EFFECTS OF RACIALIZED TRACKING ON RACIAL GAPS IN SCIENCE SELF-EFFICACY, IDENTITY, ENGAGEMENT, AND ASPIRATIONS: CONNECTION TO SCIENCE AND SCHOOL SEGREGATION

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ABSTRACT

Given the concentration of economic growth and power in science fields and the current levels of racial stratification in schooling, this study examined (1) the effects of race on students' connectedness to science and career aspirations, (2) the extent to which these effects were moderated by school racial composition and racialized tracking, and (3) the differences in modeling effects using separate variables for race and gender (i.e., White, Black, Hispanic, female) versus race/gender (e.g., White female, Black male, etc.). Using the lens of racial formation theory, this study situated access to science knowledge as a racial project, conferring and denying access to resources along racial lines. Reviews of the literature on science self-efficacy, identity, engagement, and career aspirations revealed an under-emphasis on school institutional factors, such as racial composition and racialized tracking (which are important in sociological literature), as shaping student outcomes. The study analyzed data from the nationally representative High School Longitudinal Study that surveyed students in 2009 during their freshman year in high school and again in 2012 during most students' junior year ($n = 6{,}998$). Affective ratings (in self-efficacy, identity, engagement) and career aspirations for students measured in 2012 were examined as dependent variables and a variable for racialized tracking was estimated given schools' placement of students in advanced science coursework in 2012. Although school racial composition was not found to moderate race on outcome effects, primary analyses demonstrated that the presence of racialized tracking in the students' schools did moderate these effects. Overall these results suggested that the student subgroups most often at a disadvantage compared to

White students for the science outcomes studied were Hispanic males and females; Black students' ratings and aspirations were largely on par or exceeded those of their White counterparts. In addition, results indicated that racialized tracking served to exacerbate gaps for Hispanic students and may also diminish career aspirations for Black students. Finally, while examining effects by race/gender did provide some additional insight and nuance in the interpretation of these results, there were clear instances where these more detailed analyses were not needed or may have obscured results that were clearer when aggregated by race. Given these results, implications for policy, practice, and future research are discussed.

To the great teachers in my life,

the greatest of whom have been

my parents and my partner.

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CHAPTER 1

INTRODUCTION

The underrepresentation of Black and Hispanic people of color in science, technology, engineering, and mathematics (STEM) challenges notions of educational equity in the United States. While Black and Hispanic individuals comprise 29% of the nation's population and 19% of all earned bachelor's degrees, they represent only 14% of bachelor's degrees earned in STEM. As the level of the degree advances, the problem worsens; in 2012, Black and Hispanic students earned 17% of all master's degrees and 12% of all doctoral degrees but only 9% and 5% of those in STEM fields, respectively (Snyder & Dillow, 2013). Given this gap in degree attainment, it is estimated that individuals of color comprise only 7% of the United States STEM workforce (National Institutes of Health, 2013). Since STEM fields are appropriating increasing shares of our nation's economic growth (Beasley, 2012) and historically hold access to power and status in society (Gourlay, 1992; Loewen, 2007), increasing the representation of these individuals in science should be a top priority for those seeking equity and social justice.

Remedying these disparities in representation, however, is difficult given the entrenchment of inequality in our educational system as a whole. Racial disparities in STEM originate early on in individuals' educational paths (e.g, Basu & Barton, 2007; Kidman, Abrams, & McRae, 2010; Riegle-Crumb, Moore, & Ramos-Wada, 2010) and social context factors have been implicated in influencing these racial gaps (Aydeniz & Hodge, 2011; Chang, Eagan, Lin, & Hurtado, 2011; Settles, 2004; Shanahan, 2009). Research on student outcomes like achievement, attainment, or engagement suggest that the effects of both school racial composition and racialized tracking may be important in shaping these gaps (e.g., Crosnoe, 2009; Goldsmith, 2009; Hanushek, Kain, & Rivkin 2009; Tyson, 2011). Given the current degree of racial segregation in schools (Orfield, Kucsera, & Siegel-Hawley, 2012), examining the effects of school racial composition on student science outcomes may be particularly salient. In order to encourage the participation of students of color (here, Black and Hispanic students) in science and ensure equal access to educational opportunities in science, we must better understand how the racial composition of schools and the dynamics of racialized tracking affect student science outcomes.

Researchers have been attuned to the negative effects on student outcomes for students attending Black or Hispanic segregated schools (e.g. Hanushek et al. 2009; Wildhagen, 2012). A predominantly Black and/or Hispanic school might suppress student science outcomes for a number of reasons. First, such schools tend to negatively affect student attainment/achievement due to poor pedagogical practices and lack of resources (Goldsmith, 2011; Reber, 2010); such aspects can be detrimental for students' engagement and academic identities (Flores-González, 2002). Second, according to perpetuation theory, students in such segregated settings may overestimate the degree of racial hostility they will face or underestimate their ability to negotiate relations in integrated settings and therefore avoid them. This theory is supported given the connection of the experience of school segregation to later racial isolation in the workplace or preferences for social segregation (Braddock & Gonzalez, 2010; Stearns, 2010, but see Butler, 2010). It is possible that segregated schooling affects Black and Hispanic students' career choice in a similar way, leading them to avoid occupations dominated by Whites. Third, some scholars have argued that Black and Hispanic adolescents collectively enact an oppositional peer culture in response to blocked opportunities (Fordham & Ogbu, 1986). According to this view, Black and Hispanic students devalue academic achievement, equating it to a standard of White success since it does not offer the same returns on investment as it does for Whites. If a concentration of non-White students facilitates an oppositional stance towards schooling, then racial gaps in science outcomes might be exacerbated in these settings.

Alternatively, a concentration of non-White students could have positive effects on student science outcomes. Contrary to notions of peer oppositional culture, students of color generally have greater educational expectations and are more likely to report pro-school attitudes than White students (Ainsworth-Darnell & Downey, 1998; Cheng & Starks, 2002). Thus, it is plausible that attending a school with a higher proportion of non-White students can promote higher expectations for attainment and pro-school attitudes (Goldsmith, 2004; Frost, 2007), suggesting racial gaps in science outcomes could be diminished. In addition, school racial composition has consequences for organizational practices that affect student attitudes. Schools that serve mostly White or affluent families institutionalize racialized patterns of course placement–i.e., racialized tracking–or extracurricular involvement where students of color are underrepresented, leading to labeling of such courses or activities as “White” in the eyes of the student body (Carter, 2012; Kelly, 2009; Kurlaender & Yun, 2005). Researchers argue that students in such “racially stratified academic hierarchies” (O’Connor, Mueller, Lewis, Rivas-Drake, & Rosenberg, 2011) are more likely to disparage academics and view them as incompatible with their racial identities (Tyson, Darity, & Castellino, 2005; Tyson, 2011). Studies also show that engagement and socioemotional outcomes for students of color are worse in schools serving affluent or White populations (Crosnoe, 2009; Johnson, Crosnoe, & Elder, 2001; Walsemann, Bell, & Maitra, 2011; Zirkel, 2004), suggesting that the majority-White student bodies exclude students of color from their schools' social worlds. Students' engagement with science could be hindered in such schools. While prior research has examined how school racial composition can affect course taking, engagement, and socioemotional outcomes, no study has examined how it affects student science outcomes specifically.

Much of the literature on science self-efficacy, identity, engagement, and career aspirations for students tends to focus on the psychological aspects of choosing and persisting along STEM pathways (e.g., Wang, 2013). While some research on science outcomes for students of color tends to acknowledge the importance of social context, the role of school institutional forces in shaping student outcomes tends to go unexamined. More commonly, researchers implicate proximate social structures like the sociocultural context of classroom instruction (e.g., Basu & Barton, 2007), school science training programs (e.g., Merolla, Serpe, Stryker, & Schultz, 2012), or students' family and community structures (e.g., Huan-Frank, 2011). The proposed study adds to this literature by investigating the effects of two school institutional factors–school racial composition and racialized tracking–on student science outcomes.

Theoretical Framework

The theoretical perspective underpinning the formulation of this study is that of Omi and Winant's racial formation theory (1986). Omi and Winant (1986) define racial formation as the processes whereby "racial meanings pervade U.S. society, extending from the shaping of individual racial identities to the structuring of collective political action on the terrain of the state" (p. 66). Their model of racial formation provides a historical argument for the emergence of new racial meanings via social movements and state conflict. This theory is useful for the present study in at least three respects.

First, racial formation theory emphasizes the need to better understand racial gaps in science as the product of the social construction of race and racialized meanings. For Omi and Winant (1986), race is produced at the micro- and macro- levels and is produced at the cusp of the ideological and the structural (Gomez, 2002). In this context, racial meanings shape "the ways in which we understand ourselves and interact with others" as well as "structure our practical activity" (Omi & Winant, 1986, p. 66). For example, classrooms serve as sites of socialization where racial meanings are learned. Teachers of students of color who hold negative perceptions of their students' ability to succeed in science might slow the curriculum (Prime & Miranda, 2006), essentially guaranteeing students do not obtain the knowledge needed to advance in science (ideological). At the level of school policy, racialized tracking systems produce course enrollment patterns where students of color are underrepresented in advanced science courses (structural). In these ways students of color are racialized such that access to scientific knowledge and resources are limited. This study will seek to uncover the institutional or structural dynamics that produce racial gaps in science outcomes as these forces are understudied in the literature.

In addition, the racial formation process highlights the importance of key variables defined in this study–school racial composition and racialized tracking–and places them in historical context. In the racial formation process, new meanings of race arise out of conflict between the state and social movements. One such movement was the Civil Rights movement that gave rise to *Brown v. Board of Education* (1954), ending *de jure* racial segregation in schools, confirming separate was inherently unequal. This was a *rearticulation* of racial ideology away from notions of separate but equal previously confirmed in *Plessy v. Ferguson* (1896). Although school desegregation efforts made some progress following *Brown* in terms of equalizing schooling for students of color and establishing racially integrated schooling, these gains were soon lost in part due to the implementation of racialized tracking that ensured, even in schools with a racial mix of students, White students and students of color would be segregated in different classrooms. The new rearticulation of racial ideology that emerged from this set of racial dynamics is one in which the racialized structure of schooling is left unnamed, masked by colorblind notions of choice and ability (i.e., students choose their classes or are recommended based on prior achievement). Residential segregation, the dynamics of which had been churning since the start of the 1900s, also contributes to the failure of *Brown,* ensuring and justifying the resegregation of schools (Fiel, 2013). In examining the effects of school racial composition and racialized tracking on racial gaps in science outcomes, I will attempt to challenge the current rearticulation of racial ideology by defining the extent to which school structures define racial inequities and mask racism under the guise of colorblind notions of choice. While notions of unmasking legitimizing forms of inequality are echoed in other social theories (e.g., Bourdieu, 1994; Foucault, 1980), the use of racial formation specifically centralizes the racial dynamics involved in structuring inequality.

Finally, in the context of segregated schooling and racialized tracking policies, science access in schools is defined as a *racial project* – an agenda that both defines what race means in a particular context and confers and denies resources along racial lines. Schools in which students of color are the majority tend to have lower access to resources, lower access to high quality curricula, and lower access to advanced course offerings. In integrated or predominantly White schools, students of color may come to learn that science is not for them via everyday interactions (e.g., with teachers, counselors, or administrators) or through navigating the particular social structure of the school (e.g., racialized patterns of course-taking or extracurricular involvement). Thus, in integrated or predominantly White schools, students of color may be exposed to higher levels of educational resources, yet face more inequality whereas students in schools with higher concentrations of students of color may experience greater levels of equality in the context of diminished resources (Griffin & Allen, 2006; Nunn, 2011). Examining these dynamics with a nationally representative data set has the potential to expose factors that widen gaps in science outcomes for students of color so that future research might more carefully consider the impact this "racialized social structure" has on students' connection to science (Omi & Winant, 1986, p. 60).

Definition of Racism in the Context of Racial Formation

In the context of racial formation, racism is defined as embodied in racial projects that "create or reproduce hierarchical social structures based on essentialized racial categories" (Winant, 2004, p. 45). This definition of racism draws important distinctions from historical or popular conceptions of how racism is defined. First, racism is not limited to a matter of intention or deliberately held bigoted attitudes of individuals, nor is it comprised only of discriminatory actions against individuals or groups based on race. Second, racism is not only committed against individuals such that the persistent organization of institutional inequalities (like the underrepresentation of individuals of color in STEM fields or racialized tracking) is rationalized as an immutable outcome of individual competition and choice. Instead, racism is embedded in social structure and discourse, which are subject to reform, reaction, and rearticulation. In this framework, the evidence for the racial allocation of access to education and scientific knowledge demands attention to racial stratification in the structure of schooling.

Racial Stratification in the Structure of Schooling

Although the Supreme Court's 1954 *Brown v. Board of Education* decision was supposed to have abolished school segregation, inaction and general apathy towards school integration, increases in residential segregation due to public policy and discrimination, White flight, and court reversals of school desegregation policies since the 1970s have largely maintained a system of segregated schooling. Despite an increase in the number of Black and Hispanic families moving to suburban areas, 80% and 74% of Black and Hispanic students, respectively, attend schools that are majority non-White (< 50% White). In addition, approximately 40% of these students attend Black and Hispanic segregated schools where White students comprise no more than 10% of the student body population. At the same time, the majority of White students are racially isolated, with the typical White student attending schools where 75% of the student body is White (Orfield, et al., 2012). Research supports that both scenarios–Black and Hispanic segregated schools and White segregated schools–produce unequal and problematic outcomes for all students, although particularly for students of color (e.g., Holland, 2012; Marx & Larson, 2013).

Yet this segregation of students between schools, or *first-generation segregation*, is only one part of the problem. *Second-generation segregation* within schools, or the placement of students into tracked coursework (Meier, Stewart, & England, 1989), has maintained separate schooling within institutions that are racially diverse (Tyson, 2011). Pre-*Brown*, tracking was defined along the lines of class, ethnicity, nativity, and gender, but once desegregation plans made headway in producing racially-mixed schools, curriculum differentiation became a key tactic for separating students by race (Oakes, 1985). Ranging from the physical separation of students of different races in separate classrooms to the construction of gifted programs enrolling mostly White students, tracking allowed White school officials to avoid integration (Staiger, 2006). Although racialized tracking has been challenged in the courts and deemed unconstitutional, it continues based largely on the rationalization that White students have higher average levels of achievement than students of color (Hochschild, 1984; Oakes, 1995). Still, research has shown that, holding achievement constant, students of color continue to be relegated to lower tracked curricula at greater rates than Whites (Lucas & Berends, 2007; Mickelson, 2005). Given the link between the dynamics of first- and second-generation segregation to unequal achievement outcomes for students by race, it is not a stretch to imagine that such stratification limits the potential for students of color in science specifically.

Purpose of the Study

The purpose of this study is to explore the effects of school racial composition and racialized tracking on student science outcomes (i.e., self-efficacy, identity, engagement, and career aspirations) using data from a nationally representative sample of students. In addition to this specific purpose, there are three broader goals of this study.

First, I seek to reframe the conversation in the science retention literature that tends to focus on psychological aspects of choosing a science pathway (i.e., cognitive and/or motivational factors). While this perspective is needed, it tends to downplay the role of social structure and instead focuses on individual agency. Individual agency is certainly an important part of science engagement and persistence; however, this focus constrains the types of solutions that are presented. Even the literature examining sociocultural approaches to teaching science–which tends to acknowledge the importance of social context on student science learning and engagement–presents solutions largely limited to enactment by individual educators. Attempting to move beyond these solutions, this research has the potential to inform educational policy addressing the role of school institutional structures–specifically the role of segregation within schools–in producing educational inequality.

Second, I hope to draw more careful attention to the ways that race might work in our nation's schools by presenting a decidedly anti-deficit approach to the culture of students of color. While there is certainly an argument to be made in terms of differences in material resources among schools of varied racial compositions (particularly among predominantly White schools vs. schools with high proportions of students of color), the rationale behind theories of perpetuation or oppositional culture that are, at times, used to explain racial composition effects, can display a deficit perspective towards students of color and assimilationist language (Steinberg, 2007) where progress consists of the enculturation of students of color into the White mainstream (e.g., Hanushek et al., 2009; Lee, 2007; Stearns, 2010). In this context, students of color have been characterized as lacking not only physical resources for schooling, but also certain cultural, social, and psychological assets that could only be developed in the presence of a White student body. By rejecting this stance and focusing instead on the role that school structures play in producing inequality, I hope to challenge narratives of the culture of Black and Hispanic students that continue to appear in scholarly work.

Third, this work will also examine the extent to which the primary means of examining racial inequalities in STEM–aggregating by race across gender–limits our understanding of these inequalities. Researchers examining demographic inequalities in STEM have more recently begun analyzing science outcomes by race/gender; that is, utilizing separate variables for different combinations of race and gender like White female or Black male as opposed to a single variable for gender and alongside variables for race. They argue that aggregation by either race or gender alone can produce potentially misleading interpretations where inequalities by race are over-generalized across genders (Riegle-Crumb, Moore, & Ramos-Wada, 2011; Riegle-Crumb & King, 2010). Attending to this potential is particularly important given the racialized and gendered nature of STEM fields, where Black and Hispanic girls are located at the axis of both race and gender systems of oppression. Thus, this study estimates for effects by race alone (aggregated by race) as well as by race/gender. At the very least, such an approach recognizes the potential that different student subgroups by race and gender may be disadvantaged in specific science contexts. This approach will allow for a more nuanced discussion of where inequalities lie for students of color in the context of the science outcomes studied here.

Significance of the Study

Equal access to scientific opportunities for all races is an important national goal. In a nation where scientific skills are in demand, racial gaps in STEM constitute a strain on the system as future innovators are excluded from science, hindering U.S. goals of international economic competition. Taking note, the Obama administration's "Educate to Innovate" campaign focuses particularly on advancing student involvement and achievement in science. As President Obama explains, education in this interest is pursued so that American students can not only "compete for the best jobs," often in the growing fields of science and technology, but also so that "America can out-compete countries around the world" (The White House, Office of the Press Secretary, 2011). Recognizing the value of a diverse workforce for the promotion of creative and nuanced solutions/discoveries in STEM, the final goal of "Educate to Innovate" includes an expansion of opportunities in science education and careers for students of color (The White House, 2009). While some of the President's initiatives do promote increased scientific access for underrepresented students by, for instance, increasing access to scientific technology, there is little discussion of the more insidious ways racial gaps in science manifest through the larger problems of schooling in general. This study will attempt to connect our national desire for increased participation in science to fundamental problems in the way schooling is structured in a system of racial segregation.

While national economic interests are often at the forefront of policy makers' initiatives in increasing access to scientific opportunities, the degree to which a disproportionate number of individuals of color are shut out of the economic promise that participation in STEM fields offers should be reiterated. Even in the recent context of economic downturn, the science and engineering fields are growing and occupying increasing shares of the nation's wealth. According to the Congressional Research Service, while overall employment in the United States shrank from 2008-2011 at an annual rate of 1.7%, employment in science and engineering managed to grow at an annual rate of 0.6% (Sargent, 2013). While this increase may seem modest, this advantage in comparison to general employment is consistent with historical trends (U.S. Department of Labor, 2007). From 2010-2020, the number of jobs available in science and engineering is expected to grow at a rate of 1.7%, adding 1.1 million jobs to the economy at a faster rate than overall general employment (Sargent, 2013) and employment projections to 2018 indicate that mathematics and science preparation will be central to 9 of the 10 fastest growing occupations requiring a bachelor's degree or higher (Lacey & Wright, 2009). Accompanying this increase in the share of the occupational sector, workers in science and engineering enjoy higher mean wages than the workforce in general. In 2011, the average wage for scientists and engineers was more than double that for other occupations—over $85,000 for STEM compared to just over $43,000 for non-STEM jobs (Sargent, 2013).

Although these economic indicators point to the contemporary importance of equal participation in STEM fields, it is important to remember that the hegemonic relationships between those who know and can use science permeate the history of our nation and global society (Gourlay, 1992; Loewen, 2007). As STEM industries *continue* to occupy larger and larger shares of the nation's wealth, underrepresentation of particular groups in these fields undermines their social mobility and contributes to socioeconomic inequality and social stratification (Carter, 2006). The dearth of scientists of color manifests itself in the paucity of scientific/medical research that is focused on concerns that disproportionately affect communities of color. Given the White male advantage in science and the tendency of research to have an autobiographical bias, it is unlikely that concerns such as these will rise in prominence unless racial gaps in science are addressed (Beasley, 2012). This study will seek to uncover the potential role school racial composition and racialized tracking play in shaping racial gaps in science. As I will show, racialized tracking in schools can be detrimental to how Black and Hispanic students relate to science.

Research Questions

To examine the effects of school racial composition and racialized tracking on racial gaps in student science outcomes, I will first characterize the magnitude of racial gaps that exist in student science outcomes such as science self-efficacy, identity, engagement, and STEM career aspirations. Then, given the competing stances that the literature on school racial composition effects presents, I will examine if or how school racial composition moderates these race on outcome effects (i.e., if/how school racial composition moderates the effects of race on science outcomes). I will also seek to uncover the extent to which racialized tracking functions as a means through which racial composition moderates the effects of race on science outcomes. Finally, I will examine how the interpretation of these results might be affected if disaggregated by gender within racial groups. Thus, my research questions are as follows:

1. What racial gaps exist in students' engagement, identity, and career aspirations in science Asian, Black, and Hispanic students versus White students (i.e., what are the effects of race on these science outcomes)?
2. Does school racial composition moderate race on outcome effects? If so, to what extent does racialized tracking act as the means through which school racial composition moderates race on outcome effects?
3. How does examining these dynamics by race/gender (vs. aggregated by race) affect interpretation of the results?

In the chapters that follow, I provide a detailed review of the literature, define the methods used to answer these research questions, provide a detailed analysis of the results, and discuss the implications of the study. In Chapter 2, I build a rationale for this study given a review of two bodies of literature: the science education literature which often fails to examine the effects of school institutional structures on shaping student outcomes and the sociological literature which examines the effects of racial composition and racialized tracking on general student outcomes (i.e., outcomes that are not specific to the domain of science). This review also reveals a difference in approach to how inequalities in science are explored–either with separate variables for race and gender or with variables for race/gender.

In Chapter 3, I describe the data source for this study–the High School Longitudinal Study–and define variable construction, data screening, and preliminary analyses. In this chapter I also define a plan of analysis. First, the magnitude of racial gaps that exist in students' science self-efficacy, identity, engagement, and career aspirations will be characterized. Then, the extent to which school racial composition is related these gaps will be examined; insofar as racial composition is associated with these gaps, the extent to which racialized tracking mediates these effects will be explored. Finally, analyses will be conducted by race alone as well as by race/gender to determine how exploring effects at the intersection of both race and gender affects interpretation of the results. Given preliminary results suggesting that school racial composition does not moderate the effects of race on student science outcomes for this sample, the focus of the analysis is shifted to racialized tracking as a moderator of the effects of race on student science outcomes. Primary analyses are conducted using linear and logistic regression models.

The results, provided in Chapter 4, show that for this sample, Hispanic students' affective ratings in science were lower than those of their White counterparts. In addition, results showed that Black students' affective ratings (e.g., for self-efficacy, identity, engagement) and aspirations were generally on par with or exceeded those of their White counterparts. Results also showed that racialized tracking moderated effects of race on affective ratings for Hispanic students as well as the effects of race on career aspirations for Black students. Furthermore, while more detailed analyses by race/gender did promote a more nuanced understanding of these dynamics, there were clear instances where results aggregated by race were both appropriate given trends visible by race/gender and more straightforward. Finally, in Chapter 6, these results are discussed in light of implications for theory, practice, and future research.

CHAPTER 2

REVIEW OF THE LITERATURE

Research demonstrates that in science, self-efficacy, identity, engagement, and aspirations are consequential for students' pursuit of STEM pathways. The literature demonstrates that both racial and gender gaps in these outcomes exist and that many factors influence these gaps (e.g., student motivational factors, classroom instruction, coursework). But despite the attention to race and gender inequalities in STEM, there are two major limitations to much of the current work. First, while much research pays sufficient attention to instructional quality or student psychological/motivational factors like self-efficacy as predictors of student success in STEM, there is noticeably less attention paid to school institutional factors that might influence racial gaps in efficacy, identity, engagement, and aspirations. This is particularly problematic given what we know from the sociological literature regarding the effects of two specific school institutional factors–racial composition and racialized tracking. Second, the common approach of attending to race *or* gender gaps obscures the reality of effects that occur at the intersection of both race and gender (Riegle-Crumb et al., 2011).

This chapter begins by defining terms central to this study. This is followed by a review of literature on the student science outcomes examined: self-efficacy, identity, engagement, and career aspirations. In this process the need for examinations that focus on the role school institutional factors play in influencing differences between White students and students of color is made apparent. Next, the need to specifically examine the factors of school racial composition and racialized tracking is described, given the sociological research on the effects these factors can have on general student outcomes (i.e., outcomes that are not specific to the domain of science). A rationale for examining effects by both race and race/gender is then provided.

Definition of Key Terms

Several terms are central to understanding this study and brief definitions are provided here to appropriately orient the reader. Here, the term *students of color* refers to Black and Hispanic students. While this term may include other non-White demographic groups in other contexts, its definition is restricted here given the scope of this study and these groups' position as underrepresented in STEM domains. The term *student science outcomes* refers to the specific outcomes examined in the context of this study. These outcomes are: science self-efficacy, science identity, science engagement, and STEM career aspirations. *Science self-efficacy* refers to a student's confidence that she can she can effectively complete or master science tasks (e.g., homework), skills, coursework, or activities. *Science identity* refers to the extent to which a student views herself as a "science person' and receives recognition from others as such. *Science engagement* is a general term referring to a student's *emotional, behavioral,* and *cognitive engagement* in science. *Emotional engagement* refers to a student's feelings of like, dislike, or interest in regards to science. Whereas *behavioral engagement* refers to basic student conduct and participation in school science (e.g., completing homework), *cognitive engagement* entails a student's psychological commitment to learning science and tendency to extend oneself beyond simple behavioral tasks (e.g., commitment to understanding science concepts). Together, science self-efficacy, identity, and engagement comprise the *affective ratings* examined in this study. The last outcome, *STEM career aspirations* refers to students desire to pursue a job related to science, technology, engineering, or mathematics (defined broadly as will be explained in Chapter 3, Methods).

The school contextual factors highlighted in this study are those central to racial segregation in education, both *first generation segregation* and *second generation segregation*. First generation segregation refers to segregation between schools given *school racial composition*, which is often defined by either by the proportion students of color or the proportion of White students in a school. *Second generation segregation* refers to *racialized tracking* within schools, or the systematic underrepresentation of students of color in advanced coursework.

Student Science Outcomes

Below, I review the literature on student science outcomes, specifically, self-efficacy, identity, engagement, and career aspirations. I begin by defining the rationale for examining each construct as an important outcome in the context of science education, followed by a synthesis and critique of the literature on each topic.

Science Self-efficacy

Individuals' self-efficacy, or beliefs regarding ones' abilities and results of ones' labor, have been widely studied in education research as a target for increasing student achievement (see, e.g., Pajares & Urdan, 2006). Bandura (1986) posited that self-efficacy beliefs may be superior predictors of achievement versus other more objective assessments of students' capabilities given that self-efficacy beliefs act as a mediator between previous knowledge/skill and later achievement. Research in motivation demonstrates that students' self-efficacy promotes commitment in schooling and performance across academic domains (e.g., science, mathematics, and English; Pajares,

1997) and is related to student self-regulation, mastery goals, and self-concept (Zimmerman, 2000; Urdan, 1997; Bong & Skaalvik, 2003).

In the context of science education specifically, it is postulated that students' science self-efficacy–students' beliefs regarding their confidence to effectively complete or master science tasks, skills, coursework, or activities–affects students' aspirations and choice of science tasks, their effort in completing these such tasks, and their responses in the face of hardship (Britner & Pajares, 2001; Zeldin & Pajares, 2000). As Britner and Pajares (2006) note:

> Students who have a strong belief that they can succeed in science tasks and activities will be more likely to select such tasks and activities, work hard to complete them successfully, persevere in the face of difficulty, and be guided by physiological indexes that promote confidence as they meet obstacles. (p. 486)

Conversely, students with low science self-efficacy will be more likely to avoid science tasks if possible, to put forth less effort when required to complete science tasks, and to give up when faced with challenges the that science learning involves.

Recent work on science self-efficacy has focused on gender differences with predominantly White samples of students in terms of either sources of self-efficacy or self-efficacy development over time. For younger, White students, girls may rate themselves higher than boys when it comes to science self-efficacy. For a sample of predominantly White middle school students, Britner and Pajares (2006) showed that girls rated their science self-efficacy as higher than boys and attributed this female advantage to the nature of science learning at the middle school level as heavy on language-related methods, promoting skills that girls are more adept at given this level of schooling/development (Britner, & Pajares, 2001). This female advantage does not hold true as students age, however. Larose, Ratelle, Guay, Senecal, and Harvey (2006), with a sample of predominantly White late-adolescents beginning science college programs, demonstrated that girls reported lower science self-efficacy beliefs after high school but that they were also more likely to grow in their self-efficacy beliefs as they progressed in their college programs (which promoted science career choice for these young women). As Zeldin, Britner, and Pajares (2008) note, these White male-female differences may be due to different psychological sources of self-efficacy as students progress in schooling and science becomes more male-dominated. In this context, males' science self-efficacy may be driven more so by prior achievement and females' science self-efficacy may be driven more so by social comparisons regarding their own abilities and the abilities of others and verbal/social encouragement from "significant others" in science (e.g., teachers, mentors).

While these researchers do not focus on self-efficacy development for students of color, Zelden et al. (2008), suggest that given the underrepresentation of Black and Hispanic students in science, patterns of self-efficacy development for these students may be similar to those of women in that relationships with peers, family, and their community may be more significant predictors of science self-efficacy. Research examining science self-efficacy and STEM commitment for students of color seem to support this assertion. Examining a sample of Black high school students, Austin (2010) found that mathematics and science self-efficacy were positively related to students' career intentions in this domain alongside factors like family support and that measures of previous achievement like mathematics and science grades did not predict science career intentions. Chemers, Zurbriggen, Syed, Goza, and Bearman (2011) confirmed the importance of science self-efficacy acting as a mediator between mentoring experiences and career commitment in science for Hispanic and Native undergraduate and graduate students.

Missing from this research are studies that focus on racial group differences as opposed to examining samples solely comprised of either White students or students of color. In addition, while these studies examined individual sources of self-efficacy (e.g, prior achievement) or contextual factors that are person-centered (e.g., relationships with family or significant others), there is a lack of attention paid in this research to the institutional dimensions of context that might influence students' science self-efficacy development. Shifting attention towards institutional factors, particularly those that are known to differentially affect students of color like school racial composition and racialized tracking, extends the current literature by attending to what Usher and Pajares (2008) define as "ecological" antecedents understudied in the literature on science self-efficacy.

Science Identity

Student identification with science is treated as a precursor to STEM retention where individuals with a stronger sense of identity in science are more likely to choose and persist along STEM educational and career paths (Chemers et al., 2011; Cleaves, 2005; Hughes, 2001; Lee, 1998; Perez, Cromley, & Kaplan, 2014). However, using student identity as an outcome in its own right is potentially important for at least two reasons. First, an alternative perspective to the salience of science career choice recognizes that the question at the heart of the matter is less about *what* students want to be when they grow up and more about *who* students want to be. In this context, an educational or career choice is perhaps more importantly an identity choice (Schreiner & Sjøberg, 2007). In addition, a focus on student identity tends to shift the spotlight away from what is wrong with students (e.g., their self-efficacy, achievement levels, etc.) towards larger notions of what is wrong with the structures of schooling surrounding science education. As Carlone and Johnson (2007) posit, a focus on identity "allows us to ask questions about the kind of people promoted and marginalized" (p. 1189) in the teaching and learning of science. This focus turns our attention towards the structure of science education (or education in general) and students of color who have been traditionally marginalized in this context, those for whom science identity is a particularly salient notion (e.g., Brickhouse & Potter, 2001; Elmesky & Tobin, 2005; Kidman et al., 2010; Lemke, 2001).

While conceptions of student science identity vary in the literature, a few characteristics emerge as central. Most authors agree that notions of identity are not singular (i.e., students can maintain multiple, potentially conflicting identities) and are dynamic (i.e., identities can change over time). When considering identity in science in particular, the influence of having multiple and conflicting identities arises as a source of confusion and potential disruption of student science identity development (Chemers et al., 2011; Elmesky & Tobin, 2005; Settles, 2004). Here, identities exist as "conceptualizations of the self as rooted in social relationships" where social identities may pose one source of conflict (Settles, 2004, p. 151). Carlone and Johnson (2007) echo the importance of social context, pointing out that identity is produced where the social and the individual converge. Given this, a "science identity" must encompass not only self-identification in science but also the recognition of others who see the individual as a “science person.” Malone and Barabino (2008) offer a particularly comprehensive model of science identity that includes this recognition aspect as central, overlapping with notions of social performance and competence in science (with racial, ethnic, and gender identities shifting the nature of these relationships). Given the consistent themes of identity as complex, dynamic, individual, and social, Gee’s definition of identity (1999, 2000) as the type of person one strives to be and is recognized as being in a particular time and place is the most useful and continually cited in the literature (e.g., Ayedeniz & Hodge, 2011; Brown, 2004; Carlone & Johnson, 2007). For the purposes of this study, science identity is defined as both seeing oneself as a “science person” *and* receiving consistent recognition from others as such.

While some of the literature on student science identity focuses on factors influencing identity development for females versus males without attention to race (Hughes, 2001; Lee, 1998; Schreiner & Sjøberg, 2007; Settles, 2004), it is important for the purposes of this study to focus attention on work that places student race at the center of the analysis. Much of the literature on science identity development for students of color examines science identity in the context of accounts of success or conflict. For example, Huan-Frank (2011) used student narratives to highlight how fourteen high achieving Black high school students navigated school and social spaces to positively shape their science identities and commitment to pursue scientific careers. With a large sample of undergraduate students of color in science training programs, Merolla et al. (2012) demonstrated the importance of the programs’ positive influence on student identity and intention to pursue science careers. While these studies might be characterized as highlighting student success, other research demonstrates overall identity conflict for students of color, particularly native students of color for whom boundaries between indigenous knowledge and the culture of Western science seem heavily drawn (Kidman, et al., 2010; Laubach, Crofford, & Marek, 2012). In addition, Malone and Barabino (2008) document the tensions in science identity development for Black undergraduates in predominantly White undergraduate research settings. Here, sources of conflict in student science identity development arose out of a lack of recognition for their accomplishments in science and the additional burden, marginalization, and invisibility associated with being the "only one" of color among a majority White student body and faculty.

Other authors highlight the juxtaposition of success versus conflict, identifying student qualities and environmental factors that enable or constrain identity development (Brown, 2004; Carlone & Johnson, 2007; Kozoll & Osborne, 2003). For example, the importance of recognition is echoed in Carlone and Johnson's (2007) examination of the educational trajectories of 15 high achieving undergraduate women of color pursuing science careers. The authors place students into three broad categories – *research scientists* and *altruistic scientists* who cultivated a sense of themselves in science fostered by positive feedback from others (i.e., faculty, professionals, family) versus *disrupted scientists* who perceived gender and racial discrimination and a distinct lack of recognition from the academy in their pursuit of a science identity. Brown (2004) similarly places high school students of color into categories indicating success versus conflict in the incorporation of scientific language into their discursive identities ranging from *opposition status* where students actively denied the use of scientific terminology and knowledge to *proficiency* where students were fluently engaged in scientific language as a part of their discursive identities. In the context of this work, the assimilation of students into the culture of science is stressed and the social environment of students' lives outside of school is treated as a potential source of conflict.

This body of literature is limited in at least three ways. First, the attention towards science identity development in the context of success versus failure or conflict and categorization of students into profiles indicating status as such has the tendency to obscure the notion of science identity as existing along a continuum for students. Treatments of science identity along a continuous scale could help refine our understanding of factors that contribute to student science identity development. For example, Merolla et al. (2012) measure student identification with science using a quantitative scale at three different time points recognizing an individual student's sense of identity might weaken or strengthen over time. Second, the literature tends to examine the effects of sociocultural barriers and/or student agency at the expense of attention to institutional structures that might constrain identity development (for a similar argument see Shanahan, 2009 who calls for more attention to the impact of social structure on student science identity). In most cases, attention to institutional structure is tangential as in Malone and Barabino's (2008) examination of science identity conflict for undergraduate women of color; in this study, focus is placed on the effects of negative interactions with peers and faculty members over the institutional structure of the environment as predominantly White. An exception to this trend is Olitsky, Flohr, Garder, and Billips (2010) who, examining student science identity development in the context of an urban magnet middle school, recognize the impact of the school's high school selection process that created an environment where students were labeled "smart" or not and were granted differential access to science identities, often along racial lines. Finally, there is an overall emphasis on qualitative methods in the examination of student science identity development for students of color (but see Chang et al., 2011; Merolla et al., 2012). While in many ways this is an appropriate approach given the complexity of the identity development in science, quantitative research may complement this literature by examining larger samples of students to uncover broad patterns using statistical analyses whose results can be generalized. This study seeks to address these limitations.

Science Engagement

As Fredericks, Blumenfeld, and Paris (2004) describe, engagement is a broad and multifaceted construct. While the broader engagement literature is much more divided (Sinatra, Heddy, & Lombardi, 2015), the widely used Fredericks et al. (2004) framework generally defines engagement in three ways: emotional engagement, behavioral engagement, and cognitive engagement. *Emotional engagement* involves students' feelings towards a class or academic domain and might include interest or boredom, happiness or sadness, and enjoyment or dislike of the class or instructor. Emotional engagement might also capture the value students place on the class or schooling, for example, whether the student perceives a class as worthwhile – whether out of pure interest and enjoyment or as important for future goals (the motivation literature considers differences in types of values student might hold, e.g., Eccles et al., 1983). *Behavioral engagement* focuses on student conduct and participation in classroom and school activities. This includes positive behaviors such as following classroom rules as well as indicators of effort and attention to class instruction. Behavioral engagement also refers to the degree to which students avoid negative conduct like skipping class or neglecting homework. Lastly, *cognitive engagement* entails a student's psychological commitment to learning and tendency to extend oneself beyond simpler behavioral tasks. This might involve student self-regulation, desire for challenge, and mastery orientation. While these constructs are defined separately, they often overlap in the literature where, for example, operationalization of engagement as "effort" might incorporate both student completion of homework or other standard tasks (behavioral engagement) as well as more complex notions of mental exertion and commitment to understanding ideas (cognitive engagement).

As Finn and Voelkl (1993) note, while engagement has been underutilized in the literature as an outcome of school mechanisms, its importance should not be understated. Student engagement in school has received increased attention as a potential target for increasing student academic achievement and diminishing dropout (National Research Council & Institute of Medicine, 2004). Studying engagement as an outcome is particularly salient in the context of research on the damaging consequences of student disengagement, which is more often discussed in the context of urban schooling and low-income students of color.

Both the importance of engagement and its multifaceted nature are reflected in the literature on science engagement. Qualitative work on student emotional engagement for high school science students has linked teaching practices and authentic content to students' enjoyment of science class (emotional engagement) and academic competence (Raved & Assaraf, 2011; Rodriguez, Jones, Pang, & Park, 2004). In contrast, Martinez and Guzman (2013) focused on students' cognitive engagement, in particular, their level of challenge in science classes to reveal racial gaps in student engagement. Still these authors recognized that their measure of challenge likely captured aspects of emotional engagement (like anxiety). Other authors purposefully blurred the distinctions made among the types of engagement, combining elements of two or all three to investigate engagement more broadly (Chang, Singh & Mo, 2007; Lee, Robinson, & Sebastian, 2012; Uekawa, Borman, & Lee, 2007).

Regardless of how engagement with science is conceptualized, research demonstrates differences in levels of engagement by student race. Hispanic-White differences in engagement may be particularly salient as one source of underrepresentation for Hispanic students in science. Martinez and Guzman (2013) found that Hispanic female high school students in science reported lower levels of engagement compared to Black, White, and Asian males and females (with highest levels of engagement found for Asian females). In addition, although Chang et al. (2007) and Uekawa et al. (2007) did not differentiate results by gender, they also found the lowest levels of engagement in science were among the Hispanic high school students in their samples.

Although this attention is paid to differences by student race, much of the literature on student engagement in science focuses on classroom instruction and teacher qualities as important factors promoting student engagement (Lee et al., 2012; Pickens & Eick, 2009; Raved & Assaraf, 2011; Rodriquez et al., 2004; Uekawa et al., 2007). The importance of instructional approach is also echoed in the literature on sociocultural reforms in urban science education where varied means for student participation, active classroom discourse, and cogenerative dialogues are used to promote student engagement (e.g., Barton, Tan, & Rivet, 2008; Emdin, 2010; Elmesky & Tobin, 2005; Tobin, 2006).

Taking a sociocultural perspective and defining engagement as "changes in participation" occurring when students partake in science learning in particular contexts, Ryu and Lombardi (2015) argue that engagement is both collective and individual with trajectories that begin within a social context and then are internalized by the individual. From this standpoint, classroom discourse and interactions can be an integral part of student engagement in science—but what about the larger structures of schooling? While certainly important, this focus on teacher and instructional qualities or collective engagement in science classrooms as key to student science engagement overlooks institutional and structural factors that might impinge on students' engagement in science, particularly for students of color. For example, Martinez and Guzman (2013) raise concern over the dearth of Black and Hispanic students in advanced mathematics and science courses but link this phenomenon to their finding that these students reported lower levels of engagement in such classes (and were therefore less likely to pursue such coursework). As I will describe, however, the literature on the effects of school racial composition and racial stratification in schools via tracking indicates that lower engagement could be the *consequence* of stratification instead of the cause (as Martinez & Guzman, 2013, suggest).

Although generally absent from the literature on student engagement in science specifically, the effects of school racial composition on general school engagement is echoed by Finn and Voelkl (1993) who found that while schools with a higher proportion of students of color tended to have lower levels of behavioral engagement among students, students of color indicated higher levels of emotional engagement in such schools. This research suggests that school racial composition may be an important factor to consider in examining student engagement in science.

STEM Career Aspirations

Although a large body of research examines career intentions of undergraduate students, research has shown that the intent to pursue a STEM career during the high school years may be particularly important. For one, it is during the adolescent years when most students develop realistic career aspirations based on prior experience or learning, extending beyond the more imaginative future occupations they might have entertained as children (Siegleman & Weinstock, 1991, although more recently scholars have been attuned to how education during the primary years may be consequential to students' formation of career aspirations in science; Tytler & Osborne, 2012; Tytler, Osborne, Williams, Tytler, & Cripps Clark, 2008). This insight during adolescence may be especially important to future work in science fields as intent to pursue a science career might steer students towards advanced mathematics and science coursework and enrollment in extracurricular activities that would ensure future academic success in STEM. Furthermore, Tai, Liu, Maltese, and Fan (2006) demonstrated that early career aspirations are associated with actual attainment in STEM fields. In their examination of a nationally representative dataset, they found that students who anticipated a career in STEM by age 14 were over three times more likely to actually obtain a degree in the physical sciences/engineering than students who did not hold these career aspirations.

As with the literature on student science identity, there is a large body of research that addresses gender inequality in STEM career aspirations with minimal attention paid to race. This work implicates motivational factors (e.g., Koul, Lerdpornkulrat, &

Chantara, 2010; Quinn & Lyons, 2011), perceptions of self and science or identity (Cleaves, 2005; Quinn & Lyons, 2011), coursework (Blickenstaff, 2005; Riegle-Crumb, King, Grodsky, & Muller, 2012), and gendered pedagogy or sex stereotypes (Blickenstaff, 2005; Riegle-Crumb, et al., 2012) as important factors influencing the gender gap in aspirations for certain STEM fields. Other research examines the factors influencing career aspirations in STEM for students of color with less emphasis on the role of gender. As in the literature on gender gaps, motivational factors like self-efficacy are implicated as important to science-related aspirations (Austin, 2010; Chemers et al., 2011; Quimby, Wolfson, and Seyala, 2007). Echoing the literature on student science identity, support in terms of mentoring or barriers like discrimination were also found to be salient (Chemers et al, 2011; Quimby et al., 2007). Chemers et al. (2011) found that self-efficacy and identity mediated the effects of support structures like mentoring on STEM career aspirations for students of color; that is, mentoring only had positive effects on career aspirations for students of color with high self-efficacy and identity..

While these studies highlight factors influencing aspirations for students of color specifically, other research uses nationally representative data to demonstrate differences in aspirations among racial subgroups (i.e., examine aspirations as a dependent variable affected by race and other predictors). Using data from the 2003 TIMMS, Riegle-Crumb et al. (2011) indicated that White, Black, and Hispanic females' odds of holding STEM career aspirations were significantly lower than those of White males holding constant parental education, number of books in the home, student attitudes towards school, and expectations. However, accounting for enjoyment, self-concept, and achievement in science diminished these gaps. In addition, according to their findings, Black and

Hispanic males' odds of aspiring to a STEM career were on par with those of White males despite gaps in achievement. Using ELS data for a sample of students attending 4-year colleges in 2006 who declared a major course of study, Riegle-Crumb and King (2010) found that White, Black, and Hispanic females' odds of pursuing a physical science or engineering career were significantly lower than White males whether controlling for confidence, attitudes, or prior coursework; conversely, controlling for academic preparation, Black males had significantly higher odds of pursing such careers versus White males. Although they use these data to suggest that the White male advantage in science is not as stark as one might expect, their sample is admittedly problematic since they select for students attending 4-year colleges where students of color are substantially underrepresented. Finally, Wang (2013) analyzed a sample of ELS 2006 4-year college matriculates demonstrating that relationships among 10th grade achievement and attitudes in mathematics and 12th grade mathematics self-efficacy, advanced STEM coursework, and mathematics achievement influenced students intentions to pursue a STEM career in college. According to their results, aspirations for underrepresented students of color (analyzed as a singular group combining Black and Hispanic students) exhibited the least gains from exposure to mathematics and science coursework and exhibited the most gains from early mathematics achievement compared to White and Asian students. Given the work of Riegle-Crumb and colleagues demonstrating differential patterns in aspirations by both race and gender, Wang's (2013) approach in grouping together underrepresented students potentially obscures important distinctions between student subgroups. Common to each of these studies, however, is an emphasis on students' individual-level achievement, attitudes, self-concept, or self-efficacy.

While all of these studies pay sufficient attention to student psychological or motivational factors such as attitudes or self-efficacy, there is noticeably less attention paid to structural factors or institutional constraints outside of exposure to mathematics and science coursework. Some recent work has considered the impact of the family in shaping student career aspirations in science (Archer et al., 2012; Sikora & Pokropek, 2012), but research is needed on the impact that school structures might have on student aspirations. In addition, given the ways in which science is both a gendered and racialized field and the differential patterns found by student race/gender in aspirations (Riegle-Crumb & King, 2010; Riegle-Crumb et al., 2011), it is apparent that examining effects at the intersection of both of these axes of stratification is required.

Indeed, a consistent thread throughout this examination of the science education literature is the under-emphasis on school institutional factors that might influence racial gaps in self-efficacy, identity, engagement, and aspirations. In terms of science self-efficacy, much emphasis is placed on student psychological sources of self-efficacy that derive either from the individual or from significant others (e.g. mentors, teachers). In addition, the literature on student science identity treats institutional factors tangentially, focusing instead on individual agency in the context of sociocultural barriers. In the literature on student engagement in science, much of the emphasis is on aspects of classroom instruction or teacher quality. Finally, in the literature on factors predictive of student career aspirations in science, much emphasis is placed on student psychological characteristics, again prioritizing the role of individual factors in pursuing scientific knowledge and deemphasizing the powerful role of institutional context on student aspirations. While these perspectives are valid, the lack of attention to school institutional factors influencing student science outcomes is problematic, particularly given the powerful role played by school racial composition and racialized tracking on student outcomes in general.

Effects of School Racial Composition

In what follows, I review the sociological literature examining the effects of both first generation segregation (segregation between schools) and second generation segregation (segregation within schools via racialized tracking). In the literature on first generation segregation, I begin by evaluating arguments suggesting that Black and/or Hispanic segregated schools might negatively affect student science outcomes. These claims are then measured against other research that posits high concentrations of students of color can positively affect student outcomes. This is followed by an examination of the research on the effects of school desegregation post-*Brown* and work that highlights the negative effects of predominantly White schools on students of color. Taken as a whole, this body of research suggests peer effects are the primary means through which school racial composition affects student outcomes. Finally, however, in synthesizing the literature on second generation segregation, racialized tracking is implicated as an alternative factor through which school racial composition effects operate.

First Generation Segregation

Prior research generally demonstrates that students in “segregated” schools–that is, schools with a disproportionate concentration of students of color–tend to have lower levels of achievement (Hanushek, et al., 2009; Linn & Welner, 2007; Mickelson, Bottia, & Lambert, 2013). One potential source of such inequality in achievement has to do with the lower level of resources typically available to such schools. Although some research has disputed the importance of the role of resources in general (most famously, Coleman et al., 1966), the resource argument is important in terms of material resources for science teaching specifically. Teachers in poor urban schools typically have more students per class and lack the materials or financial support needed to successfully implement novel curricula (Huinker, 1996; Waks, 1991). Updated science texts, equipment, and enrichment activities are also sparse as are opportunities for advanced coursework (Ingersol, 1999; Oakes, 1990). Not surprisingly, this dearth of resources affects both student motivation and achievement in science (Webster & Fisher, 2000). Whether or not one accepts this argument in terms of material and curricular resources, there is a vast amount of evidence that resources are important in terms of teacher characteristics. Teachers in schools with disproportionate populations of students of color tend to be less experienced/lack full certification and are more likely to be given teaching assignments outside of their field of certification (Clotfelter, Ladd, & Vidgor, 2005; Darling-Hammond, 2010; Ingersol, 1999; Mickelson & Heath, 1999). Furthermore, teachers in such schools might hold lower expectations for student ability and achievement (Delpit, 1992; Flores, 2007; Kozol, 2005; Prime & Miranda, 2006). Researchers have defined this milieu of teacher characteristics, physical, and instructional resources as "opportunity to learn" (Elliot, 1998; Solórzano, 2008) where students lacking in opportunity to learn have less experienced instructors emphasizing lower-order skills, are learning in the context of substandard curricula, and are denied physical resources for learning (e.g., instructional technology).

Another popular argument in the literature regarding the negative effects of Black and/or Hispanic segregated schooling on student outcomes has to do with peer opposition effects. Scholars have argued that Black and Hispanic adolescents collectively enact an oppositional peer culture in response to blocked opportunities (Downey, 2008; Fordham & Ogbu, 1986). According to this view, Black and Hispanic students devalue academic achievement, equating it to a standard of white success since it does not offer the same returns on investment as it does for Whites; in this context, high achieving students of color risk "acting white" in the eyes of their peers. Paulle (2013) details the extreme end of peer oppositional behavior in his ethnography of students from impoverished urban schools in New York City and Amsterdam. Students face what he describes as "micro-level social pressures" (p. xi) that become strategic coping mechanisms within their stressful school environments leading students away from a commitment to schooling and towards flashy clothing, street dealing, violence, and "collective educational demise" (p. xvii). This notion of peer opposition is contrasted with what might be termed students' peer academic orientation where students' peers display commitment to school achievement, attend class regularly, and hold intentions of enrolling in college.

Perpetuation theory offers another explanation for why schools with a concentration of students of color might suppress student science outcomes. Students in segregated settings may overestimate the degree of racial hostility they will face or underestimate their ability to negotiate relations in integrated settings and therefore avoid them. This theory is supported given the connection of the experience of school segregation to later racial isolation in the workplace or preferences for social segregation (Braddock & Gonzalez, 2010; Stearns, 2010, but see Butler, 2010). It is possible that segregated schooling affects Black and Hispanic students' career choice in a similar way, leading them to avoid occupations dominated by Whites. Beasley (2012) argues that the segregation of Black students at selective colleges deters their pursuit of such occupations, especially those in STEM fields.

Contrary to notions of peer oppositional culture and theories of perpetuation, some research supports that students of color generally have higher educational aspirations and are more likely to report pro-school attitudes than White students (Ainsworth-Darnell, & Downey, 1998; Cheng & Starks, 2002). Frost (2007) found that controlling for schools' student characteristics and mean socioeconomic status and achievement, students' expectations for attainment of a bachelor's degree were higher in schools with larger proportions of students of color, particularly for Hispanic students. Similarly, Goldsmith (2004) found that Black and Hispanic students in schools with an overrepresentation of students of color were more likely to have higher occupational aspirations and expectations for attainment than those in predominantly White schools. Black and Hispanic students in schools where students of color were the majority also had more positive attitudes towards their mathematics and science classes.

In addition, other research demonstrates that desegregated schooling can reverse some of the negative effects of segregation on achievement and attainment. Studies of desegregation efforts post-*Brown* indicate positive effects on Black student attainment (Ashenfelter, Collins, & Yoon, 2006; Guryan, 2004; Reber, 2010). In addition, Borman et al. (2004) demonstrated the positive effects of desegregation on student standardized test performance in Florida and suggested that attention to school racial composition is vital to closing racial gaps in student performance above and beyond efforts to equalize funding. Integrated schools are also more likely to offer challenging and advanced coursework with the effect of promoting higher student achievement and attainment (Mickelson, 2008; Linn & Welner, 2007). As Reber (2010) posits, an additional and often assumed means through which benefits might accrue to students of color in integrated schools is through access to and interaction with White students who tend to have higher levels of socioeconomic status and achievement.

Research on students of color in integrated schools, however, demonstrates how faulty this assumption is given the difficulties students of color face in terms of social integration in such schools and their implications for student achievement. For example, Zirkel (2004) found that Black and Hispanic elementary and middle school students were more socially isolated in their racially balanced school (where half of the student body were students of color) such that they reported lower numbers of friendships with other students. Teachers at the school were also more likely to rate these students as quiet or unpopular compared to White students. Students of color who did report higher numbers of friendships, however, also indicated higher levels of achievement-related goals; this suggests that promoting social integration of students in schools can boost academic orientation. These results are echoed in Bifulco, Bueger, and Cobb’s (2012) study of intergroup relations in a subset of ten racially integrated (to varying degrees) magnet high schools. Although they found that the schools had relatively high levels of positive intergroup relations among the Black, Hispanic, and White students in comparison to more segregated public schools in the same district, the authors found a substantial degree of within-school segregation across friendship groups by race; these effects were least pronounced in schools with the most heterogeneous racial compositions. Black and Hispanic students who reported more positive intergroup relations in schools also perceived higher academic norms among their peers, again suggesting that positive intergroup relations promote achievement-related factors. Together, these studies suggest that students of color may face higher degrees of social isolation in integrated schools compared to White students and that while integrated schooling may promote academic achievement for students of color, it depends on the racial climate of the school and the degree to which meaningful relationships can be forged among students.

Research also suggests that the barriers to social integration that students of color face in racially mixed schools are exacerbated in predominantly White schools. For example, although the high achieving Black students in DeCuir-Gunby's (2007) study appreciated the advantages that attending a White (approximately 90%) and wealthy independent school afforded them in terms of name-recognition and academic resources, they reported experiencing a hostile social climate where racist comments and attitudes were not uncommon. In addition, Marx and Larson (2012) documented the racial climate faced by Hispanic students in a predominantly White school (where Hispanic students represented only around 5% of the student body and 94% of the student body was White). In this context, teachers and administrators ignored the cultural knowledge and language of these students, emphasizing the importance of the students' assimilation to the largely White student body. The Hispanic students, acutely aware of their marginalization in the school, reported lower levels of academic and social well-being than their White counterparts. Holland (2012) and Ispa-Landa (2013) suggest that the barriers to social integration in predominantly White schools are different for male and female students of color where males are more likely to gain social status through the enactment of stereotypes of black masculinity or participation in sports–avenues that are not available to female students of color. Despite this greater degree of social integration for male students of color, the Black males in Ispa-Landa's (2013) study faced racialized stereotypes of their academic ability and commitment.

Although school factors like advanced coursework or climate are implicated in some examinations of the effects of school racial composition, this body of literature has a tendency to assume that peer effects (i.e., peer opposition or peer academic orientation) are a central means through which school racial composition effects operate. The literature on segregation within schools, however, challenges this notion, implicating racialized tracking as a key mediator of the effects of school racial composition on student outcomes.

Second Generation Segregation

There is much evidence that racialized tracking is a key factor in affecting students' educational outcomes as opposed to peer effects. Carter (2012) draws on Sampson and Wilson's (1995) notion of "ecological dissimilarity" highlighting the importance of school organizational context–particularly racialized tracking–in shaping how school racial composition affects students. In this context, ecological dissimilarity refers to the widely divergent structural and social contexts that exist along the lines of race and class; that is, due to a long history of racial segregation, discrimination, economic transformation, White flight, and urban poverty, the structural and social conditions students face differ by social group. Applied *within* schools, the notion of ecological dissimilarity highlights the different contexts students of color might face given the racial composition of schools and schools' organizational contexts. As she posits, students of color are generally underrepresented (if not entirely absent) in the most advanced courses in predominantly White schools. In diverse schools with a majority of students of color, White students might be overrepresented in such courses. Thus, tracking has become a form of second generation segregation, excluding many students of color as influenced by racialized perceptions of ability (Tyson, 2011; Mickelson, 2001).

A large body of qualitative research demonstrates the impact that racialized tracking can have on drawing symbolic boundaries around academic domains, communicating to students who belongs in advanced coursework and who does not. In the context of a "racially stratified academic hierarchy" (O'Connor et al., 2011) where students of color are disproportionately underrepresented in advanced coursework, students label these domains as White, affecting their orientation towards peers as well as school achievement and engagement (Carter, 2012; Mickelson & Velasco, 2006; Nunn, 2011). For example, Conchas (2001) demonstrated, in a school with a majority of students of color (White population < 5%), within-school program tracking isolated predominantly native-born Mexican students in lower tracked programs (alongside disproportionate numbers of Black students) which contributed to their disengagement with schooling as these courses were labeled "bad" in the eyes of the student body. The "good" programs or advanced tracks were populated by mostly White and Asian students and the small proportion of Hispanic students in them flourished. Scholars examining racialized tracking in schools note that these dynamics tend to be more pronounced in the context of science and mathematics coursework versus coursework in the humanities (Carter, 2012; Tyson, 2011). Given that teachers may view science and mathematics as "special" subjects where only students with particular skill sets and attitudes ("special" students) can be successful (Prime & Miranda, 2006), this should not be a surprising finding.

In drawing attention to the role of racialized tracking, some authors qualify or critique the attention in the literature to peer oppositional culture or the "acting white" phenomenon. For example, Tyson and colleagues (Tyson, 2011; Tyson, et al., 2005) demonstrated how racialized tracking and gifted placement across a range of middle and secondary public schools lowered aspirations for students of color. Analyzing student interviews across a range of school contexts, they demonstrate that an oppositional culture to schooling is not the norm and the "acting white" phenomenon is a product of racialized tracking (see also Mickelson & Velasco, 2006). Diamond, Lewis, and Gordon (2007) also drew attention to the unequal opportunity structure of a multiracial school where students were severely underrepresented in Advanced Placement courses and its effects on Black and White students' management of academic success and failure. They found no support for a peer oppositional culture; instead, they found that lower achieving student peer groups promoted student academic success and sanctioned failure.

Diamond et al. (2007) also highlight the role that teachers played in shaping student academic achievement in the context of racialized tracking such that Black students in higher tracked courses were acutely aware of the lowered expectations teachers held for them in comparison to their majority White peers. Nunn (2011) also echoes the importance of teacher expectations and behavior, illustrating how teachers either helped or hindered students' sense of belonging in advanced coursework. Nunn asserts that teacher pedagogical practices can exacerbate existing boundaries between White students and students of color in advanced courses (where students of color are a minority) through a dependence on practices that privilege White, middle-class norms. Both authors, however, situated the potential impact of teachers on student dispositions towards achievement as embedded within the broader context of an unequal school opportunity structure where racialized tracking is the norm.

This qualitative research on the influence of racialized tracking as a mediator of the effects of school racial composition is mirrored in the quantitative literature. Kurleander and Yun (2005) demonstrated with a sample of nearly 11,000 secondary students that students of color were less likely to be encouraged by teachers to take Honors or Advanced Placement courses in multiracial schools (where Black, Hispanic, and White students made up at least 20% of the student body each) compared to those in schools with higher concentrations of students of color. In addition, Southworth and Mickelson (2007) found that schools that are racially balanced (i.e., representative of the overall racial distribution present in their district) produced the most equal outcomes in terms of English track placement for both White and Black students in comparison to schools that were racially identified as predominantly White or Black. Other researchers have shown that as the proportion White or affluent in a school increases, students of color or low income students are less likely to advance in mathematics and science course-taking (Crosnoe, 2009; Kelly, 2009).

Other quantitative research echoes these findings with an emphasis on both racial disparities in track placement and the impact that track placement has on student achievement (Mickelson, 2001; Muller, Riegle-Crumb, Schiller, Wilkison, & Frank, 2010). These researchers have shown that across large samples of schools, students of color were underrepresented in both advanced mathematics (Muller et al., 2010) and English coursework (Mickelson, 2001). In both contexts, this underrepresentation was associated with lower student achievement; lower student course placement was associated with lower school grades (Mickelson, 2001; Muller at al., 2010), standardized test scores (Mickelson, 2001), and lower chances of enrollment in a 4-year college (Muller et al., 2010). Although these studies focused on track placement in the context of English or mathematics course-taking, academic versus vocational track placement and units of science coursework completed has been shown to affect science achievement growth rates across racial and gender student groups (Muller, Stage, & Kinzie, 2001), echoing the importance of track placement on science outcomes.

In sum, this literature highlighting the effects of racialized tracking on achievement and engagement outcomes for students of color points to the problems of treating school racial composition effects as determined by peer opposition or academic orientation. While peer effects may be one aspect through which school racial composition affects student outcomes, school organizational structures, particularly racialized tracking, are just as likely implicated. In this study I will control for student peer academic orientation in order to determine the effects that racialized tracking has on exacerbating gaps in student science outcomes.

In addition to this emphasis on the effects peer opposition/academic orientation in the literature, a few additional limitations should be noted regarding the body of work on school racial composition effects. First, there is the general tendency to equate “segregated” schooling and the negative connotations that go along with it, to schools with a concentration of students of color (Mickelson et al., 2013; Orfield et al., 2012; but see Ispa-Landa, 2013). While it is true that these school contexts tend to be under-resourced with lower levels of student achievement and socioeconomic status, they are no less “segregated” than schools whose population is dominated by White students–schools that also have deleterious effects on students, particularly students of color (e.g., Holland, 2012; Marx & Larson, 2012). In addition, while the racial composition literature tends to focus on more general student outcomes like achievement, engagement, or course-taking, the weight that scientific fields hold in terms of their share of the economic growth of this country may warrant specific attention to student science outcomes specifically. Finally, attention to the effects of racialized tracking on student science outcomes may be particularly important since patterns of student underrepresentation in advanced coursework appear to be exacerbated in mathematics and science relative to other subject areas (Carter, 2012; Tyson, 2011).

The Intersection of Race & Gender

Over the past several decades, the general trend in examining demographic inequalities in STEM fields has been to focus on either gender inequalities *or* racial inequalities. As Riegle-Crumb and King (2010) note, despite the large body of literature that exists considering gender gaps in STEM (spanning examinations that begin during childhood to studies on the careers of adults, e.g., Chipman, Brush, & Wilson, 1985; Zeldin et al., 2008), there is little research at the national level that examines inequalities for students by both race and gender (American Association of University Women Educational Foundation, 2008). As a prime example of this, while cited in the literature over 400 times, differences by race are wholly absent from Blickenstaff's (2005) review of gender inequalities in STEM undergraduate programs and careers. As previously mentioned, work examining racial differences in STEM career aspirations with national samples may also do so at the expense of attending to differences by gender within racial groups (Wang, 2013; see also Andersen & Kim, 2006). Over the past five years, Riegle-Crumb and colleagues have been conducting quantitative research examining effects by race/gender (e.g., White female, Black male, etc.) in an attempt to address this gap (Riegle-Crumb et al., 2011; Riegle-Crumb & King, 2010).

Though simplified in this context to examining effects at the intersection of race and gender only, this approach is undergirded by notions of intersectionality. Coined by critical race theorist Kimberlé Crenshaw (1995) and popularized by Patricia Hill Collins (2000), the notion of intersectionality posits that social location must be understood at the junctions of multiple systems of oppression. As Collins notes, these systems include, but are not limited to, "race, social class, gender, sexuality, ethnicity, nation, and age" (p. 299). In the context of STEM outcomes, one could assume given the racial and gender gaps in science outcomes, that the two most prominent systems of oppression are that of race and gender. From this perspective, examining mean differences by gender without considering race assumes that all males share a common experience that is distinct from the experience of all females. An emphasis on racial differences alone also generalizes the experiences of males and females within racial groups. As Riegle-Crumb et al. (2011) note, these assumptions and generalizations can generate inaccurate oversimplications that misrepresent the experiences of individuals. For instance, while some studies demonstrate lower science engagement for students of color (Chang et al., 2007; Uekawa et al., 2007), the extent to which this is true for females of color–who are at the axis of both systems of gender and race oppression–is obscured. Additionally, given the assumption of a generic "male" advantage in STEM fields, it is unclear what this might mean for males of color or particularly for Black males who have been positioned as the most academically at-risk student subgroup (Noguera, 2003).

Estimating effects by race/gender recognizes the fundamentally enmeshed ties between both race and gender. In this context, the intention is to treat the experiences of each race/gender group (e.g., Black females, Hispanic males, etc.) as potentially having unique, socially constructed histories that shape their experiences (Collins, 1998). In the very least, such an approach recognizes the potential that certain, or perhaps unpredictable, combinations of gender and race are disadvantaged in specific contexts. When studies examine effects at the intersection of race/gender, results can defy stereotypes of women and students of color as disadvantaged in STEM. For instance, Reigle-Crumb et al. (2011) found that for a nationally representative sample of eighth grade students, Black and Hispanic male odds of aspiring to mathematics and science careers were on par with those of their White male counterparts. Additionally, Hanson (2006) found that Black female high students held more positive attitudes towards science than their White female counterparts.

O'Connor, Lewis, and Mueller (2007) also lament the failure of much of the research community in examining intersectionalities, particularly in research on Black students' educational outcomes and experiences. As they note, even when attention is paid to the effects at intersection of race and gender (or race and social class) for Black students, there is a tendency to focus on one group position over another (e.g., focusing on how feminine norms shape experiences for Black and White females). To avoid the marginalization of race in these discussions, the authors ultimately advocate that researchers "examine these positions as intertwined rather than isolated and independent" (p. 454).

Despite these arguments from Riegle-Crumb et al. (2011) and O'Connor et al. (2007), there may be a larger purpose in aggregating by either race or gender depending on the context of the research. For instance, if inequalities appear to be driven more so in differences by race, then aggregation by race apart from gender supports a more parsimonious analysis and subsequently "cleaner" interpretations. While attending to potential differences by race/gender is important, the preliminary analyses may indicate that aggregation could be appropriate. Thus, in this study, results are analyzed by race and gender separately in addition to effects modeled at the intersection of race/gender to see when/where more detailed analyses contribute substantively to the conclusions drawn from the data. Since White males have historically held advantages when it comes to STEM achievement and careers, they serve as the appropriate reference group in analyses by race/gender.

Summary

In this chapter I reviewed and synthesized two bodies of literature pertinent to this study—the science education literature on student science self-efficacy, identity, engagement, and career aspirations as well as the sociological literature on the effects of school racial composition and racialized tracking on students of color. In examining the literature on these affective ratings and career aspirations in science, there was a clear lack of attention paid to the impact of school institutional structures like racial composition and racialized tracking more commonly examined in the sociological literature. However, the sociological research examines general student outcomes not specific to science. In addition, some research has called into question the common practice in quantitative analyses of using separate variables for race and gender.

Given these findings, this study examined the effects of school racial composition on students' affective ratings in science and STEM career aspirations. In addition, analyses were conducted using both separate variables for race and gender and variables for race/gender in order to determine whether or not taking an intersectional perspective adds to our understanding of these dynamics. In the next chapter, I detail the methods employed to complete these analyses.

CHAPTER 3

METHODS

This study examined the role that institutional factors such as school racial composition and racialized tracking play in influencing the affective ratings (i.e., science self-efficacy, science identity, and science engagement) and STEM career aspirations for Asian, Black, Hispanic, and White students. Three main research questions were posed. (RQ1) What are the effects of race on students' science self-efficacy, identity, engagement, and career aspirations? In other words, what racial differences exist in these outcomes for students of color compared to White students? (RQ2) Does school racial composition moderate the effects of race on science outcomes? To what extent are these moderation effects mediated by racialized tracking? (RQ3) How is the interpretation of these dynamics affected by examining effects by race/gender versus race alone (i.e., aggregated by race)? In this chapter, I describe the data source used to explore these questions, operationalize the variables used in the study, define the analytic sample, describe data management and screening, and provide basic descriptive statistics. As will be described, the research questions defined above are modified slightly by the end of this section given preliminary analyses that indicated no moderation effects by school racial composition (such that attention is shifted towards the moderating effects of racialized tracking for race on outcome effects).

Data Source

This study utilized data from the High School Longitudinal Study (HSLS), which is sponsored by the National Center for Education Statistics (NCES). Since the fall of the

2009 – 2010 school year, the HSLS follows a nationally representative cohort of ninth grade students. The overall purpose of the HSLS is to examine student trajectories beginning in the high school years and extending through college and career choice with a special emphasis on STEM pathways. Study participants include more than 25,000 students, their mathematics and science teachers, counselors, administrators, and parents.[1] The school-level data includes information on 944 public and private schools that participated in the study nationwide. Specifically, this study used the restricted-use base year data for students, parents, teachers, and their schools as well as the first follow-up data that surveyed participants during most students' junior year (2012). The restricted-use data were required in order to link student-level responses with school-level variables (i.e., this is not possible using public-use files only). Information about the HSLS can be found online at http://nces.ed.gov/surveys/hsls09/index.asp.

Dependent Variables

The dependent variables analyzed in this study are student science outcomes, specifically: science self-efficacy, science identity, science engagement (conceptualized as emotional engagement, behavioral engagement, and cognitive engagement), and STEM career aspirations.

Science Self-efficacy

Science self-efficacy was measured in 2012 with four, four-point Likert scale items where students indicated the extent to which they were certain or confident they could (1) excel on tests in science, (2) excel in the completion of assignments in science, (3) understand challenging material in their science textbooks, and (4) master the skills

[1] Teachers were surveyed during the base year only (2009).

taught in science. Although Bandura (1986) distinguishes between “confidence” (as based on past performance) and “self-efficacy” (as based on future performance), these terms are often used together by scholars (e.g., see Pajares, 1996, who notes researchers may measure self-efficacy as the “level, generality, and strength of their *confidence* to accomplish a task or succeed in a certain situation”, p. 546, emphasis added). Furthermore, in the context of these selected items, the focus is on future performance in science. The variable composite was created by NCES through principal components factor analysis and was *z*-standardized. Only students who responded to each of the four items were assigned a score. Cronbach’s alpha reliability for the scale was $\alpha = .93$.

Science Identity

Science identity was measured in 2012 with two, four-point Likert scale items where students indicated the extent to which they agreed with the following statements “You see yourself as a science person” and “Others see me as a science person”; higher scores indicated higher levels of agreement. The variable composite was created by NCES through principal components factor analysis and was *z*-standardized. Only students who responded to both items were assigned a score. Cronbach’s alpha for the scale was .89.

Science Engagement

In order to examine each of the three facets of engagement, this study utilized a combination of NCES constructed composites and researcher-constructed composites to create scores for emotional engagement, behavioral engagement, and cognitive engagement in science.

Emotional Engagement

In this study, emotional engagement was conceptualized as the value students place on science, for example, whether the student perceives science as worthwhile to their lives and future goals (more specifically positioned here as “science utility”). Eccles (2009) positions the general concept of “utility value” as part of her framework for subjective task value (which exists within the larger framework of her expectancy/value model of achievement goals for students). For Eccles (2009), the subjective task value is the “quality of the task that contributes to increasing or decreasing probability that an individual will select it” (p. 82); within this context the utility value, or the utility of the task in helping individuals obtain short-term or long-term goals/rewards, is one of four aspects of subjective task value (alongside intrinsic interest, attainment value, and costs). Looking at science utility value specifically in this study as a key component of emotional engagement was important given what we know about how students of color are presented with success stories in science fields (namely, that there is a dearth of success stories centered on individuals who look like them; Hines, 2003) and how students of color may not position science careers as realistic, obtainable goals in their lives (Archer et al., 2010).

Science utility was measured in 2012 with three, four-point Likert scale items where students indicated the extent to which they agreed with the following statements regarding whether or not they saw science as (1) is useful for everyday life, (2) useful for college, and (3) useful for a future career. Higher values indicated stronger levels of agreement. The variable composite was created by NCES through principal components factor analysis and was standardized (i.e., converted to z-scores). Only students who responded to the full set of items were assigned a non-missing value for this composite variable. Cronbach’s reliability alpha for the scale was $\alpha = .65$.

Behavioral Engagement

Behavioral engagement was measured in 2012 with two, five-point Likert scale items where students indicated how often they complied with the basic requirements of their science course (ranging from Never to Always). Specifically, students indicated how of often they (1) paid attention to their science teacher and (2) turned in their assignments on time. Higher values indicated higher frequencies self-reported of compliance. Only students who responded to both items were assigned a non-missing value for the composite sum score. Cronbach’s alpha reliability for the scale was $\alpha = .64$.

It should be noted that definitions of behavioral engagement in the literature can extend beyond it’s conceptualization here to include aspects of involvement in academic tasks (Heddy, Sinatra, Seli, & Mukhopadhyay, 2014), including behaviors displaying effort and persistence (Buhs & Ladd, 2001). However, as explained below, these aspects also overlap with operationalizatons of cognitive engagement.

Cognitive Engagement

Cognitive engagement was measured in 2012 with two, five-point Likert scale items where students indicated how often they pushed themselves beyond the basic requirements of their science course (ranging from Never to Always). Specifically students indicated how often they (1) gave up when work became difficult and (2) did as little work as possible in order to get by. Items were reverse coded and summed such that higher scores indicated higher frequencies of self-reported cognitive engagement. Only students who responded to both items were assigned a non-missing value for the composite sum score. Cronbach's alpha reliability for the scale was $\alpha = .73$.

It should be noted that this operationalization of cognitive engagement lacks precision—a limitation to the measurement of cognitive engagement that is echoed in the literature. As Sinatra, Heddy, and Lombardi (2015) note, psychological investment—when a student "expends cognitive effort in order to understand, goes beyond the requirement of the activity, uses flexible problem solving, and chooses challenging tasks" (p. 3)—is a commonly used definition of cognitive engagement; this definition overlaps with other conceptualizations of behavioral engagement that might include showing effort and persistence (Buhs & Ladd, 2001). For the purposes of this study, behavioral engagement is conceptualized as limited to simpler notions of positive conduct in the science classroom whereas cognitive engagement is conceptualized as extending "cognitive effort" and going beyond basic course requirements (as opposed to just "getting by"). However, it is acknowledged that this operationalization is a broad take on cognitive engagement that can be much more precise other studies, where for example, several items might be used to measure students' tendency to "get by" rather than display cognitive engagement; for example, see Meece, Blumenfeld, and Hoyle's (1988) factor for "superficial engagement" as a component of cognitive engagement.

Career Aspirations

In 2012, HSLS asked students to indicate their occupational aspirations at age 30. Their written responses were coded by NCES using 6-digit Occupational Information Network (O*NET) codes. These codes were used to create a binary indicator for students specifying career aspirations in STEM (1 = student aspires to hold a career in a STEM field, 0 = student does not aspire to hold a career in a STEM field). As the Institute on Education Sciences (IES) notes, definitions of STEM fields can vary (Chen & Soldner, 2013) given either the inclusion or exclusion of particular occupations in the social sciences. The matter is complicated further given students' potential desire to pursue a career in the health sciences, many of which require majoring in a STEM field of study but are often excluded from definitions of STEM career aspirations. In this study, a broad definition of STEM career aspirations was employed that included both the health sciences and psychological sciences given the high degree of projected growth of occupations in these fields (Bureau of Labor Statistics, 2013). In other words, the definition of STEM career aspirations was driven by the potential for these aspirations to translate into higher earnings in later life. See Table 3-1 for common examples of the O*NET occupations that were coded as STEM for the purposes of this study.

Table 3-1. Sample O*NET Occupations Classified as STEM fields

STEM Fields	Example O*NET Occupations
Chemical/Physical Sciences	Physicists
	Chemists
	Astronomers
Computer Sciences	Computer programmer
	Computer specialists
	Computer software engineer
Engineering	Mechanical Engineers
	Electrical Engineers
	Civil Engineers
Heath Sciences	Registered Nurses
	Physical Therapists
	Physicians
Life Sciences	Zoologists and wild life biologists
	Forensic science technicians
	Biological scientists

Table 3-1. (continued)

STEM Fields	Example O*NET Occupations
Mathematics	Actuaries
	Mathematicians
	Statisticians
Psychological sciences	Psychologists
	Clinical/counseling/school psychologists
	Industrial-organizational psychologists

Independent Variables

The independent, or focal, variables in this study include student race (and gender) and the school characteristics of racial composition and racialized tracking.

Student Race & Gender

Students who reported their race as White, Black, Hispanic, or Asian were included in this study. Binary indicators for student race as well as gender were included in initial regression models.

For subsequent models, dichotomous variables were constructed to indicate group membership for 8 different race/gender categories: White male, White female, Black male, Black female, Hispanic male, Hispanic female, Asian male, and Asian female.

School Racial Composition

Official data on school racial composition were obtained from Common Core Data (for public schools) and the Private School Universe Survey (for private schools). For the Common Core of Data, information was averaged across the last four years (2008, 2009, 2010, 2011) of available data to minimize potential measurement error in any one year's worth of data. For the Private School Universe Survey, which is administered less frequently than the Common Core surveys, the last two years of available data were used (2008, 2010). These data were used to measure school racial composition as the proportion of Asian and White students in a school.

Racialized Tracking

Racialized tracking in schools was estimated using a construct that Muller et al. (2010) defined as the "academic opportunity structure" within racially diverse schools. Similar to Muller and colleagues, advanced science coursework was defined using the Adolescent Health and Academic Achievement (AHAA) study's hierarchical ranking of science coursework (see Table 3-2; Muller et al., 2008) as well as the modal course students are enrolled in during the 11^{th} grade.

Table 3-2. AHAA Study's Ranking of Science Coursework

Ranking	Course
6	Physics
5	Advanced Science (Biology II, Chemistry II)
4	Chemistry I
3	Biology I
2	General/Earth Science
1	Basic/Remedial Science
0	No Science

In this context, "advanced" coursework could be defined as coursework beyond the modal value of the distribution. For the sample, the modal value of the distribution was 4, that is, most students were enrolled in chemistry during the first follow-up. Thus, students enrolled in advanced science or physics were deemed as being enrolled in advanced science coursework specifically. While these categories "represent a hierarchy of courses ranging from less to more advanced" given most students' course-taking patterns that adhere to a linear progression through the sequence, a minority of students course-taking may not reflect this pattern (Muller et al., 2008, p. 9).

Underrepresentation of students of color in advanced coursework was then measured using indicators for student race and advanced coursework using a log odds ratio (modified from Muller et al., 2010 p. 1045):

$$\log OR = \log\left(\frac{Pr(Y = 1|\ Asian\ or\ White)\ /\ Pr(Y = 0|\ Asian\ or\ White)}{Pr(Y = 1|\ Black\ or\ Hispanic)\ /\ Pr(Y = 0|\ Black\ or\ Hispanic)}\right)$$

where *Pr(Y=1)* indicates probability of advanced course placement and *Pr(Y=0)* indicates probability of placement in "nonadvanced" coursework. Higher values on this construct indicated greater underrepresentation of students of color in advanced coursework.

Given the formula for constructing this variable for racialized tracking, schools with samples where zero Black/Hispanic or zero Asian/White students were represented in advanced coursework were problematic. Straight calculation of this variable in such instances yields undefined values given values of zero in the denominator. Given this, values for students in 119 schools with no Black or Hispanic students in advanced coursework were recoded to a value higher than the maximum given the range observed for the variable; likewise, values for students in 23 schools with no Asian or White students in advanced coursework were recoded to a value lower than the minimum given the range observed for the variable.

Control Variables

Control variables included in this study are student characteristics for socioeconomic status, mathematics assessment scores, generational status, parental expectations, and peer academic orientation. In terms of school characteristics, school mean socioeconomic status was also included as a model control. Variables for school resources and opportunity to learn were also intended as controls, but as will be discussed, high numbers of missing values for these variables prevented their use in regression analyses.

Socioeconomic Status

Student socioeconomic status was measured with an NCES-constructed composite that was calculated using variables for parental education, occupation, and family income as reported by the students' parent or guardian.

Mathematics Assessment Score

At the time of base year survey completion, HSLS students completed a mathematics assessment in algebraic reasoning. Each student completed the 40-item assessment, which included items common to all students and selected items given students' assessed ability on the common items as low, moderate, or high.   The items were scaled by NCES using Item Response Theory (Hambleton & Swaminathan, 1984). These scores served as a control for possible selection bias into high schools since it was possible that students predisposed to scoring high on science identity or engagement would have attended high-quality schools.

Generational Status

Indicators for student generational status were constructed to indicate whether or not the student is first generation (student and parents were both born outside the U.S.), second generation (student was native born, parents were born outside the U.S.), or third generation (both the student and the parents were native born).

Parental Expectations

HSLS parents indicated their expectations in terms of their child's educational attainment on a ten-point scale ranging from "less than high school" to "complete a Ph.D., M.D., law degree, or other professional degree".

Peer Academic Orientation

Students responded to four, five-point Likert scale items regarding their number of friends who 1) got good grades, 2) dropped out of school, 3) have taken the PSAT/SAT/ACT, and 4) plan to attend a four-year college. Responses for each of these items ranged from "None of them" to "All of them". A sum score composite was created such that higher values indicated the perception of higher levels of peer academic orientation for students. Cronbach's alpha for the scale was $\alpha = .63$.

School Mean Socioeconomic Status

Mean socioeconomic status is an aggregate variable created by taking the mean of the students' socioeconomic status in each school and represents the average socioeconomic status of the school. The aggregates were *z*-standardized in a separate school-level data file for schools across the original HSLS sample and merged with the student-level data file so that estimates accurately reflect the mean and standard deviation of the school-level population.

Resources/Opportunity to Learn

During the base year survey, students' science teachers were surveyed in addition to students and parents. In HSLS, teacher-level data are compiled in the student-level data file, linked to student responses. As such, teacher responses were disaggregated to the student data, and the primary unit of analysis for this study was at the student-level. In order to tap into school resource variables and measures of opportunity to learn, several of these items were analyzed in order to create composites on different dimensions of these constructs.

One teacher self-report variable was dummy coded to indicate whether or not the teacher held a regular certificate in teaching (1 = regular certification, 0 = no certification or alternative certification). A second variable indicated the number of years the student's teacher had been teaching.

In addition, three sets of items were factor analyzed in order to create composites for students' science teacher quality, teaching emphases, and limitations on teaching. Exploratory factor analyses were conducted given the large number of potential items to be analyzed and results guided the aggregation of these items into scales. Each of the exploratory factor analyses used Principal Axis Factoring with Oblimin rotation (appropriate given the assumption of intercorrelations among the items; Keith, 2006). Across analyses, the number of factors retained was determined based on eigenvalues greater than one. Results were handled iteratively considering pattern matrix factor loadings, scree plot analysis, and theoretical concerns. Details for each set of items is provided below.

Factor Analysis For Items Tapping Students' Science Teacher Quality

Science teachers responded to eight, four-point Likert items on their perceptions of science teacher quality at their school. For example, science teachers indicated the degree to which they agreed that science teachers at their school set high standards for learning and believed all students could do well (1 = Strongly Agree to 4 = Strongly Disagree). See Table 3-3 for a listing of these items.

Table 3-3. HSLS Base Year Items Tapping Perceptions of Science Teacher Quality (1 = Strongly Agree, 4 = Strongly Disagree)

Variable	Item – Science teachers in this school…	*M*	*SD*	*n* Observed
HiStdTch	… set high standards for teaching	3.51	0.57	14862
HiStdLrn	… set high standards for students' learning	3.48	0.60	14885
DoWell	… believe all students can do well	3.22	0.64	14877
ClrGoal	… make goals clear to students	3.45	0.58	14891
GvnUp	… have given up on some students	3.01	0.77	14853
CareSome	… care only about smart students	3.52	0.60	14844
ExptLittle	… expect very little from students	3.54	0.62	14859
WrkHard	… work hard to make sure all students learn	3.49	0.58	14892

Where appropriate, items were reverse coded such that higher values corresponded to what would be perceived as higher quality. The exploratory factor analysis resulted in a one-factor solution explaining 42.7% of the variance; factor loadings ranged from .534 to .774 for each of the items. Given this one-factor solution, a sum score was created tapping teacher quality; only teachers who provided a full set of responses were assigned a score (alpha reliability for the items, $\alpha = .85$).

Factor Analysis For Items Tapping Teaching Emphases

Science teachers responded to 11, four-point Likert scale items indicating the emphasis they placed on different skills and topics when teaching. For example, science teachers indicated the degree of emphasis they placed on promoting inquiry skills and the teaching of basic concepts in science (1 = no emphasis, 4 = heavy emphasis). See Table 3-4 for a listing of these items.

Table 3-4. HSLS Base Year Items Tapping Science Teacher Emphases (1 = No Emphasis, 4 = Heavy Emphasis)

Variable	Item – Science teacher's emphasis on…	*M*	*SD*	*n* Observed
BasicCon	…teaching basic science concepts	3.78	0.44	12671
TermsFacts	…important science terms/facts	3.51	0.60	12684
StuIntrst	…increasing students' interest in science	3.46	0.59	12720
Inquiry	…science process/inquiry skills	3.56	0.57	12677
ClgPrep	…preparation for further science study	3.38	0.66	12670
EvalArg	…evaluating arguments based on evidence	3.10	0.75	12706
CommIdeas	…effectively communicating science ideas	3.26	0.66	12581
BusApps	…business/industry applications of science	2.94	0.72	12586
SciTechSoc	…relationship between science/tech/society	3.23	0.68	12562
HistNat	…history/nature of science	3.01	0.71	12580
TestPrep	…standardized test preparation	3.04	0.85	12585

The exploratory factor analysis yielded a three-factor solution and explained 42.3% of the variance. Although the final two factors' contribution to the explained variance was relatively small (both contributed approximately 6-7% of the explained variance each) and were two item factors (which may be considered weak and unstable, Costello & Osborne, 2005) there were no cross-loadings in the pattern matrix for factors with loadings > .4 and the items for the final two factors were theoretically sensible (see Table 3-5).

Table 3-5. Pattern Matrix for Exploratory Factor Analysis of Teaching Emphasis Variables

	Factor		
	1	2	3
BasicCon		.423	
TermsFacts		.775	
StuIntrst	.453		
Inquiry	.716		
ClgPrep	.556		
EvalArg	.714		
CommIdeas	.633		
BusApps			-.675
SciTechSoc			-.786
HistNat			
TestPrep			

Given the factor structure evident from the pattern matrix three sum score composites were constructed for teaching emphases on "Higher Order Skills" (factor 1), "Lower Order Skills" (factor 2), and "Connections" (factor 3; alpha reliabilities for these composites were α = .78, .49, and .77, respectively). Two items (HistNat, TestPrp) were not included in these composite scores given factor loadings < .4.

Factor Analysis For Items Tapping Teacher Resources

Science teachers responded to 29, four-point Likert scale items indicating the degree to which specific student and school factors limited their teaching. For example, science teachers indicated the degree to which they felt a lack of resources was a problem at the school and the degree to which their teaching was limited by disruptive students (1 = Not a problem/Not at all, 4 = Serious problem/A lot). See Table 3-6 for a listing of these items.

The exploratory factor analysis yielded a five-factor solution and explained 50.4% of the variance. The pattern matrix and factor loadings revealed one item cross-loading (Apathy) and two items with factor loadings < .4 (HighSTRatio, NoTexts). Although the final three factors' contribution to the explained variance was relatively small (these factors contributed 2 -5% of the explained variance each), the theoretical constructs for these factors were readily apparent (see Table 3-7 for the pattern matrix factor structure).

Table 3-6. HSLS Base Year Items Tapping Limitations on Teaching

Variable	Item	*M*	*SD*	*n* Obs.
	…is a problem at this school			
Apathy	Student apathy	2.76	0.98	14706
Cutting	Student class cutting	1.90	0.87	14796
DropOut	Students dropping out	1.97	0.88	14753
Health	Poor student health	1.65	0.72	14783
ParentInv	Lack of parental involvement	2.51	1.03	14824
Resources	Lack of teacher resources and materials	2.09	0.99	14810
StuAbsent	Student absenteeism	2.44	0.94	14811
Tardy	Student tardiness	2.26	0.90	14810
TchAbsent	Teacher absenteeism	1.36	0.60	14804
Unprepared	Students coming unprepared to learn	2.71	0.94	14822
	Teaching is limited by…			
NoParSup	lack of parent/family support	2.23	1.02	14408
BadFacilities	inadequate physical facilities	1.88	1.05	13907
DiffAbl	different academic abilities in the same class	2.52	0.93	14684
Disruptive	disruptive students	2.47	0.97	14560
HighSTRatio	high student to teacher ratio	2.30	1.06	14246
LangRange	students with wide range of language backgrounds	1.89	0.86	12440
LowMorale	low morale among students	2.25	0.96	14441
NoAdminSup	inadequate administrative support	1.71	0.94	13788
NoAuto	lack of autonomy in instructional decisions	1.59	0.84	13841
NoComp	shortage of computer hardware/software	2.11	1.07	14096
NoCompSup	shortage of support for using computers	1.90	1.04	13899
NoDemoEq	shortage of equipment for demonstrations	2.06	0.99	14173
NoEquip	shortage of instructional equipment	1.96	0.98	14088
NoPlanning	lack of planning time	2.04	1.03	14157
NoProfDel	inadequate professional learning opportunities	1.62	0.85	13558
NoTexts	shortage of textbooks for student use	1.55	0.91	13660
SESRange	students with wide range of SES backgrounds	1.83	0.91	14426
SpecialEd	students with special needs	1.93	0.87	13621
Uninterest	uninterested students	2.72	0.95	14708

Table 3-7. Pattern Matrix for Exploratory Factor Analysis on Items Tapping Limitations on Teaching

	Factor				
	1	2	3	4	5
Tardy	.662				
StuAbsent	.795				
Cutting	.757				
TchAbsent	.404				
DropOut	.734				
ParentInv	.643				
Unprepared	.566				
Health	.539				
NoParSup	.418				
Apathy	.461			-.435	
Resources		.713			
NoComp		.732			
NoCompSup		.650			
NoEquip		.870			
NoDemoEq		.865			
BadFacilities		.477			
DiffAbl			.492		
SESRange			.703		
LangRange			.571		
SpecialEd			.627		
Uninterest				-.751	
LowMorale				-.576	
Disruptive				-.475	
NoProfDel					.445
NoAdminSup					.600
NoPlanning					.554
NoAuto					.660
NoTexts					
HighSTRatio					

Given the factor structure evident from the pattern matrix five sum score composites were constructed for limitations on teaching for "Poor Climate" (factor 1), "Lack of Resources" (factor 2), "High Demands" (factor 3), "Challenging Students" (factor 4), and "Lack of Support" (factor 5). The three items with either cross loadings (i.e., Apathy) or factor loadings < .4 (i.e., NoTexts, HighSTRatio) were not included in these composites. Cronbach's alpha reliability for these sum scores ranged from α = .71 - .89.

Scope Conditions

As previously mentioned, the HSLS base year and first follow-up data contains information for over 25,000 students in 944 schools. To obtain an analytic sample, several scope conditions had to be applied to restrict this sample. First, this study excluded those participants with unit nonresponse during the first follow up; to account for this type of unit nonresponse, analytic weights provided by NCES were used and will be subsequently defined (step 1). Second, since two key variables of interest in this study were school racial composition and presence of racialized tracking in the students' school, the sample was restricted to those students who had remained in the same school during both the base year and first follow up surveys (step 2). Third, students who identified as a race other than Asian, Black, Hispanic, and White were excluded from the analysis (step 3).

The final two scope conditions were applied as needed for the construction of the variable for racialized tracking. For the fourth step, the selection of schools students came from had to have some degree of racial diversity. After Muller et al. (2010), "diverse" schools were selected such that they had at least 25% Asian and White student population and at least a 7% Black or Hispanic student population (step 4). Preliminary analysis applying scope conditions revealed 29 cases from one school that was missing official data for school racial composition. To approximate racial composition data from this school, aggregates from the student-level data were used. Official data for school racial composition were regressed on aggregated racial composition and the calculated prediction for this school was imputed for these missing values. Finally, schools students hailed from had to have variation in the proportion of students in advanced courses; students in schools with < 10% of students in advanced courses or > 90% of students in advanced courses were excluded from the analysis (step 5). See Table 3-8 for sample means on a selection of control variables at each step of the restriction of the sample given these scope conditions.

One final case was excluded from the analysis due to missing data on base year enrollment (step 3); that is, it could not be determined whether or not the student had remained in the same school during the base year and first follow up surveys. The final analytic sample for this analysis included 6,998 students across 414 schools (compared to over 25,000 students across 944 students in the original HSLS sample).

Missing Data Management

In most cases, the proportions of data missing were considered manageable. The one exception in this study was for variables supplied by science teachers (on resources and opportunity to learn) where missing data proportions were approximately 40% or higher. Thus, these variables were not included in primary analyses; instead, descriptive statistics on these variables were compiled in an attempt to glean information based on observed data only.

Table 3-8. Selected Sample Means and Proportions After Each Step of Scope Condition Application

	Full Sample		Step 1		Step 2	
	n	*M*	*n*	*M*	*n*	*M*
Asian						
Male	24243	0.044	20594	0.042	18642	0.046
Female	24243	0.043	20594	0.041	18642	0.046
Black						
Male	24243	0.058	20594	0.054	18642	0.060
Female	24243	0.052	20594	0.050	18642	0.056
Hispanic						
Male	24243	0.085	20594	0.079	18642	0.087
Female	24243	0.083	20594	0.080	18642	0.088
White						
Male	24243	0.276	20594	0.282	18642	0.311
Female	24243	0.265	20594	0.277	18642	0.306
Other						
Male	24243	0.049	20594	0.048	18642	0.000
Female	24243	0.046	20594	0.047	18642	0.000
SES	21992	0.042	18866	0.075	16997	0.079
Mathematics Score	21444	0.035	18623	0.090	16763	0.095
Peer academic orientation	15861	12.040	15861	12.040	14379	12.067
Generational Status						
First generation	15443	0.063	13939	0.061	12599	0.063
Second generation	15443	0.122	13939	0.122	12599	0.124
Third generation	15443	0.815	13939	0.817	12599	0.813
School mean SES	25206	0.052	20594	0.054	18642	0.057
School % White/Asian	25206	0.696	20594	0.701	18642	0.703
Total *n*	25206		20594		18642	

Table 3-8. (continued)

	Step 3		Step 4		Step 5	
	n	*M*	*n*	*M*	*n*	*M*
Asian						
Male	15754	0.048	9029	0.061	6999	0.063
Female	15754	0.049	9029	0.062	6999	0.063
Black						
Male	15754	0.053	9029	0.059	6999	0.058
Female	15754	0.051	9029	0.055	6999	0.052
Hispanic						
Male	15754	0.085	9029	0.094	6999	0.095
Female	15754	0.083	9029	0.092	6999	0.094
White						
Male	15754	0.321	9029	0.296	6999	0.295
Female	15754	0.311	9029	0.281	6999	0.280
Other						
Male	15754	0.000	9029	0.000	6999	0.000
Female	15754	0.000	9029	0.000	6999	0.000
SES	14377	0.115	8248	0.107	6405	0.124
Mathematics Score	14186	0.149	8119	0.184	6318	0.210
Peer academic orientation	12401	12.204	7158	12.184	5555	12.228
Generational Status						
First generation	10847	0.063	6194	0.074	4840	0.077
Second generation	10847	0.124	6194	0.150	4840	0.154
Third generation	10847	0.814	6194	0.776	4840	0.769
School mean SES	15754	0.073	9029	0.064	6999	0.078
School % White/Asian	15754	0.715	9029	0.662	6999	0.663
Total *n*	15754		9029		6999	

Table 3-9 displays the frequencies of missing data for those variables for which missing data were considered manageable.

Table 3-9. Missing Data Frequencies

	Missing	
Variable	*n*	%
Science Outcomes		
Science self-efficacy	308	4.4
Science identity	235	3.4
Science engagement		
Emotional (utility)	219	3.1
Behavioral	1372	19.6
Cognitive	1379	19.7
Career Aspirations in STEM	2092	29.9
Socioeconomic Status	594	8.5
Mathematics score	680	9.7
Parental expectations	2277	32.5
Generational status indicators	2159	30.9
Peer academic orientation	1443	20.6
Racialized tracking	95	1.4

Analyses were conducted using Full Information Maximum Likelihood (FIML) in Mplus version 7.0. FIML estimates model parameters despite missing values using all available covariate data. Likelihood functions are estimated for each individual based on the all data present in order to maximize power (Davey & Savla, 2010).

Descriptive Statistics on Science Teacher Variables

(Resources/Opportunity to Learn)

Descriptive statistics on science teacher variables are provided in Table 3-10.

Table 3-10. Descriptive Statistics for Science Teacher Variables including Resources and Opportunity to Learn

	M	*SD*	Min	Max	*n* Observed
Regular Certification	0.83	0.38	0	1	4656
Years	10.92	8.91	1	48	4653
Perceptions					
Teacher quality	27.21	3.50	14	32	4205
Teaching emphases					
High order	16.79	2.41	8	20	3597
Low order	7.32	0.86	4	8	3652
Connections	6.15	1.30	2	8	3634
Limits on teaching					
Poor climate	16.79	4.84	8	32	4211
Lack of resources	11.80	4.73	6	24	3807
High demands	8.48	2.72	4	16	3761
Challenging students	7.36	2.52	3	12	4064
Lack of support	6.99	2.67	4	16	3639

Obtaining means by race demonstrates where students of color may be at a disadvantage when it comes to teacher quality, resources, and opportunity to learn (see Table 3-11).

Table 3-11. Science Teacher Variables by Race including Resources and Opportunity to Learn

	Characteristics		Perceptions	Teaching Emphases		
	Reg Cert	Years	Tchr Quality	High Order	Low Order	Connect
Asian						
M	0.86	11.75	27.57	17.02	7.30	6.07
n	580	579	522	419	427	425
Asian-White Difference	(+) 0.03	(+) 0.54	(+) 0.40	(+) 0.16	(+) 0.00	(−) 0.09
Black						
M	0.79	9.78	27.38	16.60	7.42	6.23
n	498	498	436	371	373	375
Black-White Difference	(−) 0.05	(−) 1.43	(+) 0.21	(−) 0.27	(+) 0.11	(+) 0.08
Hispanic						
M	0.81	10.04	27.01	16.48	7.33	6.11
n	830	830	757	639	655	650
Hispanic-White Difference	(−) 0.03	(−) 1.17	(−) 0.16	(−) 0.38	(+) 0.03	(−) 0.05
White						
M	0.84	11.21	27.17	16.86	7.30	6.16
n	2748	2746	2490	2168	2197	2184

Table 3-11. (continued)

	Limitations on Teaching				
	Poor Climate	Lack of Resources	High Demands	Challenging Students	Lack of Support
Asian					
M	16.10	11.75	8.36	7.24	7.09
n	519	475	484	513	466
Asian-White Difference	(−) 0.68	(−) 0.01	(−) 0.08	(−) 0.06	(+) 0.14
Black					
M	16.87	11.80	8.52	7.61	6.83
n	428	388	379	429	369
Black-White Difference	(+) 0.09	(+) 0.05	(+) 0.08	(+) 0.31	(−) 0.12
Hispanic					
M	17.22	11.99	8.65	7.49	7.10
n	752	689	697	733	667
Hispanic-White Difference	(+) 0.43	(+) 0.24	(+) 0.21	(+) 0.18	(+) 0.15
White					
M	16.79	11.75	8.44	7.31	6.96
n	2512	2255	2201	2389	2137

While the extent to which conclusions can be drawn from these data are limited due to missing data considerations, what the available data suggest is that students of color are more likely to have teachers that are less experienced, emphasize lower order skills in their teaching, and have a higher degree of limitations on their teaching when compared to the teachers of White students.

Data Screening & Re-coding

For variables included in primary analyses, data were screened for normality, linearity, outliers, and missing values. To assess normality, histograms as well as statistics for skewness and kurtosis were examined and assessed given accepted standards for normality (i.e., where statistics for skewness and kurtosis are zero for a perfect normal distribution and skewness greater than 2 and kurtosis greater than 7 are considered moderately nonnormal, Curran, West, & Finch, 1996; Kline, 2011). To assess for linearity, bivariate relationships among the variables were screened as were a matrix of scatter plots for relationships between pairs of variables in the analysis. Bivariate correlations were also examined to identify potential problems with multicollinearity (i.e., where r is higher than .85, Kline, 2011). Univariate outliers were identified using outlier labeling rules from Hoaglin and Iglewicz (1987) and through visual inspection of histograms for the distribution of scores for each variable.

Screening revealed two variables with univariate outliers and one variable that had a severely non-normal distribution. For those variables with univariate outliers, behavioral engagement and peer academic orientation, outlier values were recoded. For behavioral engagement, 62 cases were recoded to the lowest acceptable observed value of 4. For peer academic orientation, 31 cases were recoded to the lowest acceptable observed value of 5. Only one variable had to be recoded due to severe non-normality as revealed given an examination of the histogram of its distribution–racialized tracking. This was largely due to the large number of students in schools (i.e., students from 119 schools) where there were zero Black or Hispanic students represented in advanced coursework and thus had a maximum value for the variable. Given this, the variable was recoded to serve as a binary indicator for racialized tracking in schools such that 1 indicated the student was in a school where Black or Hispanic students were underrepresented in advanced coursework (all values greater than 0 for the original values of the variable) and 0 indicated the student was in a school where Black or Hispanic students were not underrepresented in advanced coursework or may have been overrepresented (all values zero and below for the original values of the variable).

Bivariate correlations among continuously measured study variables and normality statistics for skewness and kurtosis are presented in Table 3-12.

Data were also screened for the extent to which the hierarchical nature of these data (i.e., the fact that students were nested in schools) was reflected in the outcome variables. Typically, multi-level modeling is required given the sampling structure of the HSLS. The HSLS utilized a two-stage, stratified random sampling method where schools were selected as primary sampling units from which students were randomly selected. Multi-level analysis means to account for the non-independence of cases within schools, preventing the suppression of standard errors and subsequent inflated risk of Type 1 error.

Table 3-12. Bivariate Pearson Correlations among Continuous Variables

Variable	1	2	3	4	5	6	7	8	9	10	11
Science Outcomes											
1. Self-efficacy	--										
2. Science Identity	**.52**	--									
Engagement											
3. Emotional (utility)	**.39**	**.56**	--								
4. Behavioral	**.41**	**.30**	**.25**	--							
5. Cognitive	**.44**	**.30**	**.24**	**.53**	--						
6. SES	**.10**	**.17**	**.08**	**.10**	**.07**	--					
7. Mathematics Score	**.15**	**.25**	**.19**	**.10**	**.11**	**.42**	--				
8. Parental expectations	**.10**	**.18**	**.16**	**.12**	**.09**	**.26**	**.37**	--			
9. Peer acad. orientation	**.14**	**.17**	**.14**	**.22**	**.16**	**.36**	**.38**	**.26**	--		
10. School % White/Asian	.02	**.03**	-.01	.03	**.03**	**.20**	**.11**	.01	**.12**	--	
11. School mean SES	**.07**	**.10**	**.04**	**.07**	**.03**	**.52**	**.34**	**.21**	**.35**	**.38**	--
Skewness	-0.32	0.03	-0.52	-0.89	-1.21	0.31	-0.11	-0.45	-0.61	-0.62	0.44
Kurtosis	-0.11	-0.61	0.57	0.30	1.08	-0.20	-0.13	-0.42	0.05	-0.68	0.02

Note. Correlations significant at $p < .05$ denoted with bold font.

To assess the extent to which students' affective ratings and career aspirations were affected by clustering within schools, intra-class correlation coefficients (ICCs) were estimated (in the case of the dichotomous outcome, STEM career aspirations, a modified ICC was estimated, see Twisk, 2006, p. 46). ICCs serve as an estimate of the between-group variance in a variable, or the degree to which the variance is affected by clustering. In instances where ICC values are less than .05 (i.e., less than 5% of the variable variance is due to clustering), multilevel modeling is not necessary (Bickel, 2007). Table 3-13 contains ICC values for each of the dependent variables in this study for students clustered in schools.

Table 3-13. Intra-class Correlation Coefficients for Science Outcomes by School

Dependent Variable	ICC
Science Self-efficacy	0.042
Science Identity	0.034
Science Engagement	
Emotional Engagement (utility)	0.019
Behavioral Engagement	0.046
Cognitive Engagement	0.035
STEM Career Aspirations	0.009

Given all ICC values were less than .05 for the dependent variables in the study, analyses proceeded without attending to the multilevel structure of the data (i.e., the amount of between-group variance was so low as to warrant aggregation across schools).

Descriptive Statistics for Analytic Sample

Descriptive statistics for the analytic sample are presented in Table 3-14. Means are provided for continuous variables; for dichotomous and binary categorical variables, means represent proportions in the data. Statistics are presented as weighted and unweighted; NCES provides analytic weights to account for over-sampling of specific student populations and survey nonresponse. This study used the weight W2W1PAR, appropriate for analyses of student responses across the base year and first follow-up along with responses from the parent survey.

As Table 3-14 shows, for NCES constructed scales that were *z*-standardized with the original HSLS sample, mean scores for science self-efficacy, identity, and utility for this sample were around zero (i.e., the mean for the larger HSLS student sample). In general, students indicated generally high levels of both behavioral and cognitive engagement with mean ratings around 8 with a max of 10. Across the sample, 49% of the students aspired to a STEM career as broadly defined for the purpose of this study.

The unweighted sample was approximately 13% Asian, 11% Black, 19% Hispanic, and 56% White, with about equal proportions of males and females within each racial group. In addition, this sample was slightly higher in socioeconomic status and mathematics test scores given means slightly higher than zero for this sample on scales originally *z*-standardized with the larger HSLS student sample. The unweighted sample also included 8% first generation students, 16% second generation students, and 75% third generation students. In general, students rated their peers' academic orientation as relatively high with a mean rating of 12 (min = 5, max = 16).

Table 3-14. Descriptive Statistics for the HSLS Analytic Sample (6,998 students across 414 schools)

	Unweighted		Weighted		Range	
	M	*SD*	*M*	*SD*	Min	Max
Science Outcomes						
Science self-efficacy	0.044	1.012	0.064	0.997	-2.47	1.64
Science identity	0.056	1.016	0.075	1.004	-1.74	1.86
Science Engagement						
Emotional (utility)	0.018	0.984	-0.016	0.969	-2.30	1.00
Behavioral	8.314	1.522	8.306	1.519	4.00	10.00
Cognitive	8.304	1.834	8.390	1.820	2.00	10.00
Career Aspirations in STEM	0.492	0.500	0.522	0.500	--	--
Race/gender						
Asian	0.126	--	0.051	--	--	--
Male	0.063	--	0.024	--	--	--
Female	0.063	--	0.027	--	--	--
Black	0.110	--	0.142	--	--	--
Male	0.058	--	0.059	--	--	--
Female	0.052	--	0.082	--	--	--
Hispanic	0.189	--	0.257	--	--	--
Male	0.095	--	0.127	--	--	--
Female	0.094	--	0.129	--	--	--
White	0.575	--	0.551	--	--	--
Male	0.295	--	0.287	--	--	--
Female	0.280	--	0.264	--	--	--
Socioeconomic Status	0.130	0.791	0.039	0.815	-1.75	2.57
Mathematics Score	0.209	0.952	0.207	0.946	-2.48	2.92
Parental Expectations	7.047	2.283	7.139	2.228	1.00	10.00
Generational Status						
1st Generation	0.082	--	0.063	--	--	--
2nd Generation	0.162	--	0.156	--	--	--
3rd Generation	0.756	--	0.781	--	--	--
Peer Academic Orientation	12.114	2.454	11.940	2.364	5.00	16.00
School Characteristics						
Racialized Tracking	0.663	--	0.692	--	--	--
% White/Asian	0.663	0.180	0.633	0.184	0.25	0.93
Mean Socioeconomic Status	0.078	0.401	0.047	0.358	-0.85	1.51

Note. NCES provides analytic weights to account for over-sampling of specific student populations and survey nonresponse. This study used the weight W2W1PAR, appropriate for analyses of student responses across the base year and first follow-up along with responses from the parent survey. Means for dichotomous indicators represent proportions in the data.

In terms of school characteristics, 66% of students in the unweighted sample attended schools with racialized tracking and the average racial composition of students' schools was 66% Asian/White. Students were also in schools that were slightly higher in socioeconomic status compared to schools across the HSLS sample in that the means (both weighted and unweighted) are slightly above zero.

Data Analysis

I anticipated that students of color would be less likely to aspire to careers in science and indicate lower affective ratings in science in comparison to White students. I also anticipated that school racial composition would moderate these race on outcome effects such that students of color in predominantly White schools may be at a larger disadvantage compared to students in more racially diverse schools. In addition, I expected that racialized tracking (operationalized as school academic opportunity structure) would mediate the effects of school racial composition on student science outcomes. Finally, I anticipated that analyses by race/gender as opposed to race alone would reveal a more nuanced understanding of where inequalities lie in examining these STEM outcomes for students.

Preliminary analyses revealed essentially no difference in effects for student science outcomes on race (or race/gender) given school racial composition (i.e., for this sample, school racial composition was not acting as a moderator). Given this, the focus of the analyses turned to racialized tracking as a moderator of effects for science outcomes on race (or race/gender). That is, I anticipated that racialized tracking would moderate the effects of race on student affective ratings in science and STEM career aspirations.

To determine if students of color had lower affective ratings in science, linear regression models were estimated in Mplus version 7.0 and coefficients for race were interpreted as differences in ratings/aspirations versus White students (as a reference group), holding all else constant. To determine if racialized tracking moderated these effects, interactions were introduced between race variables and the dichotomous indicator for racialized tracking. This allowed for 1) an interpretation of the interaction effect to determine the extent to which Black-White or Hispanic-White differences were widened in schools with racialized tracking and 2) an interpretation of the conditional effects for student race in schools without racialized tracking. Finally, to examine how analyses by race/gender provided a more nuanced understanding of these dynamics, models were re-estimated utilizing variables for race/gender as opposed to variables for race and gender alone.

Analyzing racial differences in STEM career aspirations required modified analysis techniques given the binary structure of the variable. Instead of linear regression, logistic regression analyses were conducted in Mplus. Coefficients were estimated as logit coefficients and to ease interpretation odds ratios were calculated. Odds ratios, calculated by taking the exponential function of the logit coefficient for a predictor, represents the proportionate difference in the odds on the dependent variable given a one unit change in the predictor. In instances where the predictor variables are continuous, positive semi-standardized odds ratios are provided as a supplement in the text to indicate the change in odds given a one-standard deviation unit change in the predictor. If the odds ratio for a predictor variable is calculated by $OR = e^{\beta}$, where β is the logit coefficient, then the positive semi-standardized form is calculated by $SS^{OR} =$

$e^{|\beta| * S.D.}$, using the absolute value of the logit coefficient and where S.D. is the standard deviation of the predictor (Kaufman, 1996).

It should be noted that an alpha level of $p < .05$ was adopted for all of the subsequent analyses. To account for multiple comparisons given analyses by race alone and race/gender, some researchers may assert that one needs to account for multiple comparisons by adjusting the alpha level by the number of analyses (here 2 such that $p < .05/2 = .025$). However, such a correction could also be problematic since as analyses become more detailed by race/gender, the likelihood of obtaining significance is diminished (Moran, 2003). The concern here is a practical one: in this context given both rationales for examining effects by race and race/gender and the reality that researchers often approach the issue from one standpoint or the other (at least as presented in published research), I do so here utilizing the *p* value of .05 as used in the broader literature. This $p < .05$ standard was adopted with the understanding that the use of multiple comparisons and a large number of analyses increases the risk of Type 1 error making this a potential limitation of the study.

Limitations

In addition to the increased risk of Type I error due to the adoption of a $p < .05$ standard for all subsequent analyses, there are other limitations to this study that must be acknowledged. First, the dependent variables measuring students' affective ratings of self-efficacy, identity, and engagement are all scales made up of a very limited number of items. This raises questions regarding the validity of these constructs and the extent to which each meaningfully measures the constructs identified. Absent validation studies for these constructs, all drawn conclusions must be interpreted in light of this concern.

In addition, the inclusion of racialized tracking as a moderator is not expected to hugely contribute to the change in R^2 between the models given (1) the small amount of variance in the dependent variables at the school-level (see Table 3-13) and (2) the crude measure of racialized tracking as a dichotomous indicator. The reality of examining these student-level science outcomes is that getting at institutional-level predictors given quantitative methods is difficult given the tendency of these methods to underestimate effects of institutional factors. As O'Connor et al. (2007) explain, for example, including prior achievement as a control variable is often assumed to be a valid means of taking students' prior academic ability into account, rather than serving as a proxy for students' exposure to educational opportunity. As they note, "previous achievement may well serve as a proxy for racial discrimination–systematically poor educational experiences and opportunities" captured in student test scores (p. 546). In this context, it may be expected that a binary indicator for racialized tracking may not contribute largely to the proportion of variance explained in the dependent variables but still demonstrate a significant effect that is illustrative dynamics more readily apparent given qualitative examinations of racialized tracking in schools.

Furthermore, these models are expected to account for small portions of the variance in the measured outcomes given the explicit focus on variables for race and racialized tracking alongside a limited number of control variables. As with any study, it is possible that there are variables omitted from this study that, if included, could change the results observed. Given recent research on the effects of familial characteristics in the promotion of STEM aspirations and orientation for students (e.g., Dabney, Chakraverty, & Tai, 2013), one potential set of variables that could be valuable in this regard are those of family capital (i.e., social and cultural capital derived from the family, Kanno & Cromley, 2013). While this study did control for student socioeconomic status and parental expectations for attainment, other family capital variables could include family composition (i.e., two-parent vs. single parent) or whether or the student has a parent currently employed in a STEM field (Moakler & Kim, 2014). Given the focus of this study on school institutional factors as influencing student science outcomes, these additional family capital variables were not viewed as vital to the models and were thus not included. In addition to the possibility that relevant variables were omitted from this study, it is also possible that the large number of tests conducted in this study have contributed to Type I error causing some significant findings to be spurious.

Finally, there are three concerns regarding research design and results interpretation that should be mentioned. The first has to do with the use of both White students and White males as reference categories in this research. While this approach is appropriate given the standing of White students and particularly White males in positions of advantage with science fields, it supports an underlying approach to scholarship in which Whiteness is positioned as the ideal to be obtained. Hopefully, recognizing the problematic nature of such an approach and explicitly rejecting this underlying assumption helps repositioning the use of this approach as a tool for drawing out inequalities rather than lionizing Whiteness as a universal standard. Additionally, while the results of these analyses will be interpreted using causal language in terms of the effects of predictor variables on measured outcomes, it should be noted that causality is notoriously difficult to establish and in many ways this study falls short of what might be considered "gold standard" approaches in establishing causal effects with observational data (e.g., propensity scores, see Schneider, Carnoy, Kilpatrick, Schmidt, & Shavelson, 2005). Thus, interpretations stated using causal language must be interpreted with this mind. Finally, and related to high standards of establishing causality, it should be noted that both the dependent variables in this study and racialized tracking were measured during the HSLS first follow-up in 2012. Since these variables were measured at the same time-point, it is possible that science self-efficacy, identity, engagement, and aspirations predict placement into advanced coursework; in other words, the threat of reverse causality is an issue. Future studies could improve on this research by controlling for lagged dependent variables (student affective ratings and aspirations measured during the base year in 2009), measuring racialized tracking in 2009, or incorporating a cross-lagged path model design, each of which would strengthen causal arguments.

CHAPTER 4

RESULTS

In this chapter, I present the results of regression analyses examining (1) differences in affective ratings and STEM career aspirations between White students and students of color, (2) the extent to which racialized tracking in schools moderates these effects, and (3) how the interpretation of these results differ when modeled with race/gender variables versus race alone (i.e., aggregated by race). These three points will be addressed for affective ratings in science (self-efficacy, identity, engagement [emotional, behavioral, cognitive]) as well as for STEM career aspirations. The results of regression models specified are presented in Tables 4-1 through 4-12.

As will be discussed, the results reported herein showed that for this sample, Hispanic students' affective ratings in science were lower than those of their White counterparts. In addition, results showed that Black students' affective ratings were generally on par with their White counterparts and that Black students had STEM career aspirations that were commensurate with or exceeded those of their White counterparts. Results also showed that racialized tracking moderated effects of race on affective ratings for Hispanic students as well as the effects of race on career aspirations for Black students. Furthermore, while more detailed analyses by race/gender did promote a more nuanced understanding of these dynamics, there were clear instances where results aggregated by race were both appropriate given trends visible by race/gender and more straightforward. Following a detailed reporting of these results, I report on general trends and provide an overall summary of the results.

Science Self-Efficacy

Regression results for science self-efficacy are presented in Tables 4-1 and 4-2, first by race and gender separately and then by race/gender. In each instance, the chi square tests for the independence models were significant (χ^2 = 92.91-18.02, *p*s = .000) indicating that the relationships specified between science self-efficacy and the predictors were meaningful. These models accounted for approximately 9-10% of the variance in student science self-efficacy.

Self-efficacy: Differences by Race (RQ1)

Model 1 in Table 4-1 shows the racial gaps that exist in science self-efficacy across schools. While Asian students self-efficacy ratings were on par with White students (β = -.055, *p* = .719), Black students' ratings were higher in comparison to White students by .263 standard deviations, holding all else constant (*p* = .004). By contrast, Hispanic students' ratings were lower than White students by .265 standard deviations (*p* = .005). Females' ratings were also lower than males by .278 standard deviations (*p* = .000). There were no significant effects of racialized tracking overall, however this model assumes that the effects of racialized tracking are the same for students of all races.

Table 4-1. Regression Results of Science Self-Efficacy on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race[a]						
Asian	-0.055	0.151	-.055	-0.293	0.195	-.297
Black	0.263**	0.092	.263	0.204	0.145	.203
Hispanic	-0.265**	0.095	-.265	-0.072	0.126	-.073
Female	-0.277***	0.058	-.278	-0.271***	0.058	-.272
Socioeconomic Status	0.069†	0.039	.056	0.065†	0.039	.053
Mathematics Score	0.119**	0.042	.113	0.117**	0.041	.111
Parental Expectations	0.024	0.016	.055	0.024	0.016	.055
Generational Status[a]						
1st Generation	0.302*	0.142	.301	0.302*	0.137	.301
2nd Generation	0.142	0.111	.144	0.140	0.110	.141
Peer Academic Orientation	0.040*	0.016	.096	0.04*	0.016	.094
School Characteristics						
Racialized Tracking	-0.037	0.060	-.037	0.024	0.075	.024
% White/Asian	-0.003	0.200	-.001	0.014	0.198	.003
Mean Socioeconomic Status	-0.202*	0.094	-.072	-0.205*	0.093	-.074
Interaction Effects						
Asian*Racialized Tracking				0.303	0.236	.307
Black*Racialized Tracking				0.068	0.171	.068
Hispanic*Racialized Tracking				-0.294†	0.155	-.294
Intercept	-0.452†	0.251	-.453	-0.497*	0.253	-.499
Loglikelihood			-65944.390			-54615.025
χ^2 H_0			92.914***			105.966***
df			13			16
R^2			.086			.092

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White, 3rd generation

Table 4-2. Regression Results of Science Self-Efficacy on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race/Gender[a]						
Asian Male	-0.162	0.134	-.165	-0.016	0.200	-.013
Asian Female	-0.239	0.235	-.242	-0.869**	0.276	-.874
Black Male	0.273*	0.130	.275	0.445*	0.181	.448
Black Female	-0.029	0.125	-.029	-0.230	0.208	-.229
Hispanic Male	-0.265†	0.136	-.267	-0.126	0.181	-.126
Hispanic Female	-0.554***	0.111	-.553	-0.294†	0.172	-.295
White Female	-0.282***	0.073	-.284	-0.292*	0.128	-.293
Socioeconomic Status	0.068†	0.039	.056	0.061	0.039	.050
Mathematics Score	0.119**	0.042	.113	0.117**	0.041	.111
Parental Expectations	0.025	0.016	.055	0.025	0.016	.055
Generational Status[a]						
1st Generation	0.305*	0.141	.305	0.288*	0.137	.288
2nd Generation	0.143	0.114	.143	0.138	0.112	.138
Peer Academic Orientation	0.040*	0.016	.094	0.040*	0.016	.094
School Characteristics						
Racialized Tracking	-0.037	0.060	-.037	0.018	0.114	.020
% White/Asian	-0.007	0.201	-.001	0.004	0.200	.001
Mean Socioeconomic Status	-0.200*	0.096	-.072	-0.202*	0.096	-.073
Interaction Effects						
AM*Racialized Tracking				-0.184	0.218	-.186
AF*Racialized Tracking				0.796*	0.370	.792
BM*Racialized Tracking				-0.228	0.220	-.231
BF*Racialized Tracking				0.263	0.242	.263
HM*Racialized Tracking				-0.224	0.232	-.225
HF*Racialized Tracking				-0.371†	0.201	-.371
WF*Racialized Tracking				0.013	0.151	.013

Table 4-2. (continued)

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Intercept	-0.440[†]	0.247	-.441	-0.481[†]	0.253	-.482
Loglikelihood			-56821.046			-18748.625
χ^2 H_0			94.131***			118.024***
df			16			23
R^2			.087			.096

Note. [†]$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White male, 3rd generation.

Self-efficacy: Moderation of Effects by Racialized Tracking (RQ2)

To relax this assumption, interactions were specified between student race and racialized tracking in Table 4-1, Model 2 (ΔLRS = 11329.365, *p* = .000. There was a marginally significant interaction effect for Hispanic students indicating that the difference in ratings for Hispanic students' science self-efficacy would be exacerbated in schools with racialized tracking by .294 standard deviations (*p* = .057). Since the addition of race*racialized tracking interactions made the interpretation of the main effects conditional (so that any race effects were in reference to students attending a school without racialized tracking), Model 2 in Table 4-1 shows that the Hispanic-White difference in ratings was attenuated in schools without racialized tracking. In such schools, there was not a significant gap in science self-efficacy ratings in comparison to White students (β = -.073, *p* = .567).

Self-efficacy: Results by Race/gender (RQ3)

Breaking these effects out by race/gender provides a more nuanced look at which students are at a disadvantage when it comes to science self-efficacy. Model 1 in Table 4-2 shows differences in science self-efficacy by race/gender, holding all else constant. Similar to the prior model, examining race effects apart from gender, there appear to be no significant difference in science self-efficacy ratings when comparing either Asian males (β = -.165, *p* = .227) or Asian females (β = -.242, *p* = .308) to White males. However, the advantage for Black students was driven primarily by Black males in the sample such that Black males' science self-efficacy ratings were higher than those of White males by .275 standard deviations, holding all else constant (*p* = .035); there was not a significant difference comparing Black females and White males (β = -.029, *p* =

.816). Both Hispanic males and Hispanic females' ratings were lower in comparison to White males. Hispanic males' ratings were .267 standard deviations lower than White males, although this effect was marginally significant (p = .052) whereas Hispanic females' ratings were .553 standard deviations lower than White males, an effect that was statistically significant (p = .000). White females' ratings were also lower than White males by -.284 standard deviation units (p = .000).

Model 2 in Table 4-2 shows how racialized tracking moderates these effects (ΔLRS = 38072.421, p = .000). There was a marginally significant interaction effect for Hispanic females such that being in a school with racialized tracking exacerbated the Hispanic female-White male difference in ratings by .371 standard deviations (p = .065). The main effect for Hispanic females (now conditional on being in a school without racialized tracking) shows that the large and highly significant gap in ratings compared to White males was diminished in size and became marginally significant (β = -.295, p = .088). In addition, although there was not a significant interaction effect for Hispanic males, the conditional effect in Model 2 shows that there was no significant gap in ratings of science self-efficacy for Hispanic males compared to White males in schools with no racialized tracking (β = -.126, p = .489). In addition, there was a significant, positive interaction effect for Asian females such that racialized tracking benefited Asian females in terms of their science self-efficacy (β = .792, p = .031). Prior to adding interactions between race/gender and racialized tracking, Asian females' ratings did not differ significantly compared to those of White males (β = -.242, p = .308). However, the conditional effect for Asian females in Model 2 shows that Asian females' ratings in schools with no racialized tracking were .874 standard deviations lower than White males, holding all else constant (p = .002). White females' ratings in schools without racialized tracking were similar to White females' ratings across schools, scoring .293 standard deviations lower than White males (p = .023).

Comparing results by race only (Table 4-1) to those by race/gender (Table 4-2) reveals where results by race only might obscure substantive distinctions in the results; specifically, such a comparison more readily reveals where aggregation by racial subgroups for males and females might be inappropriate. For one, the effects for Asian students in Table 4-1 suggest no differences in science self-efficacy given comparing students in schools with or without racialized tracking. However, effects by race/gender in Table 4-2 suggest that Asian females' science self-efficacy ratings are bolstered in schools with racialized tracking. In addition, consider the effects for Hispanic students in both sets of results. The added value of estimating effects by race/gender shows that this overall effect for Hispanic students found in Table 4-2 seems to be driven more so by effects for Hispanic females in particular.

Self-efficacy: Significant Controls

A number of control variables included in the models did have significant effects on students' science self-efficacy, such as mathematics scores, peer academic orientation, and generational status. Increasing students' mathematics scores by one standard deviation corresponded to around a .10 standard deviation increase in science self-efficacy ratings, holding all else constant (p = .004-.005). Likewise, a one standard deviation increase in students' rating of their peers' academic orientation led to a .10 standard deviation increase in science self-efficacy (p = .010-.012). First generation students' ratings were approximately .30 standard deviations higher than third generation students (p = .027-.036). In addition, in terms of school context controls, a one standard deviation decrease in school mean socioeconomic status corresponded to a decrease in student science self-efficacy ratings by about .07 standard deviations (p = .028-.038).

Science Identity

Regression results for science identity are presented in Tables 4-3 and 4-4. For each set of results, chi square tests for the independence model were significant (χ^2 = 123.72-147.53, *p*s - .000). These models accounted for 11-13% of the variance in student science identity.

Identity: Differences by Race (RQ1)

Model 1 in Table 4-3 provides results for science identity on race demonstrating that while Asian (β = -.055, p = .712) and Black (β = -.069, p = .548) student ratings in science identity did not significantly differ from the ratings of White students, Hispanic students; ratings were significantly lower in comparison. Holding all else constant, Hispanic students' ratings were .284 standard deviations lower than White students (p = .002). In addition, females' ratings were .214 standard deviations lower than males (p = .000). Similar to modeling effects for science self-efficacy, there was no significant effect for racialized tracking (β = .037, p = .537).

Table 4-3. Regression Results of Science Identity on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race[a]						
Asian	-0.057	0.153	-.055	-0.421†	0.247	-.420
Black	-0.068	0.113	-.069	-0.123	0.164	-.123
Hispanic	-0.285**	0.094	-.284	-0.023	0.123	-.023
Female	-0.214***	0.058	-.214	-0.204***	0.057	-.202
Socioeconomic Status	0.146**	0.046	.118	0.143**	0.046	.116
Mathematics Score	0.142***	0.036	.134	0.137***	0.036	.129
Parental Expectations	0.040**	0.014	.089	0.04**	0.014	.089
Generational Status[a]						
1st Generation	0.376**	0.137	.375	0.374**	0.135	.371
2nd Generation	0.113	0.112	.113	0.113	0.111	.113
Peer Academic Orientation	0.034*	0.015	.081	0.032*	0.015	.076
School Characteristics						
Racialized Tracking	0.036	0.058	.037	0.118†	0.069	.117
% White/Asian	-0.030	0.186	-.006	-0.016	0.184	-.003
Mean Socioeconomic Status	-0.174*	0.088	-.062	-0.180*	0.088	-.064
Interaction Effects						
Asian*Racialized Tracking				0.475†	0.267	.473
Black*Racialized Tracking				0.059	0.207	.059
Hispanic*Racialized Tracking				-0.398**	0.145	-.398
Intercept	-0.502*	0.242		-0.550*	0.241	
Loglikelihood			-66095.128			-54747.418
χ^2 H_0			123.718***			138.731***
df			13			16
R^2			.109			.119

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White, 3rd generation.

Table 4-4. Regression Results of Science Identity on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race/Gender[a]						
Asian Male	-0.130	0.164	-.132	-0.426	0.388	-.429
Asian Female	-0.153	0.217	-.155	-0.714*	0.299	-.713
Black Male	0.151	0.151	.152	-0.035	0.235	-.034
Black Female	-0.387*	0.154	-.385	-0.439*	0.216	-.435
Hispanic Male	-0.262*	0.113	-.261	-0.065	0.166	-.063
Hispanic Female	-0.465***	0.121	-.461	-0.283†	0.164	-.283
White Female	-0.156*	0.067	-.154	-0.314**	0.110	-.313
Socioeconomic Status	0.147**	0.045	.120	0.145**	0.045	.118
Mathematics Score	0.148***	0.036	.139	0.147***	0.036	.139
Parental Expectations	0.039**	0.014	.087	0.039**	0.014	.086
Generational Status[a]						
1st Generation	0.375**	0.136	.375	0.373**	0.134	.371
2nd Generation	0.118	0.112	.118	0.117	0.111	.116
Peer Academic Orientation	0.034*	0.015	.080	0.031*	0.015	.073
School Characteristics						
Racialized Tracking	0.031	0.058	.030	0.008	0.094	.007
% White/Asian	-0.029	0.186	-.005	-0.012	0.184	-.002
Mean Socioeconomic Status	-0.188*	0.088	-.067	-0.188*	0.088	-.067
Interaction Effects						
AM*Racialized Tracking				0.388	0.397	.388
AF*Racialized Tracking				0.766*	0.360	.757
BM*Racialized Tracking				0.237	0.296	.236
BF*Racialized Tracking				0.077	0.279	.077
HM*Racialized Tracking				-0.323	0.201	-.323
HF*Racialized Tracking				-0.256	0.200	-.257
WF*Racialized Tracking				0.231†	0.137	.229

Table 4-4. (continued)

Predictor	Model 1			Model 2		
	b	*SE*	β	*b*	*SE*	β
Intercept	-0.517*	0.243		-0.475[†]	0.250	
Loglikelihood			-56955.192			-18870.639
χ^2 H$_0$			126.638***			147.543***
df			16			23
R^2			.114			.126

Note. [†]$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White male, 3rd generation.

Identity: Moderation of Effects by Racialized Tracking (RQ2)

Model 2 in Table 4-3 shows the results after adding interactions for race and racialized tracking into the model (ΔLRS = 11347.71, p = .000). There was a significant interaction effect for Hispanic students such that racialized tracking exacerbated the gap in science identity ratings for these students (β = -.398, p = .006). As the conditional effect for Hispanic students shows, Hispanic students in school without racialized tracking did not have science identity ratings that were significantly different from those of White males (β = -.023, p = .853). In addition, there was a marginally significant interaction effect for Asian students suggesting these students were advantaged in schools with racialized tracking (β =.473, p = .777). The conditional effect for Asian students demonstrated that ratings for Asian students in schools with no racialized tracking were .420 standard deviations lower than White students, holding all else constant (p = .089). In addition, the conditional effect for racialized tracking, representing the effect of racialized tracking for White students, suggests that science identity ratings for White students attending schools with racialized tracking were higher by .117 standard deviations when compared to their counterparts in schools without racialized tracking (although this effect was marginally significant, p = .086).

Identity: Results by Race/gender (RQ3)

Model 1 in Table 4-4 displays results by race/gender, holding student and school characteristics constant. Although there were no significant differences in science identity ratings for Asian males (β = -.132, p = .482), Asian females (β = -.155, p = .479), and Black males (β = .152, p = .318) compared to White males, there were significant differences comparing White males to Black females, Hispanic Males, Hispanic Females, and White females. Black and Hispanic females appeared to be at the largest disadvantage. Holding all else constant, Black females' ratings were .385 standard deviations lower than White males (*p* = .012) whereas Hispanic females' ratings were .461 standard deviations lower than White males (*p* =. 000). Hispanic males were at a disadvantage, too, with ratings .261 standard deviations lower than White males (*p* = .020). In addition, White females' ratings were .154 standard deviations lower than White males (*p* = .021).

Model 2 in Table 4-4 displays results upon adding in race/gender*racialized tracking interaction variables to the model (ΔLRS = 38084.553, *p* = .000). There was a significant interaction effect for Asian females (β = .757, *p* = .034) and a marginally significant interaction effect for White females (β = .229, *p* = .093) such that these students' ratings were higher in schools with racialized tracking. The conditional effects of race/gender for these students also demonstrate these effects. Asian females' ratings in schools without racialized tracking were .713 standard deviations lower than White males (*p* = .017) whereas the results of Model 1 indicated no significant difference between Asian females and White males holding school characteristics constant. Additionally, White females' ratings in schools without racialized tracking were .314 standard deviations lower than their White male counterparts (*p* = .004), an effect that is over double the size of the gap evidenced in Model 1 with school characteristics held constant. There was essentially no effect of racialized tracking for White males given the nonsignificant coefficient for the school characteristic given in Model 2 (β = .007, *p* = .936).

Although significant interaction effects were not observed for Hispanic males and females, comparing Table 4-4 Model 1 effects for race/gender and Model 2 conditional effects for race/gender suggest that racialized tracking has a disparate impact for these student subgroups. In schools without racialized tracking, Hispanic males' science identity ratings did not differ significantly from those of White males (β = -.063, p = .695), although a gap was observed holding school characteristics constant in Model 1 (β = -.261, p = .020). Additionally, the gap for Hispanic females observed in Model 1 (β = -.461, p = .000) appeared to be reduced in size and became marginally significant when comparing Hispanic females and White males in schools without racialized tracking (β = -.283, p = .084).

Overall, the models suggest Asian male and Black students' science identity ratings were largely unchanged regardless of whether or not they attended schools with racialized tracking. Similar to Model 1, there were no significant difference in ratings observed between both Asian males (β = -.429, p = .272) and Black males (β = -.034, p = .880) in schools without racialized tracking versus their White male counterparts. In addition, the negative coefficient for Black females observed in Model 1 while holding school characteristics constant was still observed when comparing ratings for Black females versus those of White males in Model 2 (β = -.435, p = .042).

Comparing Tables 4-3 and 4-4 demonstrates how running results both by race alone and by race/gender can provide a more complete understanding of these data. First, while the results by race/gender clearly show the distinction in Hispanic male and female effects, the results are much more neatly summarized in the results by race alone with the interpretation of a significant interaction effect for Hispanic students alongside the conditional effects for race that show how racial gaps in science identity are diminished for these students in schools without racialized tracking. However, results by race/gender show how both Asian females and White females science identity ratings were higher in schools with racialized tracking–results that are obscured in Table 4-3 when estimating effects by race alone.

Identity: Significant Controls

Several control variables in the model were significant. First generation students' ratings were approximately one-third of a standard deviation higher in science identity than their third generation counterparts (p = .005-.006). A one standard deviation increase in student socioeconomic status or mathematics score contributed to just over a .10 standard deviation increase in science identity (ps = .001-.002 and .000, respectively). Finally, both peer academic orientation and school mean socioeconomic status proved to be significant predictors of science identity. A one standard deviation increase in peer academic orientation corresponded to a .07-.08 standard deviation increase in science identity (p = .024-.044). In addition, in terms of school content controls, a one standard deviation increase in school mean socioeconomic status was associated with a .06-.07 standard deviation decrease in student science identity (p = .033-.048).

Science Engagement

In what follows, results from regression analyses for science engagement on race (or race/gender) are presented, operationalizing science engagement as three separate constructs for (1) emotional engagement (specifically, utility), (2) behavioral engagement, and (3) cognitive engagement.

Emotional engagement

Regression model results for science utility (a proxy for emotional engagement) are presented in Tables 4-5 and 4-6. Chi square values for the independence models were significant ($\chi^2 = 71.17 – 82.23$, *p*s = .000). These models accounted for approximately 7% of the variance in student science utility.

Emotional Engagement: Differences by Race (RQ1)

Table 4-5 shows regression results for science utility on student race. As depicted in Model 1, there were no significant differences for either Asian students (β = .123, *p* = .348) or Black students (β = .066, *p* = .539) versus White students. However, Hispanic students' ratings were significantly lower than White students by .185 standard deviations, holding all else constant (*p* = .036). Female student science utility ratings were not significantly different from those of their male counterparts (β = .034, *p* = .557) and the effect for racialized tracking on science utility was essentially zero (β = .004, *p* = .938).

Emotional Engagement: Moderation of Effects by Racialized Tracking (RQ2)

Model 2 in Table 4-5 shows regression results for emotional engagement in science (or science utility) after adding interaction effects for race and racialized tracking (Δ*LRS* = 11315.572, *p* = .000). While there are no significant interaction effects, the conditional effects of the model are suggestive of differences between the racial groups given racialized tracking in schools. As in Model 1 holding school characteristic constant, there were no significant differences in Model 2 comparing either Asian students (β = .274, *p* = .185) or Black students (β = .166, *p* = .379) to White students in schools without racialized tracking.

Table 4-5. Regression Results of Emotional Engagement in Science (Science Utility) on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race[a]						
Asian	0.085	0.091	.123	0.192	0.145	.274
Black	0.046	0.075	.066	0.116	0.132	.166
Hispanic	-0.130*	0.062	-.185	-0.056	0.093	-.080
Female	0.023	0.042	.034	0.024	0.041	.034
Socioeconomic Status	0.018	0.031	.021	0.016	0.031	.019
Mathematics Score	0.110***	0.027	.149	0.110***	0.027	.149
Parental Expectations	0.013	0.012	.041	0.013	0.012	.042
Generational Status[a]						
1st Generation	0.347***	0.079	.494	0.348***	0.080	.494
2nd Generation	0.058	0.086	.083	0.058	0.087	.083
Peer Academic Orientation	0.020†	0.011	.069	0.020†	0.011	.067
School Characteristics						
Racialized Tracking	0.003	0.043	.004	0.052	0.048	.074
% White/Asian	0.023	0.013	.006	0.033	0.133	.009
Mean Socioeconomic Status	-0.116†	0.067	-.059	-0.116†	0.067	-.059
Interaction Effects						
Asian*Racialized Tracking				-0.144	0.159	-.208
Black*Racialized Tracking				-0.097	0.157	-.137
Hispanic*Racialized Tracking				-0.112	0.113	-.160
Intercept	-0.407*	0.137		-0.442*	0.172	
Loglikelihood			-48278.176			-36962.604
χ^2 H_0			71.172***			73.002***
df			13			16
R^2			.065			.066

Note. $^{\dagger}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$. [a]Omitted: White, 3rd generation.

Table 4-6. Regression Results of Emotional Engagement in Science (Science Utility) on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race/Gender[a]						
Asian Male	0.047	0.108	.066	0.340[†]	0.204	.488
Asian Female	0.119	0.117	.167	-0.030	0.149	-.043
Black Male	0.056	0.122	.080	0.241	0.167	.342
Black Female	0.046	0.096	.065	-0.035	0.183	-.051
Hispanic Male	-0.164[†]	0.084	-.234	-0.111	0.141	-.159
Hispanic Female	-0.093	0.083	-.131	-0.127	0.109	-.181
White Female	0.093	0.049	.007	-0.130[†]	0.077	-.186
Socioeconomic Status	0.018	0.031	.020	0.014	0.031	.016
Mathematics Score	0.110***	0.027	.149	0.111***	0.027	.150
Parental Expectations	0.013	0.012	.041	0.014	0.012	.040
Generational Status[a]						
1st Generation	0.346***	0.079	.490	0.345***	0.079	.490
2nd Generation	0.064	0.084	.091	0.061	0.085	.088
Peer Academic Orientation	0.022*	0.011	.074	0.021*	0.011	.070
School Characteristics						
Racialized Tracking	0.002	0.043	.002	-0.041	0.072	-.059
% White/Asian	0.022	0.135	.006	0.024	0.133	.006
Mean Socioeconomic Status	-0.121[†]	0.067	-.062	-0.113[†]	0.072	-.058
Interaction Effects						
AM*Racialized Tracking				-0.363[†]	0.210	-.522
AF*Racialized Tracking				0.202	0.196	.297
BM*Racialized Tracking				-0.226	0.215	-.325
BF*Racialized Tracking				0.116	0.209	.164
HM*Racialized Tracking				-0.090	0.176	-.128
HF*Racialized Tracking				0.048	0.137	.069
WF*Racialized Tracking				0.197*	0.096	.281

Table 4-6. (continued)

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Intercept	-0.412*	0.172		-0.372*	0.171	
Loglikelihood			-39153.47			-1088.219
χ^2 H_0			71.580***			83.228***
df			16			23
R^2			.066			.073

Note. $^{\dagger}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$. [a]Omitted: White male, 3rd generation.

However, while Model 1 demonstrated that Hispanic students' ratings were significantly lower than White students, holding school characteristics and all else constant (β = -.185, *p* = .036), Model 2 effects for Hispanic students in schools with no racialized tracking compared to their White counterparts showed no significant difference (β = -.080, *p* = .546). That is, in schools without racialized tracking specifically, there were no significant differences in science utility between Hispanic and White students. There was also no significant effect of racialized tracking for White students given the conditional effect for the school characteristic was nonsignificant in Model 2 (β = .074, *p* = .803).

Emotional Engagement: Results by Race/gender (RQ3)

Model 1 in Table 4-6 shows the regression results by race/gender. Comparing Asian males (β = .066, *p* = .663), Asian females (β = .167, *p* = .310), Black males (β = .080, *p* = .647), and Black females (β = .065, *p* = .631) to White males showed that there were no significant differences in science utility between these student subgroups holding school characteristics and all else constant. Effects for Hispanic females (β = -.131, *p* = .263) and White females (β = .007, *p* = .913), too, exhibited no significant differences in science utility when compared with their White male counterparts. However, Hispanic males did differ at least marginally significantly when compared to White males, with ratings lower by .234 standard deviations (*p* = .052).

Model 2 in Table 4-6 displays results after adding interactions between race/gender and racialized tracking to the model (Δ*LRS* = 38065.251, *p* = .000). There was a significant interaction effect for White females such that this student subgroup was at an advantage in schools with racialized tracking (β = .281, *p* = .041). Looking at the conditional effect for White females, results demonstrate that in schools with no racialized tracking, White females' ratings were lower than White males by .186 standard deviations, although this effect is marginally significant (p =.092). There was also a marginally significant interaction effect for Asian males such that this student subgroup was at a disadvantage in schools with racialized tracking (β = -.522, p = .085). The conditional effect for Asian males shows that in schools with no racialized tracking, Asian males' ratings were lower than those of White males by .488 standard deviations (p = .095). In schools without racialized tracking, Asian females (β = -.043, p = .838), Black males (β = .342, p = .149), Black females (β = -.051, p = .849), and Hispanic females (β = -.181, p = .429) ratings on science utility did not differ significantly from those of their White male counterparts; these results echoed what was found holding school characteristics constant in Model 1. However, the marginally significant difference in science utility for Hispanic Males in Model 1 (β = -.234, p = .052) was diminished in Model 2 such that Hispanic Males' ratings did not differ significantly from those of White males in schools without racialized tracking (β = -.186, p = .243).

Comparing results from Tables 4-5 and 4-6 show how results by race/gender might qualify findings estimated by race alone. For example, while results from Table 4-5 suggest that Hispanic students' difference in science utility ratings compared to White students is diminished in schools without racialized tracking, results for race/gender in Table 4-6 show that this result is driven by effects for Hispanic males. In addition, results by race/gender show White female ratings in science utility were higher in schools with racialized tracking. Finally, results in Table 4-6 show how Asian males might actually be at an advantage in science utility in schools without racialized tracking (although this result is conceptually counterintuitive).

Emotional Engagement: Significant Controls

Tables 4-5 and 4-6 show that there were a few student/school characteristics that significantly predicted student science utility ratings. Again, student generational status was a significant predictor of student ratings on science utility such that first generation students' ratings were approximately half a standard deviation higher than those of third generation students ($\beta = .49$, $p = .000$). Student mathematics scores also significantly predicted student science utility ratings such that a one standard deviation increase in achievement corresponded to a .15 standard deviation increase in science utility ($p = .000$). Peer academic orientation was also a significant predictor of science utility; for a one standard deviation increase in peer academic orientation, students' science utility ratings increased by approximately .07 standard deviations, holding all else constant ($p = .040\text{-}.060$). Finally, in terms of school context controls, school mean socioeconomic status negatively predicted science utility such that a one standard deviation increase in mean socioeconomic status corresponded to a .06 standard deviation decrease in science utility.

Behavioral engagement

Regression results for students' behavioral engagement in science are presented in Tables 4-7 and 4-8. Chi square statistics for the independence models were significant ($\chi^2 = 50.23\text{-}66.51$, ps = .000); the models accounted for approximately 7-8% of the variance in student behavioral engagement in science.

Table 4-7. Regression Results of Behavioral Engagement in Science on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race[a]						
Asian	-0.450†	0.268	-.297	-0.049	0.255	-.032
Black	-0.150	0.179	-.097	0.052	0.286	.034
Hispanic	-0.470**	0.163	-.309	-0.489†	0.261	-.323
Female	-0.021	0.103	-.014	-0.026	0.101	-.018
Socioeconomic Status	0.041	0.095	.022	0.039	0.094	.021
Mathematics Score	-0.064	0.068	-.040	-0.058	0.069	-.036
Parental Expectations	0.087**	0.027	.128	0.087**	0.027	.128
Generational Status[a]						
1st Generation	0.035	0.291	.025	0.033	0.289	.021
2nd Generation	0.064	0.220	.041	0.077	0.219	.050
Peer Academic Orientation	0.108***	0.027	.169	0.108***	0.027	.169
School Characteristics						
Racialized Tracking	-0.116	0.105	-.076	-0.070	0.107	-.046
% White/Asian	0.133	0.314	.016	0.129	0.317	.016
Mean Socioeconomic Status	-0.182	0.181	-.043	-0.178	0.181	-.042
Interaction Effects						
Asian*Racialized Tracking				-0.512	0.343	-.338
Black*Racialized Tracking				-0.267	0.356	-.176
Hispanic*Racialized Tracking				0.026	0.288	.019
Intercept	6.570***	0.400		6.541***	0.407	
Loglikelihood			-66928.931			-55613.193
χ^2 H_0			50.247***			53.892***
df			13			16
R^2			.072			.073

Note. $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. [a]Omitted: White, 3rd generation.

Table 4-8. Regression Results of Behavioral Engagement in Science on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race/Gender[a]						
Asian Male	-0.602	0.436	-.402	0.018	0.327	.013
Asian Female	-0.223	0.237	-.149	-0.076	0.343	-.050
Black Male	0.278	0.262	.182	0.096	0.526	.063
Black Female	-0.366	0.228	-.239	0.045	0.341	.029
Hispanic Male	-0.400[†]	0.223	-.264	-0.543	0.370	-.357
Hispanic Female	-0.452*	0.205	-.297	-0.384	0.303	-.253
White Female	0.100	0.107	.066	0.019	0.169	.014
Socioeconomic Status	0.038	0.095	.021	0.036	0.093	.019
Mathematics Score	-0.047	0.065	-.029	-0.037	0.065	-.023
Parental Expectations	0.087**	0.026	.128	0.088**	0.026	.129
Generational Status[a]						
1st Generation	0.025	0.292	.016	0.023	0.289	.016
2nd Generation	0.050	0.220	.033	0.067	0.215	.044
Peer Academic Orientation	0.105***	0.027	.163	0.103***	0.026	.161
% White/Asian	0.084	0.312	.010	0.101	0.314	.012
School Characteristics						
Racialized Tracking	-0.123	0.103	-.080	-0.130	0.157	-.085
Mean Socioeconomic Status	-0.200	0.178	-.047	-0.199	0.178	-.047
Interaction Effects						
AM*Racialized Tracking				-0.754	0.541	-.499
AF*Racialized Tracking				-0.197	0.399	-.127
BM*Racialized Tracking				0.234	0.594	.156
BF*Racialized Tracking				-0.559	0.432	-.366
HM*Racialized Tracking				0.239	0.409	.158
HF*Racialized Tracking				-0.092	0.383	-.062
WF*Racialized Tracking				0.116	0.212	.077

Table 4-8. (continued)

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Intercept	6.588***	0.399		6.591***	0.410	
Loglikelihood			-57784.612			-19731.351
χ^2 H_0			57.294***			66.514***
df			16			23
R^2			.079			.083

Note. [†]$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White male, 3rd generation.

Behavioral Engagement: Differences by Race (RQ1)

Model 1 in Table 4-7 displays regression results for students' behavioral engagement in science on student race, racialized tracking, and student/school control characteristics. As the results show, Hispanic students' behavioral engagement ratings were significantly lower than those White students by about half a point, or .309 standard deviations (p = .004). In addition, Asian students' ratings were significantly lower than those White students to a commensurate degree, although this effect was marginally significant (β = -.297, p = .093). There was no significant difference between the behavioral engagement ratings of Black and White students (β = -.097, p = .404). Additionally, there was neither a significant difference between male and female students (β = -.014, p = .839), nor was there a significant difference between students in schools with or without racialized tracking (β = -.076, p = .267).

Behavioral Engagement: Moderation of Effects by Racialized Tracking (RQ2)

Model 2 in Table 4-7 displays results upon adding in interactions between race and racialized tracking to the model (ΔLRS = 11315.738, p = .000). While none of these interactions were significant, there were some differences observed in the conditional effects for race. Upon the inclusion of race*racialized tracking interactions, the difference in ratings for Hispanic students became marginally significant, although the magnitude of the coefficient remains nearly the same; that is, in schools without racialized tracking, Hispanic students' ratings are still approximately half a point lower, or -.323 standard deviations lower than White students, holding all else constant (p = .061). The gap in ratings between Asian students and White students, however, became nonsignificant such that differences in behavioral engagement ratings between these subgroups is essentially zero in schools without racialized tracking, holding all else constant (β = -.032, *p* = .849). In schools without racialized tracking, Black students' ratings, too, did not differ significantly different from those White students (β = .034, *p* = .856).

Behavioral Engagement: Results by Race/gender (RQ3)

Model 1 in Table 4-8 displays results from the inclusion of race/gender variables in the model, instead of separate race and gender variables. In this model, Hispanic females' ratings were significantly lower than those White males by nearly half a point, or .297 standard deviations, holding all else constant (*p* = .027). Ratings for Hispanic males, too, were lower than those of White males to a similar degree, although this effect was marginally significant (β = -.264, *p* = .072). Aside from these differences between Hispanic and White students, the behavioral engagement ratings of Asian males (β = -.402, *p* = 167), Asian females (β = -.149, *p* = .346), Black males (β = .182, *p* = .288), Black females (β = -.239, *p* = .108), and White females (β = .066, *p* = .350) were not significantly different versus those of White males.

Model 2 in Table 4-8 provides regression results for the model including interactions between race/gender variables and racialized tracking (Δ*LRS* = 38053.261, *p* = .000). Although there were no significant interaction effects observed, conditional effects of race/gender for Hispanic females, indicated that for students in schools without racialized tracking, differences between Hispanic females and White males were not significant (although the size of the coefficient was only slightly smaller, β = -.253, *p* = .849). In addition, the marginally significant Hispanic male-White male gap in ratings observed in Model 1 also became nonsignificant considering students in schools without racialized tracking (again, although the size of the coefficient was similar to what was observed in Model 1, β = -.357, p = .142). Similar to Model 1, behavioral engagement ratings for Asian males (β = .013, p = .956), Asian females (β = -.050, p = .825), Black males (β = .063, p = .856), Black females (β = .029, p = .894), and White females (β = .014, p = .910) in schools without racialized tracking were not significantly different versus those of White males.

Behavioral Engagement: Significant Controls

Among the student and school characteristics included as control variables in predicting behavioral engagement, only two student characteristics emerged as significant predictors–parental expectations and peer academic orientation. Peer academic orientation was a slightly more substantively significant predictor than parental expectations. A one standard deviation increase in students' rating of their peer's academic orientation corresponded to a .16-.17 standard deviation increase in behavioral engagement (p = .000). For a one standard deviation increase in parental expectations for attainment, student ratings on behavioral engagement in science were higher by approximately .13 standard deviations (p = .001).

Cognitive engagement

Regression results for student cognitive engagement in science are displayed in Tables 4-9 and 4-10. Chi square statistics for the independence models were significant (χ^2 = 60.85-68.93, ps = .001) and the models accounted for approximately 7% of the variance in student cognitive engagement in science.

Table 4-9. Regression Results of Cognitive Engagement in Science on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race[a]						
Asian	-0.606*	0.282	-.333	-1.039**	0.381	-.571
Black	-0.019	0.204	-.011	0.239	0.348	.219
Hispanic	-0.761***	0.206	-.419	-0.497†	0.290	-.349
Female	-0.085	0.119	-.046	-0.078	0.118	-.042
Socioeconomic Status	0.098	0.092	.044	0.094	0.093	.042
Mathematics Score	0.041	0.079	.021	0.040	0.079	.021
Parental Expectations	0.026	0.032	.032	0.027	0.031	.033
Generational Status[a]						
1st Generation	0.663**	0.246	.362	0.672**	0.243	.371
2nd Generation	0.52*	0.258	.287	0.496†	0.261	.274
Peer Academic Orientation	0.124***	0.035	.162	0.121***	0.035	.158
School Characteristics						
Racialized Tracking	-0.103	0.123	-.056	0.028	0.126	.015
% White/Asian	0.075	0.339	.008	0.097	0.337	.010
Mean Socioeconomic Status	-0.515**	0.195	-.101	-0.515**	0.195	-.101
Interaction Effects						
Asian*Racialized Tracking				0.535	0.421	.192
Black*Racialized Tracking				-0.353	0.415	-.307
Hispanic*Racialized Tracking				-0.386	0.334	-.374
Intercept	6.903***	0.450		6.826***	0.455	
Loglikelihood			-67930.069			-56609.684
χ^2 H_0			60.847***			64.744***
df			13			16
R^2			.069			.072

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White, 3rd generation.

Table 4-10. Regression Results of Cognitive Engagement in Science on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Race/Gender[a]						
Asian Male	-0.636†	0.341	-.349	-0.815†	0.420	-.448
Asian Female	-0.666†	0.344	-.366	-1.326*	0.521	-.732
Black Male	0.126	0.312	.068	0.574	0.409	.317
Black Female	-0.195	0.267	-.105	-0.059	0.471	-.033
Hispanic Male	-0.804**	0.247	-.441	-0.606	0.383	-.333
Hispanic Female	-0.801**	0.287	-.440	-0.505	0.402	-.277
White Female	-0.073	0.124	-.041	-0.136	0.204	-.075
Socioeconomic Status	0.097	0.092	.043	0.089	0.092	.040
Mathematics Score	0.046	0.079	.024	0.046	0.079	.024
Parental Expectations	0.026	0.031	.031	0.025	0.031	.031
Generational Status[a]						
1st Generation	0.656**	0.248	.358	0.646**	0.244	.354
2nd Generation	0.530*	0.260	.292	0.524*	0.264	.286
Peer Academic Orientation	0.126***	0.035	.163	0.124***	0.034	.161
School Characteristics						
Racialized Tracking	-0.109	0.121	-.061	-0.015	0.180	-.009
% White/Asian	0.063	0.338	.006	0.077	0.336	.008
Mean Socioeconomic Status	-0.531**	0.194	-.104	-0.533**	0.194	-.105
Interaction Effects						
AM*Racialized Tracking				0.211	0.484	.119
AF*Racialized Tracking				0.827	0.605	.453
BM*Racialized Tracking				-0.583	0.548	-.321
BF*Racialized Tracking				-0.196	0.554	-.108
HM*Racialized Tracking				-0.324	0.428	-.180
HF*Racialized Tracking				-0.406	0.508	-.222
WF*Racialized Tracking				0.087	0.252	.049

Table 4-10. (continued)

	Model 1			Model 2		
Predictor	*b*	*SE*	β	*b*	*SE*	β
Intercept	6.896***	0.450		6.847***	0.464	
Loglikelihood			-58804.809			-20752.104
χ^2 H_0			61.239***			68.927***
df			16			23
R^2			.070			.074

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$. [a]Omitted: White male, 3rd generation.

Cognitive Engagement: Differences by Race (RQ1)

Model 1 in Table 4-9 displays regression results for cognitive engagement on separate variables for race and gender, racialized tracking, and student/school control characteristics. Results show that both Asian and Hispanic students' ratings were significantly lower in cognitive engagement when compared to those of White students. Holding all else constant, Asian students' ratings were just over one half of a point, or .333 standard deviations, lower than those of White students (p = .031). Hispanic students' ratings were approximately three-quarters of a point, or .419 standard deviations, lower than the ratings of White students (p = .000). There were no significant differences in cognitive engagement between Black students compared to White students (β = -.011, p = .927). In addition, there were neither significant differences observed between males and females in the sample (β = -.046, p = .746), nor between students in schools with or without racialized tracking (β = -.056, p = .405).

Cognitive Engagement: Moderation of Effects by Racialized Tracking (RQ2)

Model 2 in Table 4-9 displays regression results for cognitive engagement after the inclusion of race*racialized tracking interaction variables (ΔLRS = 11320.385, p = .000). While none of these interaction effects were significant, the conditional effects of race are suggestive of differences when accounting for racialized tracking. In schools without racialized tracking, Asian students' ratings were one point, or just over half a standard deviation, lower in cognitive engagement versus those of White students (β = .571, p = .006); this larger gap between Asian and White students compared with Model 1 when holding school characteristics constant (β = -.073, p = .031) suggests that Asian students are at a larger disadvantage in schools without racialized tracking. Conversely, cognitive engagement ratings for Hispanic students in schools without racialized tracking were about half a point, or .349 standard deviations, lower when compared to their White counterparts–a difference that was marginally significant (*p* = .086). Compared to the Hispanic-White gap in Model 1 (β = -.419, *p* = .000), this indicates that Hispanic students cognitive engagement ratings were slightly higher in schools without racialized tracking, relative to the ratings of their White counterparts.

Cognitive Engagement: Results by Race/gender (RQ3)

Model 1 in Table 4-10 displays results when including race/gender variables in the model as opposed to separate variables for these student characteristics. As the results show, Asian males' and Asian females' cognitive engagement ratings were significantly lower compared to those of White males, although these effects were marginally significant . Ratings for Asian males (β = -.349, *p* = .062 and Asian females (β = -.349, *p* = .053) were just over one half a point, or one-third of a standard deviation, lower than the ratings of White males. In addition, cognitive engagement ratings for Hispanic males and Hispanic females were significantly lower than the ratings of White males by nearly 1 point, or approximately .440 standard deviations, holding all else constant (*p* = .001 and .005, respectively). Black males' (β = .068, *p* = .686), Black females' (β = -.105, *p* = .465), and White females' (β = -.041, *p* = ,554) cognitive engagement ratings did not differ significantly from those of their White male counterparts.

Model 2 in Table 4-10 displays regression results after the inclusion of race/gender*racialized tracking interaction variables to the model (Δ*LRS* = 38052.705, *p* = .000). While none of these interaction effects were significant, the conditional effects for race/gender are suggestive of differential effects given racialized tracking. For instance, in schools without racialized tracking, the Asian male-White male difference in cognitive engagement ratings was larger than what was observed in Model one, though again the difference was marginally significant ($\beta = -.448$, $p = .053$). For Asian females, the effect was significant such that cognitive engagement ratings for Asian females in schools with racialized tracking were over one point, or .732 standard deviations, lower versus those of White males ($p = .011$). While the Asian-White difference for Asian students' cognitive engagement appears to be higher in schools without racialized tracking, the Hispanic-White difference is diminished slightly and is no longer significant. In schools without racialized tracking, cognitive engagement ratings for Hispanic males and Hispanic females were about half a point, or .30 standard deviations, lower than the ratings of White males (p = .114 and .209, respectively). There were no significant differences observed between either Black males ($\beta = .317$, $p = .160$), Black females ($\beta = -.033$, $p = .900$), or White females ($\beta = -.075$, $p = .505$) compared to White males in schools with no racialized tracking.

Here, a comparison of results by race/gender provided only a minor qualification to the results estimated by race alone. As Table 4-10 shows, the advantage for Asian students appeared to be driven by effects for Asian females more so than Asian males. However, the effects for Hispanic students between the two tables are very similar and more neatly summarized given results by race alone in Table 4-9.

Cognitive Engagement: Significant Controls

In terms of controls, generational status of the student, peer academic orientation, and school mean socioeconomic status had significant effects. First generation students' ratings were significantly higher than those of third generation students by about .33-.37 standard deviations (p = .006-.008); second generation students' ratings were also higher than third generation students by approximately .27-.29 standard deviations (p =.041-.057). A one standard deviation increase in peer academic orientation also positively predicted cognitive engagement by about .16 standard deviations (p = .000). Finally, a one standard deviation increase in school mean socioeconomic status corresponded with a .10-.11 standard deviation decrease in student cognitive engagement in science.

Career Aspirations

Logistic regression was used to model effects for STEM career aspirations since it was operationalized as a dichotomous outcome (1 = STEM career aspirations, 0 = non-STEM career aspirations). Tables 4-11 and 4-12 display logistic regression results for STEM career aspirations. Likelihood Ratio Statistics for the estimated versus null models were significant indicating that the relationships specified between STEM career aspirations and the predictors included are meaningful (*LRS* = 3378.16-41417.71, *p*s = .000). These models predicted approximately 12-15% of the variance in the latent outcome underlying the logistic regression modeling of STEM career aspirations.

Career Aspirations: Differences by Race (RQ1)

In terms of race, Black students' odds were significantly different from those of White students such that the odds of aspiring to a STEM career were just over one and a half times higher for Black students versus White students (*OR* = 1.674, p = .044; see Model 1 in Table 4-11).

Table 4-11. Logistic Regression Results of STEM Career Aspirations on Race and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	*OR*	*b*	*SE*	*OR*
Race[a]						
Asian	0.075	0.403	1.078	-0.431	0.628	0.650
Black	0.515*	0.256	1.674	1.400**	0.427	4.057
Hispanic	-0.374	0.255	0.688	-0.298	0.418	0.742
Female	0.403*	0.160	1.497	0.384*	0.158	1.469
Socioeconomic Status	0.151	0.142	1.162	0.133	0.138	1.143
Mathematics Score	0.272**	0.102	1.312	0.283**	0.100	1.328
Parental Expectations	0.019	0.039	1.019	0.024	0.039	1.024
Generational Status[a]						
1st Generation	1.446**	0.422	4.246	1.447**	0.429	4.249
2nd Generation	1.119**	0.353	3.063	1.069**	0.355	2.912
Peer Academic Orientation	0.071†	0.039	1.074	0.068†	0.039	1.070
% White/Asian	0.080	0.504	1.084	0.039	0.511	1.040
School Characteristics						
Racialized Tracking	-0.127	0.166	0.881	0.047	0.173	1.049
Mean Socioeconomic Status	-0.049	0.260	0.952	-0.019	0.261	0.981
Interaction Effects						
Asian*Racialized Tracking				0.791	0.716	2.205
Black*Racialized Tracking				-1.207*	0.502	0.299
Hispanic*Racialized Tracking				-0.103	0.470	0.902
Intercept	-1.379*	0.641		-1.453*	0.658	
Loglikelihood			-56859.796			-45549.262
LRS			3380.104***			14690.638***
df			13			16
R^2			.121			.135

Note. $^{\dagger}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$. [a]Omitted: White, 3rd generation.

Table 4-12. Logistic Regression Results of STEM Career Aspirations on Race/gender and Racialized Tracking

	Model 1			Model 2		
Predictor	*b*	*SE*	*OR*	*b*	*SE*	*OR*
Race/Gender[a]						
Asian Male	-0.314	0.503	0.730	-0.234	0.907	0.792
Asian Female	0.733	0.552	2.081	-0.551	0.732	0.576
Black Male	0.527	0.385	1.694	1.209†	0.663	3.351
Black Female	0.852*	0.332	2.345	1.673**	0.545	5.327
Hispanic Male	-0.496	0.377	0.609	-0.550	0.670	0.577
Hispanic Female	0.046	0.307	1.047	0.043	0.308	1.044
White Female	0.336†	0.178	1.399	0.068	0.270	1.071
Socioeconomic Status	0.151	0.141	1.163	0.143	0.137	1.154
Mathematics Score	0.270**	0.101	1.310	0.289**	0.100	1.335
Parental Expectations	0.019*	0.039	1.019	0.025	0.039	1.026
Generational Status[a]						
1st Generation	1.463***	0.424	4.321	1.438**	0.426	4.212
2nd Generation	1.146***	0.347	3.146	1.103**	0.343	3.014
Peer Academic Orientation	0.075†	0.039	1.078	0.068†	0.039	1.070
School Characteristics						
Racialized Tracking	-0.134	0.164	0.874	-0.140	0.238	0.870
% White/Asian	0.082	0.503	1.085	0.064	0.511	1.066
Mean Socioeconomic Status	-0.068	0.255	0.934	-0.039	0.257	0.962
Interaction Effects						
AM*Racialized Tracking				-0.089	1.005	0.915
AF*Racialized Tracking				2.072*	0.946	7.941
BM*Racialized Tracking				-0.864	0.793	0.422
BF*Racialized Tracking				-1.124†	0.643	0.325
HM*Racialized Tracking				0.119	0.755	1.126
HF*Racialized Tracking				0.009	0.000	1.009
WF*Racialized Tracking				0.388	0.341	1.474

Table 4-12. (continued)

	Model 1			Model 2		
Predictor	*b*	*SE*	*OR*	*b*	*SE*	*OR*
Intercept	-1.390*	0.641		-1.336*	0.666	
Loglikelihood			-47737.624			-9698.071
LRS			3378.155***			41417.708***
df			16			23
R^2			.125			.146

Note. $^{\dagger}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$. [a]Omitted: White male, 3rd generation.

The odds of aspiring to a STEM career for Asian students (*OR* = 1.078, *p* = .852) and Hispanic students (*OR* = 0.688, *p* .143) were not significantly different from those of White students. In addition, females' odds aspiring to a STEM career were about one and a half times greater compared to those of males, holding all else constant (*OR* = 1.497, *p* = .012). Finally, the odds of aspiring to a STEM career for students in schools with and without racialized tracking were not significantly different (*OR* = 0.881, *p* = .443).

Career Aspirations: Moderation of Effects by Racialized Tracking (RQ2)

Model 2 in Table 4-11 displays the results upon adding interactions with race and racialized tracking variables to the model (Δ*LRS* = 11310.534, *p* = .000). There was a significant interaction for Black students such that these students' aspirations were suppressed in schools with racialized tracking (*OR* = 0.299, *p* = .016). In deciphering the meaning of this interaction, using calculated predicted probabilities for STEM career aspirations is instructive (See Figure 1). Even in schools with racialized tracking, the probability that Black students would aspire to STEM careers essentially matched or exceeded the predicted probability of STEM career aspirations for students of other racial groups; in schools with racialized tracking, Black students' probability of aspiring to a STEM career was 52%. However, the probability that Black students in schools with no racialized tracking would aspire to STEM careers was 78%, a predicted probability for STEM career aspirations that exceeded that of all other racial groups. This is echoed given the conditional effect for Black students, indicating that the odds of aspiring to a STEM career for Black students in schools without racialized tracking is four times larger than those of White students (*OR* = 4.057, *p* = .001).

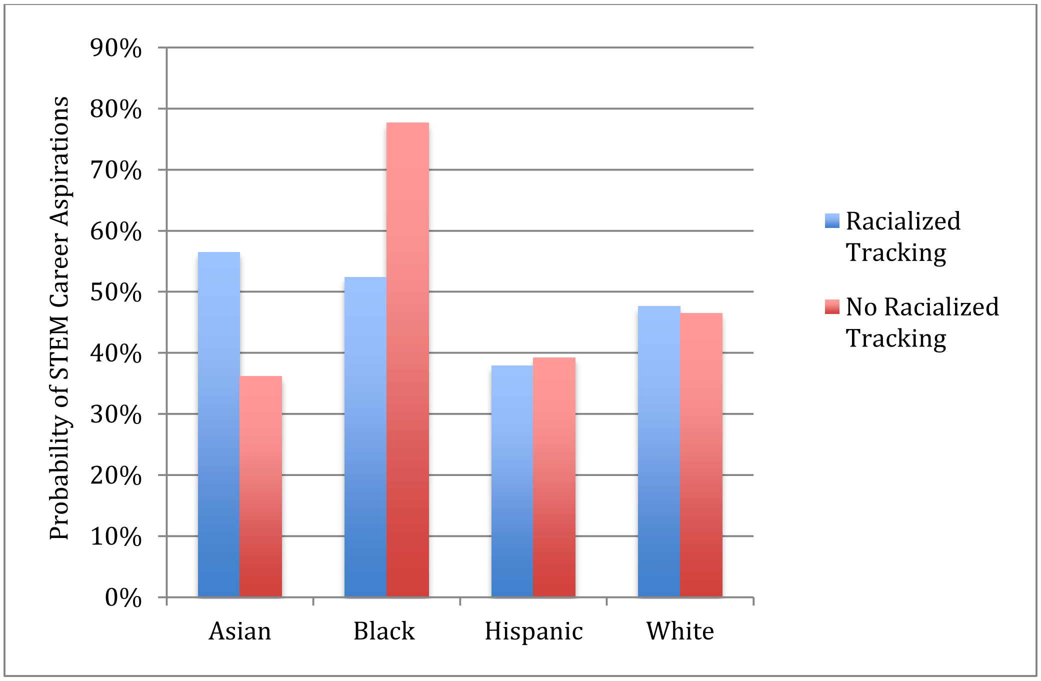

Figure 4-1. Predicted probabilities of STEM career aspirations by race. Predicted probabilities were calculated for 3rd generation students who are average on socioeconomic status, mathematics scores, parental expectations and are in schools of average mean socioeconomic status and proportion of White students.

Career Aspirations: Results by Race/gender (RQ3)

Model 1 in Table 4-12 displays regression results for STEM career aspirations when including variables for race/gender as opposed to separate variables for race and gender alone. These results demonstrate that the odds of aspiring to a STEM career were over two times greater for Black females than for White males (*OR* = 2.345, *p* = .010). In addition, White female odds of aspiring to a STEM career were 40% greater than those of White males, although this effect was only marginally significant (*OR* = 1.399, *p* = .059). The odds of aspiring to a STEM career for Asian males (*OR* = 0.730, *p* = .532), Asian females (*OR* = 2.081, *p* = .184), Black males (*OR* = 1.694, *p* = .171), Hispanic males (*OR*

= 0.609, *p* = .189), and Hispanic females (*OR* = 1.047, *p* = .882) were not significantly different compared to White males, holding all else constant.

Model 2 in Table 4-12 displays results after adding interactions for race*racialized tracking to the model (Δ*LRS* = 38039.553, *p* = .000). As Table 4-12 shows, there was a significant interaction effect for Asian females such that STEM career aspirations for these students were bolstered in schools with racialized tracking (*OR* = 7.941, *p* = .029). In addition, there was a marginally significant interaction effect for Black females suggesting that STEM career aspirations for these students were suppressed in schools with racialized tracking (*OR* = 0.325, *p* = .080). Figure 2 displays the predicted probabilities of STEM career aspirations for students by race/gender in schools with and without racialized tracking. The probability of Asian females aspiring to STEM careers in schools with racialized tracking is 45 percentage points higher than in schools without racialized tracking (76% versus 31%, respectively). Conversely, the probability of Black females aspiring to STEM careers in school with racialized tracking is 27 percentage points lower than in schools without racialized tracking (54% versus 81%, respectively).

The conditional effects for race/gender echo these results. Whereas the odds of aspiring to a STEM career for Black females were over two times greater than White males holding school characteristics constant (*OR* = 2.345, *p* = .020), the odds for Black females in schools without racialized tracking were over five times higher than those for White males (*OR* = 5.327, *p* = .002). The conditional effect for Black males was marginally significant; in schools with no racialized tracking, the odds of aspiring to a

STEM career for Black males were over three times higher than those of White males, holding all else constant (*OR* = 3.351, p = .068; see Figure 2).

Comparing these results to those obtained for effects by race alone reveal a few points of distinction. For one, the effects for Black students appear to be driven more so by effects for Black females specifically; that is, to the extent that racialized tracking moderates the effect of race on career aspirations for Black students, these effects are stronger for Black females. In addition, results by race/gender clearly show that Asian females are significantly advantaged by racialized tracking. This is most readily apparent by comparing predicted probabilities by race/gender and racialized tracking estimated given both sets of model results (see Table 4-13). Whereas modeling effects by race alone would suggest that being in a school with racialized tracking would increase Asian females' predicted probability of aspiring to a STEM career by 20%, effects by race/gender show that this difference in predicted probability between Asian females in schools with or without racialized tracking could be as large as 45%.

Career Aspirations: Significant Controls

In terms of model controls, mathematics scores and student generational status were significant predictors of STEM career aspirations.

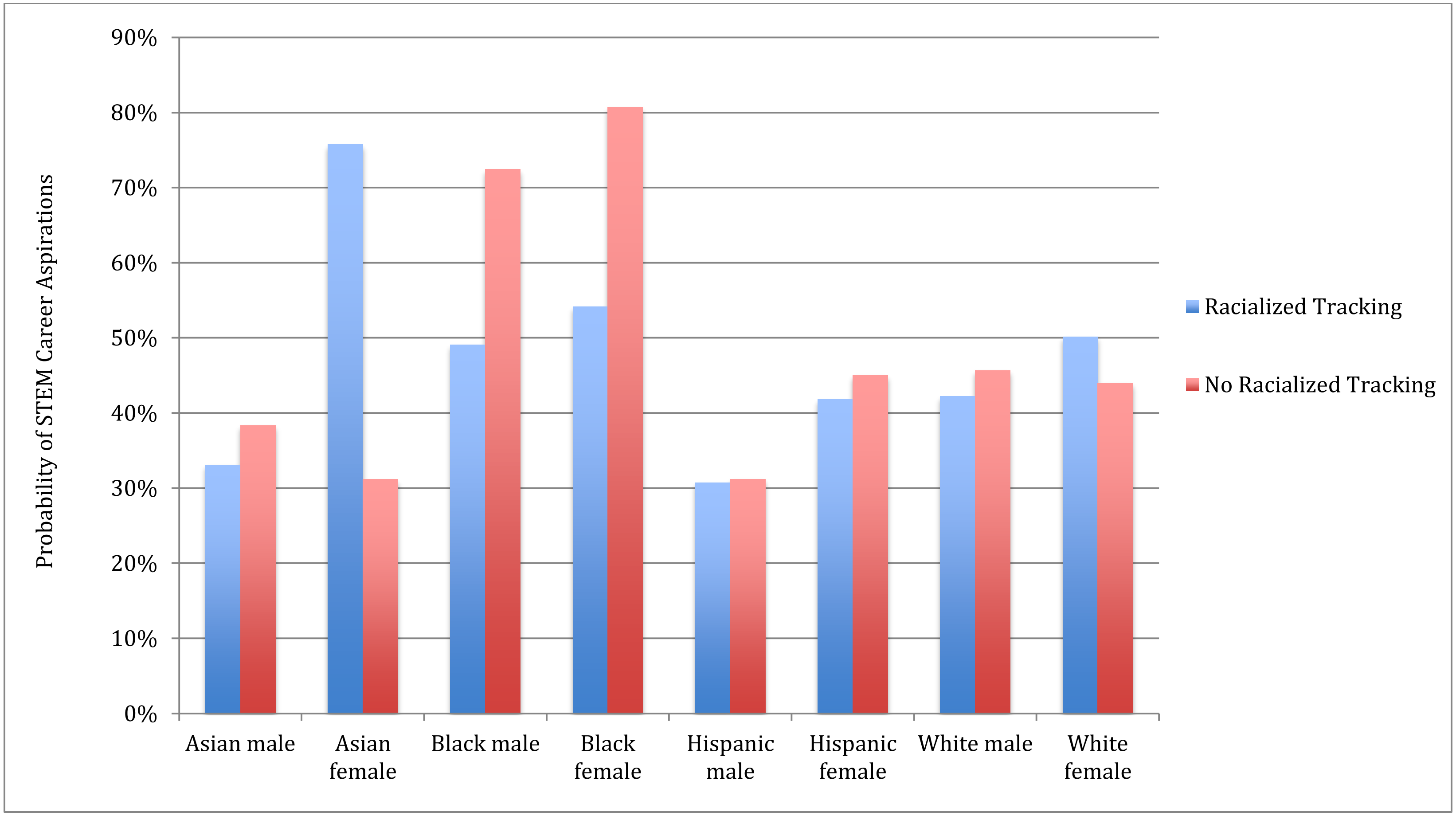

Figure 4-2. Predicted probabilities of STEM career aspirations by race/gender. Predicted probabilities were calculated for 3rd generation students who are average on socioeconomic status, mathematics scores, parental expectations and are in schools of average mean socioeconomic status and proportion of White students.

A one standard deviation increase in mathematics scores corresponded to higher odds of aspiring to a STEM career such that higher scoring students' odds were about 1.3 times greater than lower scoring students, holding all else constant (semi-standardized odds ratios ranged 1.29 – 1.31 [not shown in Tables 4-11 and 4-12, although they align closely with reported odds ratios], *p* = .004-.008; again, semi-standardized odds ratios are provided as a supplement in the text to indicate the change in odds given a one-standard deviation unit change in the predictor for this analytic sample, see Kaufman, 1996).

Table 4-13. Predicted Probabilities for STEM Career Aspirations by Race/gender and Racialized Tracking

	Effects by Race		Effects by Race/Gender	
	Racialized Tracking	No Racialized Tracking	Racialized Tracking	No Racialized Tracking
Asian				
Male	52%	32%	33%	38%
Female	61%	41%	76%	31%
Black				
Male	48%	74%	49%	72%
Female	57%	81%	54%	81%
Hispanic				
Male	33%	35%	31%	31%
Female	42%	44%	42%	45%
White				
Male	43%	42%	42%	46%
Female	52%	51%	50%	44%

Note. Predicted probabilities shown are for 3rd generation students who are average on socioeconomic status, mathematics scores, parental expectations and are in schools of average mean socioeconomic status and proportion of Asian and White students.

Both first and second generation students' odds of aspiring to a STEM career were greater than those of third generation students. First generation students' odds of aspiring to a STEM career were over four times higher than those of third generation students (*OR* = 4.2-4.3, p = .001); second generation students odds of aspiring to a STEM career were about three times higher than those of third generation students (*OR* = 2.9-3.1, p = .001-.003). In addition, peer academic orientation was a marginally significant predictor of STEM career aspirations such that a one standard deviation increase in peer academic orientation increased the odds of aspiring to a STEM career by 17-19% (positive semi-standardized odds ratio ranged 1.17-1.19 [not shown in Tables 4-11-4-12], p = .054-.085).

Summary

Taken together, these analyses paint a more complex picture of racial/gender gaps than what might be expected given prior literature that tends to focus on either the disadvantages faced by females or students of color. For this national sample of students from diverse schools, and holding school characteristics constant, the student subgroups that were most clearly at a disadvantage when it came to looking at the science outcomes observed were Hispanic males and females. Holding school characteristics constant, the ratings for Hispanic students in this sample were significantly lower than those White students on measures of science efficacy, identity, and engagement. Black students' ratings, on the other hand, were largely on par with those of their White counterparts (holding school characteristics constant). In fact, results showed that Black males' ratings were significantly higher than White males in science self-efficacy and Black females odds of aspiring to a STEM career were significantly higher than those of White males. While some prior research would suggest that Black students would be at a disadvantage when it comes to these science outcomes, holding school characteristics constant, the only case where Black students were at a clear disadvantage was in considering science identity ratings for Black females versus White males.

In terms of the moderating effects of racialized tracking on the effects for these science outcomes on race or race/gender, the results provided suggestive evidence that racialized tracking may exacerbate gaps for Hispanic students and may also diminish career aspirations for Black students. Although at times driven more so by effects for either Hispanic males or females, Hispanic students fared better in schools without racialized tracking on measures of science self-efficacy and identity (and to some degree on measures of engagement, at least for emotional and cognitive engagement). In addition, the odds of aspiring to a STEM career were higher for Black males and females in schools without racialized tracking compared to their odds in schools with racialized tracking. The results also suggested that Asian females may benefit from being in schools with racialized tracking in the sense that their ratings on these outcomes appeared to suffer in schools without racialized tracking. For example, Asian females fared better in schools with racialized tracking on outcomes of science self-efficacy, identity, cognitive engagement, and STEM career aspirations. Results also suggested that White females may also derive a benefit from racialized tracking, faring better on measures of science identity, emotional engagement, and career aspirations in schools with racialized tracking.

These results were estimated by both race alone and race/gender in an attempt to draw out instances where the predominant means of analyzing racial disparities in STEM (i.e., by using separate variables for race and gender) might limit our understanding of these inequalities. In most cases, the results estimated by race/gender draw out important distinctions not readily apparent in the results estimated by race alone. For instance, generalizing effects for science identity across Black students in this sample masks the gaps in science identity that are persistent for Black females versus White males, even in schools without racialized tracking. In addition, the advantages conferred to Asian females (and to a lesser extent White females) would remain obscured given results estimated by race alone. Still, there were instances where results estimated by race/gender were substantively focused around effects by race alone (e.g., results for behavioral engagement where Hispanic student gaps were consistent for males and females); in such instances, there is not much to be gained from and perhaps something to be lost in increasing the complexity of analyses by focusing on results by race/gender.

CHAPTER 5

DISCUSSION

In this study, I examined the effects of race and race/gender on student affective ratings in science and STEM career aspirations as well as the extent to which these effects were moderated by school racial composition and racialized tracking. Black or Hispanic racially isolated schooling has been shown to have negative effects on student achievement and academic dispositions owing to inequalities in resources between these school and schools with higher proportions of White students, peer oppositional effects, or notions of perpetuation (Darling-Hammond, 2010; Goldsmith, 2011; Stearns, 2010). Conversely, other research demonstrates that predominantly White schools tend to institutionalize racialized patterns in course-taking and pose barriers to social integration for students of color that also negatively influences their academic dispositions (DeCuir-Gunby, 2007; Tyson, 2011). Still, despite this emphasis on institutional factors in the sociological literature, much of the research examining inequalities in student orientation towards science and STEM career aspirations from the perspective of science education researchers focuses on student-level characteristics as predictors of science aspirations (e.g., Koul et al., 2010; Quinn & Lyons, 2011, Riegle-Crumb et al., 2011). In addition, some researchers have questioned the validity of modeling effects using race and gender as separate variables insofar as such an approach belies effects that occur at the intersection of race and gender (Riegle-Crumb et al., 2011). To address this lack of attention to institutional factors shaping race-based inequalities in STEM and to explore the extent to which modeling effects using separate variables for race and gender falls short of providing a nuanced examination of such inequalities, this study sought to uncover the ways both school racial composition and racialized tracking moderated effects of race (or race/gender) on student affective ratings in science (self-efficacy, identity, and engagement) and STEM career aspirations.

Thus, I asked three research questions: (1) What are the effects of race on student science self-efficacy, science identity, science engagement, and STEM career aspirations (i.e., what race-based inequalities exist in examining these outcomes)?, (2) How are these effects moderated by school racial composition? By racialized tracking in schools?, and (3) How is the interpretation of these effects different if modeling with variables for race/gender versus separate variables for race and gender alone?

The following sections answer each of these questions in the context of the analytic sample utilized from the HSLS. I conclude by outlining implications for policy and future research.

RQ1: What are the effects of race on student science self-efficacy, science identity, science engagement, and STEM career aspirations?

While this study unsurprisingly found that Asian students' ratings were largely on par compared to their White counterparts, several distinctions could be made in terms of Hispanic-White differences and Black-White differences for this sample.

Consistent with prior research, the Hispanic students' in this study rated their self-efficacy, identity, and engagement with science lower than that of their White counterparts (Chang et al., 2007; Martinez & Guzman, 2013; Uekawa et al., 2007). Whereas some prior research has focused on specific aspects of engagement (e.g., cognitive engagement conceptualized as "challenge", Martinez & Guzman, 2013), this study operationalized the three dimensions of engagement in science to show that the Hispanic students in this study had lower ratings in emotional, behavioral, and cognitive engagement when compared to their White counterparts. Given the implications of self-efficacy, identity, and engagement on student achievement and attainment in science (Weiner, 2000; Carlone & Johnson, 2007; Darling-Hammond, 1997), these results repeat the need for practitioners and researchers to address such inequalities. What makes this need particularly salient in this context was the fact that Hispanic students from this sample were drawn from schools with relative advantages in terms of racial diversity (i.e, these schools were not by definition “racially isolated” or as racially segregated as some of the other schools surveyed from the HSLS sample; Orfield & Lee, 2005) and school socioeconomic status and mathematics scores (i.e., students were in schools with slightly higher scores on both indicators compared with the HSLS sample as a whole, see Table 3-8. If ratings of Hispanic students in schools across the country had been examined (similar to Chang et al., 2007 or Martinez & Guzman, 2013) or students specifically in urban schools (similar to Uekawa et al., 2007) it is likely that the gap in ratings between Hispanic and White students observed here would be even larger given known associations between higher resourced and higher achieving schools and student outcomes. As will be discussed, these results will also point towards how these Hispanic-White difference in ratings might be diminished once accounting for racialized tracking in schools.

In reference to Black-White differences in ratings, these results do not necessarily fit the narrative that might be expected given what we know about the underrepresentation of Black individuals in science. For one, Black students rated their emotional, behavioral, and cognitive engagement on par with that of their White counterparts. This is consistent with research from the National Education Longitudinal Study (NELS:88), demonstrating no substantively significant differences in a science engagement ratings across tenth and twelfth grades between Black and White students (Chang et al., 2007). In addition, Black males science self-efficacy ratings were significantly higher across schools when compared to their White male counterparts. There results also echo findings from Chang et al. (2007) who showed that the Black students in their sample rated their self-beliefs in science (specifically, science self-concept) as significantly higher than their Asian, Hispanic, and White counterparts. It should be noted, however, that Black females in the current study did not assess their self-efficacy as significantly different from that of their White counterparts.

For this sample, Black students' odds of aspiring to a STEM career were also higher than those of their White counterparts. While on the surface this might appear to be at odds with much of the literature on STEM career aspirations finding lower rates of aspiring to a STEM career for Black students (or at least for Black females as in Riegle-Crumb et al., 2011), these findings are at least partially due to the more comprehensive operationalization of what constitutes a career in STEM that was adopted for this study. As previously mentioned, given the often ambiguous and conflicting operationalizations in the literature, this study took the stance that what matters in conferring the title of "STEM" career is that career's opportunity for access to greater economic benefit. Thus, STEM careers in this study included healthcare and psychological sciences, fields which include occupations currently among those with the fastest job growth but which also might be left out of some studies' definitions of a STEM career. Prior work has also pointed out that Black students aspiring to STEM careers (defined broadly in this way) reportedly do so more often in the spirit of altruism and a desire to give back to society and their communities (Carlone & Johnson, 2007; Huan-Frank, 2011).

While generally the Black students in this sample rated their dispositions towards science as on par with those of their White counterparts, the one context in which Black students appeared to be at a disadvantage was when it came to Black females' ratings of science identity. Thus, females of color from this sample–both Black and Hispanic females–indicated lower levels of science identity compared to their White male counterparts. If Black-White differences in ratings were to emerge from this sample, it is not unsurprising that these differences were apparent for Black females in measuring identity as opposed to some of the other outcomes examined given how extensively both racial identity conflicts with science (i.e., science as a White and Western domain, Kidman et al., 2010; Laubach et al., 2012) and gender identity conflicts with science (i.e., science as male-dominated with masculine norms for participation; Blickenstaff, 2005). It is not a stretch to imagine that despite Black female ratings that are on par with White males in terms of self-efficacy, Black females do not identify with science given their unique position at the intersection of both race and gender systems of oppression (Collins, 2000).

RQ 2: How does school racial composition or racialized tracking moderate effects of race on science outcomes?

It was originally hypothesized that school racial composition (measured as the proportion of White and Asian students in a school) would moderate the effects of race (or race/gender) on science outcomes. However, the extent to which racial differences for students would be attenuated or exacerbated was unclear. Prior research implicates peer oppositional culture, a dearth of resources, or notions of perpetuation of preferences for segregated settings to suggest that ratings and aspirations for students of color in schools with lower proportions of White and Asian students would be suppressed (Downey, 2008; Darling-Hammond, 2010; Braddock & Gonzalez, 2010). Still other studies have implicated exclusionary practices in predominantly White schools (e.g., racialized tracking; Tyson, 2011) or greater pro-school attitudes and aspirations (Goldsmith, 2004; Frost, 2007) among students of color suggesting that in schools with greater proportions of White students, ratings and aspirations of students of color could be diminished.

Preliminary analyses, however, did not find support for significant moderation effects for science outcomes on race (or race/gender) by school racial composition. In some sense, this result is not wholly surprising since the definition of the sample for these analyses excluded schools based on defined criteria for school racial composition (i.e., at least 25% White and Asian and at least 7% Black or Hispanic), a requirement that was needed in order to appropriately construct the variable measuring racialized tracking in schools. This ensured that the sample of students in this analysis came, at least in some sense, from schools that were relatively racially "diverse".

Thus, one reason for these negative findings is that schools in which school racial composition could potentially have the largest effects–as Frankenburg, Lee, and Orfield (2003) define as "intensely segregated" schools (those with > 90% Black and Hispanic populations) or "apartheid" schools (those with > 99% Black and Hispanic populations) – have been excluded from this study. In drawing these distinctions, however, it is interesting to note how the delineation of schools with proportions of White students greater than 90% are not similarly labeled as "intensely segregated" or "apartheid" schools. While it seems sensible that this distinction in terminology could be due to the differences in resources tied to schools with a concentration of students of color versus schools that are predominantly White, it seems problematic to fail to assign a problematic label to schools that are predominantly White even though the deleterious effects these schools can have on students of color that has been well documented in the literature (e.g., DeCuir-Gunby, 2007, Marx & Larson, 2012). Another potential reason for these negative findings has to do with the way racial composition in schools was measured (i.e., as a continuous proportion of the White and Asian students in a school). While simple proportions are commonly used in the literature on school composition effects (e.g., Hanushek et al., 2009; Goldsmith, 2009), other researchers define categories based on common school racial composition profiles (e.g., mixed, predominantly White, predominantly Black and Hispanic; Goldsmith, 2004) or define a binary indicator for segregation based on a cut-off proportion of students of color in schools (e.g., Mickelson, 2001).

Given these negative findings, this analysis focused on the moderation effects for science outcomes on race (or race/gender) by racialized tracking, controlling for peer academic orientation and other student and school characteristics. Before discussing these findings further it is worth noting that the majority of students in the analytic sample were in schools with some degree of racialized tracking in advanced science coursework–more precisely, nearly 70% of students in the sample were in such schools (see Table 3-14). As you will recall from Chapter 3, the operationalization of racialized tracking in this study is essentially an indicator of Black and Hispanic underrepresentation in advanced science coursework in a school. Thus, 70% of the students in this sample, aside from the many student-level or classroom-level factors that could affect students' affective ratings or aspirations in science were also in an environment essentially treating advanced science spaces as more White and Asian. While prior work as noted such disparities in smaller subsets of racially diverse schools and across a range of course domains (Tyson, 2011; Carter, 2012), this observation is a testament to the degree of separation between students of different races in science courses specifically.

Taken as a whole, these findings suggest that racialized tracking may moderate the effects of race on science affective ratings and that these effects are particularly important for addressing Hispanic-White differences in ratings, particularly in terms of science self-efficacy and science identity for Hispanic students. These results are in line with research that documents the negative impact racialized tracking has on Hispanic students of color (Nunn, 2011; Valenzuela, 1999). For instance, Nunn (2011) documents how the underrepresentation of Hispanic students in advanced coursework across two schools–one racially diverse and one predominantly White–fuels negative perceptions of the academic ability of Hispanic students in the schools and contributes to a sense of discomfort and intimidation for Hispanic students in advanced coursework. While not focused on advanced coursework in science specifically, it is not a far stretch to imagine that these dynamics could be exacerbated in science classes given the status of the science as more White dominated than domains such as English or History. While Martinez and Guzman (2013) suggest that lower levels of engagement in mathematics and science contribute to lower frequencies of advanced course-taking for Hispanic students, these results and prior research on the effects of racialized tracking support that such causal assertions are not easily teased apart and suggest that school-level predictors of student engagement in science be examined rather than focusing on what could be perceived as student-level deficiencies.

It is interesting to note that in so far as racialized tracking acted as a moderator for affective science ratings on race, the effects were more pronounced for science self-efficacy and identity (as opposed to measures of engagement) in that Hispanic-White differences in science identity and engagement in schools *without* racialized tracking were essentially zero (see Tables 4-1 and 4-3). This suggests that racialized tracking may have an effect on how Hispanic students' view their abilities in school science and the degree to which science aligns with their identity, but that this is perhaps less so when considering Hispanic students' behavioral and cognitive engagement in science (see Tables 4-7 and 4-9). Perhaps in the context of student engagement in science, classroom factors like teacher quality and culturally relevant pedagogy (Basu & Barton, 2007) may be more relevant targets for reducing White-Hispanic differences in behavioral and cognitive engagement in science.

Results for the moderation of race on affective ratings for Hispanic students should be interpreted in light of the generally low effect sizes observed for racialized tracking. This calls into question the practical significance of the results for researchers and policy makers. However, as previously stated in Chapter 3, quantitative methods like those employed here tend to underestimate institutional effects (O'Connor et al., 2007). In addition, it could be argued that effects for racialized tracking are underestimated here given its measurement at a single point in time only. Still, other research focusing on student-level psychological or achievement-related factors promoting STEM affective ratings may produce larger effect sizes. However, given (1) the persistence of Hispanic-White gaps in attainment and representation in STEM fields and (2) the emphasis in the literature on student (or at times, familial) characteristics as shaping these gaps and corresponding lack of attention to school institutional factors, the practical significance of these results should not be dismissed.

While previous work has focused on Black students' negotiation of school environments that have institutionalized racialized tracking from an ethnographic framework (O'Connor et al., 2011; Tyson, 2011), the results as reported here offer some quantitative support for the ways in which racialized tracking negatively affects STEM career aspirations for Black students. However, instead of observing how racialized tracking exacerbates Black-White differences in aspirations, with Black students odds of aspiring to STEM careers as lower than those of their White counterparts, the results show that Black students' odds of aspiring to a STEM career (as defined in this study) were greater than those of their White counterparts and in schools without racialized tracking, this advantage is even larger. As previously mentioned, the Black students in this sample did not fit the stereotype of being less engaged or invested in science with lower STEM career aspirations. This result is encouraging as these affective characteristics have the potential to predict attainment in STEM. As more waves of data become available through HSLS, monitoring these students' potential paths to college STEM programs will provide evidence to suggest whether these characteristics are stable enough to steer more Black students towards STEM pathways. In addition, these encouraging results regarding Black students STEM aspirations should not be interpreted as nullifying concern regarding Black underrepresentation in STEM fields. As noted previously, a very broad definition of STEM careers was utilized in this study, in addition to estimating results for a smaller analytic sample of students from the larger HSLS sample (given several scope conditions based on student and school characteristics). Furthermore, while aspirations are a necessary prerequisite to attainment, they are by no means a guarantee of or an equivalent to attainment.

One cause for concern with these results is that they seem to suggest a pattern where White females and Asian females may be at a relative disadvantage compared to White males in schools *without* racialized tracking. For Asian females, this appeared to be the case for science self-efficacy, identity, and STEM career aspirations; for White females, this appeared to be the case for science identity and emotional engagement. Given the raced and gendered nature of science as a domain, it is possible that in schools without racialized tracking, Asian and White females are not able to exercise their racial privilege to the same extent as they may be in schools without racialized tracking. In such a context, their position of oppression by gender is more readily apparent. Thus, while a policy goal in education moving forward should be the elimination of racialized tracking in advanced science coursework, this cannot be absent policies that address gender oppression in science.

There are also some interesting points to make regarding variables included as controls. Peer academic orientation was the one control variable that acted as a significant (or in the case of career aspirations, marginally significant) predictor of positive affective ratings and aspirations in science. These data confirm what is known about the significant influence of peers on adolescents' educational dispositions (Crosnoe, Cavanaugh, & Elder, 2003). By contrast, parental expectations emerged as a significant predictor of students' identity and behavioral engagement in science only. If students' actual success in STEM fields depends on a network of these positive affective dispositions and early aspirations, then promoting positive academic dispositions among peers could be a more fruitful means of advancing participation in science than focusing on parental influence. In addition, first generation students were fairly consistently more positively oriented towards science and STEM careers. Again, this pattern fits the general trend in research pointing towards "generational declines" in achievement/attainment in research comparing characteristics of immigrant students to those from later generations (García Coll & Marks, 2012). However, as researchers have pointed out, these differences should not necessarily be used to highlight notions of inherent differences among students, but rather to recognize both those potential differences alongside the institutional structures that shape these differences (Randolph, 2013; Valenzuela, 1999). Finally, mathematics scores were also a relatively consistent predictor of affective ratings and aspirations. While this is not surprising in and of itself, it was interesting to see that mathematics scores were not a significant predictor of behavioral or cognitive engagement in science, two factors that were most closely tied to student behaviors in science. Although not measured by HSLS during the survey years examined, data made available by later waves of the study should allow for the inspection of the degree to which *science* achievement specifically predicts later science engagement.

RQ 3: How does examining these dynamics by race/gender affect interpretation?

These results were estimated by both race alone and race/gender in the interest of determining where the predominant means of analyzing STEM inequalities (i.e., by using separate variables for race and gender) might obscure important distinctions to be made within racial groups. In general, the additional step of analyzing by race/gender to probe for these differences was worthwhile; analyzing by race/gender with White males as a reference group repositioned the analyses to highlight a Black female-White male gap in science identity that was persistent regardless of whether or not Black female students were in schools with racialized tracking. Analyses by race/gender also more readily highlighted the ways in which Asian females and White females may be provided an advantage in schools with racialized tracking when compared to White males. These types of findings support arguments made by Riegle-Crumb et al. (2011) and Muller et al. (2001) who highlight their own interesting findings by race/gender to argue that focusing on aggregate differences by either race or gender alone are potentially misleading.

While analyses by race/gender did promote a more nuanced understanding of where inequalities lie in examining these STEM outcomes, an argument could be made for the value in examining aggregate differences by race. There were subtle differences between effects for Hispanic males and females but on the whole, both their results aggregated by race or broken out by race/gender with a White male reference had similar patterns. Attending to these distinctions in too much detail could obscure the basis of these results–that for this sample and in this particular context, there are White-Hispanic differences in science affective ratings that should be cause for alarm. While Riegle-Crumb et al. (2011) are right to say that researchers should "go further than exploring whether different factors may lie behind gender disparities on the one hand and racial/ethnic disparities on the other," there may still be cause to aggregate results if those results disaggregated by race/gender show clear patterns suggesting that race is the driving force behind the examined disparities (p. 462).

Implications for Theory & Research

The theoretical perspective underpinning the formation of this study was Omi and Winant's racial formation theory (1986). This perspective was necessary given its focus on the construction of race and racial meanings via "racial projects" which exist as the units that constitute racial formation, embedded in specific sociohistorical contexts. These units, arising out of both social interactions and institutional structures, shape notions of race and contribute to overarching norms and beliefs surrounding race. Racial projects communicate racial meanings by linking the structural and ideological where "as structures emerge and influence meanings, meanings evolve and in turn shape social structures" (Staiger, 2006, p. 11).

This may study support the use of racial formation theory in understanding race-based educational inequalities. For one, the use of racial formation in this context places a focus on understanding the institutional causes for inequalities in affective ratings and STEM career aspirations among White or Asian students and students of color. More often used to expound on macro political and historical dynamics between the state and social movements, the underutilization of racial formational theory in educational research minimizes the role that schools play as a key institution of the state in molding citizens' racial identities. As Staiger (2006) notes, the school is a central location for the nexus between racial meanings and structure as the micro-level interactions among students and educators/administrators are shaped by and in turn shape the educational/racial policies of the state. By situating the role of racial segregation in the form of racialized tracking as a central feature in shaping race-based gaps in science outcomes, this study aims to contribute to the analysis of institutionalized productions of race which scholars identify as an area that is underanalyzed in education research (O'Connor et al., 2007).

In this context, tracking is named as a racial project that contributes to the formation of racial meanings placing students of color outside of science and STEM fields in the guise of choice or prior achievement. This study also situates science access in schools as a racial project beyond dynamics involving racialized tracking specifically. While analyses involving resources for science teachers were limited given large proportions of missing data for these variables, the data available suggests that Black and Hispanic students are more likely to be learning science in the context of limited resources. Compounded with dynamics of racialized tracking, the additive effects of multiple structural factors acting as barriers for students of color work to ensure that these students do not gain access to STEM fields.

This study contributes to the research on race-based inequalities in STEM in three ways. First, this study utilizes quantitative analyses to elucidate the effects of racialized tracking. Much of the prior research examined racialized tracking from an ethnographic or qualitative approach (e.g., Carter, 2012; Nunn, 2011; O'Connor et al., 2011; Olitsky et al., 2010; Tyson, 2011). This study adds to a limited body of work that attempts to estimate effects for racialized tracking utilizing quantitative methods (see Mickelson, 2001; Muller et al., 2010). Second, prior research modeling racialized tracking quantitatively did not necessarily focus on tracking in science courses specifically so this research helps expand the literature in this sense as well. Furthermore, this study utilizes a large secondary data set in order to model these effects. While there were limitations to this approach–for example, the construction of the variable for racialized tracking had to be estimated utilizing data from around 30 students sampled per school, instead of being based on counts of the total numbers of students in each school (as in Muller et al., 2010)–the use of such a construct with this type of data opens up possibilities for examining racialized tracking quantitatively given other NCES-sponsored data. Finally, this study adds a more measured approach to some calls in the literature for examinations of race/gender effects in lieu of modeling effects by race and gender as separate constructs. While the results reported here do support calls from Riegle-Crumb et al. (2011) to take an intersectional approach in estimating race/gender based effects in relation to student outcomes, these calls are not unqualified. While it is true that modeling effects by race/gender may reveal dynamics that should not be aggregated by either race or gender, there may be times when aggregation is appropriate and simplifies the interpretation of the data. While analyses by race/gender provided a more nuanced look at race and gender based inequalities in these models, the argument could be made that in some cases, aggregating by race is supported (e.g., in looking at Hispanic-White differences across affective ratings).

Implications for Policy & Practice

The practical implications of these results are aimed at both schools and parents. For one, schools should assess their placement practices and racial composition of advanced courses in science. As Tyson (2011) argues any school practices that clearly separate students by race constitute institutional racism (even in spite of the often relied upon rationale of student intellectual ability) and should be examined and reconfigured such that students of all races represented in the school are recognized as high achieving. Such shifts in representation in advanced course taking could help diminish the perspective that science is a White domain. Second, parents of students of color in integrated schools must be prepared to advocate for their children when it comes to advanced course placement in science. Valenzuela (1999), focusing on the role that social capital (i.e., a network of "exchange relationships" or a collective process of support surrounding peers, parents, and school authorities) plays in promoting the academic success of Hispanic students, repeatedly asserts oppressive institutional practices like tracking can be difficult to thwart even when social capital is working in favor of the student. Still, in the face of unresponsive institutions embracing the practice of racialized tracking, one of the only means of disrupting such patterns, at least on a micro-level, is the refusal of the parents or families of students of color to accept lower course placements for their children. For instance, this is a recurring theme in participant interviews for Karolyn Tyson's current research project examining the history of racialized tracking in an integrated suburban school district. Post-*Brown*, Black students who were able to enroll in college preparatory or advanced coursework against the pattern of relegation to special education or lower-tracked levels for the majority of students of color were able to do so only after their parents refused to accept their placement as such and demanded changes from school officials.

Implications for Future Research

There are many potential directions for future research examining the effects of racialized tracking and school racial composition. For one, this study employed one very specific operationalization looking at racialized tracking into advanced coursework in science specifically. Advanced coursework was defined as coursework beyond the modal distribution in the sample; alternative conceptualizations of "advanced coursework" could reveal results that are different from what was observed here. For example, instead of defining advanced coursework as coursework beyond the modal distribution in the sample given AHAA's science course rankings, it could be defined as placement into honors or Advanced Placement/International Baccalaureate courses. In addition, in constructing the racialized tracking variable, underrepresentation of students of color was considered jointly for both Black and Hispanic students. Separate racialized tracking variables could be constructed for Black underrepresentation and Hispanic underrepresentation specifically.

The release of subsequent waves of HSLS data will increase opportunities for more rigorous analyses. For instance, while this study focused on student self-reports of course-taking during the first follow-up, the upcoming release of transcript data will provide a more valid means for ranking students' science course-taking to determine students' enrollment status in advanced coursework. In addition, the inclusion of a third wave of data for students, set to commence in 2016 will provide opportunities for longitudinal analyses and will allow for modeling of students longer-term STEM career aspirations in the form of their actual choice of college major.

Finally, given the lack of conclusions that could be drawn related to potential effects of racial segregation between schools, more work must be done to parse out the ways that first generation segregation limits the potential for students of color to enter STEM fields. Studies examining science identity and engagement for students of color in hyper-segregated schools–both predominantly Black and Hispanic or predominantly White–have the potential to drive home just how entrenched the barriers to STEM access are given the dynamics that rule in segregated schools (e.g., the lack of resources in Black and Hispanic segregated schools or the exclusionary practices often at play in schools that are predominantly White). Problematizing the larger unequal structures of schooling (including racial segregation between and within schools) in connection to our nation's desire to promote STEM participation has the potential to redirect efforts in educational reform away from strategies might serve as modest remedies to the problem of lower STEM participation for students of color (e.g., bringing in role models for students of color or increasing the use of technology in impoverished schools) towards more meaningful change. Such limited attempts will do little to change the underrepresentation of students of color in science if the larger issues of racial segregation in schools are left unaddressed.

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