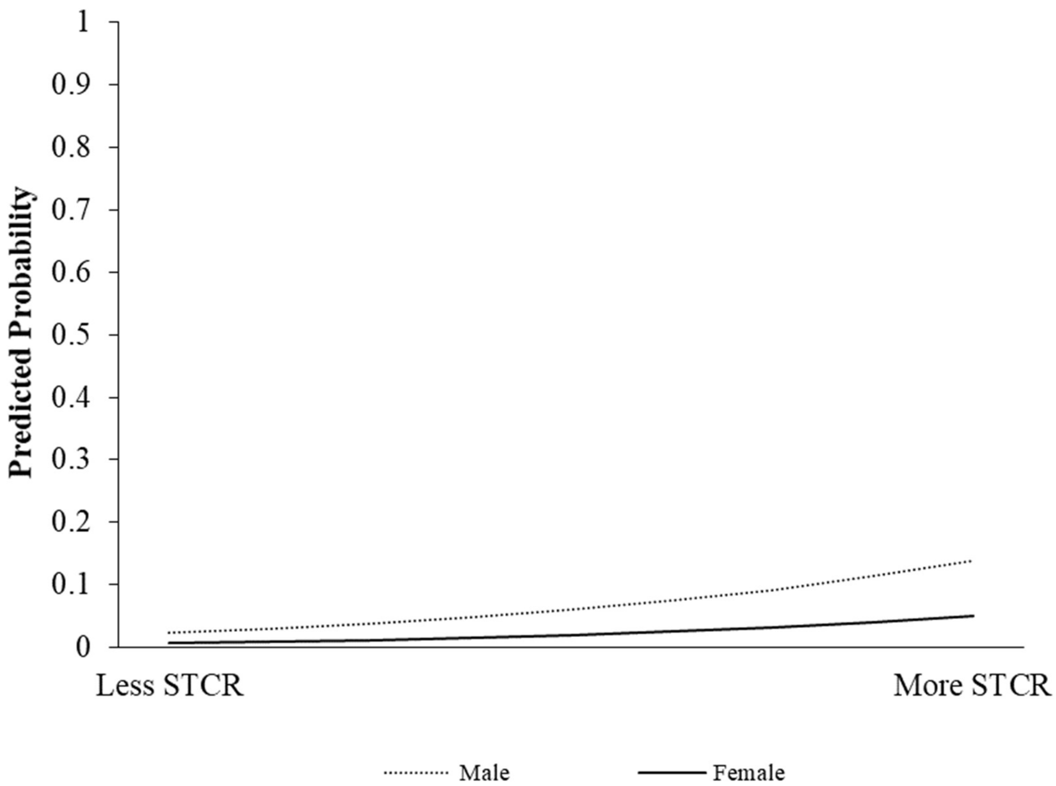


*Figure 38. Predicted Probabilities of Further Persistence in in STEM, the Interaction Effect by Sex and College STEM Credits. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of STCR: "Lower STCR" is 2 SD below the grand mean of SCCL, and "Higher STCR" is 2 SD above the grand mean. STCR = STEM course credits earned in undergraduate programs.*

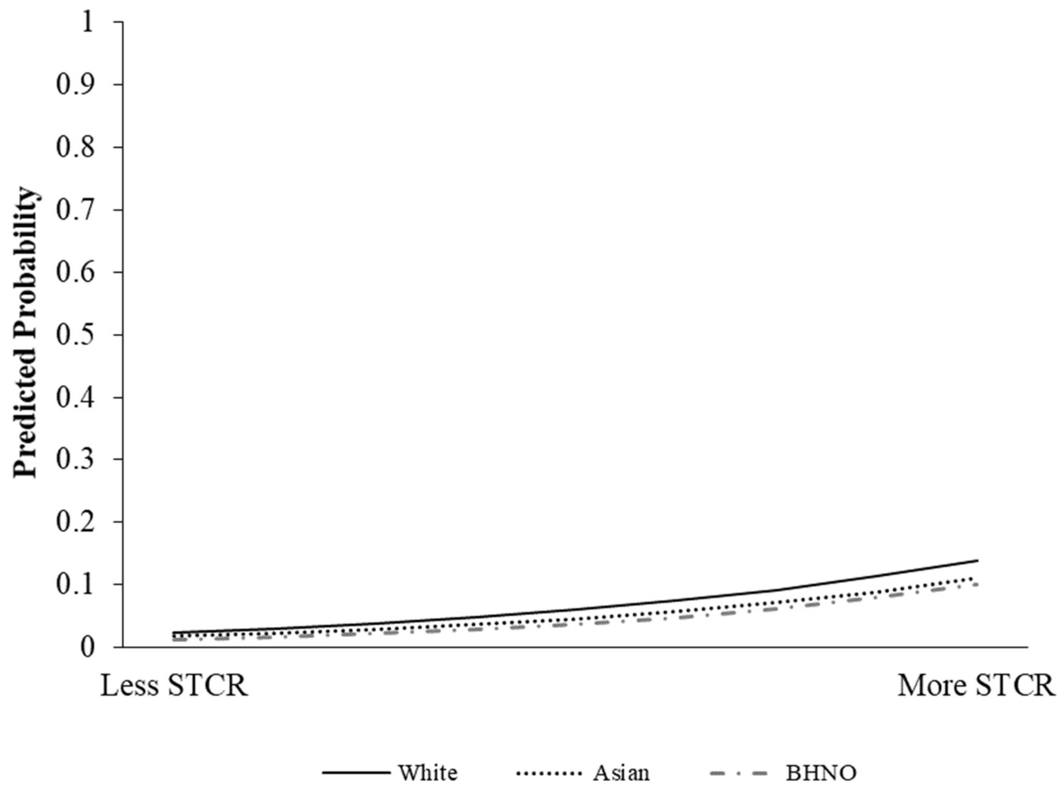


*Figure 39. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Race and College STEM Credits. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of STCR: "Lower STCR" is 2 SD below the grand mean of SCCL, and "Higher STCR" is 2 SD above the grand mean. STCR = STEM course credits earned in undergraduate programs. BHNO = Black, Hispanic, Native American, and other races.*

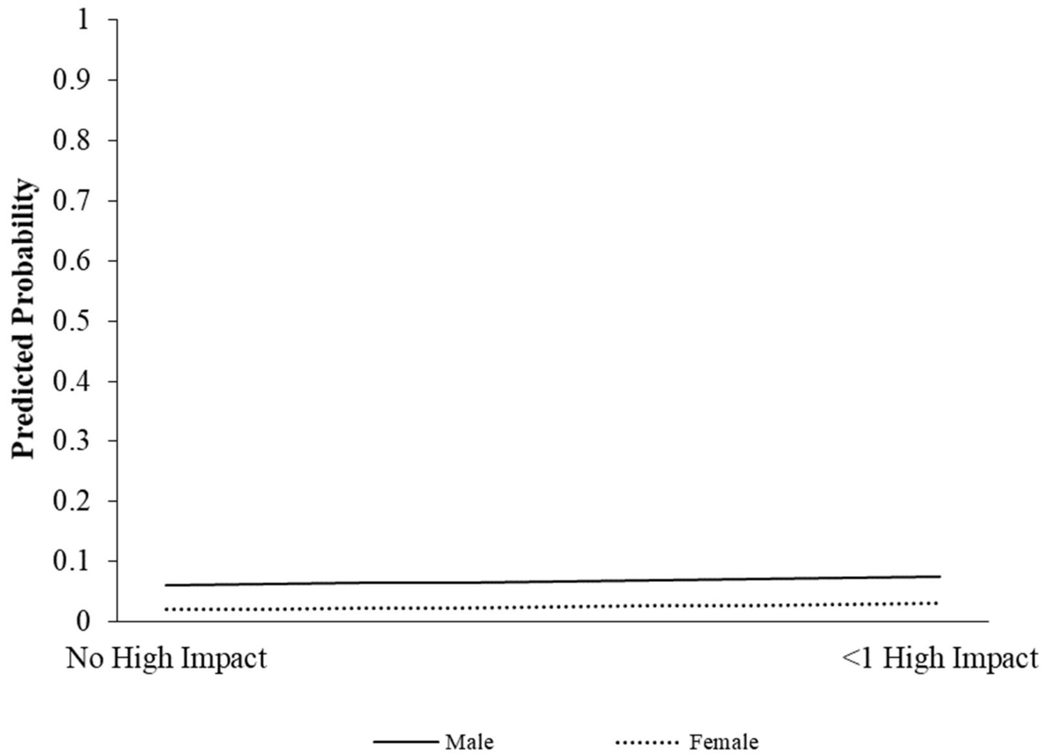


*Figure 40. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Sex and High Impact Activities.*

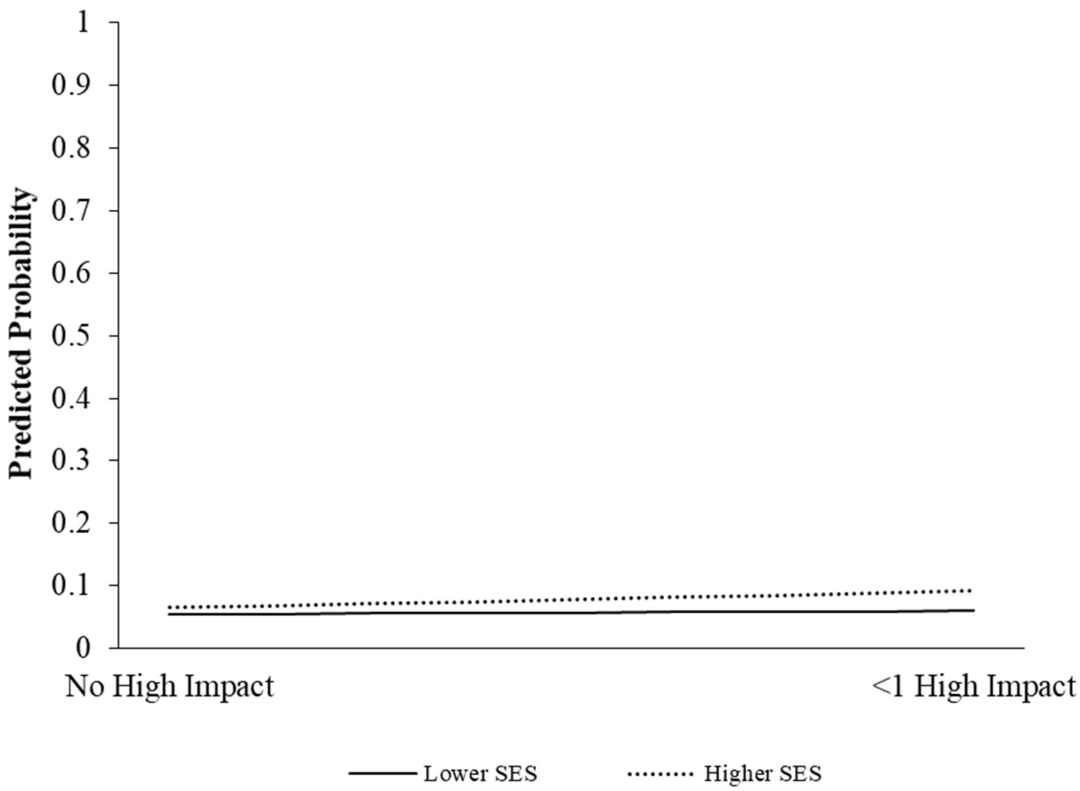


*Figure 41*. *Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by SES and High Impact Activities. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES.*

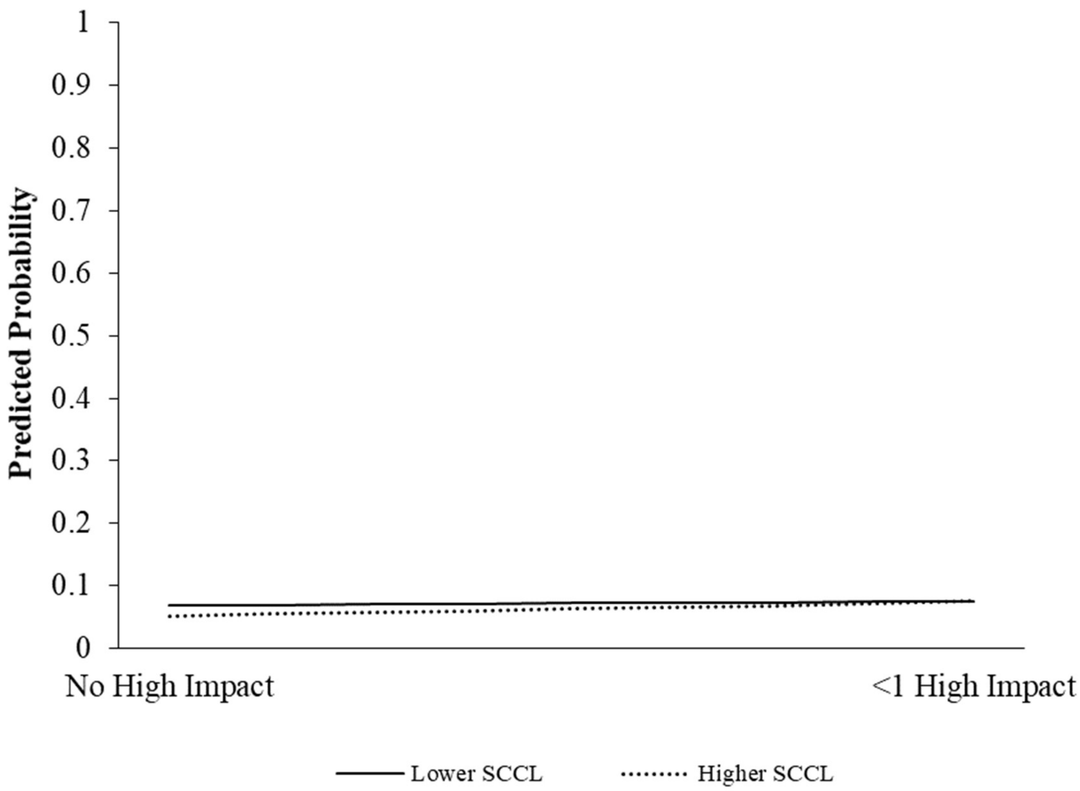


*Figure 42. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by High School Academic Pressure and College High Impact Activities. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCCL: "Lower SCCL" is 2 SD below the grand mean of SCCL, and "Higher SCCL" is 2 SD above the grand mean. SCCL = school climate of academic pressure.*

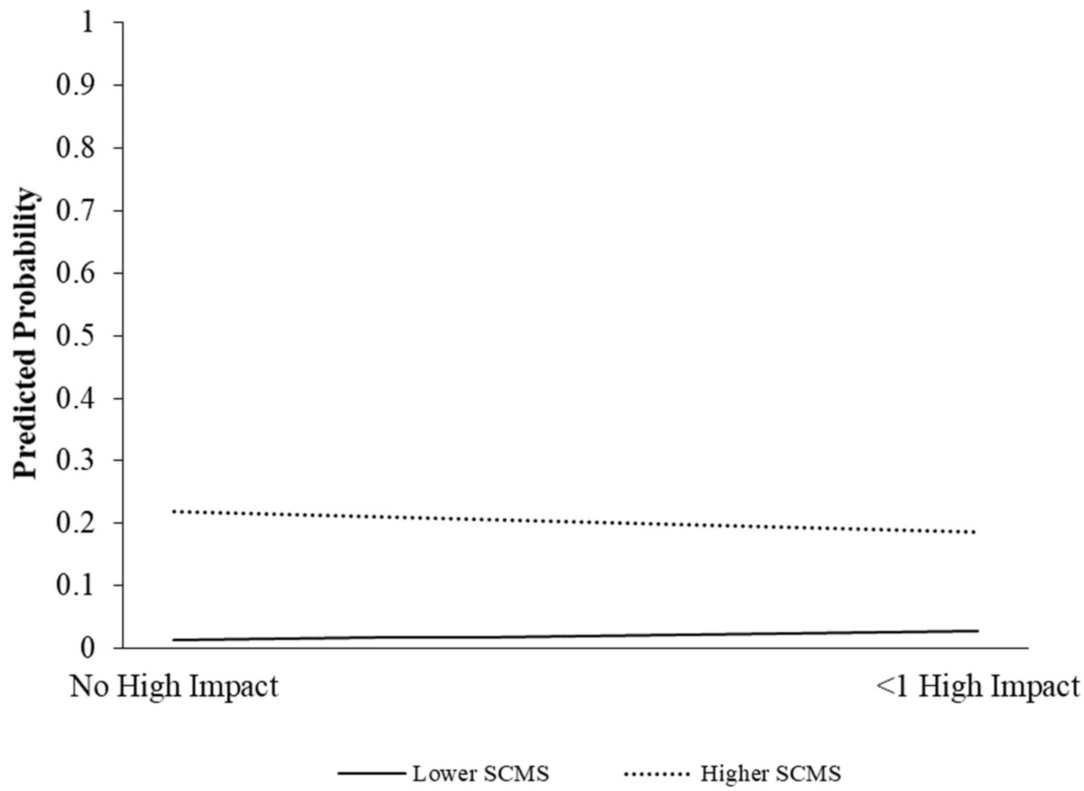


*Figure 43. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by High School Rate of Federal Meal Subsidy and College High Impact Activities. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SCMS: "Lower SCMS" is 2 SD below the grand mean of SCMS, and "Higher SCMS" is 2 SD above the grand mean.*

Model F was the final model, which contained all significant variables including three-way interaction terms. As seen in Table 36, the model fit (BIC) decreased compared to the previous model (difference = 106,330 − 105,573 = 757). The differences in the probabilities of further persistence in STEM after college graduation in terms of identification and race varied by the number of STEM credits students took at college (Figure 44). Taking more STEM credits at college increased the probability of persistence for Asian students identified as high-achieving; the probability for Asian students identified as high-achieving exceeded the probability for White students identified as high-achieving at two standard deviations above the average number of credits of college STEM courses (.43 for Asian students and .31 for White students who were identified as high-achieving). The predicted probabilities for non-identified BHNO students were almost zero regardless of the number of STEM credits earned, which was noteworthy in comparison to the non-identified students of other races, whose probabilities increased by taking more STEM credits. Taking more STEM credits in college also increased the probabilities of further persistence for students from higher-SES families and for non-identified students from lower-SES families. However, taking more STEM credits decreased the probability of persistence of students identified as high-achieving from lower-SES families; the predicted probability decreased from 0.29 to 0.16 at −/+2 *SD* of STEM credits even though the effect size was small ($\gamma = 0.02$, $SE > 0.00$, $p < .001$) (Figure 45).

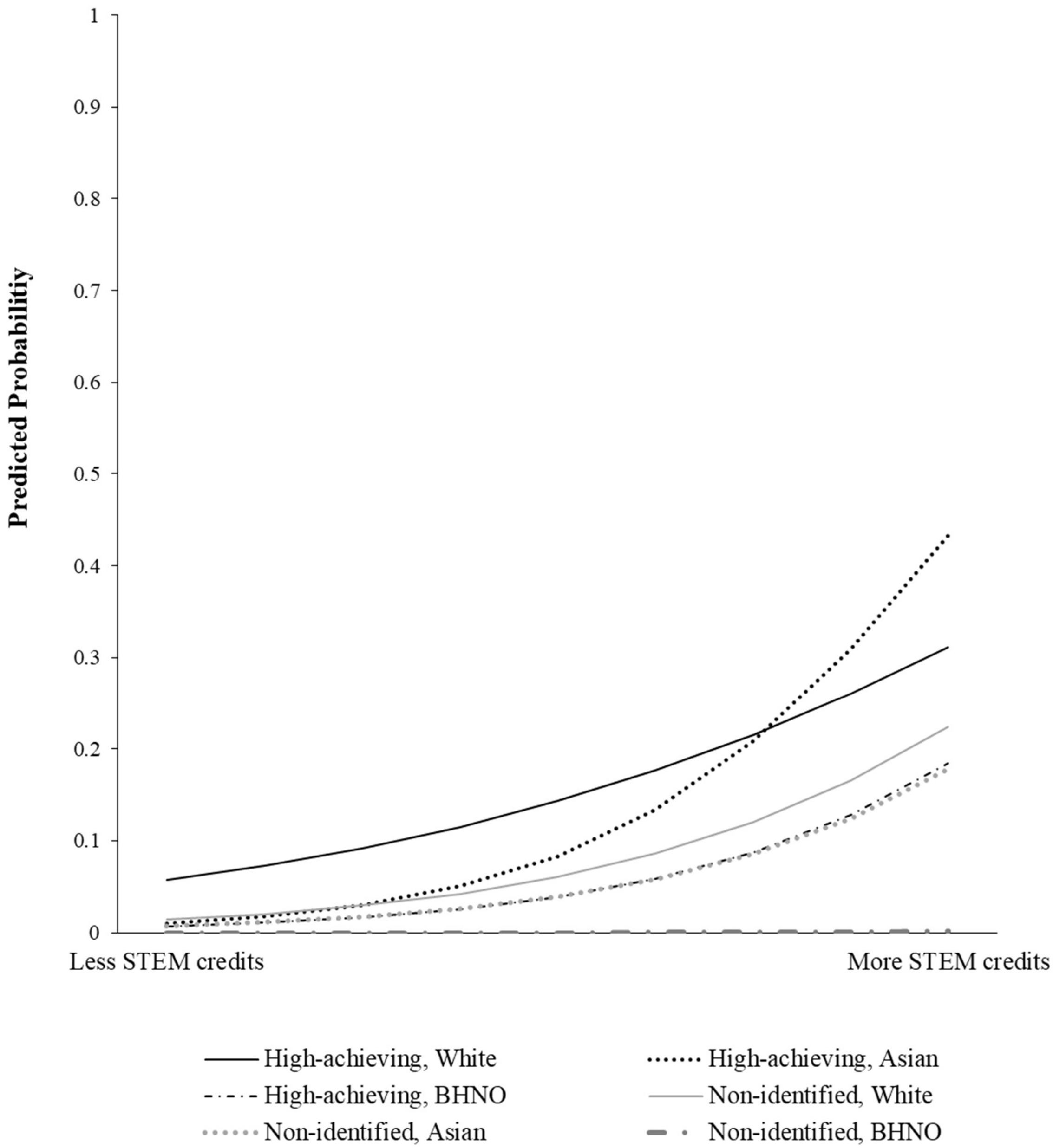


*Figure 44. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification, Race, and College STEM Credits. Note that two lines are overlapped (high-achieving BHNO and non-identified Asian), and that a line is flat along the y-axis (non-identified BHNO).*

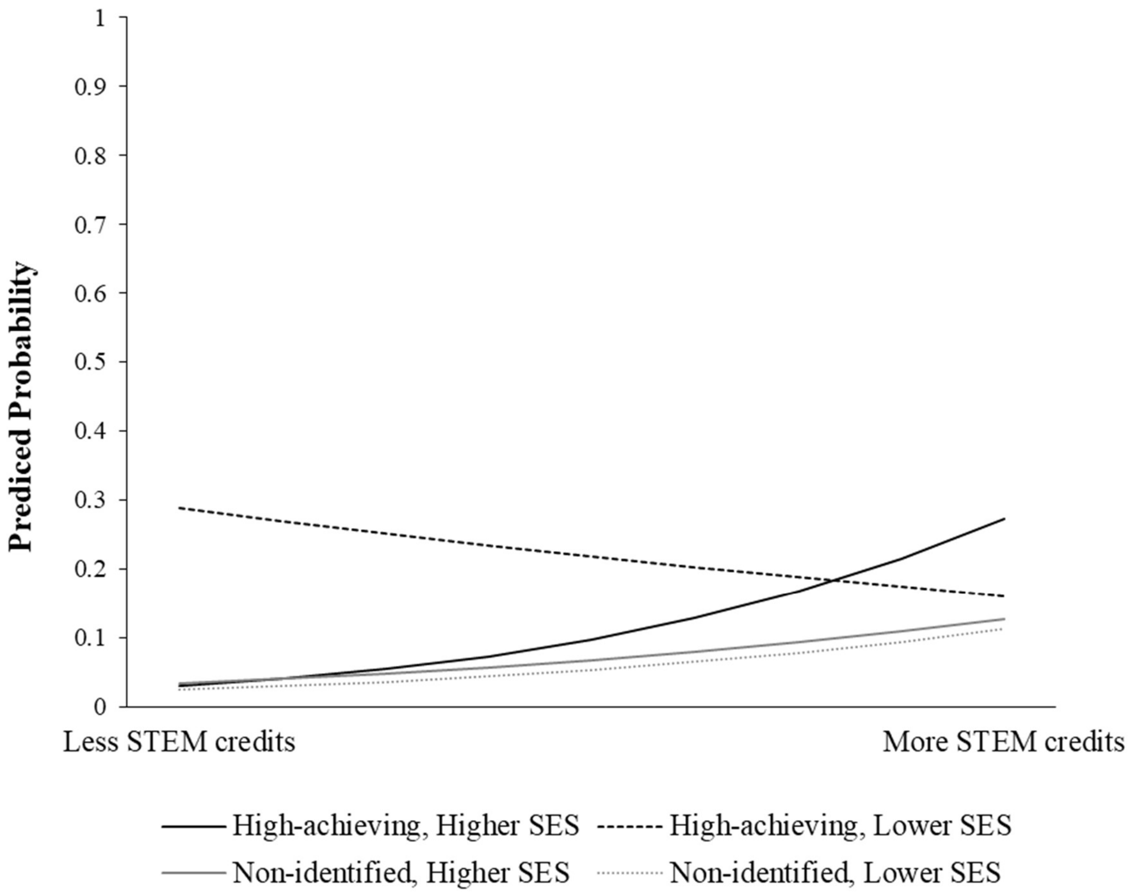


*Figure 45. Predicted Probabilities of Further Persistence in STEM, the Interaction Effect by Identification, SES, and College STEM Credits. To illustrate the interaction effect, I estimated probabilities at two higher and lower points of SES; "Lower SES" is the first-quartile SES, and "higher SES" is the fourth-quartile SES.*

# CHAPTER 5 DISCUSSION

This study began by addressing the question: why do high-school students identified as high-achieving in math and science, despite their high achievement in these fields, not select, persist, and succeed on STEM pathways after high school graduation? Through an investigation using data of a nationally representative cohort of U.S. students, I examined a hypothetical model of a talent development path in STEM (Figure 1) and found significant associations between several student- and school-level factors and traditionally desirable academic and career outcomes along STEM pathways. Based on the literature review, I defined the traditionally desirable academic and career choices on STEM pathways in terms of three key outcome variables: (1) entrance into postsecondary STEM education, (2) persistence and completion of postsecondary STEM education, and (3) further persistence in STEM fields after college graduation. Thus, the study concentrated on the longitudinal paths of college-bound students who prepared for college entrance while they were attending high schools and who pursued 4-year undergraduate programs in STEM.

Throughout this investigation of the three key outcome variables, I examined the effects of uncontrollable and controllable factors on student decisions and persistence on STEM paths. Sex, race, and socioeconomic status were student-level uncontrollable covariates (i.e., variables that students could not choose or control) that crucially influenced them throughout their lives. School percentage of the federal meal subsidy (SCMS) and school climate of academic pressure (SCCL) were school-level covariates that students could not control. The significant effects of these uncontrollable variables provided a baseline understanding of the disparities along STEM career pathways. Given that high-school achievement in math and science was a crucial factor that influenced postsecondary STEM entrance, persistence, and achievement (Astin, 1993;

Smyth & McArdle, 2004; Nicholls et al., 2007), this study controlled for the effects of achievement in college entrance exams. Therefore, I could examine whether or not the effects on the dependent variable probabilities were the same for students identified as high-achieving and students not identified. Any significant interaction effects of high achievement and student- or school-level covariates implied that some academic and career decision patterns of high achievers differed from those of non-identified students.

I also examined the effects of moderators: whether any negative effects of covariates were moderated by students' levels of mathematics self-efficacy (MSE) or the number of advanced courses (ADC) that they took at high school. In contrast to the uncontrollable covariates, these moderators were controllable factors that the students could themselves influence. Of course, these variables could have been affected by the uncontrollable factors and other environmental factors that were not included in this study; for example, the number of advanced courses that students took during high school could have been significantly influenced by student race or school environment (Barnard-Brak et al., 2011; Bell et al., 2009; College Board, 2012; Oakes, 1992; Roderick et al., 2011; Roderick et al., 2006). Nevertheless, the significant effects of these controllable variables indicated that educators, policy makers, and the students themselves could make efforts to reverse the negative effects on STEM pathways of the uncontrollable factors. I examined the moderators' effects with two-way and three-way interaction terms that measured the interaction of identification with each covariate with each moderator. I summarized and discussed the major findings as follows.

## Discussion of Major Findings

### Preliminary investigations for gathering validity evidence

Before investigating the main research questions, I analyzed and presented evidence of validity regarding two constructs of interest in this study: mathematics self-efficacy (MSE) and school climate of academic pressure (SCCL). I gathered evidence based on the internal structure and relations of these constructs to other variables (American Educational Research Association [AERA], American Psychological Association [APA], & National Council on Measurement in Education [NCME], 2014).

In terms of the scale for MSE, the results of CFA supported a single-factor model using four items to measure the construct. Among the five items included in the ELS:2002, I excluded one item because of correlated errors with other variables, which implied the interdependence of errors among items and thus a violation of the assumption of a factor model without a relevant theoretical background. These results could be used as evidence of validity based on internal structure, suggesting that the four items of the MSE scale were internally consistent and conformed to the construct of MSE on which the proposed score interpretations were based (AERA et al., 2014). The results of discriminant function analysis implied that the four items of MSE were significantly associated student achievement in math and science, which added validity evidence based on relations to other variables. The revealed relation between MSE and achievement in math and science was particularly important, in terms of interpreting the MSE scores, as the significance of a scale is determined by its relation to other measures (Embretson, 2007).

The scale for school climate of academic pressure involved a hypothetical model. The ELS:2002 included items to measure the construct of school climate, but no evidence of validity for it has been reported in published papers. School climate of academic pressure was a school-level construct and referred to the atmosphere of competitiveness at school, as rated by school administrators on a 5-point Likert scale. I hypothesized the construct with five items included in the original ELS:2002 data set; but, from the results of CFA, I excluded one item due to a low factor loading. The adequate values of model fit indices, factor loadings, and internal consistency coefficients gave evidence of validity based on internal structure. I also found that the four items of the scale were associated with average school math achievement, which provided evidence of validity based on a relation to another variable. Even though this was not a thorough investigation gathering evidence of validity, but rather a preliminary examination, these results implied that the two scales could be used to measure the constructs of MSE and SCCL, respectively.

**Disproportions in the identification of high-achievers**

I operationally defined a student identified as high-achieving in math and science as one who scored in the 95th percentile or above in math or science in college entrance exams. Based on the literature review, I decided that the use of college entrance exam scores would be appropriate for the purpose of the study, given that talented individuals in math and science could be expected to have attained a certain level of expertise and be able to demonstrate explicit achievements in the fields by late adolescence (Feldhusen, 2005; Subotnik et al., 2011). Furthermore, these exams were standardized and accessible for the whole national cohort who intended to enter postsecondary education, so the exam scores were available for this investigation of students' experiences in postsecondary education. As expected, students identified as high-achieving by the criteria of this study were more likely than non-identified students to enter postsecondary STEM education and to persist in STEM after college graduation. These results supported the findings of prior studies; high achievement in math and science effectively predicts STEM entrance and persistence (e.g., Adelman, 1999; French et al., 2005; Lubinski et al., 2001; Nicholls et al., 2007; Seymour & Hewitt, 1997; Tyson, 2011; Wang, 2013).

However, there were severe disproportions in the numbers of students identified as college-bound high-achievers, based on the uncontrollable covariates. Female, Black, Hispanic, Native American, and other-race students, students from families of the first quartile SES, and students who attended schools with higher levels of academic pressure were less likely to be identified as high-achievers than students in the corresponding reference groups. The disproportions were particularly severe by race and SES; only 0.27% to 2.39% of students of Black, Hispanic, Native American, or multiple races were identified as high-achieving, whereas 15.44% of Asian and 5.58% of White students were identified as high-achieving. Furthermore, only 33% of students identified as high-achieving were from families of the lower three quartiles of SES, whereas 67% of students identified as high-achieving were from families in the top quartile of SES. These results are not surprising according to the prior research revealing that Black, Hispanic, Native American, and multiple races have been underrepresented and underserved in gifted education (e.g., Plucker, Burroughs, & Song, 2010; Plucker, Hardesty, & Burroughs, 2013; Yoon & Gentry, 2009). However, considering that achievement in college entrance exams in math and science can effectively predict the success of students on traditional STEM pathways (e.g., Smyth & McArdle, 2004; Nicholls et al., 2007), students in these groups (female, BHNO, lower SES) might have been disadvantaged from the start in terms of entering STEM paths, based on their college entrance exam scores.

In sum, using this identification method, students in the traditionally underrepresented groups within STEM education and fields (e.g., female, Black, Hispanic, Native, and low SES) were severely underrepresented as high-achieving in this sample. The implications of this are two-fold. First, the use of college entrance exam scores may under-identify students in traditionally underserved groups in STEM. If this is the result of these students experiencing disadvantages in their school and social environments, schools and society may need scaffolding and opportunity to develop their latent talents. Second, the underrepresentation is itself insightful. It suggests that disadvantaged (thus, non-identified as high-achieving) but talented students are likely to remain in disadvantaged environments in STEM after high-school graduation, rather than having another chance to develop their talents, as STEM fields usually require postsecondary education. Given that achievement in college entrance exams is a critical index representing the “expertise” and “explicit achievement” that talented students in STEM have developed at high school, it might be important for policy makers, researchers, and educators to investigate why college entrance exam scores were disproportionate in terms of student- and school-level covariates.

Another limitation of this identification method is that it missed the opportunity of investigating talented students in untraditional career-development tracks. It is noteworthy that students identified as high-achieving by the criteria of this study, and therefore considered as talented students in the fields, were defined only in terms of the traditional talent-development paths of STEM.

**Entrance into postsecondary STEM**

Unsurprisingly, students identified as high-achievers in math and science were more likely to follow STEM pathways through postsecondary education than the non-identified students. The odds of entrance for students identified as high-achieving students were 7.85 times the odds for non-identified students. The student-level and school-level covariates were all significant in predicting entrance, but the differences by covariate also differed by high-achieving identification. Comparing the pattern of students identified as high-achievers with that of non-identified students, the gaps by race widened for high-achievers; White and Asian students were much more likely to enter than BHNO students (BHNO, OR = 0.49, Asian, OR = 2.09 when White students were reference group). In terms of SES, lower levels of SES did not represent a disadvantage for students identified as high-achieving (OR = 0.25 when comparing the first-quartile of SES to the fourth-quartile of SES), but did for non-identified students (OR = 1.62 when comparing the first-quartile of SES to the fourth-quartile of SES). For students identified as high-achieving, those with lower SES were more likely to enter STEM paths than students who had higher SES (OR = 1.62). These results are not consistent with previous studies of general students revealing that students with a lower SES were less likely to enter and complete postsecondary paths than those with a higher SES (Carneiro & Heckman, 2002; Heckman, 2000). Thus, it gives implications to policy makers and educators that a success on college entrance preparations might be a critical chance for talented students in math and science from lower SES families to develop their talents in STEM paths. However, school-level poverty did not yield the same results. For students identified as high-achieving those who attended schools with higher rates of federal meal subsidy were less likely to enter STEM than those who attended schools with lower rates of federal meal subsidy. These results are consistent to the findings of a study that school poverty rate is a stronger predictor of academic failure than student-level poverty (Vanderharr et al., 2006).

As expected, the two moderators increased the probabilities of STEM entrance, regardless of identification. But, for students identified as high-achieving, the number of advanced courses taken was more strongly associated with STEM entrance than for non-identified students (OR = 1.89). As for the significant results of the three-way interaction effects, the two moderators affected the gaps in STEM entrance by covariate for students identified as high-achieving. The gaps by race widened as students identified as high-achieving had higher levels of mathematics self-efficacy (MSE). MSE increased the probabilities of STEM entrance for students identified as high-achieving and non-identified BHNO students, but the degrees to which the probabilities increased were small compared to the increases for White and Asian students (Figure 15). In line with this, the probabilities did not change for BHNO students identified as high-achieving as they took more advanced courses in math and science, a contract to the result for White students identified as high-achieving (Figure 25). These results contrast the findings of prior studies that argued that mathematics self-efficacy was associated with persistence in STEM for Black and Hispanic students just as much as for other ethnicities (Wang, 2011). It is not certain when and why BHNO students who took advanced courses determined not to enter STEM paths. A possible reason for the lower effectiveness of the moderators for BHNO students might be the lack of same-race role models, as Cooper (2011) identified. However, more research is needed to identify further reasons why BHNO students are less affected by MSE and to find other moderators to promote STEM entrance among BHNO students. Furthermore, it is needed to investigate how BHNO students experienced and performed in high school advanced courses in math and science and in which ways many of those talented students decided not to enter into postsecondary STEM.

Unlike race, as the levels of MSE increased among high-achievers, the entrance probability gaps narrowed between students from schools with higher and lower rates of SCMS (Figure 24). The probability of STEM entrance increased with the number of advanced courses taken in math and science for students identified as high-achieving from higher SES families, but it decreased for students identified as high-achieving from lower SES family (Figure 26). Just like the observation that students identified as high-achieving from lower SES families were more likely to enter into STEM than students identified as high-achieving from higher SES families, this result is not self-explanatory. Since only a few prior studies have dealt with the effects of SES on persistence and achievement in STEM, I have found no study addressing the effects of SES on the STEM pathways of students identified as high-achieving, specifically. More explanatory research is required, both to replicate the study of this topic and to find out the reasons behind these unique results; why and how are students identified as high-achieving of lower SES selecting STEM paths in postsecondary education compared to students identified as high-achieving of higher SES?

**Persistence in postsecondary STEM**

The second research question dealt with the hazard and survival probabilities of students identified as high-achieving persistence in STEM in postsecondary education. In the baseline estimation, I found no significant difference between students identified as high-achieving and non-identified students in the hazard probabilities of completing a bachelor's degree in a STEM field. This result was not consistent to the results of the other two research questions, which identified that students identified as high-achieving were more likely than non-identified students to enter and further persist on STEM pathways. In addition, the result is also inconsistent to prior studies revealing that high school achievement and rigorous math and science curriculum were consistently associated with STEM persistence (Chang et al., 2014; Chen & Soldner, 2013; French et al., 2005; Mendez et al., 2008). However, it is important to note that the estimation of the hazard model was based on a restricted sample of students—those who entered STEM fields as of 2006—resulting in a total of 1,010 individuals. Therefore, the results for these baseline estimates only applied to those students who had entered into STEM fields within two years of high school graduation; whereas, the results for the other prior studies and the two research questions applied to the nationally-representative cohort. Considering that the variations in the national cohort are much greater than in the restricted sample, it is understandable that the hazard probabilities of persistence did not differ by identification. Additionally, this gives another insight that students who achieved the 95 percentiles in college entrance exams might not necessarily make distinct talent development in STEM once they enter in a bigger pond. This could be understandable by the big-fish-little-pond effect (Marsh & Parker, 1984), which implies that high-achieving students in high school (a small pond) might have difficulties in persistence once they get in a bigger pond. Further studies are needed to investigate the underlying reasons for the relatively low persistence rate in spite of students' high achievement in math and science.

The main analyses of *research question 2* concentrated on the hazard probabilities of students identified as high-achieving graduating from college with a STEM major. By the time of the second and third years of the study (four and five years after high-school graduation), when most of the students who had entered STEM fields as of 2006 graduated, many fewer BHNO students had graduated from college with a STEM major compared to White and Asian students (OR = 0.61 when comparing to White students). Considering that this analysis was performed only with a restricted sample of students, those who were identified as high-achievers and who had entered into STEM fields as of 2006, this result implies a serious disparity in STEM education by race and demands further investigation to identify the reasons. Higher levels of MSE and ADC significantly predicted the hazard probabilities, but the moderating effects of MSE and ADC were not significant for BHNO students ($\gamma = 0.03$, $SE = 0.22$, $p = 0.90$).

**Further persistence**

For *research question 3*, I examined whether further persistence in STEM fields differed by identification, the covariates, and the moderators. I found that the odds of students identified as high-achieving were five times the odds of non-identified students further persisting in STEM through graduate studies or in workplaces in STEM fields. This result supports the findings of the Study of Mathematically Precocious Youth (SMPY) that showed that high-ability students identified by college entrance exams before the age of 13 were more likely than non-identified students to pursue doctoral degrees and to achieve scientific, technical, or occupational accomplishments by their early 20s (Benbow & Arjmand, 1990; Lubinski et al., 2001). In terms of the significant interaction effect of identification and BHNO race, the gap in the probabilities of further persistence between White and BHNO students decreased for students identified as high-achieving (high-achieving OR = 1.20, non-identified OR = 1.60). Interestingly, however, the school-level covariates increased the gap among groups of students identified as high-achieving. Students identified as high-achieving who attended schools with lower levels of academic pressure and higher rates of SCMS were more likely to persist in STEM fields after college graduation (Figure 35 and Figure 36).

Two moderators, number of STEM credits and high impact activities taken in college, were positively associated with further persistence in STEM. However, the moderators did not work effectively for BHNO students compared to White and Asian students; in particular, the probability of further persistence for BHNO students identified as high-achieving was even lower than the probability for non-identified White students as they took more STEM credits at college. Taking more STEM credits in college also increased the probability of further persistence for students identified as high-achieving from families of the fourth-quartile SES.

**Limitations and Suggestions for Further Research**

One limitation of this study was its sample size by sub-groups. Although the ELS:2002 contained data collected from a large, nationally representative cohort, the sample sizes of some sub-groups were too small to estimate probabilities or to compare them with other groups. For example, the number of Native American students was approximately 110, when rounded to the nearest ten, among a total of 13,250 students; when the data were restricted to students identified as high-achieving, only one student Native American met the criteria as high-achieving. The numbers of students of Black, Hispanic, and multiple race students identified as high-achieving were also too small (unweighted $n$ = less than 10, 30, and 20 when rounded to the nearest ten) to estimate probabilities by race for the effects of covariates and moderators. Further, since only a small sample was analyzed, and it was combined, caution must be taken in generalizing the findings for BHNO students to each race. It would be worth studying the effects of covariates and moderators on a larger sample of BHNO students to facilitate comparisons among the races and thus provide more specific results.

As stated, the identification method was another limitation of this study. Because the study used a quantitative investigation to estimate and compare probabilities in talent-development paths of STEM, the use of such a large data set and the use of college entrance exam scores in the data set could be rationalized, particularly based on the relevant literature review. However, there obviously existed an equity issue in the use of college entrance exam scores, which might have resulted from unequal access to the exams or implicitly or explicitly disadvantaged environments hindering the achievements of traditionally underserved students in STEM. Whatever the reasons were, the use of the exam scores limited the number of talented students included from underrepresented groups, which resulted in a limitation to reliability in interpreting the results for students in those groups. Furthermore, as stated previously, this approach targeted college-bound students and could not reveal the effects of covariates on untraditional talent development paths in STEM, such as the route of skipping postsecondary education and still successfully working in STEM. In response to this limitation, further studies using different approaches are recommended. For example, qualitative studies with a sample of talented individuals who took untraditional talent development paths might provide insights for educating and developing talented students in traditionally minority groups in the fields.

In terms of research question 2, using the variable of “a success in the STEM persistence” could not diagnose problems and barriers behind the failure in the STEM persistence. Using discrete-time hazard models, this study revealed when and with what circumstances students were more likely to graduate from college with a STEM major. However, since I used secondary data, I could not use the variables of drop out from STEM paths and had limitations to explain when and why students were more likely to drop out from college in STEM pathways. The latter approach using the variable of “a failure in the STEM paths” is more desirable to investigate when college students in STEM have difficulties and when they need assistance to persist and achieve in STEM paths, and which might give more implications to educational policy and practices.

The preliminary study for evidence of validity could also be further expanded with future studies. In this study, I performed confirmatory factor analysis and discriminant function analysis on the constructs to provide evidence of validity based on internal structure and relations to other variables, respectively. However, there are a lot more ways to thoroughly examine the evidence of validity of a construct. For example, further research could analyze the content of the items of the two constructs to provide evidence based on test content, which is essential for the use of the test scores (AERA et al., 2014). Another analytical approach would be to simply improve the thoroughness of the analysis; for example, a structural equation model with latent variables, based on the results of CFA in this study, might result in more accurate estimations than those from discriminant function analysis. Further validation studies would have merit as the ELS:2002 data are publicly available and the psychological variables are worth studying with such a large high-school student sample.

Finally, the data concerning further persistence in STEM relied on self-reported information, which could be another limitation. Given that these data came from the follow-up survey administered eight years after high-school graduation, it is possible that the students could have made responses with insincere attitudes that could distort the results. A large number of skipped or missed responses on the question concerning further persistence in STEM occupations also increased the possibility of yielding biased results. It is recommended that this study be replicated, particularly the third research question, with other data sets.

## Conclusion

Despite the limitations of this study, it has many merits. First, this study used a quantitative approach to investigate high-school students' talent-development pathways in STEM over 12 years of adolescence and early adulthood. In other words, in this study, I estimated the probabilities of attaining desirable outcomes on STEM pathways based on talent and career-development theories. Unlike prior studies in STEM education, I controlled for the effects of high achievement in college entrance exams, so the results revealed that the effects of some covariates were unique for students identified as high-achieving or non-identified students. This corresponds to the “All STEM for Some” approach (Atkinson & Mayo, 2010), which addressed the necessity of focusing on talented students by providing the best educational pipeline. The unique patterns and needs of students identified as high-achieving are expected to be helpful for the improvement of policies and educational practices concerning those students. Further, based on the baseline estimates of probabilities provided by this study, I expect more research to be conducted dealing with the reasons for the significant effects promoting or preventing desirable outcomes on STEM pathways. For example, this study revealed that students identified as high-achieving from low-SES families were more likely to enter postsecondary STEM paths than students identified as high-achieving from higher-families, which contrasted the result that low levels of SES are usually associated with low performance in STEM (Carneiro & Heckman, 2002; Heckman, 2002; Hill & Gordon, 2008; Hill & Winston, 2006). More thoroughly designed research concerning the effects of student- and school-level poverty is needed as future research to reveal the underlying causes for these effects among high-achievers.

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