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Teacher Self-Efficacy and Mathematics Achievement Among Racial and Ethnic Minority Students: Evidence from the High School Longitudinal Study of 2009

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Eliud Partida as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Education.

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Abstract

Teacher Self-Efficacy and Mathematics Achievement Among Racial and Ethnic Minority Students: Evidence from the High School Longitudinal Study of 2009
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Current data suggests that for every 1000 U.S. high school students only about a dozen from Racial and Ethnic Minority (REM) groups will obtain a STEM degree and pursue a STEM occupation. These numbers underscore the wealth of untapped talent in our high schools and the pressing need to broaden participation among REM students in STEM. Yet, policies aimed at improving teacher quality as a vehicle for broadening participation of REM students in STEM use measures that at best, are only weakly associated with positive educational outcomes for REM students. This study contributes an ecological perspective and analysis to advance current conceptions, research and policy around STEM teacher quality and improving the educational outcomes for REM students in STEM. It applies multilevel modeling to data from the High School Longitudinal Study of 2009 to examine the relationship between *Teacher Self-Efficacy* and the *Mathematics Achievement* of REM high school students. The results showed that *Teacher Self-Efficacy* was strongly associated with the *Mathematics Achievement* of REM students, even after controlling for prior achievement, individual student characteristics, and teacher quality measures such as teaching certification, subject-matter expertise, and years of teaching experience. Furthermore, *School Climate* was found to moderate the relationship between *Teacher Self-Efficacy* and the *Mathematics Achievement* thereby underscoring the particular importance of both teacher beliefs and school context for REM students. The final model detected no *Mathematics Achievement* gap between the REM student subgroup and the general student population. However, Asian and Black students performed statistically significantly above and below the national average respectively. Finally, model comparisons revealed notable differences in the relative influence of individual, teacher, and school factors on the *Mathematics Achievement* of American Indian, Black/African American, Hispanic, and Hawaiian/Pacific Islander student subgroups. Limitations and implications for policy and practice are discussed.

Dedication

For Dad

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Teacher Self-Efficacy and Mathematics Achievement Among Racial and Ethnic Minority Students: Evidence from the High School Longitudinal Study of 2009

In the last decade, there has been renewed interest and focus on STEM education reform. The STEM acronym is generally used to describe issues related to Science, Technology, Engineering and Mathematics but recently, it has come to represent an educational zeitgeist reminiscent of the Sputnik era. At that time (1957), the Soviet Union's successful launch of the first earth-orbiting satellite signaled a direct threat to U.S. dominance in science and technology. The response was swift; galvanizing politicians, educators and the public in support of the *National Defense Education Act* of 1958 (Urban, 2010). The curricular reforms that followed—spearheaded mostly by scientific committees and government agencies—sought to reform science and mathematics education in their own image, that is, favoring deeper conceptual understanding of science topics and its processes (inquiry) rather than the emphasis on vocational training being promoted by progressive educators of the era (Bybee, 2013). While prolific—in terms of the curricular materials borne out of this era—the reforms were short-lived, giving way to the accountability movement set into motion by the release of the seminal report *A Nation at Risk: The Imperative for Education Reform* (1983). In the decades that followed, the call for increased rigor in mathematics and science education was operationalized into a system of curricular standards, testing and accountability measures codified in the No Child Left Behind Act of 2001. Despite having a modest impact on mathematics achievement at the elementary level, the legislation had little impact at the secondary level mathematics or science (Dee & Jacob, 2010). Today, there is again a call to reform STEM education and while threats are more nebulous (i.e., globalization, knowledge economy, etc.) the refrain is familiar— if the U.S. is to sustain global competitiveness, it must develop a highly skilled 21st-century workforce and doing so will depend heavily on reforming STEM education (Bybee, 2007; National Reseach Council, 2011).

The thrust of the argument for STEM education reform is primarily economic. The information age and globalization of markets present unique challenges that call for more highly skilled technological workforce. Industries such as communication, transportation, logistics, manufacturing, energy, and healthcare all increasingly rely on high-skilled workers with specialized technical training and/or advanced degrees in the STEM disciplines. Moreover, technological advances and innovation resulting from basic and applied research are expected to fuel the engines that will drive economic growth and security well into the future. Thus, the high school diploma—which was once considered the base-level of preparation for entry into workforce—is no longer sufficient for individuals to enter the technologically demanding occupations of the 21st century. As such, reforming STEM education is seen as critical for the future economic security of the nation (National Research Council, 2011).

A major challenge to meeting the demand for a STEM workforce is that certain groups are underrepresented in STEM fields, yet they make up an increasing proportion of the U.S. population (National Academy of Engineering, 2014). For instance, with respect to Hispanics and black non-Hispanics in the workforce, each of these groups accounts for only six percent of STEM workers, but 14 and 11 percent of overall employment, respectively (U.S. Department of Commerce 2011). From 2000 to 2009, Hispanics as a share of the overall workforce increased by four percent, while their representation among STEM occupations increased by only one percent. Non-Hispanic black workers increased as a percentage of the overall workforce by one percent over this time period, while their share of STEM workers held constant. In part, this can be attributed to the lower high school and college graduation rates among these groups; however; among college graduates, Hispanics and black non-Hispanics are less likely to major in STEM fields, and, among STEM majors, individuals in these groups are less likely to ultimately end up in STEM jobs (U.S. Department of Commerce 2011a).

Women are also underrepresented in the STEM domains. In 2009, women earned 57 percent of all bachelor's degrees awarded, up from 54 percent in 1993 (U.S. Department of Commerce, 2011b). However, at the same time, the share of bachelor's degrees awarded to women in mathematics and statistics declined by 4 percent and in computer science by 10 percent. Consequently, while women have comprised a growing share of the college-educated workforce, their share of the STEM workforce has not increased. Only 14 percent of engineers are women, as are just 27 percent of individuals working in computer science and math positions. Women's increased participation in the STEM workforce is essential to alleviating the shortage of STEM workers.

The broad challenge for improving STEM education is thus two-fold, as aptly captured in the title of the 2010 report: *Prepare and Inspire: K–12 Science, Technology, Engineering, and Math (STEM) Education for America's Future* (PCAST, 2010). The first is to better prepare students to enter the 21st century workforce. The second is to broaden participation by 'inspiring' more students—particularly those from underrepresented groups—to pursue advanced degrees and careers in STEM. Accordingly, what follows is a closer examination of the STEM career and educational landscapes in the U.S.; including STEM employment trends, K-12 mathematics and science learning, high school course-taking in mathematics, and interest and motivation in

STEM. Lastly, this chapter concludes with an explanation of the importance of this study within the broad educational, policy and research context described.

STEM Occupation Outlook

The outlook for STEM employment can be summed up as high wages and increasing opportunity for those with the advanced eduction and training required for these jobs (BLS, 2017). According to the Bureau of Labor Statistics (2017) , there were approximately 8.6 million STEM jobs in 2015, representing a 10.5 percent growth rate since 2009 compared to 5.2 percent for non-STEM occupations. Of these, computer occupations and engineers saw the highest job gains of any other STEM occupation. Combined, these two occupations comprised 5.5 million of the 8.6 million or 64% of STEM jobs in 2015. The growth in demand for these jobs has driven salaries for STEM occupations. Of the 100 STEM occupations included in the 2015 BLS report, 93 had wages above the national average. The national average for all STEM occupations was $87,570 compared to $45,700 for non STEM occupations. Accordingly, STEM occupations require higher levels of education compared to non-STEM occupations. Virtually 100% of STEM employment was in occupations that require at least some post-secondary education. Of these jobs, 73 percent, namely software developers and engineers, require at least a bachelors degree compared to only 21 percent in all other non-STEM occupations. These trends are projected to continue into the next decade with the fastest STEM occupations expected to grow at a rate of between 23 and 33 percent. With strong demand for highly skilled STEM workers projected to continue into the next decade, there are concerns about our educational system's ability to keep pace with the demand.

Data from the National Center for Educational Statistics suggest that these concerns are warranted. They place the total number of STEM degrees conferred in 2016 (including certificates below the associates level) at approximately 668,000 representing a 5% increase from the year prior (NCES, 2019). In terms of raw numbers and current trends, these data suggest that our education system will indeed need to find ways to bolster the STEM educational and career pipelines. In the following section, I will discuss the two broadest inputs that are being targeted by policy makers as possible solutions to the shortage of STEM workers. The first is improving the preparation of K12 students to pursue post-secondary degrees in STEM and the second is increasing the number of students who not only choose STEM degrees but ultimately pursue STEM occupations.

K-12 Mathematics and Science Learning

As discussed above, there is virtually no pathway into STEM occupations that does not require rigorous preparation in mathematics and science. From research scientists and engineers, to high-skilled technical workers, preparation for these occupations begins in K-12 schooling. Broadly speaking, the preparation of U.S. students in STEM is often measured by their performance on national and international standardized assessments such as the National Assessment of Educational Progress (NAEP), the Programme for International Student Assessment (PISA), and the Trends in International Mathematics and Science Study (TIMSS). The NAEP is the largest ongoing nationally representative assessment of fourth, eighth and twelfth graders in various subject areas including mathematics, science and more recently technology and engineering literacy. In contrast, both PISA and TIMSS compare U.S. student's performance in mathematics and science with that of students from other countries. Every 3 years since 2000, PISA has assessed 15-year old students in mathematics, science and technology literacy—that is, how well students are able to apply their knowledge of mathematics, science and technology to solve problems they are likely to encounter in real-life. Similarly, TIMSS assesses the mathematics and science performance of fourth and eighth graders every four years as well as in advanced mathematics and physics in student's last year of schooling. Together, these assessments provide insights into how well U.S. students are prepared in STEM domains as well as how they perform relative to students from other nations.

Over the past several decades, numerous reports have decried the underperformance of U.S. students on the aforementioned benchmarks of science and mathematics achievement (Bybee, 2007). While student's average mathematics scores on NAEP have shown a modest increase since it was introduced in 1990, the trend has flattened in recent years (see Appendix A). Furthermore, in 2015, only 40% percent of fourth graders, 33% of eighth graders, and 25% of twelfth graders achieved a level of proficient or higher in mathematics (Appendix B). Similarly, 38% of fourth graders, 34% of eighth graders, and 22% of twelfth graders achieved a level of proficient or higher on the science assessment (Appendix C).

These general trends also hold true across socio-economic, racial and gender lines; however, there are substantial gaps in average scores and proficiency levels across these groups. For instance, the gap in average mathematics and science scores between students who qualify for free and reduced lunch and students who do not, is between 23 and 29 points across all grade levels (Appendix B). Similarly, the gaps in math and science achievement between white students and their Black and Hispanic counterparts start at 18 and 24 points respectively (Appendix B & C). Gender differences are less pronounced with males outscoring female students by between two to five points in grade 12 and virtually no differences in grades four or eight. To put these gaps in average mathematics and science achievement into perspective, consider that in 2015, students who were either poor, Black or Hispanic performed about as well as their White and Asian counterparts did when the assessment was first administered in 1990.

Data from the Program for International Assessment (PISA) 2015, and the Trends in International Mathematics and and Science Study (TIMSS) show a similar improvement pattern to NAEP; however, U.S. students score well below other industrialized countries. For instance, while the average mathematics achievement scores of U.S. fourth and eighth graders have increased by 21 & 26 points respectively since TIMSS 1995, they are 54 & 62 points below the average scores of fourth and eighth grade students from the top 5 performing countries (Provasnik et al., 2016). Similarly, PISA 2015 results show that U.S. 15-year olds scored below the Organization for Economic Co-operation and Development (OECD) average; in fact, they scored behind 36 other education systems. In contrast, U.S. 15-year olds fared slightly better in science literacy; scoring virtually the same as the OECD average and behind 18 other systems (NSB, 2018).

Overall, the U.S. has shown some improvement in mathematics and science achievement at both the national and international levels over the last 20 years. However, the modest gains in overall scores have not erased persistent achievement gaps between socio-economically disadvantaged, Black and Hispanic students and their more affluent White and Asian counterparts. Moreover, compared to other industrialized nations, U.S. students typically rank near the middle or the bottom of the pack suggesting that by these measures, U.S. students are not as well prepared as students from other developed countries to enter STEM fields. Still, some argue that performance on international benchmarks—or any other standardized test for that matter—are poor indicators of student's preparation and prospects for future careers. They point out that measures of achievement do not capture other important skills (i.e., creativity, communication, critical thinking etc.) that matter more than scores on standardized tests. Furthermore, students may have little to no incentive do well on a test that they perceive as having little relevance to their future or educational aspirations, especially given the ubiquity of high-stakes, low-relevance tests that have characterized the U.S. education system for the past 3 decades (Koretz, 2017).

High School Coursetaking in Math and Science

Another measure of how well students are prepared to pursue STEM degrees are the courses they take during their secondary schooling. Students who aspire to go to college in the U.S. must meet minimum course requirements and take college admissions exams such as the Scholastic Aptitude Test (SAT) and the American College Testing (ACT). While the minimum high-school graduation course requirements vary from state to state and sometimes by school district, college admission requirements are more uniform. By and large, most 4 year colleges require a minimum of three years of mathematics; specifically algebra I, geometry, and algebra II; and 3 years of science, including at least one year of a laboratory science course (Bromberg & Theokas, 2016). However, while meeting the minimum requirements help students gain entry into college, it is those who take more advanced mathematics and science courses that are more likely to persist in earning STEM degrees in college (Tyson, Lee, Borman, & Hanson, 2007; Wang, 2013). Therefore, high-school course-taking patterns, particularly advanced courses, are good indicators for how well prepared students are to pursue and earn STEM degrees in college.

According to the National Science Board (2018), approximately 89% of students who graduated high school in 2013 completed algebra II or higher (Appendix D). Of these, approximately 25% stopped with algebra II; 24% took trigonometry or other advanced math; 22% took calculus and 19% took calculus or higher. Put differently, approximately two out of every three high school students in the U.S. will take an advanced mathematics (beyond algebra II) course during high school; and four in ten will take calculus. In contrast, socio-economically disadvantaged, Black and Hispanic students are much less likely to take advanced mathematics courses. For instance, whereas 37% of students in the top SES quintile took advanced mathematics courses, only 9% of students in the bottom SES quintile did. Similarly, Black and Hispanic students took advance courses at a rate of 15% and 9% respectively compared to 22% of white students (Appendix D). Asians had the highest rate of advanced mathematics course-taking across all groups at 50%.

Compared to mathematics, a smaller number of students took advanced science courses with 79% of students who graduated high school in 2013 taking at least 1 general science course and 21% at least one advanced course (Appendix E). Put differently, whereas two in three students take advanced math, only about 1 in 5 take advanced science. Moreover, economically disadvantaged, Black and Hispanic students were less less likely to take advanced science courses. The number of students in the highest SES quintile who took advanced science courses outnumbered those from the lowest SES quintile by a factor of 3 to 1. The percentage of Blacks and Hispanics who took advanced science classes were 14% and 16% respectively. Asian students were once again more likely to take advanced courses with a 51.5% taking an advanced class and 20% taking advanced physics.

The course taking patterns described above suggests that a majority of students are meeting the minimum requirements for college admission eligibility. Collectively, 89% and 79% of high school students take advanced mathematics and science courses respectively. Yet, eligibility does not necessarily translate into college admission and admission does not mean that students are prepared and will persist in rigorous STEM majors. Several studies place post-secondary STEM attrition rates somewhere in the range of 50% with the strongest correlate being prior preparation (Chen, 2009; Bettinger 2010; Lowell et al. 2009; Zumeta and Raveling 2002). Many colleges and universities, particularly those who serve populations that are underrepresented in STEM, offer remediation courses for freshman despite evidence indicating that students who take less rigorous courses during their freshman year are more likely to drop out (Chen, 2013). Therefore, although high school students may be taking the required coursework to get into college, the post-secondary data suggests that these courses may not be adequately preparing them to succeed in college. Data from both NAEP and the American College Testing (ACT) exams echo this claim, putting the percentage of college-bound high-school completers that are prepared for college-level STEM coursework at between 37%-42% (Kena et al., 2016). These percentages drop to between 21%-27% for Hispanics and 11%-13% for Blacks. Thus, while students are taking the coursework and exams necessary to enter college, there appears to be a disconnect between the level of preparation students receive at the high-school level and the rigor demanded of college-level coursework.

Transitions into STEM Majors

In order for students to enter STEM careers, they must first choose to pursue post-secondary education. Using data from a nationally representative sample of high school students, Datlon, Ingels and Fritch (2016), found that approximately 76% of study participants who were 9th graders in 2009, were either enrolled or planned to enroll in a post-secondary degree program in 2013; 42% in a bachelor's degree program and another 34% in an associate's degree program (Appendix F). The rates were lower for socio-economically disadvantaged, Black and Hispanic students. Among students in the lowest SES quintile, only 15% enrolled or planned to enroll in a bachelor's degree program, compared to 67% of those in the top SES quintile. For Blacks and Hispanics the rates were 32% and 25% respectively compared to white and Asian students who were at 50% and 52% respectively. The numbers for associates degrees were more even with Blacks and Hispanics enrolling at rates of 35% and 41% respectively, compared to 30% for both White and Asian students. There were no gender-based differences in either bachelor's degree or associate's degree pursuits with percentages mirroring the overall program enrollment rates. These results are consistent with both achievement and course enrollment data; namely, that factors related to socio-economic status and race play a major role in students post-secondary pursuits; particularly in relation to enrollment in Bachelor's degree programs.

The percentage of who enroll in post-secondary degree programs are just the first part of picture of STEM degree attainment. Dalton et al., (2016) also reported the percentage of high school students who identified STEM majors as their post-secondary course of study (Appendix G). Overall, approximately 23% of study participants who graduated high school in 2013 identified a STEM major as their field of choice. These percentages were slightly higher for those seeking Bachelor's degrees with 32% choosing STEM majors compared to 17% of those pursuing Associate's degrees. While there were virtually no gender differences in post-secondary enrollment rates, there were significant differences in STEM major choice with males out numbering females by approximately two to one. Differences along socio-economic lines were also pronounced with students in the bottom SES quintile choosing STEM majors at a rate of 17% in Bachelor's degree programs and 29% in Associate's degree programs compared to 30% and 35% respectively for students in the highest quintile. Asian students had the highest rates of STEM major choice, with those pursuing Bachelor's degrees choosing STEM majors at a rate of 53%; and those pursuing Associates degrees at 27%. These rates were 23% & 12% and 28% & 16% for Black and Hispanic students respectively (Appendix G). The rates for STEM major choice for White student's were not markedly different than the rates of non-Asian students with 32% choosing STEM Bachelor's majors and 16% choosing STEM Associate's degree program majors. This data suggests, that with the exception of Asian students, the rates of STEM degree choice are fairly even across racial lines but differences are more pronounced across socio-economic and gender lines.

The Importance of Teachers

Improving the quality and number of STEM teachers is a major focus of current policy efforts (PCAST, 2011). Federal programs such as the Robert Noyce Teacher Scholarship, Teacher Quality Partnership, and Math for America provide tuition and salary supplements to individuals with STEM degrees who obtain their teaching certification and commit to teach in a high-need school for a minimum number of years. On the whole, these programs provide extensive professional training, support, and mentorship that prepare them to become mathematics and science teachers in teacher shortage areas. The central assumption of this strategy is that highly qualified teachers, that is, those that have a strong background in the content, will be more effective teachers. While there is some evidence that teacher exams are positively correlated with student outcomes, a recent literature review conducted by the National Council on Teacher Quality reports the effect size of such teacher examinations to be between 1-3% of a standard deviation (Putman & Walsh, 2021) , making teacher examinations among the weakest predictors of achievement in the literature (Hattie, 2009). That is not to say that licensure examinations are not important or should not be used as signals of teacher quality but rather that effective teaching requires a broader set of knowledge, skills and practices that go beyond the teachers knowledge of the subject being taught. In his seminal synthesis of meta-analyses, Hattie (2009) found teacher beliefs and teaching approaches to be among the strongest predictors of student achievement with *Teacher Collective Efficacy* to be the highest predictor of achievement above all other student, home, teacher or curricular influences. *Collective Efficacy* is defined as the shared belief among teachers at a school that they have the ability to bring about the academic success of the students they teach. The effect size of *Teacher Collective Efficacy* is estimated to be in the range of 1.7 standard deviations which is of much more practical significance when compared to the range of effect sizes reported for teacher examinations on student achievement. There is no doubt that teachers matter and the overwhelming evidence points to teacher beliefs as a major source of variation in academic achievement (Cherry, 1986). Less clear is whether or not the effect of teacher beliefs is consistent across racial groups. Furthermore, the fact that *Collective Teacher Efficacy* was found to the top predictor of achievement signals that teacher effectiveness is not a personal characteristic but rather a function of both the explicit and implicit social structures within a school that support teachers in promoting the academic success of their students.

Need for Ecological Perspectives

Prepare and inspire are the two primary directives for STEM education reform. The data presented here, show that on the 'preparation' side, there are uneven achievement outcomes in STEM along socio-economic and racial lines. In addition, there are also disparities along these lines with respect to proportion of individuals who pursue post-secondary STEM degrees and ultimately choose STEM careers. These patterns are consistent from primary grades through college ultimately resulting in a shrinking proportion of students remaining on paths towards STEM careers. A simple thought experiment can illustrate the point. Considering a hypothetical representative population of 1000 U.S. high school students, the data suggests that by the end of their K-12 educational trajectory, we might expect 420 of these students to enroll in a Bachelor's degree program after high school. Based on national benchmarks, we might also estimate that less than half of them would be adequately prepared for college level mathematics and science coursework. Of these college-bound students, approximately 137 would choose to pursue STEM degree programs with 32 being female and 105 male. Furthermore, approximately 113 of them would be either White or Asian, 13 would be Hispanic and 10 would be Black. Considering attrition rates for STEM majors, only 66 would actually complete their degree (Appendix H). Lastly of the graduating class of STEM majors, six would be Hispanic and six would be Black. The number of Native American or others would be 1 or 0. This illustrative model, while rudimentary, represents the central challenge of broadening participation in STEM.

Thus, there is a need to understand how to better prepare students in mathematics and science as well as how to increase interest in STEM pursuits for all students, especially those that have been historically underrepresented in these fields. This includes both understanding how to improve achievement in STEM but also the factors that result in these gaps in outcomes. Given the economic impetus for education reform, policies around STEM education often follow labor market models that point in increased teacher quality, quantity and academic standards as the main levers to increasing achievement. However, these input/output models often treat schools and school systems as black boxes that explain little about why or how the inputs lead to the observed outputs. Understanding these interrelations is critically important because it moves towards a more nuanced understanding—one that places achievement within a network of individual, school and societal factors that make up an opportunity context that influences educational and societal outcomes (Pollack, 2017). From this perspective educational systems can be characterized as an ecology of opportunity that can be analyzed and understood at different levels of organization and as such provide more explanatory power for describing observed phenomenon. Such an understanding is needed to develop practical solutions in the form of interventions and or policies that support the development of systems that spark, develop and sustained interest and achievement in STEM.

From a theoretical standpoint, the field of STEM Education research has turned its attention to motivation and interest development (Potvin & Hasni, 2014). This line of inquiry stems from the troubling and repeated finding that interest in STEM domains declines across schooling (Potvin & Hasni, 2014). Even more troubling is the fact that these patterns seem to be more salient in developing countries and are not attributable to differences in achievement—that is, in developed countries with above average achievement in STEM domains, students seem to be less interested in STEM compared those developing countries (Olsen & Lie, 2011). These patterns point to a need to move beyond measures of achievement as important indicators for future STEM career interests. Achievement alone does not explain why or why not students become interested or choose to pursue STEM careers therefore more research is needed to understand the factors that are driving these decisions in young people. Nevertheless, achievement in general and mathematics achievement in particular is an important educational outcome that has major implications for who does and does not 'qualify' to pursue STEM degrees and careers. This is particularly important given the strong relationship between prior mathematics achievement and persistence in post-secondary STEM degrees. Thus, examining the relationship between teacher practices, beliefs, and mathematics interest and mathematics achievement will contribute to the theoretical understanding of how these factors interact and shape future educational and career decisions.

This study seeks to contribute to the theoretical, practical and policy dimensions of the problem by investigating Mathematics Achievement from an ecological perspective, that is, one that examines how multiple factors at various levels of analysis interact to produce educational outcomes. In Chapter Two, I draw on the Museus et al. (2011) Racial and Ethnic Minority (REM) STEM Model as an organizational tool to review the literature on factors that have been found to both limit and promote the success of REM students in STEM pursuits. The REM STEM model, while useful for identifying both inputs and outputs at both the school and individual levels, is limited in explaining the processes involved from a theoretical perspective. That is, it highlights several inputs (e.g., lower school funding, teacher quality, curriculum) as well as outcomes (e.g., achievement, college major, academic preparation) but ultimately it is a "black box" model that says little about the processes that involved in producing these outcomes. Therefore, in addition to the REM STEM model, I will draw on sociological, socio-cognitive and psychological theories to not only examine inputs and outputs but also to theorize about the mediating processes involved across different organizational levels namely the school and individual. Given the importance of context and relationships to this analysis I draw on Emile Durkheim's idea structural functionalism as the theoretical basis for how structural features of a context can have effects on individuals within this context. I also draw from Albert Bandura's Socio-cognitive theory to theorize about how student interactions with their context can lead to both affective and cognitive outcomes including mathematics achievement. As such this study will seek to answer the following research questions:

1. Does the variation of *Mathematics Achievement* of REM students within and between schools differ from that of the general student population?
2. Are higher levels of *Teacher Self-Efficacy* generally associated with higher levels of *Mathematics Achievement* among REM students?
3. To what extent is the *Mathematics Achievement* of REM students attributable to differences in *Mathematics Teacher's Self-Efficacy* after controlling for *Student Characteristics*?
4. To what extent is the *Mathematics Achievement* of REM students attributable to differences in *Mathematics Teacher's Self-Efficacy* after controlling for both *Student Characteristics* and *Teacher Quality*?
5. Does the nature of the relationship between *Mathematics Teacher Self-Efficacy* and the *Mathematics Achievement* of REM students vary across schools?
6. Does the *School Context* influence the relationship between *Mathematics Teacher Self-Efficacy* and the *Mathematics Achievement* of REM students?

7. How does the nature of the relationship between *Mathematics Teacher Self-Efficacy*, *Mathematics Achievement* and *School Context* vary across REM subgroups?

Chapter 3 describes the theoretical and statistical basis for using Multi-level modeling, variables used, and the analytic approach. Chapter 4 includes an analysis of the results in three parts. The first part includes descriptive statistics for all the variables including select cross tabulations for achievement outcomes by race and socio-economic status. Next, an analysis of the correlation matrix for all the variables included in the model is provided. Finally, the results of each statistical model are provided and discussed in relation to the research questions. The implications for both theory and policy as well as potential next steps for research are discussed in Chapter 5.

Chapter 2. Review of Literature

Introduction to Literature Review

The disparities in educational outcomes among underrepresented groups is among the most widely studied aspects of education since the publication of the Coleman Report (1966) over 50 years ago. This seminal study was the first to highlight important sociological factors that contributed to disparities in educational outcomes for racial and ethnic minority students including the social composition of the school, the student's sense of control of their environment and future, the verbal skills of teachers, and the student's family background (Coleman, 1966). More recently, the attention on STEM education has resulted in a body of research into the STEM-related educational experiences of underrepresented groups and factors that contribute to gaps in the educational outcomes of these groups.

While the term underrepresented minority or URM is widely used in research and policy, some scholars argue that the term itself is harmful because it obfuscates the origins of inequality for Black, Brown and Indigenous people (Bensimon, 2017; McNair et al., 2020; Walden et al., 2018). According to Bensimon (2017), this bypasses the "race question" which constitutes a form of malpractice that erases the unique experiences and histories of Black, Indigenous People of Color. This argument extends to a wide range of terms such as '*at risk*', *urban*, *underprivileged*, *underserved*, *under-resourced*, which signal race but avoid explicit mention of it. In response, the term Black Indigenous People of Color (BIPOC), has been adopted by various groups as a way to center the unique histories, voices and experiences of of Black and Indigenous people in the United States (Garcia, 2020). Despite ongoing discussion among academics, activists and allies, there is no consensus for which term or terms best serve to both build solidarity among oppressed groups while also maintaining and amplifying each group's unique history and shared experiences with oppression in the United States. Deo (2021) urges scholars to examine the language we adopt and carefully match it to our data, priorities and conclusions. With this in mind, this study will use the following terms with respect to racial and ethnic identities while also acknowledging that racial identification is complicated and that racial categories, language and labels may not fully represent the experiences, histories and voices of any one group either collectively or individually.

> *Race*–Categorizations that are created by humankind based on the hereditary traits of different groups of people, thereby creating socially constructed distinctions. Racial identification is complicated and racial categories overlap, meaning that one person can fit into two or more of the racial categories.
>
> *Ethnicity*–Identity based on a person's nationality or tribal group. Each racial group consists of many different ethnicities. For the purposes of this study, ethnicity is an identity based on membership in a segment of a larger society that does not share the same culture with other segments of society.
>
> *Racial and ethnic minority (REM) students*–Students who identify as Asian American and Pacific Islander (AAPI), Black, Hispanic, or Native American. Mixed-race individuals are excluded in this definition.
>
> *Asian American and Pacific Islander*–Although Asian Americans and Pacific Islanders are two distinct groups, they are often lumped together under this term and categorized as one race. Where statistics or literature refers to both groups, I use the term "Asian American and Pacific Islander," which refers to a person with origins in East Asia, Southeast Asia, the Indian subcontinent, or the Pacific Islands. Asian Americans include, but are not limited to, Americans of Bangladeshi, Cambodian, Chinese, Filipino, Hmong, (Asian) Indian, Indonesian, Japanese, Korean, Laotian, Malaysian, Pakistani, Sri Lankan, Taiwanese, Thai, and Vietnamese descent. Pacific Islanders include, but are not limited to, Native Hawaiian, Guamanian/Chamorro, Samoan, Tongan, and Fijian groups.
>
> *Black*–Persons with origins in any of the Black racial groups of Africa or persons with ethnic origins in the Black racial groups of the Caribbean, Central America, South America, and other regions of the world.

Hispanic–Persons having ethnic origins in the peoples of Mexico, Puerto Rico, Cuba, Central America, South America, or other Spanish cultures and communities. This word includes groups who identify as Chicano, Latino, and Mexican American.
Native American: This word refers to a person having ethnic origins in the indigenous peoples of North America and who identifies with indigenous tribes or communities. This category includes American Indians and Native Alaskans.

White–Persons with ethnic origins in the peoples of Europe, White peoples of North Africa, or peoples of the Middle East.

As discussed in the introduction, reducing student group differences in educational outcomes is a key challenge that policy makers (and practitioners) face in broadening participation in STEM pursuits. Generally referred to as the "achievement gap," educational disparities between students who are economically and culturally enfranchised and those who are not can be conceptualized as nested sources of gaps in opportunity and achievement across different units of analysis (Ream, Ryan, & Espinoza, 2012). This ecological view, urges researchers to consider the various factors and interactions that give rise to patterns in educational outcomes at various levels of analysis. Given the focus of policy makers with achievement outcomes, this literature review will first examine the extant literature on the relationship between academic preparation and future success in STEM pursuits. Next, it will examine the research around the factors that have been shown to negatively impact the success of racial and ethnic minority students in STEM as well as those factors that promote their success. Lastly, this chapter will conclude by situating this study at the convergence of the various lines of inquiry described.

Academic Preparation and STEM Success

The future prospects for students engaging and finding success in STEM degrees increases dramatically when they are rigorously prepared in secondary mathematics and science.

The courses students take in middle and high-school, the rigor of these courses and student performance in these classes by and large determine how likely a student to receive further training in STEM fields. For instance, using data from the National Education Longitudinal Study 1988 which tracked 8th grade students for 12 years, Adelman (2006) found that the rigor of academic preparation students received in their secondary schooling was the strongest predictor of them completing a baccalaureate degree; even after controlling for other precollege factors. Although, Adelman's (2006) findings reflected aggregate completion rates across all majors and were not specific to STEM degrees King (2015) analyzed the same dataset and found that students with rigorous secondary school mathematics preparation were about one and a half times more likely to persist in a STEM majors compared to those less well prepared. King (2015) also noted that prior mathematics achievement predicted persistence even after controlling for socioeconomic status, gender and race. Thus, rigorous secondary mathematics appears to be an important protective factor that contributes to persistence in post-secondary STEM majors. This is particularly important given the low rates of racial and ethnic minority choosing to pursue Bachelor's degrees in STEM and the persistent gaps in mathematics achievement already discussed.

School Funding

At the broadest level, scholars view inequitable educational outcomes as resulting from social class and power dynamics whereby disparities are a result of historical and current socio-cultural forces such as conscious and unconscious bias, cultural capital, as well as systemic oppression (Delpit, 2012; Sensoy & DiAngelo 2017; Tatum 2017). These explanations range from societal and cultural norms about who does or does not have the 'natural' aptitude to pursue certain careers or courses of study. Socio-cultural norms and biases are believed to impact achievement by shaping perceptions about who can and cannot be successful in STEM as portrayed in media and reinforced both conscious and subconsciously in society. This results in systems that create and reproduce inequities in educational opportunities for racial and ethnic minorities such as unequal school funding, tracking into remedial courses, underrepresentation in advanced placement courses, exposure to under-qualified teachers as well as low expectations from teachers (Museus, Palmer, Davis, & Maramba, 2011). Together these factors contribute to persistent and systemic disparities in the academic preparation of racial and ethnic minority students by limiting their opportunities to pursue higher education and STEM careers.

School funding is one such factor that has been found to have a significant impact on educational outcomes in general and STEM educational outcomes in particular. A large portion of school dollars comes from local property taxes which results in the inequities because racial and ethnic minorities are much more likely to live in schools that are in neighborhoods with a lower than average tax base and thus receive less per pupil spending compared to school is more affluent areas (Adelman, 2006; Flores, 2007; Oakes 1990). This often results in schools not having adequate facilities, curricular materials, staffing as well as other forms of support for students such as tutoring, special programs and other forms of educational opportunities like field-trips or science laboratories that provide students with early exposure to STEM careers (May & Chubin, 2003). According to data from the National Assessment of Educational Progress (NAEP), approximately 35% of students of color (Black and Hispanic) attend schools where more than 75% of students qualify for free and reduced lunch (Flores, 2007). As a result, inequities in school funding disproportionately limit the educational opportunities that racial and ethnic minority students' have to succeed in mathematics and science (Wenglinsky, 1997).

Academic Tracking

Academic tracking has also been found to have a negative impact on the academic preparation of racial and ethnic minority students. Academic tracking refers to the systemic practice of restricting access to college preparatory and/or advanced placement courses in ways that disproportionately exclude racial and ethnic minority students. In practice, academic tracking may take the form of imposing what are deemed to be merit-based pre-requisites to enroll in certain courses or advanced academic tracks (Oakes, Gamoran, and Page, 1992). These may include grades, test scores or sometimes even teacher recommendations. While intentional or not, these practices lead to systemic exclusion of racial and ethnic minorities because when enacted, these policies make an assumption that students are playing on an even playing field and are also based on very narrow notions of ability. Furthermore, studies have shown that students learn more when exposed to rigorous curriculum and advanced concepts regardless of their prior achievement (Gamoran, Porter, Smithson & White, 1997). More troubling, is the fact that racial and ethnic minority students are more likely to be tracked into remedial tracks than their white counterparts even after controlling for standardized assessments (Gándara, 2006; Flores, 2007; Oakes 1995). This suggest that tracking as a systemic practice is biased against racial and ethnic minorities even when the tracking is based on 'objective' measures. Given the fact that academic tracking can start as early as elementary school (Oakes & Lipton, 1990), it poses a significant barrier to racial and ethnic minority student's opportunities and access to rigorous STEM curriculum which in turn has a negative impact on their level of preparation to pursue advanced education and careers in STEM fields.

Related to academic tracking, racial and ethnic minority students are underrepresented in advanced placement courses which limits their preparation for advanced studies and STEM career pursuits. In a study of a nationally representative sample of high school students, Adelman (2006) found that racial and ethnic minorities were less likely to attend schools that offered advanced placement courses in advanced mathematics such as trigonometry and calculus compared to their white and asian counterparts. One explanation for this pattern is based on a supply and demand argument which reasons that schools don't offer AP courses unless they have 'advanced' students to fill these courses. This notion runs counter to the research showing that students of all abilities experience learning benefits from exposure to rigorous curriculum regardless of their prior achievement. These benefits include higher performance on standardized college entrance exams as well as school persistence (Bonous-Hammarth, 2006; Fergus, 2009). According to Ladson-Billings (1997), the lack of exposure to demanding and rigorous curriculum serves as gatekeeper for racial and ethnic minority students to pursue opportunities in college and beyond. Similarly, Moses & Cobb (2001) see the lack of access to rigorous mathematics curriculum, specifically Algebra, as critical not only for equal access to economic opportunity but also as a pre-requisite for full participation as a citizen of a democratic society. Thus, access to rigorous curriculum is an important factor that must be taken into account when examining educational outcomes for racial and ethnic minority students.

Teacher Quality, Expectations and Pedagogy

While there is little debate that teachers are among the most important factors that contribute to educational outcomes, there is less consensus around what constitutes teacher quality (Boonen, Van Damme, and Onghena 2014; Hanushek 2011; Harris and Sass 2011; Jackson, Rockoff, and Staiger 2014; Stronge, Ward, and Grant 2011). Some researchers investigate the extent to which teacher characteristics such as experience, education, salary, exam scores, and certification can account for differences in student achievement (Hanushek & Rivkin, 2006). In contrast, others are more more concerned with outcomes than identifying specific characteristics employ evaluation systems that determine the 'value added' a teacher has on student academic achievement (Darling-Hammond et al., 2012). Still others, seek to identify competencies or practices that have the highest impact on student learning and achievement to better support teacher development (Hattie, 2009; Marzano, 2003; Walberg, 2006). Regardless of the measures used the salient pattern is that "highly qualified" teachers, by any indicator, are less prevalent at high-poverty and high-minority schools (NSB, 2016).

According to the National Science Board (2016), Black and Hispanic students were half as likely to be taught by teachers with a master's or other advanced degree than their white counterparts. In other studies researchers have repeatedly found that teachers with less than 3 years experience are twice as likely to teach schools that predominantly serve Black and Hispanic students (Flores, 2007; Darling-Hammond, 2000; Ladson-Billings, 1997). Similarly teachers who teach at high-poverty schools are disproportionately inexperienced compared to those who teach in low-poverty schools (Moore, 2000). The scale of this problem was laid bare by Akiba et al., (2007) who found that among 46 countries, the U.S. ranked 41st in teachers with a mathematics major. Thus, the problem of inexperienced teachers has both racial, and socio-economic dimensions and is by comparison a more serious problem in the United States than many other countries.

The teacher quality issue is being addressed at the national level through programs designed to provide incentives and scholarships for highly qualified individuals that have degrees and/or STEM career experience to become STEM teachers (Zambon, 2011). There is ample evidence showing that teachers who have a degree in the subject have a positive impact on educational outcomes (Goldhaber and Brewer, 2000; Hill, Rowan, and Ball, 2005); however, more recent evidence suggest that teachers require additional knowledge and skills to become effective teachers of racially and ethnically diverse students in STEM (Ganley, Partida, Mills, 2019). Thus, teacher quality is being defined both in terms of subject matter competency as well as competencies related to teaching culturally and linguistically diverse students (Poplin and Bermúdez, 2019). These competencies include knowledge of culturally responsive practices that leverage students culture, language and unique identities as assets to enhance motivation and learning. Highly competent teachers that have advanced degrees in the subject they teach and use culturally responsive teaching practices promote achievement by exposing students to rigorous curriculum in a caring and supportive environment that actively seeks to counter persistent educational inequities.

Another issue related to teacher quality is teacher expectations of students; specifically low expectations of racial and ethnically diverse students in math and science courses (Bissell, 2000; Collins, 1992; Thompson, Warren, and Carter 2004). The relationship between teacher expectations and student's academic achievement is a reciprocal one. It is a negative feedback loop where teacher's low expectations have a negative impact on student achievement and lower student achievement has a negative impact on teacher expectations (Cherry, 1987). Coupled with the fact that racial and ethnic minority are more likely to struggle academically, these students are disproportionately impacted by lower academic expectations. Ochoa (2013) describes phenomenon as 'academic profiling' that results in less privileged students having starkly different educational experiences that limit their educational opportunities despite their potential for success. In mathematics and science classes racial and ethnic minorities (and women) are "profiled" as lacking ability in STEM fields through subtle messages that such disciplines are White and Asian male domains. Other research shows that racial and ethnic minority students are particularly influenced—both positively and negatively—by their perceptions of their teachers expectations in mathematics and science courses (Clewell, Anderson, and Thorpe, 1992).

In contrast to academic profiling, culturally responsive teaching is an approach to teaching culturally and linguistically diverse students that has been shown to enhance learning and increase student achievement (Hammond, 2015). Hammond asserts that culturally responsive teaching is a matter of activating children's brains no matter who the children are and creating an environment of curiosity, experiment and play that gives them an opportunity to see themselves as competent members of an academic community. Hammond asserts that culturally responsive teaching practices comprise four dimensions including (1) awareness; (2) learning partnerships; (3) information processing; and (4) community of learners and learning environment. The awareness dimension includes teachers' knowledge of the socio-political factors that result in systemic inequities for culturally and linguistically diverse students including the role that schools play in perpetuating and countering such inequities. Learning partnerships refers to the idea that teachers see themselves as student's learning partners by supporting both their cognitive and affective development so they can become independent learners. Information processing includes teaching kids how to think and providing them with various ways to relate to, and make sense of academic content in a manner that leverages their rich cultural and life experiences. Lastly, the community of learners dimension is characterized by an environment that is academically and socially safe for learning and one in which students see themselves as part of a learning community that values and supports each other's learning. Studies on culturally responsive teaching show that this approach helps students strengthen their connection with school and enhance learning (Kalyanpur & Harry, 2012; Tatum, 2009). Culturally responsive teaching is also supported by neuroscience research showing that it helps students build fluid intelligence, also referred to as intellective capacity (Hammond, 2014). Anderson (1990) and Tate (1994) argue that approaches to mathematics and science teaching that fail to draw on the cultures and traditions of racial and ethnic minority students causes those students to view these subjects as the exclusive domain of White males which keeps them from identifying or seeing themselves in these roles. Other research shows that incorporating culturally responsive approaches in mathematics and science classroom has a positive impact on Black, Native American, Hispanic and Southeast Asian American students (Denson, Avery, and Schell, 2010; Tate 1995; Nelson-Barber and Estrin, 1995; Kiang, 2002). These studies show that culturally responsive approaches appear to be important in improving the educational outcomes including academic success of Racially and Ethnic Minority students.

Teacher Self-Efficacy

Within the teaching domain, self-efficacy has been theorized and operationalized as both personal and general self-efficacy (Kim & Seo, 2018). Personal self-efficacy is most closely aligned with Bandura's (1977) conception self-efficacy and refers a teachers belief in their own ability to successfully perform a teaching-related task such as managing a classroom, implementing an instructional strategy, or engaging students in learning. Alternatively, general self-efficacy is more closely aligned with Rotter's (1966) locus of control theory in which teacher efficacy is the teacher's belief as to whether control of reinforcement lies externally, in the environment, or internally, within themselves (Tschannen-Moran & Hoy, 2001). This difference has led to some inconsistencies in the literature with respect to the link between teacher self-efficacy and student achievement; however, the general finding has been that teacher self-efficacy is positively associated with student achievement regardless of the scale used (Kim & Seo, 2018). Furthermore, the strength of the association is influenced by teacher (i.e., years of experience), student (i.e., family background, gender, prior achievement) and school (i.e., location, composition) variables. This is consistent with Bandura's (2006) assertion that self-efficacy is strongly context dependent which also underscores the challenge in drawing inferences when teacher, student and school contextual factors are not available or are not taken into account.

Teacher Self Efficacy has been found to be positively associated with quality classroom practices and processes, achievement as well as teacher well-being (Zee & Koomen, 2016). Teachers with higher levels of Self-efficacy engage in quality classroom practices that promote learning including: process-oriented instruction; differentiation; accommodating learning goals; relating content to students' lives; and use of effective teaching strategies that support inclusive education (Allinder, 1995;Martin, Sass, & Schmitt, 2012; Thoonen, Sleegers, Oort, Peetsma, & Geijsel, 2011; Wertheim & Leyser, 2002). In addition, teachers with high self-efficacy tend to engage more in professional development and are more likely to try out new approaches to improve their practice (Geijsel, Sleegers, Stoel, and Kruger, 2009). Therefore, teacher self-efficacy may indirectly influence student achievement by improving students' learning context thereby increasing opportunities to learn.

Student Self-Efficacy

Self-efficacy refers to confidence in one's ability to successfully complete a specific task. Self-efficacy has been shown to influence behavioral outcomes such as selection, persistence and effort to complete similar tasks in the future (Bandura 1986). Furthermore, the theory asserts that that there are four major sources of information that influences self-efficacy beliefs: (a) past performance accomplishments, (b) exposure to and identification with efficacious models (vicarious learning), (c) access to verbal persuasion and support from others, and (d) experience of emotional or physiological arousal in the context of task performance. Of these four sources, past performance accomplishments have the greatest influence on self-efficacy (Bandura 1986). Several studies have found links between racial and ethnic minority student's self-efficacy in STEM (confidence in their ability to learn math and science) and their future success in STEM (Colbeck, Cabrera, and Terenzinim, 2001; Prena et al., 2009). In a study of students spanning pre-college to post-secondary employment, Leslie, McClure, and Oaxaca (1998) found that self-efficacy to be an important predictor of success in STEM for racial and ethnic minority students. Similarly, Holt (2006) used NELS data (88:00) to reveal links between racial and ethnic minority student's mathematics self-efficacy and their enrollment in higher level mathematics courses. Holt also found that racial and ethnic minority students with higher mathematics self-efficacy were more likely to persist in STEM education. In a more recent study, Cheema and Galluzo

(2013) analyzed data from a U.S. representative sample of 4733 students who took the 2003 Program for International Student Assessment (PISA) and found that self-efficacy was a significant predictor of math achievement over and above that accounted for by demographic characteristics. The conclusion that can be drawn from these studies is that self-efficacy is robust predictor of success in STEM for racial and ethnically diverse students.

Self-efficacy has also been linked to influencing other important educational outcomes for racial and ethnic minority students such as such as interest and goals. In a study of 216 sixth grade student's Turner, Steward and Lapan (2004) found that self-efficacy predicted math and science career interest even after controlling for socio-economic variables and gender. In a study of 426 Mexican American 8th graders, Navarro, Flores and Worthington (2007) found mathematics self-efficacy was a strong predictor of both math and science interest and goals. In a similar study, Austin (2010) found that among 396 African American students, MSE was the strongest factor in relation to students' career decision. However; the role of self-efficacy can have a confounding impact, especially for students who have high self-efficacy but are poorly prepared (Seymour & Hewitt, 1997). According to Seymore and Hewitt, racial and ethnic minority students who come from high schools where they are viewed as being academic superior compared to their peers may develop strong confidence but lack the advanced skills necessary to succeed in advanced college STEM courses. This can result in a students feeling overwhelmed and at greater risk of dropping out or switching out of STEM tracks.

Interest in STEM

Public interest in science and science education has ebbed and flowed over the past 50 years (Yager & Penick, 1986); however, interest in mathematics and science among school-aged children has seen a steady decline (Potvin & Hasni, 2014). Given the role of interest in the STEM education literature as a predictor of positive education and career outcomes, interest development is particularly relevant in understanding persistence and success in STEM for racial and ethnic minority students (Museus, Palmer, Davis, & Maramba, 2011; Singh, Chang & Dika, 2010).

According to Krapp and Prenzel (2011), the concept of interest as it relates to educational pursuits in was first expounded by John Dewey (1913). Dewey was the first to describe interest as an integrative process that resulted from the interaction on an individual and the environment. The concept interest as a focus of psychological research lost favor to behaviorist notions of motivation in the early 20th century; however, its utility in vocational psychology as a motivational construct is still in use today. The Holland scale describes broad level career interest according to 5 domains, namely, Realistic, Investigative, Artistic, Social, Enterprising and Conventional (RIASEC). This Holland scale has been used for decades to match individuals with careers that are well aligned with RIASEC interest patterns. For instance, students with an interest profile that favors Investigative and Social domains might be well suited for a career as a science teacher; on the other hand, someone who prefers realistic and artistic domains might be better suited for a career in industrial design. Another important feature of the Holland scale is that is that interest profiles are believed to be relatively stable over time giving them a 'trait' quality.

Efforts to explain learning and differences in educational attainment led to a resurrection of the interest construct from its 'Dewinian' roots. According to Dewey, interest was neither a personal trait nor a quality of the object, rather interest emerged from the interaction between the individual and the object of interest. This is often referred to as the content specificity of interest —that is, interest is always directed at something whether it be an object whether it be real or abstract (Krapp & Prenzel, 2011). Interest is also generally divided into two forms, namely individual and situational.

Individual interest is characterized by a relatively stable and enduring tendency or predisposition to engage with the object of interest. An example of this might be a child who spends hours practicing basketball can be said to have a well-developed and enduring personal interest. In addition to the tendency to engage, individual interest is also associated with positive experiential states such as enjoyment, competence, self-regulation, efficacy, and personal meaning.

Situational interest on the other hand is a fleeting and unstable but and mostly externally mediated. Situational interest can thus be triggered by unique novelty, discrepancy, affect, personal value, or emotion. Situational interest is also associated with improved attention and recall (Krapp & Prenzel, 2011; Hidi & Renninger, 2006). Furthermore, Krapp and Prenzel (2011) argue that interest has an intrinsic character that results when individuals are able to integrate the interest-related goal with their preferred values and ideals. This is particularly relevant in formal learning as individual's engaged in high-interest activities will have a heightened readiness to acquire and regulate new knowledge in the interest domain which leads to improved learning (Hidi, 1990). While the intrinsic quality makes interest a strong driver of learning, some argue interest to be a worthwhile educational outcome in and of itself, especially given its association with other adaptive qualities such as personal meaning and value. These affective domains are stronger predictors of future engagement in STEM domains thus interest should be thought of as a goal not just a mediator of increased achievement (Bybee & McCrae, 2011).

While there are many different ways that researchers define and operationalized interest (Potvin & Hasni, 2014; Krapp & Prenzel, 2011; Bybee & McCrae, 2011), there is ample evidence that shows that the critical time for student to develop interest in math and science is between 8 and 12 years of age and that interest in STEM shows a steady decline across K-12 schooling (Alexander, Johnson, & Kelley, 2012; Carlone, Scott, & Lowder, 2014). The sharpest decline has been found to occur between the transition from elementary to middle school and the highest gender gap in interest also occurring at this time. In a meta-analysis conducted by Hoff et al. (2008), declines in interest are found to be better explained by normative developmental changes rather than due to differences in ability and or achievement. This is consistent with international studies that have shown science and mathematics achievement to be poor predictors in interest in science (Awan, Sarwar, Naz, & Noreen, 2011). Another significant pattern found found both in the U.S. and across countries is the gender differences in subject interest with females favoring biological sciences over males and males preferring the physical sciences (Baram-Tsabari & Yarden, 2011). The consistency of these general patterns suggests that the simplistic view of declining interest may be more reflective of socio-developmental processes rather than reflective of a societal deterioration of values or ability. Therefore, understanding how to trigger, sustain and develop interest in STEM is a major area of research. As described earlier, interest in STEM domains can be described broadly such as someone who is an avid reader of science magazines and books. However, broad interest in science does not always translate to interest in STEM pursuits (higher education or career in STEM). There is ample research that show positive outcomes for both situational and individual interest but one line of inquiry that is of particular relevance in STEM education is identifying how interest in STEM pursuits develops over time, especially given the fact that interest in STEM tends to declines as students get farther along in their education.

Reframing REM STEM

The preceding review of literature identified several factors that have been shown to both impede and promote the success of REM students in STEM. Accordingly, the REM STEM model summarizes these factors into educational inequities (school funding, low teacher quality, low teacher expectations) and those that promote success, namely culturally responsive teaching practices and early exposure to STEM careers. These inputs are shown to influence K-12 outcomes related to early dispositions (i.e., interest, self-efficacy, aspirations and expectations) as well as academic preparedness in STEM and entry into STEM majors in college. As mentioned earlier, the REM STEM model advances the the field of STEM education research by incorporating a more comprehensive set of features that more accurately reflect the educational experiences of REM students. Nevertheless, the REM model is limited in its lack of theoretical coherence that make it possible to hypothesize or explain the processes by which the educational inputs result in the outcomes. Despite this, it serves as a useful framework in that it identifies the factors that have been found to be important for the success of REM students in STEM.

In the next Chapter, I will discuss a refined version of the REM STEM model to include theoretical perspectives that provide both conceptual and operational clarity, that is, one that reflects the hierarchical, social, cultural and psychological relationships between constructs. This revised model will form the basis for the specification of the statistical models used to interrogate the research questions posed in Chapter 1.

Chapter 3. Research design, methods and data

Objectives, research questions and hypothesis

The preceding literature review offers a range of perspectives for explaining disparities in educational outcomes in STEM. At the individual level, several psychological, cognitive and personal characteristics have been shown to be associated with STEM educational outcomes including demographic, self-perceptions, knowledge, abilities and attitudes. Individual characteristics are in turn shaped by a variety of contextual factors including family, educational inequities, curricula, exposure to STEM careers, opportunities and access to STEM specific support programs, parental expectations and involvement. The Racial and Ethnic Minorities (REM) in STEM model has been proposed by Museus et al., to illustrate the various factors that exist among the various variables that contribute to the educational outcomes of REM students. Appendix I.

This study investigates the nature of the relationship between *Mathematics Teacher Self-Efficacy* on the *Mathematics Achievement* of REM students. While there is some evidence to support the hypothesis that *Teacher Quality* is positively associated with mathematics achievement, large-scale empirical studies on the effects of Teacher beliefs on Mathematics Achievement of REM students have not been conducted. Moreover, empirical studies into teacher quality have focused solely on traditional variables such as level of education, certification and teacher experience (Hanushek 2011). Lastly, while many studies report positive effects, very few report actual effect size of teacher quality. These limitations are important to address as policy-makers seek to make informed decisions about how to improve the educational outcomes of REM students in STEM. This study will address these shortcomings by using Multi-

Level Modeling (MLM) to investigate the impact of *Mathematics Teacher Self-Efficacy*—broadly defined as Teacher's beliefs about their ability to bring about the academic success of their students—on *Mathematics Achievement*. The analysis will also examine how contextual factors promote and/or undermine this relationship within schools and in particular for REM students. Data from the High School Longitudinal Study of 2009 (HSLS:09) is used to answer the following research questions:

1. Does the variation of *Mathematics Achievement* of REM students within and between schools differ from that of the general student population?
2. Are higher levels of *Teacher Self-Efficacy* generally associated with higher levels of *Mathematics Achievement* among REM students?
3. To what extent is the *Mathematics Achievement* of REM students attributable to differences in *Mathematics Teacher's Self-Efficacy* after controlling for *Student Characteristics*?
4. To what extent is the *Mathematics Achievement* of REM students attributable to differences in *Mathematics Teacher's Self-Efficacy* after controlling for both *Student Characteristics* and *Teacher Quality*?
5. Does the nature of the relationship between *Mathematics Teacher Self-Efficacy* and the *Mathematics Achievement* of REM students vary across schools?
6. Does the *School Context* influence the relationship between *Mathematics Teacher Self-Efficacy* and the *Mathematics Achievement* of REM students?
7. How does the nature of the relationship between *Mathematics Teacher Self-Efficacy*, *Mathematics Achievement* and *School Context* vary across REM subgroups?

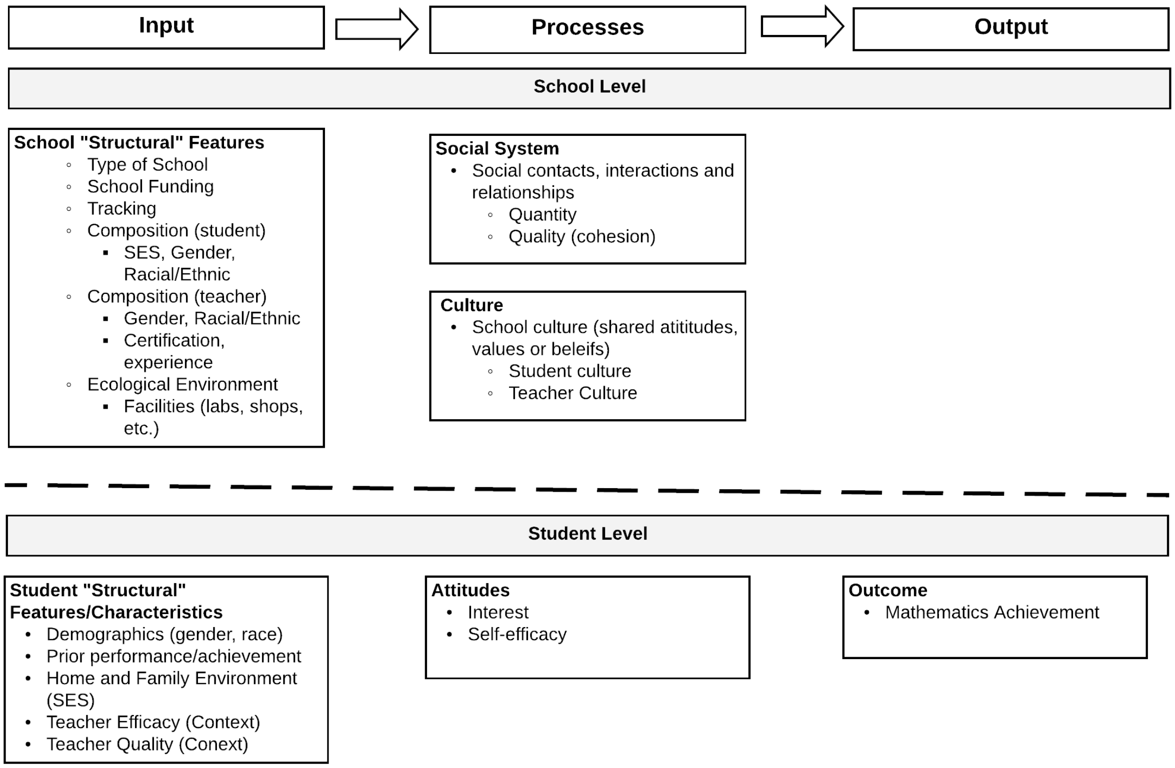
Theoretical Framework

The design of this study is informed by the Racial and Ethnic Minorities in STEM (REM STEM) Model (see Appendix I) proposed by Museus et al. (2011). The REM STEM model provides a rich set of factors that have been found in the literature to influence educational outcomes at different levels of analysis and in various educational contexts. It situates STEM outcomes within a system that more accurately reflects the various opportunity contexts that lead to disparities in STEM outcomes. As discussed in the preceding literature review, school funding, teacher quality, teacher expectations, and academic tracks result in structural inequities of REM students. These inequities in turn influence individual student dispositions, academic preparation and ultimately choices about pursuing STEM. In addition, school factors related to culturally relevant curricula and culturally responsive pedagogy have an influence on the success of REM students in STEM. Using the REM STEM Model as an organizing framework, this study seeks to examine the relationship between Teacher beliefs and Mathematics achievement while controlling for some of the important factors that have been shown to influence STEM educational outcomes.

While the REM STEM model provides a useful framework to that relates school inputs to outcomes related to STEM Education; it lacks the theoretical coherence needed to hypothesize about why certain inputs may result or influence certain outcomes (Good & Wenstein, 1986). This is typical of black-box models and studies that identify effects but cannot provide theoretically sound explanations for why or how school features effect cognitive outcomes. Van Houtte & Van Maele, (2011) lay out the theoretical basis for using teacher culture as school feature to reveal the impact of teacher practices on individual student outcomes. This approach relies on the assumption that teachers within a school context form (sub)cultures based on shared experiences and responses to problems within the school context. It also draws a clear distinction between the concepts of school climate and school culture which are often conflated in the school effectiveness research. While there are conceptualizations and taxonomies of school climate, Anderson (1982) argues that Tagiuri's (1968) taxonomy is the most conceptually coherent as it provides a useful framework to theorize about socially mediated processes within a school context. Tagiuri's (1968) taxonomy comprises four broad subcategories of school climate including: ecology; milieu; social system; and culture. The ecology refers to the physical material features of a school such as its building characteristics, age of building, size and other qualities related to the decor or physical space. The social milieu refers to the composition of a school both in terms of the students and teachers at the school. Examples of this would be the Socioeconomic, ethnic or gender composition of the students and/or teachers. Other compositional characteristics could be teacher experience aggregated at the school level. The social system is concerned with the patterned relationships of persons and/or groups. The features of a school relate to both formal and informal patterns or rules of operating or interacting at the school. The social system can be conceived as operating at both the individual and school levels. For instance, the administrative organization or instructional program of a school (i.e., tracking or ability grouping) can be characterized as a school feature that influences teacher-student, teacher-teacher or even teacher-parent relationships. Lastly, culture within the this framework is include variables that reflect shared norms, belief systems, values, cognitive structures, and meanings of persons within the school. Examples of culture variables can include teacher expectations, teacher approach to discipline or student belonging. While Tagiuri's (1968) school climate model provided both an intuitive and theoretically sound taxonomy, it presented analytic challenges related to the limitations of the statistical techniques available at that time. Given the nested nature of school contexts (students nested in classrooms nested in schools), the methods did not yet exist to deal with the violation of assumptions needed for OLS regression models. More recently, researchers have rediscovered Tagiuri's School Climate Model and have used it to hypothesize and test the role of socially mediated processes that have historically confounded large scale, empirical studies of school effects (Van Houtte, 2005). Van Houtte (2005) suggests this breakthrough will help bridge the divide between large-scale empirical school effect studies that while generalizable, often lack explanatory power. That is, they may detect an effect but have little to say about the underlying mechanism that results in the effect. Taking direction from Van Houtte (2011), Figure 1 below shows a reconceptualization of the REM STEM model to reflect the hierarchical nature of the school context and organized into Tagiuri's School Climate taxonomy.

Figure 1.

Two-level REM STEM Model adapted according to school climate taxonomy.



The central relationship examined in this study is that of *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement*. While the positive correlation between *Teacher Self-Efficacy* and *Mathematics Achievement* has been established in the literature, less clear is whether traditional teacher qualifications as defined in the literature (e.g., in field degree, certification and experience) actually benefit REM students. Furthermore, there is growing body of research that suggest teaching practices and teacher beliefs are perhaps more important in promoting the academic achievement compared to traditional measures (Czerniak & Chiarelott, 1990; Guskey, 1988; Stipek, Givvin, Salmon, & MacGyvers, 2001). However, the relative importance of teacher practices and beliefs compared to traditional teacher quality measures as they relate to mathematics achievement is unclear. In addition, this study will include various contextual factors that have direct associations with mathematics achievement but are not always addressed in non-empirical studies. In this conceptualization, *Teacher Sellf-Efficacy* is shown at the student level to represent part of the student's learning context *not* the particular teacher effects on the student outcomes. Therefore, in the aggregate, *Teacher Self-Efficacy* represents, on average, students' prior experience with teachers of varying levels of self-efficacy beliefs.

Participants

The population in this study comprises students who participated in the High School Longitudinal Study of 2009 (Ingels & Dalton, 2013). The HSLS surveyed a nationally representative sample of 9th grade high school students in 2009 and again in 2012 when they were in 11th grade and 2 years post graduation. The primary focus to the HSLS is on Science, Technology, Engineering and Mathematics (STEM) career trajectories. The restricted data file was obtained from the National Center for Educational Statistics (NCES) (Ingels et al. 2011). The REM subsample includes students who identified as American Indian/Alaskan Native, Black/African American, Hispanic, or Pacific Islander on in the 2009 questionnaire, and whose self-reported racial identity matched their school records.

Research Design

Data Collection

The HSLS:09 data was collected using a two-stage random sample design. In the first stage, schools were randomly selected from the universe of schools in the United States. In the second stage, students were randomly selected from the sampled schools. The sample of schools in the base year included public (including charter schools) and private schools from all 50 states as well as Washington D.C.. A total of 944 of 1,889 schools participated in the base year.

A total of 26,305 students were randomly sampled from the 944 participating schools in Fall 2009. Approximately 4.2% of the sampled students were excluded from the data collection due to study ineligibility resulting in 25,206 study-eligible students. Study-eligible students completed an in-school survey and a mathematics assessment. Additional information describing the student's school and home environment were collected via parent, administrator, counselor and teacher questionnaires. Teacher and parent questionnaires were linked to student survey.

The first follow-up took place in Spring of 2012 and included 25,184 of the 25,206 eligible base-year sample students. The students questionnaire included questions related to various aspects of their high school experience including course-taking, college choice preferences, admission tests and family background. A random sampling of parents of study-eligible students were selected to complete the parent questionnaire. Administrators and counselors were also surveyed in the second follow-up; however, only administrators were surveyed from both base-year school and the schools that students transferred to. Counsellors were only surveyed from the base-schools.

In 2013, an update survey was administered to 25,167 of the 25,168 students that were eligible in the first follow-up in 2012. Of these, 1,767 were not fielded for the 2013 update because they were non-respondents for both the base-year and first follow-up. Some additional sample-eligible students dropped out of the study yielding a total student sample of 23,318. Surveys were administered to either the student or the parent to obtain data on high-school completion status as well as post-secondary education and work-related experiences. Transcripts for students were also obtained from all the schools the student had attended.

Of the 23,318 study participants who participated in the 2013 update survey, 23,316 were interviewed between March 2016 and January of 2017. The data collection consisted of an interview administered by various modes (Web, computer, computer-assisted). The interview included questions related to four broad areas including High School, Post Secondary Education, Employment and Family and community.

Measures

Table 1 below includes descriptions of the Student (Level 1), Teacher (Level 1) and School (Level 2) variables used in the analysis. It's important to note that Teachers were only surveyed if they had a study participant as their student; therefore, teacher respondents are not representative of mathematics teachers at the school. For this reason the teacher variables are aggregated at the student level for all descriptive statistics and entered at the first level in the multi-level analysis. Schools were sampled in the first step of HSLS sampling scheme and thus are representative of secondary schools in the United States in 2009. Thus, the levels of analysis for this study include student and teacher variables at level 1 and school variables at level 2.

Table 1

Study Variables

Student Variables (Level 1)	Description	Values
STU_ID	Student identifier assigned for all base year eligible students (including respondents, nonrespondents, and questionnaire ineligible	IDs randomly assigned from 10001 to 35206 across all students.
X1SEX	Sex of the sample member, taken from the base year student questionnaire, parent questionnaire, and/or school-provided sampling roster.	1=male, 2=female

X1RACE	X1RACE characterizes the sample member's race/ethnicity by summarizing the following six dichotomous race/ethnicity composites. 1=American Indian/Alaskan Native, non-Hispanic; 2=Asian, non-Hispanic; 3=Black/African American, non-Hispanic; 4=Hispanic, no race specified; 5=Hispanic, race specified; 6=More than one race, non Hispanic; 7=Native Hawaiian/Pacific Islander, non Hispanic; 8=White, non Hispanic	1 - 8 (categorical)
X1TXMTSCOR	The math standardized T score provides a norm-referenced measurement of achievement, that is, an estimate of achievement relative to the population (fall 2009 9th graders) as a whole. It provides information on status compared to peers. The standardized T score is a transformation of the IRT theta (ability) estimate, rescaled to a mean of 50 and standard deviation of 10.	24.018 - 82.2
X2TXMTSCOR	The math standardized T score provides a norm-referenced measurement of achievement, that is, an estimate of achievement relative to the population (spring 2011 11th graders) as a whole. It provides information on status compared to peers. The standardized T score is a transformation of the IRT theta (ability) estimate, rescaled to a mean of 50 and standard deviation of 10.	22.2 - 84.9
X1SES	This composite variable is used to measure a construct for socioeconomic status. X1SES is calculated using parent/guardians' education, occupation, and family income and locale (urbanicity). Variable was standardized to a mean of 0 and standard deviation of 1.	-2.45 - 4.08
X1MTHEFF	This variable is a scale of the sample member's math self-efficacy; higher X1MTHEFF values represent higher math self-efficacy. Variable was created through principal components factor analysis and standardized to a mean of 0 and standard deviation of 1.	-2.92 - 1.62
X1MTHID	This variable is a scale of the sample member's math identity. Sample members who tend to agree with the statements "You see yourself as a math person" and/or "Others see me as a math person" will have higher values for X1MTHID. This variable was created through principal components factor analysis (weighted by W1STUDENT) and standardized to a mean of 0 and standard deviation of 1.	-1.73 - 1.76
Teacher Variables (Level 1)	Description	Values
X1TMEFF	This variable is a scale of the base year math teacher's self-efficacy; higher values represent greater self-efficacy. Variable was created through principal components factor analysis (weighted by W1MATHTCH) and standardized to a mean of 0 and standard deviation of 1.	-3.26 - 3.01
M1MTHYRS912	Years Math teacher has taught high school math	1-31
X1TMCERT	Math teacher's math teaching certification	1=Yes, 0=No
M1BAMAJ2	BA in Mathematics or Mathematics intensive major (i.e., Physics, Engineering, Computer Science, Statistics)	1=Yes, 0=No
M1SEX	Math teachers sex.	1=Male, 2=Female
X1TMRACE	Math teacher's race-ethnicity composite. 1=American Indian/Alaskan Native, non-Hispanic; 2=Asian, non-Hispanic; 3=Black/African American, non-Hispanic; 4=Hispanic, no race specified; 5=Hispanic, race specified; 6=More than one race, non Hispanic; 7=Native Hawaiian/Pacific Islander, non Hispanic; 8=White, non Hispanic	1 - 8
School Variables (Level 2)	Description	Values
SCH_ID	School identifier assigned for the base year sample high school.	IDs randomly assigned from 1001 to 1944 across all high schools.

SCHSES	The School's Compositional Socio-Economic Status (School SES) is derived from the Student Socio-Economic Status (Student SES) aggregated at the school level. The mean School SES for HSLS:09 schools (N=944) is estimated to be -.01 with a standard error of .02 and a standard deviation of .43.	-.44 - .42
X1SCHOOLCLI	This variable is a scale of the administrator's assessment of his/her school's climate. Higher values represent more positive assessments of the school's climate (i.e. fewer problems are indicated). Variable was created through principal components factor analysis (weighted by W1SCHOOL) and standardized to a mean of 0 and standard deviation of 1.	-4.22 - 1.97
A1FREELUNCH	Percent of student body receiving free or reduced-priced lunch	0 - 100
A1HISPSTU	Percent of student body of Hispanic/Latino/Latina origin	0 - 100
A1WHITESTU	Percent of student body that is White	0 - 100
A1BLACKSTU	Percent of student body that is Black or African American	0 - 100
A1ASIANSTU	Percent of student body that is Asian or Pacific Islander	0 - 100
A1AMINDIANSTU	Percent of student body that is American Indian or Native Alaskan	0 - 100
A1SCHTYPE	School type. 1=regular school (not including magnet or charter), 2=charter school, 3=special program school or magnet school, 4=vocational or technical school, 5=alternative school	1-5
X1SCHCONTROL	School control	1=public, 2=private
X1LOCALE	School local (urbanicity). 1=city, 2=suburban, 3=town, 4=rural	1 - 4 (categorical)

Method

The analysis consists of four parts: 1) a descriptive analysis of all the student, teacher and school variables listed in Table 1; 2) an analysis of all the first order correlations of the Level 1 and Level 2 variables respectively; 3) an analysis using Multi-level Modeling (MLM) to examine the variation in *Mathematics Achievement* within and between U.S. High Schools with particular focus on the relationship between *Teacher Self-Efficacy* and the *Mathematics Achievement* ; and 4) a comparison of the final multi-level analysis across REM subgroups. The first three parts of the analysis were conducted using a subsample of REM HSLS:09 respondents (N=6,006). In the final analysis (Part 4), the multilevel models were re-run using subsample all of the REM subgroups (American Indian/Alaskan Native, Black/African American, Hispanic, or Pacific Islander) as well as White and Asian subpopulations for comparison.

Multi-Level Modeling (MLM) is a regression-based approach that is favored over OLS when the structure of the data is nested (students within schools) as is the case here. The advantage of using MLM over OLS is that it corrects for the underestimation of standard error and variance parameters by partitioning the variance into within and between cluster components (i.e., schools). Furthermore, MLM makes it possible to examine the sources of variation across levels which allows researchers to interrogate questions not possible through OLS (Rabe-Hesketh & Skrondal, 2012). Five successive models predicting math achievement were specified as shown below and estimates were obtained using the "Mixed" function in Stata with maximum likelihood estimation. The school identifier (SCH_ID) was used as the grouping variable for the analysis with appropriate sampling weights. Model comparisons were done using -2 Log Likelihood estimates to conduct Chi-square difference tests. Within and between group variance reduction for successive models was also calculated and analyzed for each model. For all models, Student and Teacher variables are treated as Level 1 variables and School variables are treated as Level 2. What follows are descriptions, model specifications and associated research questions for each of the models in this analysis.

Null Model

RQ1: Does the variation of Mathematics Achievement of REM students within and between schools differ from that of the general student population?

The null model is the simplest multilevel model which allows for school effects on *Mathematics Achievement*, but without explanatory variables. The null model in this analysis is specified as:

Null model: $X2TXMTSCOR_{ij} = \beta_0 + u_j + e_{ij}$

where $X2TXMTSCOR_{ij}$ is the 11th grade algebraic reasoning score for the i^{th} individual in school j, β_0 is the overall mean of $X2TXMTSCOR$ (across schools), u_j is the school-level (Level 2) residual, also called the school random effects, and e_{ij} denotes the individual residuals (Level 1). Accordingly, the variance can be partitioned into the between school (Level 2) variance σ_u^2 and the within school (Level 1) variance σ_e^2 which are used used to calculate the Interclass Correlation Coefficient (ICC). The ICC is a measure of the amount of variance that is attributable to the clustered nature of the data. The ICC is calculated by dividing the between school variance by the total variance:

$$\text{ICC} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$$

Typical ICC values for educational attainment range from .5 to .25 and can be interpreted as the correlation of between two randomly selected individuals within a group (i.e, school). Therefore, higher ICC values can signal the presence of school factors that are influencing outcomes and is often used to justify the use of MLM versus OLS. As mentioned earlier, this model is run using data from the entire population of HSLS:09 high school student respondents. The null model can also be specified by level as:

Level 1: $X2TXMTSCOR_{ij} = \beta_0 + e_{ij}$

Level 2: $\beta_{0j} = \beta_0 + u_j$

To answer the *RQ1*, parameter estimates for the null model were first calculated using the entire population of students (N=21,444). Next the null model parameter estimates were calculated using the subpopulation of REM student respondents (N=6,006). The nature of the level 2 (school) variation was examined by plotting the school residuals along with standard errors to draw comparisons between the general population and the REM subpopulation respectively.

Model 1

RQ2: Are higher levels of Teacher Self-Efficacy generally associated with higher levels of Mathematics Achievement among REM students?

Model 1 extends the school effects model (Model 0) by adding *Mathematics Teacher Self-Efficacy (* $X1TMEFF$ *)* as an explanatory variable. It's important to mention once again that because teachers are not a unit of analysis, $X1TMEFF$ is a student level variable that can be characterized as a feature of the student's learning context. As such, Model 1 is specified as:

Model 1: $X2TXMTSCOR_{ij} = \beta_0 + \beta_1 X1TMEFF_{ij} + u_j + e_{ij}$

where $X2TXMTSCOR_{ij}$ is the algebraic reasoning score in 11th grade for the i^{th} student in school j, and where the overall relationship between $X2TXMTSCOR$ and $X1TMEFF$ is represented by a straight line with intercept β_0 and slope β_1. Moreover, the intercept for a given group j can be expressed as $\beta_{0j} = \beta_0 + u_j$ where the intercept for a given group β_{0j} will differ from the overall intercept β_0 by an amount of u_j and where u_j is a school effect (level 2) or residual that is assumed to follow a normal distribution with a mean of 0 and a variance σ_u^2. Model 1 can also be specified by level as:

Level 1: $X2TXMTSCOR_{ij} = \beta_{0j} + \beta_1 X1TMEFF_{ij} + e_{ij}$

Level 2: $\beta_{0j} = \beta_0 + u_j$

To answer the research *RQ2*, Model 1 parameter estimates were calculated using the REM student subpopulation (N = 6,006).

Model 2

RQ3:To what extent is the Mathematics Achievement of REM students attributable to differences in Mathematics Teacher's Self-Efficacy after controlling for Student Characteristics?

Model 2 adds student level (Level 1) controls to estimate the extent to which *Mathematics Achievement* is attributable to *Teacher Self-Efficacy* after controlling for differences in student characteristics. The controls included are *Socio-Economic Status* ($X1SES$), prior *Mathematics Achievement* ($X1TXMTSCOR$), *Student's Mathematics Self-Ffficacy* ($X1MTHEFF$), *Mathematics Identity (* $X1MTHID$ *)*, and *Student Gender* ($X1SEX$). With the exception of the outcome variable ($X2TXMTSCOR$) all of the other variables are from the first wave of data-collection which occurred when students were in 9th grade. While this is a limitation of the study design (student and teacher attitude data was only collected in first wave), it does not pose any major methodological concerns. That is this is a predictive model of early high-school experiences and context (9th grade) on future outcomes (11th grade). As such, Model 2 is specified as follows:

Model 2: $X2TXMTSCOR_{ij} = \beta_0 + \beta_1 X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + u_j + e_{ij}$

where the overall relationship between $X2TXMTSCOR_{ij}$ and $X1TMEFF_{ij}$ is conditioned on student control variable matrices and coefficient vectors represented as $\boldsymbol{\alpha STUDENT}$. The student control variables are standardized to a mean of 0 and standard deviation of 1 therefore, β_0 represents the mean of $X2TXMTSCOR$ conditioned on mean values (0) across all control control variables. Moreover, given the control variables are standardized to a mean of 0 and standard deviation of 1, betas for these models can be interpreted as standardized betas. Model 2 can also be specified by level as:

Level 1: $X2TXMTSCOR_{ij} = \beta_0 + \beta_1 X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + e_{ij}$

Level 2: $\beta_{0j} = \beta_0 + u_j$

To answer the *RQ3*, Model 2 parameter estimates were calculated using the REM student subpopulation (N = 6,006).

Model 3

RQ4: To what extent is the Mathematics Achievement of REM students attributable to differences in Mathematics Teacher's Self-Efficacy after controlling for both Student Characteristics and Teacher Quality?

Model 3 adds teacher (Level 1) controls to estimate the extent to which *Mathematics Achievement* is attributable to *Teacher Self-Efficacy* after controlling for differences in student and teacher characteristics. The teacher control variables include: *Mathematics Certification* ($X1TMCERT$), *Years Teaching Experience* ($M1MTHYRS912$) and *Mathematics Bachelor's Degree* ($M1BAMAJ2$). As previously mentioned, the teacher variables included at Level 1 because teachers are not representative of the teacher population at the school. Only mathematics teachers with HSLS:09 student participants were surveyed; therefore, teacher characteristics can only be interpreted as part of the student's learning context. Furthermore, teacher responses to the Teacher Questionairre occurred in the first wave of data collection when the students were in 9th grade. As is the case with the previous model, this is a limitation of the study and data but is not a methodological concern so long as results are interpreted as such. Model 3 is specified as follows:

Model 3: $X2TXMTSCOR_{ij} = \beta_0 + \beta_1 X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + \boldsymbol{\delta TEACHER} + u_j + e_{ij}$

where the linear relationship between $X1TMEFF$ and $X2TXMTSCOR$ is conditioned on the set of student control variables included in Model 2 ($\boldsymbol{\alpha STUDENT}$) as well as the 3 teacher quality control variable matrices and coefficient vectors represented as $\boldsymbol{\delta TEACHER}$. *Teacher Certification* ($X1TMCERT$) is a dichotomous variable that is equal to 1 of the student's mathematics teacher is fully certified to teach secondary mathematics. Years of teaching experience ($M1MTHYRS912$) is the number of years the teacher has taught secondary mathematics and is mean centered. Lastly, ($M1BAMAJ2$) is a dichotomous variable indicating whether or not the mathematics teacher has a bachelor's degree in a mathematics or mathematics intensive field. The $M1BAMAJ2$ and $X1TMCERT$ variables are reverse coded so that 0 = *BA in Mathematics* and *Certified to Teach Mathematics*, respectively. Thus, in model 3, the intercept β_0 should be interpreted as the overall mean of $X2TXMTSCOR$ conditioned on average (mean = 0) student characteristics and whose teachers have the average number of years experience, hold a Bachelor's Degree in Mathematics or related field, and are fully certified to teach secondary mathematics. Model 3 can also be represented by level as:

Level 1: $X2TXMTSCOR_{ij} = \beta_0 + \beta_1 X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + \boldsymbol{\delta TEACHER} + e_{ij}$

Level 2: $\beta_{0j} = \beta_0 + u_j$

To answer the *RQ4*, Model 3 parameter estimates were calculated using the REM student subpopulation (N = 6,006).

Model 4

RQ5: Does the nature of the relationship between Mathematics Teacher Self-Efficacy and the Mathematics Achievement of REM students vary across schools?

Model 4 relaxes the fixed slope constraint of $\beta_1 MTEFF_{ij}$ and allows it to vary randomly across schools. As such, Model 4 is specified as:

Level 1: $X2TXMTSCOR_{ij} = \beta_{0j} + \beta_{1j} X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + \boldsymbol{\delta TEACHER} + e_{ij}$

Level 2: $\beta_{0j} = \beta_0 + u_{0j}$ (random intercept of $X2TXMTSCOR$)

Level 2: $\beta_{1j} = \beta_1 + u_{1j}$ (random slope of $X1TMEFF$)

where σ^2_{u1} is the variance of the school's mean slope β_{1j} and σ_{u01} is the covariance between the school's intercept β_{0j} and slope β_{1j}. To answer the *RQ5*, Model 4 parameter estimates were calculated using the REM student subpopulation (N = 6,006).

Model 5

RQ6: *Does the School Context influence the relationship between Mathematics Teacher Self-Efficacy and the Mathematics Achievement of REM students?*

Model 5 adds two school contextual factors namely *School Climate, School Size* and an interaction term between *School Climate* and *Mathematics Teacher Efficacy*. It is notable that *School Type (Public vs Private)*, *Percent of Students on Free and Reduced Lunch*, *School SES*, as well as *School Locale*, were not included in the model due to co-linearity with student level *SES*. *SES* is a composite variable that is derived with locale (urbanicity), therefore *School Locale* (e.g., city, suburban, town, rural) was also omitted from Model 5. As such, Model 5 is specified as:

$$\text{Level 1: } X2TXMTSCOR_{ij} = \beta_{0j} + \beta_{1j}X1TMEFF_{ij} + \boldsymbol{\alpha STUDENT} + \boldsymbol{\delta TEACHER} + \beta_{10}SCHCLIMATE_{j} + \beta_{11}CLIxMTEFF + \beta_{12}SCHSIZE + e_{ij}$$

$$\text{Level 2: } \beta_{0j} = \beta_{0} + u_{0j} \text{ (random intercept of } X2TXMTSCOR\text{)}$$

$$\text{Level 2: } \beta_{1j} = \beta_{1} + u_{1j} \text{ (random slope of } X1TMEFF\text{)}$$

where $SCHCLIMATE$ is a scale of the administrator's assessment of his/her school's climate. Higher values represent more positive assessments of the school's climate. $SCHSIZE$ is a proxy variable that is derived from the number of full-time mathematics teachers at the school. Higher number of teachers are assumed to be needed for larger student populations and by extension represent larger schools. This variable was added to the analysis to address convergence issues with the model. By centering the $SCHSIZE$ variable around the grand mean for all schools, the coefficients for Model 5 can be interpreted as being conditioned on average *School Size*. An interaction term between *School Climate* and *Mathematics Teacher Self-Efficacy* $(CLIxMTEFF)$ is included to test the hypothesis that the *Mathematics Teacher Efficacy* effect is moderated by the conditions at the school, namely *School Climate*. To answer the *RQ6*, Model 5 parameter estimates were calculated using the REM student subpopulation (N = 6,006).

RQ7: *How does the nature of the relationship between Mathematics Teacher Self-Efficacy, Mathematics Achievement and School Context vary across REM subgroups?*

To answer *RQ7*, all 6 models (including the null) were specified as detailed above and estimated for each racial subgroup, A full analysis using the entire student population (N=21,444) was also conducted for comparison.

Limitations

The limitations of this study are common among survey research. The first is the issue of construct validity, that is, we can never be certain whether what we seek to measure is what is being measured. While the measures in this study were carefully constructed and validated, the coefficients of reliability for most of the composite variables was .65 which is marginally reliable. Another limitation to this approach is that it positions mathematics achievement as the ultimate outcome. While mathematics is an important outcome of education within the STEM context, it is certainly not the only outcome. Other outcomes include choice and persistence in additional mathematics courses, improvement or perhaps even interest in mathematics. Some argue that focusing solely on achievement perpetuates the notion that the only certain students are set out to be successful in mathematics. In so far as this study helps to show that success can be nurtured through good teaching and supportive school environments then achievement can be measure of a healthy mathematical ecology not individual ability or product.

Lastly, as already mentioned, the teacher data supply contextual information for students, who in turn constitute the unit of analysis. The teacher sample is not representative of teachers in the school. The design of this component does not provide a standalone analysis sample of teachers, but instead permits specific teacher characteristics and practices to be related directly to the learning context and educational outcomes of sampled students.

Protection of Human Subjects

This study will used a restricted dataset from the National Center of Education Statistics. All analysis followed proper protocols for protection of participant identity and will go through IRB review. It is expected that this study will be declared exempt as it only reports non-identifyable aggregate data.

Statement about researcher positionality

I have been in the field of education for nearly 20 years, first as a Teacher and now as Director of a Teacher Education Program at a graduate university. As a first generation college graduate who aspired to enter the medical field, my trajectory into teaching was preceded by varying degrees of success as a STEM student. While I was not terrible at mathematics, it was not my strongest subject and I was not adequately prepared to be successful at a prestigious undergraduate research institution. I failed calculus the first time I took it and the best I was able to do was earn a C+ which to me was a big accomplishment. I eventually moved away from the sciences much in the same way the research describes. I questioned my ability, my belonging and my goals. Later, after becoming a teacher, I began to see this same questioning in my students and I did my best to encourage and help them understand that it was not a question of ability but a matter of having the right attitude (this was before mindset was in fad). When I look at the research on achievement, we don't see the full story. We don't see the difference that teachers make in the lives of students who through their experiences in the classroom, gain confidence in their abilities and are inspired to get better. As a teacher educator, I see the impact teachers make every day, but this story is not always evident in the data. I would like to contribute to this in a small way by trying to find that story in a manner that is most compelling to policy makers, rigorous research.

Chapter 4. Results

Descriptive Analysis

The results of this study are organized into three sections. The first section includes univariate summary statistics for all of the variables included in the analysis as well as well as select cross tabulations to examine variation in the independent and dependent variables, namely, Mathematics Achievement and Mathematics Teacher Self-Efficacy. The second section presents first-order correlations for all school-level and student level variables respectively. The final section provides the results and analysis of the five successive multi-level models specified in the previous chapter.

Student Characteristics.

Table 2 shows summary statistics and frequencies for all student level variables in this study. It includes summary statistics for Mathematics Achievement, Socio-economic Status and Motivation variables. Frequencies for categorical variables including Gender and Student Race are also summarized. With the exception of the S*tandardized Mathematics Score* for 11th Grade, all of the remaining variables were collected during the base-year of HSLS:09. Sampling weights were used to estimate population means for all of the continuous variables in Table 2. The frequencies of categorical variables are unweighted therefore they do not represent population estimates. For instance, Asians were oversampled in HSLS:09 therefore the percentage of Asian students in the HSLS:09 sample is 7.8% , a much higher percentage than the actual percentage in the U.S. population. The oversampling assures that Asian students are not underrepresented in the sample. All subsequent analyses utilize the appropriate sampling weights to account for the complex stratified sampling design of HSLS:09.

Table 2.

Summary Statistics of Student Characteristics

	%	M (SE)	SD	Cronbach's α	n
Mathematics Standardized Score 9th Grade		50.00 (0.19)	10.00		24,658
Mathematics Standardized Score 11th Grade		50.00 (0.19)	10.00		24,955
Mathematics Gain (difference between grade 9 & 11)		0.11 (0.10)	7.20		24,725
Student Mathematics Self-Efficacy		0.01 (0.01)	1.00	0.90	21,802
Socio-Economic Status		-0.08 (0.01)	0.75		25,205
Sex					
Female	49.23				10,557
Male	50.77				10,887
Total	100				21,444
Student Race/Ethnicity					
Amer. Indian/Alaska Native, non-Hispanic	0.76				163
Asian, non-Hispanic	7.80				1,672
Black/African-American, non-Hispanic	10.34				2,218
Hispanic, no race specified	0.95				204
Hispanic, race specified	15.44				3,311
More than one race, non-Hispanic	8.92				1,912
Native Hawaiian/Pacific Islander, non-Hispanic	0.51				110
White, non-Hispanic	55.28				11,854
Total	100.00				21,444

Note. Mean, standard error, standard deviation and number of observations for continuous variables were estimated using student-level data and analytic weights to account for complex sampling design of HSLS:09. Tabulations for categorical variables represent unweighted frequencies of base-year study eligible, questionnaire capable respondents (n = 21,444). n = analytic sample size.

* p<0.05, ** p<0.01, *** p<0.001 (remove if not applicable)

Mathematics Achievement. The *Mathematic Standardized Score* for both 9th and 11th grade are based on the results of the Algebraic reasoning exam administered to students in both 9th and 11th grade. Eleventh grade exam scores are centered to a mean of 50 and a standard deviation of 10. For comparison purposes with other predictor variables, 9th grade exam scores were standardized to a mean 0 and standard deviation of 1. While not every student took the exam in both years, the table shows weighted population estimates that account for student non-response rates in 9th and 11th grade respectively.

Mathematics Self Efficacy. *Student Mathematics Efficacy* is a measure of how well students think they can do well in their mathematics class. It is derived from student answers to questions about how much they agree/disagree with the following statements about their mathematics course: 1) You are confident that you can do an excellent job on tests in this course; 2) You are certain that you can understand the most difficult material presented in the textbook used in this course; 3) You are certain that you can master the skills being taught in this course; and 4) You are confident that you can do an excellent job on assignments in this course. The mean of *Student Mathematics Efficacy* is standardized to a mean of 0 and a standard deviation of 1. The coefficient of reliability (alpha) is 0.90 suggesting moderate internal consistency.

Socio-Economic Status. Student S*ocio-Economic Status* is a composite measure comprising parent/guardian's education, occupation, and family income and locale (urbanicity). The mean Socio-Economic Status was standardized to a mean of o and a standard deviation of 1.

Gender. The unweighted proportion of female students in the HSLS:09 sample is 49.23% versus 50.77% male. The slight difference from expected proportions in the general population is adjusted for by using appropriate sampling weights in all subsequent analyses.

Race. As mentioned above, the Student *Race/Ethnicity* percentages shown in Table 2 represent sample frequencies not population estimates. Some racial/ethnic groups were oversampled to make sure they were adequately represented in the sample. The largest proportion of students in the sample are white, who comprise 55.28% of the sample. The second largest group was Hispanic students followed by Black and Asian each comprising 16.39, 10.34

and 7.80 percent respectively. Approximately 8.92 percent of the student sample identified as more than one race. Lastly, American Indian/Alaskan Natives and Native Hawaiian/Pacific Islander made up the smallest segments of the student sample comprising 0.76 and 0.51 percent respectively.

Mathematics Teacher Characteristics.

Table 3 shows summary statistics and frequencies for student's mathematics teacher variables used in this study. It includes summary statistics for *Mathematics Teacher Self-Efficacy*, *Years of Experience*, *Certification*, *Education*, and *Race*. Frequencies for categorical variables include mathematics teacher's *Sex* and *Race*. All of the Teacher variables were collected during the base-year of HSLS:09 from student respondents who were enrolled in a mathematics score. Accordingly, appropriate sample weights and survey design parameters were used to estimate population means of each respective continuous variable. In contrast, categorical variables represent unweighted frequencies therefore should not be interpreted as population estimates. It also important to note that teachers are not the unit of study therefore means, totals and frequencies of teacher variables are not generalizable to all mathematics teacher but rather represent features of the student's learning context.

Table 3

Summary Statistics of Mathematics Teacher Characteristics

	%	M (SE)	SD	Cronbach's α	n
Mathematics Teacher Self Efficacy		0.00 (0.04)	1.00	0.71	23,197
Years of Experience		9.63 (0.20)	8.36		25,159
Regular state cert/adv prof certificate					
Yes	79.75				12,769
No	20.25				3,242
	100.00				16,011
Mathematics or Related Degree*					
Yes	37.88				6064
No	62.12				9943
Total	100.00				16,007
Sex					
Female	60.36				9,679
Male	39.64				6,356
Total	100.00				16,035
Mathematics Teacher's Race/Ethnicity					
American Indian/Alaska Native, non-Hispanic	0.18				163
Asian, non-Hispanic	2.41				1,672
Black/African-American, non-Hispanic	3.42				2,218
Hispanic, no race specified	0.36				204
Hispanic, race specified	3.31				3,311
More than one race, non-Hispanic	1.42				1,912
Native Hawaiian/Pacific Islander, non-Hispanic	0.04				110
White, non-Hispanic	88.86				11,854
Total	100.00				21,444

Note. Means for continuous variables represent population estimates calculated using student-level data and appropriate sampling weights to account for complex sampling design of HSLS: 09. Tabulations for categorical variables represent frequencies base-year respondents mathematics teachers. Only Students that were enrolled in a mathematics class and whose mathematics teacher responded to the teacher questionnaire are included. n = analytic sample size.

* Includes Mathematics, Statistics, Engineering, Physics and Computer Science

Teacher Self-Efficacy. *Mathematics Teacher Self-Efficacy* is a scale of student's base year mathematics teacher's self-efficacy; higher values represent greater self-efficacy. It is derived from teacher answers to questions about how much they agree/disagree with the following statements: 1) *The amount a student can learn is primarily related to family* *background*; 2) *If students are not disciplined at home, they are not likely to accept any discipline at school*; 3) *You are very limited in what you can achieve because a student's home environment is a large influence on their achievement*; 4) *If parents would do more for their children, you could do more for your students*; 5) *If a student did not remember information you gave in a previous lesson, you would know how to increase their retention in the next lesson*; 6) *If a student in your class becomes disruptive and noisy, you feel assured that you know some techniques to redirect them quickly*; 7) *If you really try hard, you can get through to even the most difficult or unmotivated students*; and 8) *When it comes right down to it, you really can not do much because most of a student's motivation and performance depends on their home environment*. *Mathematics Teacher Self-Efficacy* is standardized to a mean of 0 and a standard deviation of 1. The coefficient of reliability (alpha) is 0.71 suggesting moderate internal consistency. According to Bandura (1997), all items in self efficacy scales should be phrased as “can do” statements, so that they are a measure of personal ability and competence, not just a reflection of personal beliefs and thoughts. However, not all of the statements designed to assess *Teacher Efficacy* in the HSLS:09 scale conform to this dictate. This could explain why the coefficient of reliability is lower than is typically found for self-efficacy scales (i.e., the student self-efficacy scale conforms to Bandura’s dictate and has a reliability coefficient of .90).

Years of Experience. The mean years of experience of HSLS:09 student’s mathematics teacher is 9.63 years with a standard error of .20 and a standard deviation of 8.36. This suggests that there is a large amount of variation with a majority of teachers ranging between 1 - 18 years of mathematics teaching experience.

Certification. The proportion of students with teachers holding mathematics teaching certification is estimated to be .79 with a standard error of 0.01 and a standard deviation of .41. This includes teachers who have either a regular or advanced teaching certification from their state. It does not include teachers with temporary, partial or those that are currently in progres.

Mathematics Degree. The proportion of HSLS:09 student respondents who were taught by mathematics teachers with at least a Bachelor's degree in mathematics or related field is 37.88% versus 62.12% who were not. This includes teachers with a Bachelor's degree in Mathematics, Statistics, Engineering, Physics or Computer Science.

Gender. The proportion of HSLS:09 study respondent with female mathematics teachers is 60.36% versus 39.64% male teachers.

Race. As mentioned earlier, the *Race/Ethnicity* percentages shown in 3 represent sample frequencies of student HSLS:09 respondents. The largest proportion of study students had white teachers, comprising 88.86% of the sample. The second largest group was Hispanic students followed by Black and Asian each comprising 3.67, 3.42 & 2.41 percent respectively. Approximately 1.42 percent of the student respondents had mathematics teachers who identified with more than one race. Lastly, American Indian/Alaskan Natives and Native Hawaiian/Pacific Islander made up the smallest segments of the students mathematics teachers comprising 0.18 and 0.04 percent respectively.

School Characteristics.

Table 4 shows summary statistics and frequencies for school characteristics variables used in this study. It includes summary statistics for *Mathematics Teacher Self-Efficacy*, *Years of Experience*, *Certification*, *Education*, and *Race*. Frequencies for categorical variables include mathematics teacher's *Sex* and *Race*. All of the Teacher variables were collected during the base-year of HSLS:09 from student respondents who were enrolled in a mathematics course. Accordingly, appropriate sample weights and survey design parameters were used to estimate population means of each respective continuous variable. In contrast, categorical variables represent unweighted frequencies therefore should not be interpreted as population estimates. It also important to note that teachers are not the unit of study therefore means, totals, and frequencies of teacher variables are not generalizable to all mathematics teacher but rather represent features of the student's learning context.

Table 4

Summary Statistics of School Characteristics

	%	M (SE)	SD	Cronbach's α	n
School Compositional SES		-0.01 (0.02)	0.43		944
School Climate		0.00 (0.06)	1.00	0.89	738
Free and reduced lunch (%)		35.92 (1.56)	26.85		860
Student Body Ethnic Composition (%)					
American Indian/Alaskan Native		1.74 (0.54)	8.39		861
Asian or Pacific Islander		2.86 (0.31)	6.38		864
Black or African American		11.72 (1.19)	20.10		865
Hispanic/Latino/Latina		11.87 (0.96)	19.63		866
White		70.83 (1.97)	30.43		865
School Type					
Regular school not incl magnet/charter	93.35				828
Charter school	1.92				17
Special program school or magnet school	3.49				31
Vocational or technical school	0.45				4
Alternative school	0.79				7
Total	100.00				887
School Control					
Public	80.63				716
Private	19.37				172
Total	100.00				888
School Locale					
City	28.81				272
Suburb	35.49				335
Town	12.39				117
Rural	23.31				220
Total	100.00				944

Note. Mean, standard error, standard deviation and total valid observations for continuous variables were estimated using school-level data and sampling weights to account for complex sample design of HSLS:09. Percentages were tabulated from the total number of base year schools (n = 944). Crombach's alpha values for composite variables were obtained from HSLS: 09 documentation. n = analytic sample size.

School Compositonal SES. The *School's Compositional Socio-Economic Status* (School SES) is derived from the *Student Socio-Economic Status* (Student SES) aggregated at the school level. The mean *School SES* for HSLS:09 schools (N=944) is estimated to be -.01 with a standard error of .02 and a standard deviation of .43. This is very similar to the mean of individual student socio-economic status; however, there is less variation between schools than between individuals. This is expected because we expect students within a school to be more similar than individuals picked at random from the population. Nevertheless, *School SES* can be interpreted as the average socio-economic status of the students within a given school. Higher values represent higher levels of the parent's/guardian's educational attainment, household income and occupational prestigue.

School Climate. Schol Climate is a scale of administrator's assessment of problems at the school. It is derived from responses to questions about the frequency of a variety of incidents including: 1) physical conflicts at the school; 2) robbery or theft; 3) vandalism; 4) illegal drug usage; 5) alcohol usage; 6) drug selling on or near school grounds; 7) student position of weapons; 8) physical abuse of teachers; 9) student racial tensions; 10) student bullying; 11) student verbal abuse of teachers; 12) student in-class misbehavior; 13) student acts of disrespect for teachers; and 14) student gang activities. The scale of *School Climate* is centered to a mean of

0 and a standard deviation of 1. The coefficient of reliability (alpha) is 0.65 suggesting moderate internal consistency.

Free and Reduced Lunch. The average proportion of students the receive free and reduced lunch across schools is estimated to be 39.92% with a standard error of 1.56 and a standard deviation of 26.85. This suggests that there is a large amount a variability across schools with respect to the proportion of the student population who qualify for free and reduced lunch services. It is important to note that this estimate includes all types of schools including private and parochial schools therefore it is any analysis should include controls to control for differences between public and private schools. For instance, the mean proportion of receiving free and reduced lunch services in public schools is 44.90% with a standard deviation of 23.56, a significant difference both practically and statistically. Subsequent analysis thus include both estimates of *Free and reduced lunch* while controlling for *School Type* (Traditional/Non-Traditional) and *School Control* (Private vs Public).

Student Body Ethnic Composition. The *Racial/Ethnic Student Composition* is the average proportion of various racial groups across U.S. schools. The highest proportion of students across schools is White students who on average comprise 70.83% of the students in U.S. schools. The next highest are Hispanic and Black students each comprising 11.87% and 11.72% respectively. American Indian/Alaskan Native and Asian or Pacific Islander make up the lowest proportion on average comprising 1.74% and 2.86% respectively. It is important to note that the compositional data was derived from the school administrator survey, not from student level respondents. Therefore these estimates represent population estimates for U.S. schools in 2009.

School Type. Five different school types are represented in the schools sampled in HSLS:09 with 93.35% being regular or "traditional" public schools. Other types included Charter Schools which comprised 1.92% of schools as well as Magnet, Vocational/Technical, and Alternative Schools each comprising 3.49%, 0.45% and 0.79% respectively. It is important to note that Charter Schools as well as Vocational/Technical schools are also considered public. For this reason, subsequent analysis uses both *School Type* and *School Control* (public/private) as control variables.

School Control. The proportion of schools in the HSLS:09 sample under public control is 80.63% compared to 19.37%of that are private. Generally speaking, private schools tend to be associated with her Socio-Economic status therefore all subsequent analysis include school type as a control variable to mitigate confounding school effects with SES effects.

School Locale. The four distinct school locales include City, Suburban, Town and Rural. The proportion of schools in each of these were derived from data from the Common Core of Data and the Private School Survey. The locale with the highest proportion of schools was Suburb followed by City with 35.49% and 28.81% respectively. Approximately 23.31% of schools are in rural areas and 12.39% are in towns.

Patterns of Achievement and Teacher Self Efficacy.

This section contains a closer examination of the dependent and the independent variables in this study namely Mathematics Achievement and Mathematics Teacher Self-Efficacy. Each of these variables are examined across Race, Gender, Socio-Economic Status and School Characteristics to reveal variation across these various groups and provide some initial insight into patterns of variation across various groupings.

Table 5

Mathematics Achievement by Race

	(1)	(2)	(2-1)
Amer. Indian/Alaska Native, non-Hispanic	-6.92 (2.13)** 10.67 163	-4.56 (1.31)*** 9.32 126	1.44 (1.09) 7.71 124
Asian, non-Hispanic	7.81 (0.64)*** 15.32 1,672	7.99 (0.69)*** 15.02 1,705	0.69 (0.32)* 9.20 1,467
Black/African-American, non-Hispanic	-4.88 (0.42)*** 7.94 2,218	-4.68 (0.36)*** 6.91 2,123	0.51 (0.32) 5.79 1,897
Hispanic, no race specified	-4.98 (1.36)*** 7.23 204	-3.86 (0.85)*** 6.38 346	0.41 (0.81) 3.82 153
Hispanic, race specified	-1.87 (0.32)*** 7.79 3,311	-1.90 (0.30)*** 7.26 2,860	0.03 (0.20) 5.76 2,805
More than one race, non-Hispanic	-0.22 (0.39) 9.91 1,912	-0.02 (0.40) 9.63 1,676	0.28 (0.30) 7.29 1,647
Native Hawaiian/Pacific Islander, non-Hispanic	-2.92 (2.01) 9.88 110	-0.72 (2.19) 8.96 89	1.33 (2.65) 8.78 89
White, non-Hispanic	1.81 (0.19)*** 9.74 11,854	1.75 (0.19)*** 9.86 10,663	-0.06 (0.11) 6.93 10,441

Note. Mean (standard error), standard deviation & number of observations for student's standardized mathematics achievement score in baseyear (1), first follow up (2) and difference (2-1). Subpopulation estimates were calculated using student-level data and sampling weights to account for complex sampling design of HSLS:09. For each column, the Wald significance test tests the hypothesis that the difference between the subgroup mean and the population mean (see Table 2) is equal to zero.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Mathematics Achievement by Race

Table 19 shows subpopulation estimates of mathematics achievement in students 9th, 11th grade and the change between their achievement between 9th and 11th grade across racial subgroups. Mathematics scores for both 9th and 11th grade were mean centered therefore estimates represent the differences between the subpopulation mean and the overall population mean. The results for the base year (1) indicate that there are significant differences along racial lines. This is consistent with the well-documented patterns of "achievement gaps" across racial groups. Overall, Asian students outperform all other subgroups outscoring other students by an average of 7.81 points. This difference is both statistically significant and practically significant as an effect size of roughly .75 is rather large in educational contexts. Similarly, White students on average outperform the general population by 1.81 points which translates into an effect size of .18. All other racial groups show either no difference from the mean or score lower compared to the entire student population. American Indian/Alaskan Native on average score 6.92 points below the mean and have the highest variation with a standard deviation of 2.13. Black and Hispanic students also score lower on average with the subpopulation of Hispanic with no racial identity scoring 4.98 points lower on average than the entire student population and with a standard deviation of 1.36. Similarly, Black students on average scored 4.88 points lower than the national average while Hispanic students who specified a race scored 1.87 points lower. The differences for Black and Hispanic students compared to the national average were both statistically significant at the .001 level, signaling that the difference is extremely unlikely to be a chance occurrence. Native Hawaiian/Pacific Islander students also scored lower than the National average; however, that difference was not statistically significant, in part due to the small sample size and large standard deviation. Overall, the patterns match longstanding trends in educational inequity in mathematics education.

The mean achievement scores for the first follow up (2) follow similar trends to those in the base year. With the exception on Asian students all other subgroups there was no difference between their relative performance in the base year (1) versus the first follow up (2). That is to say that every subgroups performance stayed the same relative to the National Average. This is reflected in the Math Gain column (2-1) which shows Asian students gaining 0.69 points between 9^{th} and 11^{th} grade. This was statistically significant at the .05 level. No other group made gains (or losses) that were statistically significantly different than their base-year outcomes. This does not mean that these groups did not improve their achievement, it just means that the relative achievement gap for the various racial groups did not change.

Table 6

Mathematics Achievement Gain by Group

	(1)	(2)	(2-1)
School Control			
Private	4.50 (0.51)*** 13.20 3,933	5.64 (0.52)*** 13.29 3,749	1.27 (0.22)*** 9.49 3,459
Public	-0.35 (0.20) 9.26 17,511	-0.43 (0.20)* 9.15 16,845	0.02 (0.10) 6.59 15,164
Locale			
City	-0.21 (0.41) 9.26 6,067	-0.19 (0.41) 9.12 5,852	0.25 (0.17) 6.01 5,259
Suburban	0.87 (0.29)** 9.91 7,636	0.99 (0.32)** 9.75 7,378	0.21 (0.16) 6.64 6,577
Town	-1.83 (0.55)** 9.00 2,580	-1.77 (0.36)*** 8.75 2,447	0.08 (0.32) 6.61 2,247
Rural	-0.05 (0.30) 9.28 5,161	-0.28 (0.32) 9.04 4,917	-0.20 (0.18) 6.86 4,540
Gender			
Male	-0.10 (0.25) 10.10 10,887	0.04 (0.24) 9.94 10,382	0.32 (0.12)* 6.83 9,349
Female	0.10 (0.25) 9.17 10,557	-0.03 (0.24) 9.07 10,206	-0.09 (0.13) 6.53 9,274
Socio-Economic Status (SES)			
Low SES	-5.21 (0.33)*** 8.22 3,434	-4.84 (0.34)*** 7.26 2,918	0.34 (0.20) 6.15 2,833
Middle SES	-0.55 (0.17)** 9.16 12,491	-0.64 (0.17)*** 8.85 10,909	0.00 (0.12) 6.84 10,762
High SES	6.67 (0.22)*** 10.30 5,519	7.00 (0.24)*** 10.39 5,039	0.26 (0.16) 7.69 5,028

Note. Mean (standard error), standard deviation, & number of observations for student's standardized mathematics achievement score in baseyear (1), first follow-up (2), and difference (2-1). Subpopulation estimates were calculated using student-level data and sampling weights to account for complex sampling design of HSLS:09. For each column, the Wald significance test tests the hypothesis that the difference between the subgroup mean and the population mean (see Table 2) is equal to zero.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Mathamatics Gain by Group

Table 20 above shows mean mathematics achievement for various groupings of students including: *School Control*, *Locale*, *Gender*, and *Socio-Economic Status* (SES). Students in private schools showed the biggest gains in *Mathematics Achievement* increasing by 1.27 points from the base year to the first follow-up. In contrast, students in public schools showed no gains in mathematics achievement during the same time period. In fact, students in public schools scored .35 and .43 points lower than the National average in 9th (1) and 11th (2) grades respectively; however, the difference was only statistically significant in 11th grade.

Student's mathematics achievement also varied by *Locale* with students from suburban locales outperforming students from the other 3 locales. Suburban students on average scored 0.87 and 0.99 points higher than the National average in the 9th and 11th grade respectively. This difference was statistically significant at the .01 level. In contrast, students from Town locales on average scored lower by 1.83 and 1.77 points in 9th and 11th grade respectively. On average, students from rural and city locales did not differ from the National mean in either 9th or 11th grade.

There were no differences between male and female students mathematics achievement relative to the National average. Both performed similarly in both 9th and 11th grade with male students showing a slight gain 0.32 between assessments. This difference was statistically significant at the .05 level. So while female students show a slightly downward trend, there is not enough evidence to conclude that they perform any different than the national average.

Lastly, mean mathematics achievement was tabulated across low, middle and high SES groups. As expected, students in the highest SES group performed above the National average by 6.67 and 7.00 points in 9th and 11th grade respectively. In contrast, students in the lowest SES group scored 5.21 and 4.84 points below the National average across the same time periods. Students in the middle SES group also scored lower compared to the National average, with means of -0.55 and -0.64 respectively in 9th and 11th grade. All the differences in base year and first follow up mathematics achievement means were statistically significant at the .01 level or lower. None of the SES groups showed significant gains or losses relative to the National averages. That is, each group performed consistently across 9th and 11th grade.

Table 7

Mathematics Achievement Gain by Race and SES

	(1)			(2)			(2-1)		
	Low	Middle	High	Low	Middle	High	Low	Middle	High
Amer. Indian/Alaska Native, non-Hispanic	-14.59 (1.48)***	-6.29 (1.39)***	7.03 (2.27)**	-11.61 (2.53)***	-4.07 (1.07)***	6.69 (1.84)**	0.83 (3.54)	2.35 (1.51)	-1.08 (1.39)
	6.39	9.08	9.25	7.82	7.42	7.75	8.54	6.94	6.69
	38	97	28	27	75	24	26	74	24
Asian, non-Hispanic	-0.44 (1.74)	6.17 (0.52)***	12.79 (0.73)***	2.35 (1.43)	5.90 (0.59)***	12.98 (1.01)***	2.90 (0.92)**	0.24 (0.50)	0.64 (0.59)
	16.20	12.96	14.08	12.70	13.21	15.41	9.87	7.94	10.33
	183	786	703	173	723	639	154	677	636
Black/African-American, non-Hispanic	-7.70 (0.61)***	-4.72 (0.47)***	1.79 (0.92)	-7.16 (0.65)***	-4.29 (0.43)***	1.49 (0.79)	0.82 (0.55)	0.49 (0.40)	-0.29 (0.66)
	6.87	7.48	9.89	5.82	6.52	8.86	5.01	5.65	7.76
	496	1,367	355	427	1,174	327	412	1,158	327
Hispanic, no race specified	-7.37 (1.16)***	-2.19 (2.17)	0.97 (0.85)	-6.33 (1.08)***	-2.09 (1.99)	1.22 (0.00)***	0.72 (0.98)	0.08 (1.18)	-2.11 (0.00)***
	6.18	7.65	2.61	5.26	6.66	0.00	3.92	3.62	0.00
	110	92	2	104	82	1	80	72	1
Hispanic, race specified	-4.56 (0.49)***	-0.80 (0.37)*	5.15 (0.69)***	-4.18 (0.47)***	-0.97 (0.40)*	4.44 (0.99)***	0.20 (0.38)	0.00 (0.30)	-0.64 (0.85)
	6.78	7.64	9.15	6.17	7.13	10.19	5.28	5.64	8.52
	1,187	1,727	397	999	1,469	362	985	1,458	362
More than one race, non-Hispanic	-3.50 (0.79)***	-1.41 (0.45)**	6.50 (0.69)***		-1.34 (0.47)**	7.22 (0.81)***	-0.35 (0.75)	0.30 (0.36)	0.64 (0.73)
	9.23	8.86	10.94		8.55	10.67	7.21	6.94	8.48
	254	1,225	433		1,066	385	201	1,062	384
Native Hawaiian/Pacific Islander, non-Hispanic	-1.11 (1.38)	-4.80 (2.25)*	8.09 (2.08)**	-9.16 (4.18)*	-1.43 (1.67)	11.68 (4.17)*	-7.89 (4.08)	2.18 (3.11)	3.93 (2.03)
	7.61	8.95	8.26	8.95	6.57	12.85	8.74	8.11	6.46
	21	72	17	14	59	16	14	59	16
White, non-Hispanic	-4.53 (0.39)***	0.58 (0.20)**	6.76 (0.21)***	-4.54 (0.46)***	0.28 (0.18)	7.22 (0.23)***	0.13 (0.29)	-0.26 (0.14)	0.32 (0.16)*
	9.55	8.90	9.27	8.50	8.87	9.42	7.01	6.70	6.84
	1,145	7,125	3,584	971	6,261	3,285	961	6,202	3,278

Note. Mean (standard error), standard deviation, & number of observations for student's standardized mathematics achievement score in baseyear (1), first follow-up (2), and difference (2-1). Subpopulation estimates were calculated using student-level data and sampling weights to account for complex sampling design of HSLS:09. For each column, the Wald significance test tests the hypothesis that the difference between the subgroup mean and the population mean (see Table 2) is equal to zero..

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Mathematics Gain by Race and SES

Table 7 above shows patterns of mathematics performance across Race and SES groups. With few exceptions, achievement patterns are consistent across racial groups with performance increasing according to SES grouping. That is, students in higher SES groups within the same racial group tend to outperform those in the lower SES groups. A notable exception seems to be middle SES Native Hawaiian/Pacific Islander students who were the lowest performing group in the base year mathematics assessment. However, it is likely that the low number of students in these groups make scores more susceptible to outliers. Overall, the pattern of SES is clear and consistent; increases in SES tranlate to increases in achievement for all students. With respect to *Mathematics Gain*, only Asian students in the low SES group showed significant increases in relative achievement (compared to National average) increasing 2.90 points. The tabulation across this many groups while helpful to see broad patterns is not ideal for any substantive analysis due to the low frequencies in many of the groupings. It does however confirm the importance of SES across racial groups as well as highlights the fact that SES alone cannot make up for where students start off.

Table 8

Teacher Quality Characteristics by Student Race

	SELF EFFICACY	YRS EXPERIENCE	MATH CERTIFICATION	B.A. MATHEMATICS
Amer. Indian/Alaska Native, non-Hispanic	-0.46 (0.38) 0.89 95	-2.19 (1.48) 7.22 115	-0.26 (0.12)* 0.44 115	-0.20 (0.08)* 0.33 115
Asian, non-Hispanic	0.07 (0.10) 1.32 1,077	0.51 (0.64) 10.05 1,250	-0.02 (0.03) 0.53 1,252	0.10 (0.03)** 0.63 1,252
Black/African-American, non-Hispanic	0.08 (0.07) 0.76 1,336	-0.92 (0.47)* 6.05 1,524	-0.06 (0.03) 0.32 1,526	-0.02 (0.03) 0.35 1,523
Hispanic, no race specified	-0.32 (0.14)* 0.71 174	-2.28 (1.28) 5.04 194	-0.09 (0.05) 0.30 194	0.07 (0.06) 0.32 194
Hispanic, race specified	-0.11 (0.08) 0.79 2,130	-0.53 (0.34) 5.67 2,434	-0.05 (0.03) 0.32 2,446	0.01 (0.03) 0.36 2,441
More than one race, non-Hispanic	-0.05 (0.07) 0.90 1,266	-0.26 (0.39) 7.13 1,414	0.02 (0.02) 0.35 1,422	0.03 (0.02) 0.44 1,416
Native Hawaiian/Pacific Islander, non-Hispanic	-0.37 (0.17)* 0.93 69	-0.13 (1.34) 7.75 83	0.03 (0.06) 0.36 83	0.10 (0.10) 0.47 82
White, non-Hispanic	0.05 (0.03) 0.88 8,070	0.55 (0.24)* 8.07 9,165	0.03 (0.01)** 0.35 9,188	0.00 (0.02) 0.45 9,175

Note. Mean (standard error), standard deviation, & number of observations for *Teacher Quality* characteristics are reported. Student *Race* subpopulation estimates were calculated using student-level data and sampling weights to account for complex sampling design of HSLS:09. For each column, the Wald significance test tests the hypothesis that the difference between the subgroup mean and the population mean (see Table 3) is equal to zero.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Teacher Quality by Student Race

Table 8 above shows mean estimates for *Teacher Quality* characteristics across student Race including *Teacher's Self Efficacy*, *Years of Experience*, *Mathematics Certification* and *Mathematics Degree*. Means were calculated from student level data based on student's mathematics teacher responses to the teacher questionnaire in HSLS:09. Since teachers are not a unit of analysis, the *Teacher Quality Characteristics* can only be interpreted as features of the student's learning context and are not representative of any teacher population either at the school or at large. All of the Teacher Quality variables included in Table 8 were mean centered so estimates reflect differences from the population mean. Population mean estimates for Teacher Quality characteristics are presented in Table 3. Wald significance test were performed to test the hypothesis that the difference between the subpopulation mean and the overall population mean is equal to 0. There is some evidence that *Teacher Quality* indicators vary across student race. With respect to Mathematics Teacher Self-Efficacy, both Hispanic students with no race specified, and Native Hawaiian/Pacific Islander on average have mathematics teacher's with lower Self-Efficacy. The mathematics teachers of these groups have mean self-efficacy scores of -0.32 (0.14) and -0.37 (0.17) respectively. These differences are significant at the .05 level. Given that mean Mathematics Teacher Self-Efficacy is centered to 0 and a standard deviation of 1, these differences roughly correspond to effect sizes. There is no theoretical or intuitive basis to offer any explanations about why such differences might exists. However, despite being statistically significant, the relatively small sample sizes of the subpopulations is a reminder that these estimates are more susceptible to outliers or influenced by chance variation.

With respect to *Years of Experience*, Black students on average are taught mathematics by teachers with less years of experience. Their teachers have on average 0.92 less years of experience compared to the population mean. In contrast, White students on average are taught mathematics by teachers with 0.55 more years of experience. Both of these differences are significant at the .05 level. This pattern is consistent with Black students being disproportionately tracked to lower mathematics classes and the fact that these classes are more often than not taught by less experienced teachers (citation needed).

With the exception of American Indian/Alaskan Native students, Teacher Certification is fairly even across racial groups. American Indian/Alaska Native students are on average taught by a lower proportion of certified teachers. The difference is .26 lower which means that just over half (0.79 -0.26 = 0.53) of American Indian/Alaskan Native students in HSLS:09 were taught by teachers that were fully certified to teach high school mathematics. In addition, only 18%, roughly 1 in 5, American Indian/Alaskan Native students in HSLS:09 were taught by mathematics teachers with a Bachelor's degree in a mathematics or mathematics related field. The shortage of minimally qualified mathematics teachers for this population is particularly stark. In contrast, the proportion of White students that are taught by fully certified mathematics teachers is 3% higher compared to the national average. Lastly the proportion of Asian students that are taught by teachers with a Bachelor's degree in Mathematics or mathematics related field is 10% higher than the national average. This translates to more than half of Asian students in HSLS:09 were being taught by teachers with a Bachelor's degree in mathematics or related field. Overall the pattern in Teacher Quality characteristics seem to fall along the extremes of the achievement continuum with Black and American Indian/Alaskan Native students being disproportionately taught by teachers with less teaching qualifications compared to White and Asian students.

Table 9

Teacher Quality Characteristics by Group

		SELF EFFICACY	YRS EXPERIENCE	MATH CERTIFICATION	B.A. MATHEMATICS
School Control					
		0.43 (0.07)***	3.40 (0.74)	-0.24 (0.04)	24.57 (1.08)
	Private	1.08	14.29	0.67	17.07
		2,708	3,176	3,176	3,174
		-0.03 (0.04)	-0.27 (0.21)	0.02 (0.01)	23.64 (0.39)
	Public	0.89	7.24	0.35	11.51
		11,509	13,003	13,050	13,024
Locale					
		-0.11 (0.09)	-0.10 (0.39)	-0.03 (0.03)	25.08 (0.72)
	City	0.80	6.43	0.34	10.42
		4,009	4,494	4,495	4,495
		0.09 (0.05)*	-0.45 (0.27)	0.00 (0.02)	23.94 (0.56)
	Suburban	0.88	7.20	0.36	11.49
		4,895	5,597	5,621	5,608
		-0.01 (0.10)	0.13 (0.56)	0.00 (0.03)	22.41 (1.61)
	Town	0.84	6.73	0.36	11.32
		1,779	2,105	2,106	2,091
		0.03 (0.06)	0.75 (0.48)	0.04 (0.02)	22.05 (0.58)
	Rural	0.83	7.91	0.33	10.11
		3,534	3,983	4,004	4,004
Gender					
		-0.01 (0.03)	-0.20 (0.22)	0.00 (0.02)	23.69 (0.42)
	Male	0.88	7.39	0.36	11.49
		7,200	8,181	8,206	8,188
		0.01 (0.05)	0.21 (0.24)	-0.01 (0.01)	23.72 (0.40)
	Female	0.88	7.41	0.36	11.29
		7,017	7,998	8,020	8,010
Socio-Economic Status (SES)					
		-0.13 (0.06)*	-1.26 (0.36)	-0.05 (0.02)	24.21 (0.67)
	Low SES	0.82	5.94	0.35	10.83
		2,266	2,567	2,570	2,566
		-0.01 (0.04)	-0.06 (0.21)	0.01 (0.01)	23.70 (0.40)
	Middle SES	0.92	7.62	0.37	11.83
		8,250	9,377	9,413	9,393
		0.17 (0.04)***	1.35 (0.31)	0.01 (0.02)	23.26 (0.51)
	High SES	0.91	9.06	0.40	12.03
		3,701	4,235	4,243	4,239

Teacher Quality by Group

Note. Mean (standard error), standard deviation, & number of observations for *Teacher Quality* characteristics are reported. Student *Group* subpopulation estimates were calculated using student-level data and sampling weights to account for complex sampling design of HSLS:09. For each column, the Wald significance test tests the hypothesis that the difference between the subgroup mean and the population mean (see Table 3) is equal to zero.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

With the exception of *Teacher Self-Efficacy,* Teacher Quality characteristics showed little variation across School Control, Locale, Gender and Socio-Economic Status. Subpopulation estimates were not statistically significantly different across any of these groups. However, students in Private Schools, Suburban Locales, and student with high *Socio-Economic Status* tended to be taught by mathematics teachers with higher degrees of *Teacher Self-efficacy*. The highest group was students in Private schools whose *Mathematics Teacher Self-Efficacy* is 0.43 higher than the national average. Since *Mathematics Teacher Self-Efficacy* is mean centered to 0 and has a standard deviation of 1, this roughly translates to an effect size of 0.43. Students attending schools in suburban locale's were taught by teachers that on average had 0.09 higher Self-Efficacy than the national average. Lastly, the *Mathematics Teacher Self-Efficacy* tracked along student's *Socio-Economic Status* with students in lower *Socio-Economic Status* groups on average being taught by mathematics teachers with lower *Self-efficacy*. Given the strong relationship between *Socio-Economic Status* and *Mathematics Achievement* demonstrated in Table 20 , the relationship between *Mathematics Teacher Self-Efficacy*, *Mathematics Achievement* and *Socio-Economic Status* will need to considered carefully to determine how

Mathematics Teacher Self-Efficacy interacts with *Socio-Economic Status* in relation to *Mathematics Achievement*.

First Order Correlations

This section contains first order correlation matrices for both Student and School Level variables respectively. Pairwise correlations were estimated and two-tailed significance tests are reported. For readability and ease of interpretation, only significant correlations that are greater in absolute magnitude of .10 are included in Tables. See Appendix J and K for complete correlation matrix tables.

Table 10

Correlations of Level 1 Variables

Measure	1	2	3	4	5	6	7	8	9	10	11
Student Variables											
1. Grade 9 Algabraic Reasoning Score	1.00										
2. Grade 11 Algabraic Reasoning Score	**0.75***	1.00									
3. Mathematics Gain (11th-9th)	-0.34*	**0.37***	1.00								
4. Mathematics Self-Efficacy	0.31*	0.31*		1.00							
5. Mathematics Identity	**0.40***	**0.39***		**0.58***	1.00						
6. Socio-Economic Status	**0.44***	**0.44***		0.15*	0.14*	1.00					
7. Sex				-0.10*			1.00				
8. Teacher Self-Efficacy						0.11*		1.00			
9. Teaching Experience (Yrs.)	0.13*	0.13*				0.13*			1.00		
10. Certification									0.20*	1.00	
11. Bachelor's Degree											1.00

Note. Coefficients represent correlations of level 1 variables. Sex: 1=Female, 0=Male; Certification: 1=Certified to teach Mathematics, 0=No Certification; Bachelor's Degree: 1=Bachelor’s degree in Mathematics or related field, 0=other. Non significant correlations were omitted.

* correlation at 0.05 (2-tailed)

Stiudent Level Correlations

Correlations were computed for the 11 student level variables used in the subsequent multi-level models. The results shown in 10 suggest that 38 of the 55 correlations were statistically significant. As might be expected, the correlation between the 9th and 11th grade *Algebraic Reasoning Scores* was the highest, $r(18,621) = +.75, p<.05$. It has not only been empirically shown but intuitive that past performance is the strongest predictor of future performance, especially within the same domain as was the case with the Algebraic Reasoning exam. Socio-economic status was the next highest correlate with both 9th and 11th grade *Algebraic Reasoning Scores*, $r(21,441) = +.44, p<.05$ and $r(18,863) = +.44, p<.05$ respectively. The correlation between *Socio-Economic Status* and Academic Achievement is an enduring phenomena has been studied exhaustively since educational data has been collected and analyzed (citation). that The psychological constructs of Student's *Mathematics Self-Efficacy* and *Mathematics Identity* were strongly correlated $r(1,426) = +.58$, $p<.05$. with each other and also moderately correlated with both 9th and 11th grade *Algebraic Reasoning Scores*, with coefficients ranging between +.30 and +.40. Neither *Mathematics Self-Efficacy* nor *Mathematics Identity* were correlated with *Mathematics Gain*. Of the teacher characteristics, the variables with the highest correlation coefficients were *Years of Teaching Experience* and *Algebraic Reasoning Scores* in both 9th and 11th grade, $r(15,986) = +.13$, $p<.05$ and $r(15,047) = +.13$, $p<.05$ respectively. *Teacher Self-Efficacy* was only weakly correlated with *Algebraic Reasoning Scores* in 9th and 11th grade, $r(14,054) = +.08$, $p<.05$, and $r(13,273) = +.09$, $p<.05$, respectively. In general, the results suggests that students with higher levels of *9th Grade Algebraic Reasoning* (prior performance), *Socio-Economic Status*, *Mathematics Self-efficacy*, and *Mathematics Identity* were correlated with higher *11th Grade Algebraic Reasoning Scores*. However, only student's *Socio-Economic Status* was correlated with *Mathematics Gain*, although not very strongly, r(1,8622) = +.02, p<.05. Over all, the correlation patterns observed in Table 10 follow known patterns of association between personal characteristics and mathematics achievement. These results confirm the need to include these variables in any analysis seeking to examine the nature of the relationship between teacher efficacy and mathematics achievement.

Table 11

Correlations of Level 2 Variables

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14
School Variables														
1. School SES	1.00													
2. School Climate	**0.37***	1.00												
3. FRPL (%)	**-0.79***	**-0.38***	1.00											
4. Am. Ind./Alaskan Native			0.12*	1.00										
5. Asian/Pacific Islander	0.19*				1.00									
6. Black or African American	-0.29*	-0.15*	**0.42***			1.00								
7. Hispanic/Latino/Latina	-0.28*	-0.16*	**0.34***		0.11*		1.00							
8. White	**0.35***	0.20*	**-0.50***	-0.12*	-0.29*	**-0.60***	**-0.69***	1.00						
9. Private	**0.55***	**0.55***	**-0.54***		0.11*	-0.13*		0.10*	1.00					
10. Regular	0.11*		-0.19*			-0.21*		0.22*	0.11*	1.00				
11. City	0.11*				0.18*	0.10*	0.17*	-0.22*	0.20*	-0.15*	1.00			
12. Suburban	0.11*		-0.14*								**-0.47***	1.00		
13. Town	-0.11*			0.12*	-0.11*		-0.11*	0.14*			-0.24*	-0.28*	1.00	
14. Rural	-0.15*				-0.14*			0.15*	-0.18*		**-0.35***	**-0.41***	-0.21*	1.00

Note. Coefficients represent correlations of level 2 variables. FRPL = % of students at school eligible for free or reduced priced lunch program; Private: 1 = private, 0 = non-private; Regular: 1 = regular public school, 0 = charter, magnet or alternative school; City, Suburban, Town and

Rural: 1 = yes, 0 = no. Non significant correlations and correlations with coefficients of less than .10 are omitted. Coefficients of .35 or greater are shown in bold.

* correlation at 0.05 (2-tailed)

School Level Correlations

Correlations were computed for the 14 School level variables used in this analysis. Of the 91 correlations, 67 were statistically significant at the .05 level. Of the 67 correlations that were statistically significant, 13 had correlation coefficients of less than +/- .10 and were thus omitted in 11. Predictably, the strongest correlations were those associated with *School Compositional SES*. *School Compositional SES* showed strong correlations with *School Climate*, *Free and Reduced Priced Lunch* and *Private School* $r(737) = +.37; p<.05, r(859) = -.79, p<.05;$ and $r(944), = .55, p<.05,$ respectively. Schools with higher levels of *Compositional SES* have greater proportions of highly educated households with higher income and high occupational prestige therefore it is not surprising that these schools also are positively associated with *School Climate*. Schools with higher levels of *School Climate* report less problems with student misbehavior including, gang activity, violence as well as mental health issues such as drug and substance abuse among students. The positive correlation between *School Compositional SES* and *School Climate* is expected given the stressors students and schools face as a result of economic disenfranchisement, lack of resources and school funding models that draw on local property taxes. Lastly, the very strong correlation between *Compositional SES* and *Free and Reduced Priced Lunch (FRPL)* is likely an autocorrelation. Despite this, *FRPL* is more strongly associated with the racial makeup of a school suggesting some unique variation between *Compositional SES* & *FRPL*.

School Compositional SES is also negatively associated with the racial composition of schools, such that schools with higher *Compositional SES* were associated with lower proportions of *Black* and *Hispanic* students *r(864) = +.29, p<.05; r(665) = +.28, p<.05* respectively. In contrast, schools with higher Compositional SES were associated with higher proportions of *White* and *Asian/Pacific Islander* students *r(863) = +.19, p<.05; r(864) = +.35, p<.05* respectively. In addition, schools with higher proportions of *White* and *Asian* students were associated with lower proportions of *Black* and *Hispanic* students, *r(863) = -.60, p<.05; r(864) = -.69, p<.05* respectively. Overall, the results of school level correlations suggests that higher levels of *School Compositional SES* are associated closely with indicators of *School Climate* as well as the racial make-up of the school, such that schools with higher *Compositional SES* show higher levels of *School Climate* and lower proportions of *Black* and *Hispanic* students.

Mutilevel Analysis

What follows are the results of a multi-level analysis used to answer the central research questions of this study. Five successive models predicting math achievement were specified using the "Mixed" function in Stata with maximum likelihood estimation. A school identifier (SCH_ID) was used as the grouping variable for the analysis with appropriate sampling weights. Model comparisons were done using -2 Log Likelihood estimates to conduct Chi-square difference tests. Within and between group variance reduction for successive models was also calculated and analyzed.

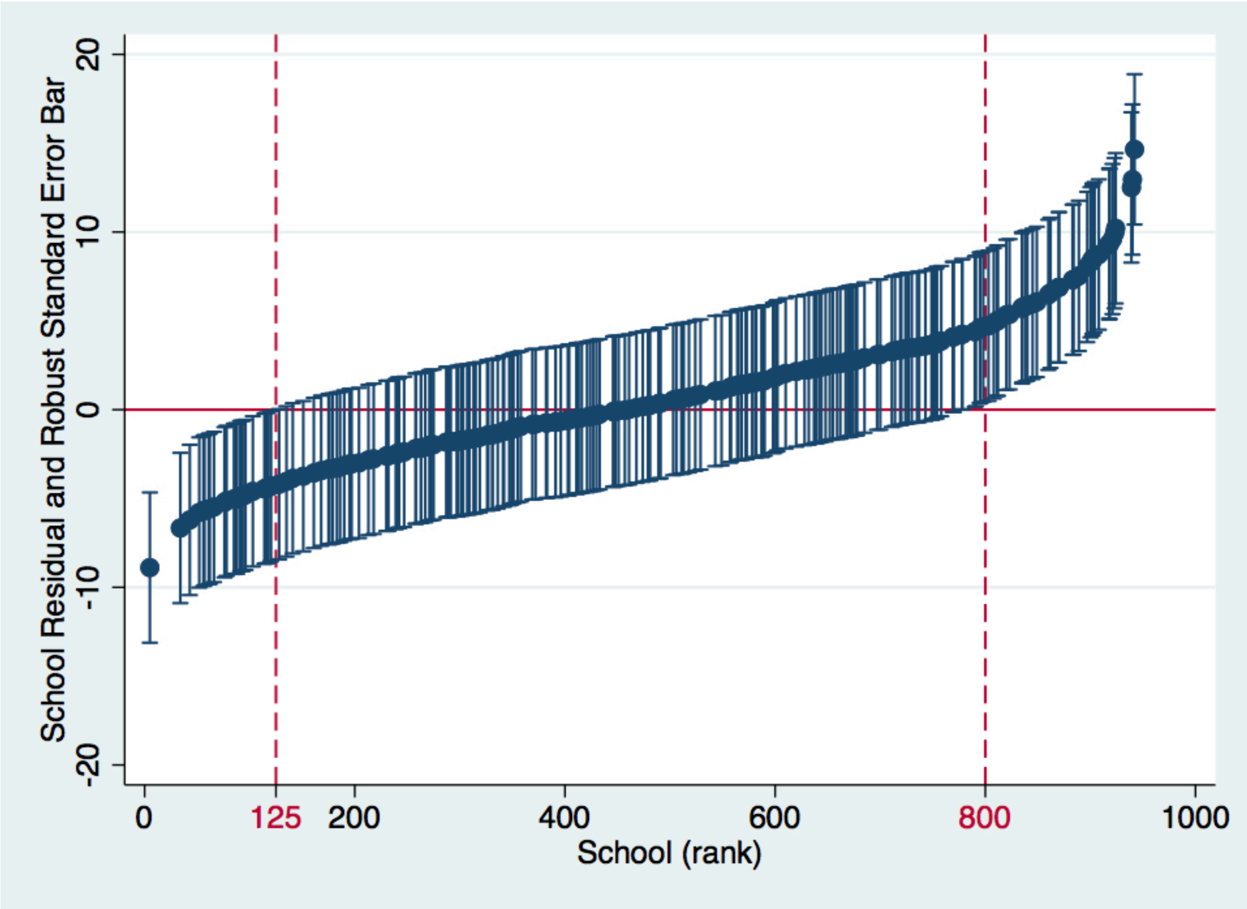
Null Model.

The overall mean of *Mathematics Achievement* (β_0) across all schools is 50.06. The between school variance in *Mathematics Achievement* is 20.08 compared to a within school variance of 75.65. The null model indicates an ICC of .21 which signals the presence of school level factors associated with algebraic reasoning scores. Put differently, an ICC of .21 indicates that 21% of the variation in algebraic reasoning scores is attributable to school groupings and therefore a multi-level analysis is not only warranted but preferable to standard regression analysis. The estimate for the Log likelihood of the null model is -1,629,481. The Log likelihood is a measure of how well the data fits the model and will be used to assess whether or not subsequent models show improvements over prior models.

Figure 2 shows the range of school residuals and 95% confidence intervals for a random sample of schools (25%) in the dataset. While school residuals can also be referred as school effects, it is important to note that the null model does not take into account prior mathematics achievement and other factors important to school outcomes; therefore, these results cannot be interpreted as "school effects" in the value added sense. The "caterpillar plot" in Figure 2 shows that the variation in school residuals is wide with most schools falling within the center band that are statistically no different than zero. The hashed lines represent the lower and upper thresholds of school effects, that is, those that fall below and and above zero respectively. We would thus expect that the schools ranked at or below 125 have school residuals that are statistically significantly less than zero and those ranked above 800 to be greater than zero.

Figure 2.

School residuals in rank order with 95% confidence intervals.



Note. School-level residuals were estimated and ranked from lowest to highest. The 95% confidence intervals around the residual estimates were standardized to the robust standard error of 2.16. For ease of visualization, only a random subset (25%) of schools are shown.

RQ1. Does the variation of Mathematics Achievement of REM students within and between schools differ from that of the general student population?

Table 12

Coefficients, Variance and Model Fit Comparison between REM and General Population

		All	REM
Mathematics Achievement (cons)	β_0	50.06 (0.28)	48.05 (0.32)***
level 1 variance	σ_e^2	75.65	69.43
level 2 variance	σ_u^2	20.08	18.14
ICC		0.21	0.21
Log likelihood		-1,629,481	-609,667

Note. Coefficients, standard errors and significance test for REM subsample of students includes American Indian/Alaskan Native, Black/African American, Hispanic, Native Hawaiian/Pacific Islander (N=4,897). Significance for intercept tests the null hypothesis $\beta_0 = 50$.

* p<0.05, ** p<0.01, *** p<0.001

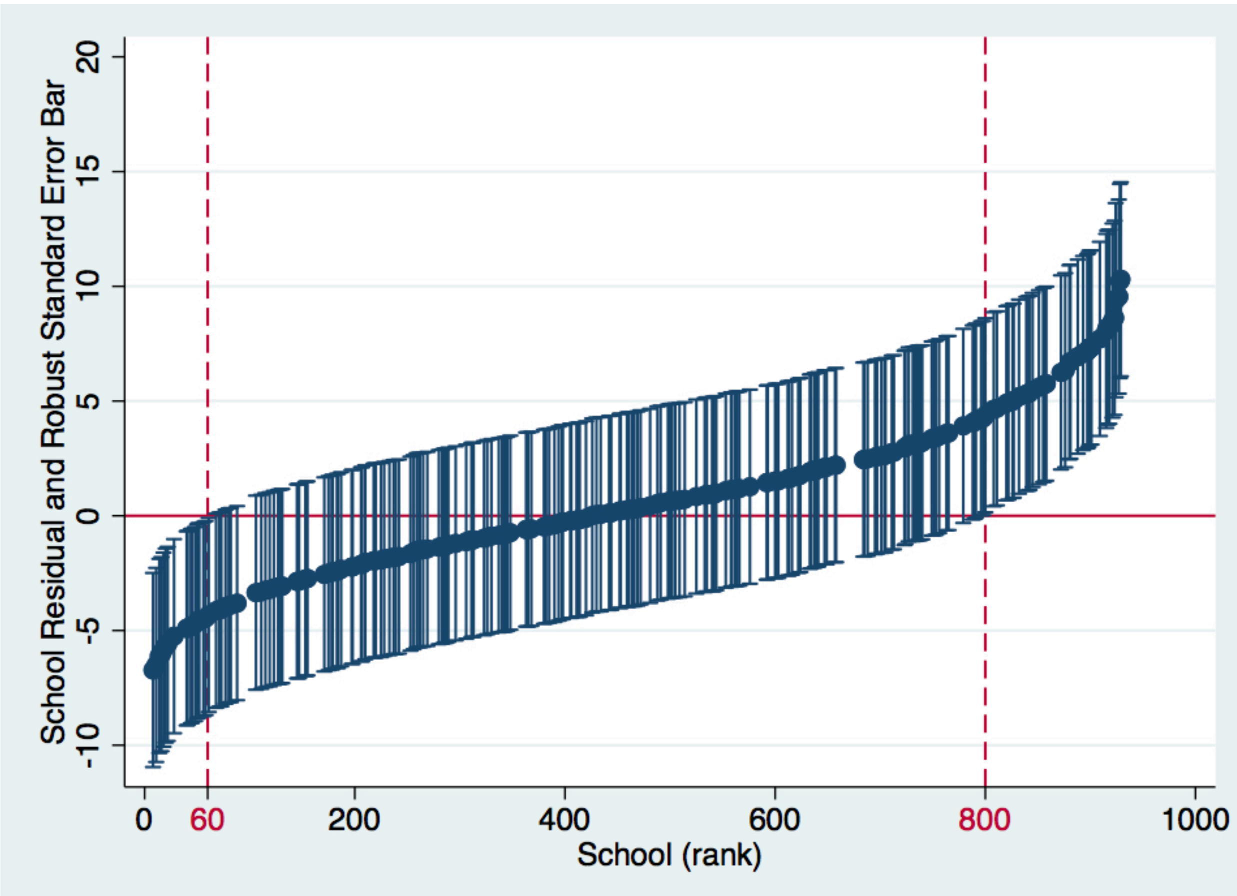
Table 12 shows null model parameter estimates obtained for the entire population of HSLS: 09 respondents as well as the REM subpopulation. Overall, the mean of Mathematics Achievement for REM students across all schools is about 2 points lower than that of the general population . The between school variance for REM students (level 2) in Mathematics Achievement is 18.14 compared to 20.08 for the general population. Similiarly, within school between-student variance for REM students in Mathematics Achievement is 69.43 compared to 75.65 for the general population. The ICC for both the general population and the REM subpopulation remained at approximately .21. These results indicate, that while there is less variation in mathematics achievement among REM students, the proportion of variation that is attributable to schools is the same, namely 21%.

Figure 3 shows the residual “caterpillar plot” for the REM student subsample. This plot confirms the residual pattern holds for REM students albeit with a lower bottom threshold residuals that are statistically less than zero. This suggests that a large majority of schools (those ranked above 60) have residuals that are statistically equal or greater than zero.

These findings suggest that mathematics achievement indeed varies both between and within schools for REM students. The overall pattern in school variation is similar to that of the entire population as a whole reinforcing the need for a multi-level analysis. The subsequent models will examine the nature of this variation for the REM subsample of students

Figure 3.

School residuals in rank order with 95% confidence intervals for REM Student Subpopulation.



Note. School-level residuals were estimated for the subpopulation of REM students (N=8,226) and ranked from lowest to highest. The 95% confidence intervals around the residual estimates were standardized to the robust standard error of 2.35. For ease of visualization, only a random subset (25%) of schools are shown.

Model 1.

Table 13 below shows coefficients, variance and Log likelihood for Model 1 specified above. For any school, an increase of 1 standard deviation in *Mathematics Teacher Self-Efficacy* (*X1TMEFF*) is associated with a 1.12 increase in *Mathematics Achievement* (*X2TXMTSCOR)*. The intercept represents the average achievement across schools with average *X1TMEFF* and is estimated as β_0 = 47.96(0.37), *p*< .001. This intercept is statistically no different than the intercept for Model 0 but statistically significantly different from the population mean of 50. The ICC for Model 1 increased from .21 to .24 which suggests that the distribution of teacher efficacy is not uniform across schools. That is, schools with higher than average mathematics achievement will tend to have higher levels of teacher efficacy and visa versa, hence more variation between schools. The overall fit of Model 1 was a significant improvement over the null model, $\chi^2_{diff}(1) = 253{,}078$, p<.001.

Table 13

Null Model vs Model 1 Coefficients, Variance and Model Fit Comparisons

		null model	Model 1
Mathematics Achievement (cons)	β_0	48.05 (0.32)***	47.96 (0.37***
Teacher Self-Efficacy	β_1		1.12 (0.30)***
level 1 variance	σ_e^2	69.43	65.55
level 2 variance	σ_u^2	18.14	20.44
ICC		0.21	0.24
Log likelihood		-609,667	-356,588
Chi Squared Difference			253,078***

Note. Coefficients, standard errors and significance test for REM subsample of students including American Indian/Alaskan Native, Black/African American, Hispanic, Native Hawaiian/Pacific Islander (N=4,897). Significance for intercept test the null hypothesis $\beta_0 = 50$.
* p<0.05, ** p<0.01, *** p<0.001

RQ2. Are higher levels of Teacher Self-Efficacy generally associated with higher levels of Mathematics Achievement among REM students? Model 1 confirms that there is a positive association between levels of *Mathematics Teachers Self-Efficacy* and *Mathematics Achievement* amont REM students such that an increase in one standard deviation in *Mathematics Teacher's Self Efficacy* predicts a increase in *Mathematics Achievement* of 1.12. This association is statistically significant at the .001 level. Furthermore, the model also revealed additional variation at the school level which suggests that *Mathematics Teacher's Self Efficacy* is not evenly distributed across schools. Still, these results do not take into account other factors that are known to be important to *Mathematics Achievement* such as prior achievement, socio-economic status and other student characteristics. In Model 2, these additional student level factors will be added to condition the effect of *Mathematic's Teacher Self-Efficacy* on individual student characteristics.

Model 2

Table 14 below shows coefficients, variance and Log likelihood for Model 2 specified above. The intercept β_0 for *Mathematics Achievement* increased from 47.96 to 49.10. Given that all of the student level variables are either standardized or mean centered, this indicates that while REM students still preform below the population mean, the gap is much narrower once individual characteristics are taken into account. The overall association between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* remained statistically significant at the .05 level but decreased in magnitude from β_1= 1.12(0.30), *p*< .001 to β_1= 0.48, *p*<.05. Thus, for any student, an increase in their *Mathematics Teacher's Self-Efficacy* is associated with an increase of 0.48 in their *Mathematics Achievement* scores (*X2TXMTSCOR)*. This translates to a modest effect size of approximately 5% after controlling for student's *Socio-Economic Status*, and other personal characteristics.

As expected, the strongest predictor of Mathematics Achievement was prior mathematics achievement (*X1TXMTSCOR)* β_3= 5.63(0.20), p < .001. Because prior achievement was standardized to a mean of 0 and a standard deviation of 1, β_3 can be interpreted as an increase in 1 stadard deviation in 9th grade *Mathematics Achievement* predicts an increase of 5.63 points on the 11th grade Mathematics Achievement of REM stuedents. The next strongest predictor of *Mathematics Achievement* for REM students was *Mathematics Identity* (*X1MTHID*) with a coefficient of β_5= 1.14 (0.25), *p*<.001 followed by *Socio-Economic Status (X1SES)* with a coefficient of β_2= 0.99 (0.22), *p*<.001. *Mathematics Teacher Self-Efficacy (X1TMEFF)* remained a statistically significant predictor of mathematics achievement with a coefficient of β_1 = 0.49 (0.25), p < .05. Neither *Gender* nor *Mathematics Self-Efficacy* were statistically significant predictors of mathematics achievement in Model 2.

The overall fit of Model 2 was a significant improvement over Model 1, $\chi^2_{diff}(5) = 109{,}164$, *p* < .001. Model 2 resulted in a moderate reduction in level 1 variance from 65.55 to 40.36. In contrast, the level 2 variance decreased sharply from 20.44 to 4.01.

Accordingly the ICC for model 2 decreased from .24 to .09 signaling that the associations between student's individual characteristics and mathematics achievement in are relatively consistent across schools for REM students.

Table 14

Model 1 vs Model 2 Coefficients, Variance and Model Fit Comparisons

		Model 1	Model 2
Mathematics Achievement (cons)	β_0	47.96(0.37)***	48.97(0.42)*
Teacher Self-Efficacy	β_1	1.12(0.30)***	0.49(0.25)*
SES with Locale (Urbanicity)	β_2		0.99(0.22)***
Prior Mathematics Achievement	β_3		5.63(0.20)***
Student Mathematics Self Efficacy	β_4		0.47(0.30)
Student Mathematics Identity	β_5		1.14(0.25)***
Gender	β_6		0.68(0.54)
level 1 variance	σ_e^2	65.55	40.40
level 2 variance	σ_u^2	20.44	4.11
ICC		0.24	0.09
Log likelihood		-356,588	-247,514
Chi Squared Difference		253,078***	109,074***

Note. Coefficients, variance and model fit parameter estimates for subpopulation of REM students including American Indian/Alaskan Native, Black/African American, Hispanic, Native Hawaiian/Pacific Islander (N = 3,672). Significance for intercept test the null hypothesis $\beta_0 = 50$.

$X1SES$ = Socio-Economic Status, $X1TXMTSCOR$ = 9th grade algebraic reasoning score, $X1MTHEFF$ = Student Mathematics Self Efficacy, $X1MTHID$ = Student Mathematics Identity, and $X1SEX = 1$ if student is Female. X1SES is derived with locale (urbanicity). All continous predictor variables are standardized to mean of 0 and standard deviation of 1.

* p<0.05, ** p<0.01, *** p<0.001 * p<0.05, ** p<0.01, *** p<0.001

RQ3. To what extent is the Mathematics Achievement of REM students attributable to differences in Mathematics Teacher's Self-Efficacy after controlling for Student Characteristics? Model 2 supports the general hypothesis that *Mathematics Teacher Self-Efficacy* plays an important role for the academic success of REM students even after conditioning the relationship on student characteristics. Overall, the mean *Mathematics Achievement* across schools was $\beta_0 = 49.07(0.42), p < .05$ a difference of 0.93 from general population mean of 50 indicating a persistent achievement gap even after controlling for *Socio-Economic Status*, prior *Mathematics Achievement*. However, the presence of a *Teacher Self-Efficacy* effect is an encouraging sign that teachers may contribute to narrowing this gap. To further test this hypothesis, the next model adds traditional measures of teacher qualifications such as *Certification*, *Bachelor's Degree*, and *Years Experience*.

Model 3.

Table 15 below shows coefficients, variance and Log likelihood for Model 3 as specified above. Overall, the mean of *Mathematics Achievement* ($X2TXMTSCOR$) across schools increased slightly to $\beta_0 =$ 49.66(0.58), *ns*. This is not statistically different than the general population mean of 50.00 which signals that REM students score about the same as the general population once individual and teacher quality factors are taken into account. The addition of the teacher variables had only a marginal impact on the variance parameters therefore the ICC remained at .09. The coefficients for $X1TMCERT$, $M1MTHTYRS912$, $M1BAMAJ2$ were β_7 = .02(.02), ns; β_8 = -.21(0.54) ns; and β_9 = -.85(0.51), ns respectively, indicating that these traditional measures of teacher quality are not statistically associated with the *Mathematics*

Achievement of REM students. Moreover, the linear relationship between *Mathematics Teacher Self-Efficacy* (*MTEFF*) and *Mathematics Achievement* decreased from β_1 = 0.49(0.25), *p*<.05 in Model 1 to β_1 = 0.39(0.23), *p*<.ns which suggests that *Mathematics Teacher Self-Efficacy* does not contribute to the *Mathematics Achievement* of REM students beyond what would be expected by chance. The Chi Square Difference test is $\chi^2_{diff}(3) = 2{,}075, p < .001$ which is strong evidence that Model 3 is a statistical improvement over Model 2. However, because the Interclass Correlation Coefficient (ICC) remained steady, it suggests that there is still unexplained variation that can be attributed to School level or contextual factors. Furthermore, Model 3 assumes that the mean *Mathematics Teacher Self-Efficacy* effect is the same across schools.

Table 15

Model 2 vs Model 3 Coefficients, Variance and Model Fit Comparisons

		Model 2	Model 3
Mathematics Achievement (cons)	β_0	48.97(0.42)*	49.56(0.57)
Teacher Self-Efficacy	β_1	0.49(0.25)*	0.39(0.23)
SES with Locale (Urbanicity)	β_2	0.99(0.22)***	1.00(0.22)***
Prior Mathematics Achievement	β_3	5.63(0.20)***	5.57(0.20)***
Student Mathematics Self Efficacy	β_4	0.47(0.30)	0.50(0.30)
Student Mathematics Identity	β_5	1.14(0.25)***	1.12(0.25)***
Gender	β_6	0.68(0.54)	0.67(0.53)
Teacher Certification	β_7		0.02(0.02)
Teacher Experience (YRS)	β_8		-0.21(0.54)
Teacher Degree	β_9		-0.85(0.51)
level 1 variance	σ_e^2	40.40	40.36
level 2 variance	σ_u^2	4.11	4.22
ICC		0.09	0.09
Log likelihood		-247,514	-245,439
Chi Squared Difference		109,074***	2,075***

Note. Coefficients, variance and model fit parameter estimates for subpopulation of REM students including American Indian/Alaskan Native, Black/African American, Hispanic, Native Hawaiian/Pacific Islander (N = 3,654). Significance for intercept test the null hypothesis $\beta_0 = 50$. SES = Socio-Economic Status, $X1TXMTSCOR$ = 9th grade algebraic reasoning score, $X1MTHEFF$ = *Student's Mathematics Self-Efficacy*, $X1MTHID$ = *Student's Mathematics Identity*, and $X1SEX$ = 1 if student is Female, $X1TMCERT$ is reverse coded so that 1 = no certification and 0 = fully certified to teach secondary mathematics, $M1MTHYR912$ is the number of years teaching secondary mathematics, and $M1BAMAJ2$ is reverse coded so that 1 = other and 0 = Bachelor's degree in mathematics or related field. All non-dichotomous predicotr variables are standardized to mean of 0 and standard deviation of 1.

* p<0.05, ** p<0.01, *** p<0.001

RQ4. To what extent is the Mathematics Achievement of REM students attributable to differences in Mathematics Teacher's Self-Efficacy after controlling for both Student Characteristics and Teacher Quality? The importance of *Mathematics Teacher Self Efficacy* on the *Mathematics Achievement* was not supported by Model 3. In fact, the linear relationship between *Mathematics Teacher Self-Efficacy* ($X1TMEFF$) and *Mathematics Achievement* ($X2TXMTSCOR$) was reduced to a level that is statistically indistinguishable from 0. Moreover, none of the teacher quality variables that were added to the model had a statistically significant associations with *Mathematics Achievement* in REM student subsample. However, it is important to note, that Model 3 assumes that the slope of the linear relationship (β_1) is fixed and therefore the same for all schools. This defies the literature which suggests that school contextual factors play an important role in shaping the student-teacher-achievement relationship. Put differently, by restricting β_1 to be equal across schools, Model 3 may be masking significance and strength of the relationship between *Mathematics Teacher Self Efficacy* and *Mathematics Achievement* across different school contexts. Model 4 will address this by including school contextual factors that are known to influence how students and teachers experience school and also impact student achievement. Model 4 will also allow β_1 to vary across schools to determine whether or not the relationship between *Mathematics Teacher Self Efficacy* and *Mathematics Achievement* in Model 3 is indeed being masked.

Model 4.

In Model 3, the linear relationship between *Mathematics Teacher Self Efficacy* and *Mathematics Achievement* was specified such that the intercept of the regression of *Mathematics Achievement* on *Mathematics Teacher Self-Efficacy* was allowed to vary randomly across schools while the slope of the regression line was assumed to be fixed. The results indicated that overall, the mean *Mathematics Achievement* of REM students was statistically no different than the mean of the general student population when conditioned on student and teacher characteristics. The coefficient β_1 of the regression line was not statistically significant; therefore, Model 3 does not support the central hypothesis of this study regarding the importance of *Mathematics Teacher Self-Efficacy* in influencing the *Mathematics Achievement* of REM students. This finding could be in part be due to the assumption that the relationship between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* (β_1) is the same across schools; an assumption that the literature review in this study suggests is unlikely. Moreover, given the patterns in *Mathematics Achievement* and *Mathematics Teacher Self-Efficacy* shown in Tables 20 and 9, it is reasonable to expect that the relationship between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* is not uniform across schools.

Table 16 below shows the model comparisons for Model 3 and Model 4.

The results in Table 16 indicate that when the slope of $MTEFF$ (β_1) is allowed to vary across schools, Model 4 is a better fit, $\chi^2_{diff}(2) = 158, p < .001$. Moreover, loosening the fixed-slope constraint revealed a modest but statistically significant relationship between Mathematics Teacher Self-Efficacy ($X1TMEFF$) and Mathematics Achievement ($X2TXMTSCOR$), $\beta_1 = 0.53(0.25), p < .05$. This means that for the average school, a 1 point increase in Mathematics Teacher Self-Efficacy ($X1TMEFF$) is associated with a .53 point increase in the school's average *Mathematics Achievement (*$X2TXMSCOR$*)* after controlling for student characteristics and other traditional measures of teacher quality. The effect of $X1TMEFF$ for school j can be estimated as 0.53 + $\hat{u}_{1j}$, and the between school variance of the slopes is 1.97. Therefore, the 95% coverage interval for the school slopes is estimated as $0.53 \pm 1.96\sqrt{1.97}$. Thus, assuming a normal distribution, we would expect the middle 95% of schools to have a slope between -2.22 and 3.28. The intercept variance (σ^2_{u0}) of 3.25 is the between school variance when the school mean of $X1TMEFF$ = 0, put differently, it is the variance of *Mathematics Achievement* conditioned on *Mathematics Teacher Efficacy*.

The positive covariance estimate of 1.05 suggests that schools with high intercept (above average *Mathematics Achievement*) tend to have a steeper average slope (above average $X1TMEFF$ effect). The intercept-slope correlation (ρ_{01}) is 0.42 which indicates a moderately strong correlation between the intercept and the slope.

Table 16

Comparison of Random Intercept (3) and Random Slope (4) Models

		Model 3	Model 4
Mathematics Achievement (cons)	β_0	49.56(0.57)	49.62(0.58)
Teacher Self-Efficacy	β_1	0.39(0.23)	0.53(0.25)*
SES with Locale (Urbanicity)	β_2	1.00(0.22)***	0.95(0.22)***
Prior Mathematics Achievement	β_3	5.57(0.20)***	5.53(0.20)***
Student Mathematics Self Efficacy	β_4	0.50(0.30)	0.48(0.30)
Student Mathematics Identity	β_5	1.12(0.25)***	1.20(0.24)***
Gender	β_6	0.67(0.53)	0.70(0.52)
Teacher Certification	β_7	0.02(0.02)	0.01(0.02)
Teacher Experience (YRS)	β_8	-0.21(0.54)	-0.20(0.53)
Teacher Degree	β_9	-0.85(0.51)	-0.80(0.51)
level 1 variance	σ_e^2	40.36	39.44
Intercept variance	σ_{u0}^2	4.22	3.25
slope variance	σ_{u1}^2		1.97
intercept/slope covariance	σ_{u01}		1.05
ICC		0.09	0.08
Log likelihood		-245,439	-245,281
Chi Squared Difference		2,075***	158***

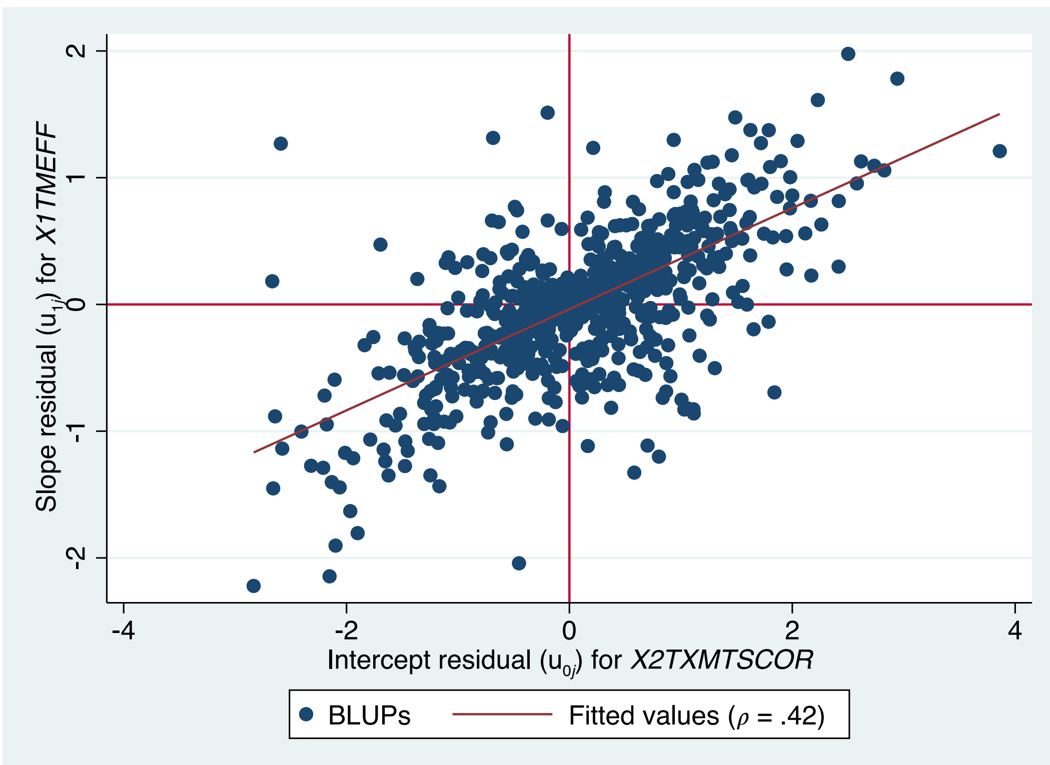
Note. Table shows coefficient comparisons of random intercept (3) and random slope (4) models. Significance test for the intercept tests the null hypothesis that β_0 = 50. Significance tests for all other coefficients ($\beta_1 - \beta_9$) tests the null hypothesis $\beta = 0$. Chi-square significance test for the model comparison is on 2 degrees of freedom to account for the addition of the σ_{u1}^2 and σ_{u01} variance and covariance parameters.

* p<0.05, ** p<0.01, *** p<0.001

To aid in visualizing this relationship, Figure 4 shows a plot of the intercept ($\hat{u}_{0j}$) and slope ($\hat{u}_{1j}$) residuals for all schools. The residuals represent the school effects on both the mean *Mathematics Achievement* and the mean *X1TMEFF* effect.

Figure 4.

Plot of the intercept and slope residuals for schools.



Note. Best Linear Unbiased Predictions (BLUPs) for school intercept (u_{0j}) and slope (u_{1j}) residuals were estimated using Stata's *predict* post-estimation command.

From the plot in Figure 4 it is possible to identify schools with lower than average *Mathematics Achievement* but stronger than average *X1TMEFF* effects. Schools in the upper left quadrant are such schools while schools on the lower left represent schools with lower than average *Mathematics Achievement* and weaker than average $X1TMEFF$ effects. The moderately strong correlation ($\rho = .42$) between the school residuals of $X1TMEFF$ and $X2TXMTSCOR$ signals the presence of school contextual factors that may be influencing this relationship. However, this does not help shed light into how this relationship might differ for REM students or how the school context may influence the $X1TMEFF$ for REM students. The next two models will examine the school contextual factors that may may be influencing this relationship followed by an analysis how these patterns differ across REM subgroups.

RQ5. Does the nature of the relationship between Mathematics Teacher Self-Efficacy and the Mathematics Achievement of REM students vary across schools? The results of the Model 3 and Model 4 comparison $\chi^2_{diff}(2) = 158, p < .001$, support the hypothesis that the relationship between *Mathematics Teacher Efficacy* and REM student's *Mathematics Achievement* varies across schools. Allowing the slope of the linear relationship between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* to vary across schools revealed the presence of a statistically significant *Mathematics Teacher Efficacy* effect $\beta_1 = 0.53(0.25), p < .05$ that was not present in Model 3. Moreover, this relationship was shown to vary across schools such that schools with higher *Mathematics Achievement* on average have higher levels of *Mathematics Teacher Self-Efficacy*. The slope/intercept covariance correlation coefficient of .42 also supports the hypothesis that the relationship between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* vary across schools. The final model will include school contextual factors to determine how they impact this relationship as well as how these relationships might vary across REM subgroups.

Model 5.

In Model 4, the addition of the random slope parameter for the $X1TMEFF$ effect revealed both a statistically significant association between $X1TMEFF$ and $X2TXMTSCOR$ at the student level as well wide variation in this relationship across schools. Model 5 adds school contextual factors such as *School Climate*, *School Size* as an interaction term between School Climate and Mathematics Teacher Self-Efficacy to examine weather or not School Climate has a moderating effect on the $X1TMEFF$ $X2TXMTSCOR$ relationship. Table 17 below compares coefficients, parameters and model fit statistics for Model 4 and 5.

Table 17

Model 4 vs Model 5 Coefficients, Variance and Model Fit Comparisons

		Model 4	Model 5
Mathematics Achievement (cons)	β_0	49.62(0.58)	49.85(0.59)
Teacher Self-Efficacy	β_1	0.53(0.25)*	1.06(0.29)***
SES with Locale (Urbanicity)	β_2	0.95(0.22)***	0.95(0.28)***
Prior Mathematics Achievement	β_3	5.53(0.20)***	5.27(0.22)***
Student Mathematics Self Efficacy	β_4	0.48(0.30)	0.33(0.39)
Student Mathematics Identity	β_5	1.20(0.24)***	1.19(0.28)***
Gender	β_6	0.70(0.52)	0.44(0.52)
Teacher Certification	β_7	0.01(0.02)	0.01(0.03)
Teacher Experience (YRS)	β_8	-0.20(0.53)	-0.27(0.53)
Teacher Degree	β_9	-0.80(0.51)	-0.77(0.55)
School Climate	β_{10}	-	0.95(0.29)**
School Climate x Teacher Efficacy (Interaction)	β_{11}	-	0.85(0.27)**
School Size	β_{12}	-	0.01(0.01)*
level 1 variance	σ_e^2	39.44	39.83
intercept variance	σ_{u0}^2	3.25	2.69
slope variance	σ_{u1}^2	1.97	0.94
intercept/slope covariance	σ_{u01}	1.05	0.95
ICC		0.08	0.06
Log likelihood		-245,281	-180,793
Chi Squared Difference		158***	64,488***

Note. Model 4 and 5 estimates for REM student subsample (n = 2,690). Significance test for the intercept tests the null hypothesis that β_{0j} = 50. Significance tests for all other coefficient tests the null hypothesis $\beta_n = 0$. Chi-square significance test for the model comparison is on 3 degrees of freedom to account for the addition of the 3 school level variables.

* p<0.05, ** p<0.01, *** p<0.001

The addition of the school contextual factors and interaction term resulted in an increase in the *Mathematics Teacher Self-Efficacy* coefficient from $\beta_{1j} = 0.53(0.25), p < .05$ to $\beta_{1j} = 1.06(0.29), p < .001$. This means that conditioned on school climate and size, an increase of *Mathematics Teacher Self-Efficacy* is associated with a 1.06 point increase in *Mathematics Achievement*. The effect size of this can be estimated by dividing 1.06 by the standard deviation of the population mean which is 10, which is equal to approximately 11% making *Mathematics Teacher Self-Efficacy* among the strongest predictors of *Mathematics Achievement* of all the Models. The addition of school contextual factors had little influence on the coefficients of the student-level predictors of *Mathematics Achievement*. The differences in coefficients β_{2-9} were all within the margin of standard errors. The estimate of the *School Climate* effect on *Mathematics Achievement* is $\beta_{10j} = 0.95(0.29), p < 01$ which translates to an effect size of approximately 10%. Thus, an increase in average *School Climate* is associated with a corresponding increase in *Mathematics Achievement*. Furthermore, Model 5 revealed that *School Climate* moderates the relationship between *Mathematics Teacher Self-Efficacy* and *Mathematics Achievement* $\beta_{11j} = 0.85(.27), p < .05$ such that a 1 point increase in School Climate would translate to an .85 increase in the effect of Mathematics Teacher Self Efficacy on Mathematics Achievement, β_{1j}. Recalling that *School Climate* is an index variable centered with a mean of 0 and standard deviation of 1, most schools (95%) would fall within -2 and +2 on the *School Climate* scale. Put differently, schools in the lower end of the *School Climate* scale (-1) would in effect wipe out the *Mathematics Teacher Efficacy* effect. This underscores the particular importance of *School Climate* for REM students. The Chi-square difference test comparing Model 4 to Model 5 was $\chi^2_{diff}(3) = 64{,}488, p < .001$ indicating strong evidence that Model 5 is a better fit for the data. The level 1 variance showed only a marginal increase of 0.39, however; the ICC decreased from .08 to .06 which signals that the addition of the contextual variables explained an additional 2% of the between school variation in *Mathematics Achievement*. The addition of the contextual factors resulted in a decrease in slope variance of *MTEFF* (σ^2_{u1}) from 1.97 to 0.36. The 95% coverage interval for *Mathematics Teacher Self-Efficacy* effects (β_{1j}), that is, the range in which we would expect 95% of schools to lie is estimated as $1.06 \pm (1.96 \times \sqrt{0.36}) = -0.12 - 2.34$. Given that this variance is conditioned on all the student and contextual variables, it signals the presence of schools with particularly high *Mathematics Teacher Self-Efficacy* effects that sizes of .23.

RQ6. Does the School Context influence the relationship between Mathematics Teacher Self-Efficacy and the Mathematics Achievement of REM students? The results of Model 5 support the hypothesis that contextual school factors, namely *School Climate* have a moderating effect on the relationship between *Mathematics Teacher Self-Efficacy* and the *Mathematics Achievement* of REM students. Overall the model showed *Mathematics Teacher*

Self-Efficacy was a strong predictor of *Mathematics Achievement* even after conditioning on individual student characteristics, prior achievement, teacher qualifications, and school climate. This relationship was found to not only be statistically significant but also of practical significance, translating into an effect size ranging from 10-20%. While these findings are encouraging, they are limited in that they do not account for differences among racial groups. In the final analysis, Model 5 will be tested to determine whether or not these patterns hold for Native American/Alaskan Natives, Black, Hispanic and Hawaiian and Pacific Islander sub groups.

RQ7. How does the nature of the relationship between Mathematics Teacher Self-Efficacy, Mathematics Achievement and School Context vary across REM subgroups? Model 5 confirmed the presence of a *Mathematics Teacher Self-Efficacy* effect on *Mathematics Achievement* for REM students. Furthermore, it confirmed the presence of an interaction effect between *School Climate* and the strength of this relationship. The analysis of the 95% coverage interval for the *Mathematics Teacher Self-Efficacy* effect indicated that the range of effect sizes would fall between 10-20%. In the final analysis, Model 5 was run for each REM subgroup to identify whether or not these patterns are consistent across groups. Table 18 below shows coefficient and parameter estimates by subgroup including the White and Asian students for comparison.

Table 18

Model 5 Coefficient, Variance and Model Fit comparisons by Subgroup

		ALL	REM	ASIAN	AMINDIAN	BLACK	HISPANIC	PACISLE	WHITE
Mathematics Achievement (cons)	β_0	50.19(0.37)	49.85(0.59)	53.41(1.39)*	49.49(0.77)	48.22(0.86)*	50.05(0.73)	51.88(1.10)	50.21(0.36)
Teacher Self-Efficacy	β_1	0.34(0.20)	1.06(0.29)***	-0.03(0.38)	1.79(0.39)***	0.73(0.35)*	1.97(0.60)***	0.23(0.69)	0.46(0.24)
SES with Locale (Urbanicity)	β_2	1.25(0.14)***	0.95(0.28)***	1.19(0.25)***	1.75(0.71)*	1.27(0.40)**	0.61(0.35)	1.18(0.61)	1.19(0.15)***
Prior Mathematics Achievement	β_3	5.79(0.13)***	5.27(0.22)***	5.72(0.44)***	5.32(0.44)***	4.71(0.43)***	4.99(0.25)***	5.64(0.62)***	5.81(0.17)***
Student Mathematics Self Efficacy	β_4	0.64(0.21)**	0.33(0.39)	0.64(0.73)	0.74(0.39)	0.19(0.68)	0.48(0.41)	1.23(0.65)	0.85(0.19)***
Student Mathematics Identity	β_5	0.96(0.16)***	1.19(0.28)***	1.47(0.41)***	0.94(0.43)*	0.63(0.42)	1.42(0.34)***	0.35(0.57)	0.92(0.18)***
Gender	β_6	0.42(0.32)	0.44(0.52)	-0.82(0.81)	-0.31(0.77)	0.99(0.83)	0.51(0.68)	-1.17(1.06)	0.37(0.35)
Teacher Certification	β_7	0.02(0.02)	0.01(0.03)	-0.02(0.04)	0.01(0.06)	0.00(0.04)	0.03(0.04)	0.04(0.06)	0.03(0.02)
Teacher Experience (YRS)	β_8	-0.34(0.43)	-0.27(0.53)	-0.07(0.66)	1.48(0.94)	-1.00(0.70)	-0.49(0.71)	0.50(1.29)	0.03(0.46)
Teacher Degree	β_9	-0.23(0.35)	-0.77(0.55)	-0.90(0.93)	0.34(0.84)	-0.20(0.77)	-0.46(0.65)	-2.10(1.05)*	-0.12(0.38)
School Climate	β_{10}	0.78(0.22)***	0.95(0.29)**	0.01(0.01)	0.01(0.01)	0.01(0.01)	0.78(0.34)*	-0.13(0.51)	0.79(0.22)***
Interaction	β_{11}	0.47(0.15)**	0.85(0.27)**	1.10(0.47)*	0.56(0.44)	0.48(0.41)	1.09(0.48)*	-0.03(0.49)	0.52(0.18)**
School Size	β_{12}	0.01(0.00)	0.01(0.01)*	-0.40(0.33)	1.18(0.42)**	0.89(0.31)**	0.01(0.01)	0.01(0.01)	0.01(0.00)
level 1 variance	σ_e^2	38.47	39.83	33.23	32.24	40.34	39.85	29.75	38.31
intercept variance	σ_{u0}^2	3.08	2.69	4.48	5.08	1.75	1.08	0.33	2.60
slope variance	σ_{u1}^2	0.64	0.94	0.06	0.01	0.14	3.88	0.73	0.95
intercept/slope covariance	σ_{u01}	0.36	0.95	-0.53	0.26	0.49	1.50	-0.49	0.05
ICC		0.07	0.06	0.12	0.14	0.04	0.03	0.01	0.06
Log likelihood		-578,717	-180,793	-45,187	-48,551	-78,409	-78,389	-16,319	-475,759
Chi Squared Difference		181,413***	64,488***	8,390***	8,998***	12,099***	27,088***	4,941***	137,221***

Note. Model 5 coefficient, variance and model fit estimates by racial group. Significance test for the intercept tests the null hypothesis that β_{0j} = 50. Significance tests for all other coefficient tests the null hypothesis $\beta_n = 0$. Chi-square significance test compares goodness of for for Model 4 and Model 5 for each respective subgroup.

* p<0.05, ** p<0.01, *** p<0.001

The central hypothesis of this study, namely the importance of *Mathematics Teacher Self-Efficacy* on *Mathematics Achievement* for REM students is supported for all REM subgroups except for *Hawaiian Native and Pacific Islander* students. The *Mathematics Teacher Self-Efficacy* effect is strongest for *Hispanic* students $\beta_{1j} = 1.97(0.60), p < .001$ followed by *American Indian/Alaskan Native* students $\beta_{1j} = 1.79(0.39), p < .001$ which translates to effect sizes of approximately .20 and .18 respectively. The central hypothesis was also supported for Black students although to a less degree $\beta_{1j} = 0.73(0.35), p < .001$. In contrast, no *Mathematics Teacher Self-Efficacy* effect was detected for *White* or *Asian* students, suggesting this phenomenon is particularly important for *American Indian/Alaskan Native*, *Hispanic*, and *Black* students. Moreover, this relationship appears to be moderated by School Climate across racial groups although the moderation effect was not statistically significant for *Asian* or *Hawaiian/ Pacific Islander* subgroups. Prior *Mathematics Achievement* and *Socio-Economic Status* are the most consistent covariate predictors of *Mathematics Achievement* across groups. On the other hand student's *Mathematics Self-Efficacy* was only significant for *White* students. The findings also showed that students *Mathematics Identity* effect was found to be statistically significant for all subgroups save *Black* and *Pacific Islander*. Lastly, with the exception of the *Mathematics Degree* effect on *Mathematics Achievement* for Pacific Islander students, the importance of traditional measures of *Teacher Qualifications* on student *Mathematics Achievement* was not supported. While these findings support the general hypothesis of this study, they also underscore the importance of not conflating REM students into one group. Overall, this study suggests that *Teacher*, *Student* and *School Context* relationship is particularly important for REM students but these patterns play out in unique ways that must be considered and analyzed separately. In the final chapter, I will discuss these findings in relation to the theoretical considerations as well as implications for policy and practice.

Chapter 5. Summary, Conclusion and Future Research

Practical Implications

This study examined the relationship between *Teacher Self-Efficacy* and the *Mathematics Achievement* of Racial and Ethnic Minority (REM) high school students. The results showed that *Teacher Self-Efficacy* was strongly associated with the *Mathematics Achievement* of REM students, even after controlling for prior achievement, student individual characteristics, and teacher quality measures such as teaching certification, subject-matter expertise, and years of teaching experience. Furthermore, *School Climate* was found to moderate the relationship between *Teacher Self-Efficacy* and the *Mathematics Achievement* thereby underscoring the particular importance of both teacher beliefs and school context for REM students. The final model detected no *Mathematics Achievement* gap between the REM student subgroup and the general student population. However, Asian and Black students performed statistically significantly above and below the national average respectively. Finally, model comparisons revealed notable differences in the relative influence of individual, teacher, and school factors on the *Mathematics Achievement* of American Indian, Black/African American, Hispanic, and Hawaiian/Pacific Islander student subgroups. These differences point to important implications for future research, policy, and practice.

The implications of these results point to important shifts in how researchers and policy makers should think about teacher quality and STEM educational outcomes. In the past 30 years, efforts to improve quality have focused on providing REM students with access to teachers who have STEM degrees and teaching certification. While basic qualifications are important, the results of this study suggest that they are of little consequence for REM students unless highly-qualified teachers also believe in their ability to bring about the academic success of their REM students and do so within a healthy school climate. Thus, measures of teacher quality must shift from a strict focus on content knowledge, degrees or certification to one that measures the degree to which REM students have access to healthy school ecologies and teachers that believe in their ability to be successful. This shift also necessitates a shift to accountability systems that place healthy school ecologies at the center of the solution rather than merely targeting individual teachers. That is not to say that traditional qualifications are not important but rather they are not direct drivers of mathematics achievement for REM students. As such, policy efforts that focus on improving the work conditions and teacher's Self-Efficacy around teaching REM students are warranted.

One such approach is Culturally Responsive Teaching (CRT). Culturally Responsive Teaching is an approach that seeks to reverse and disrupt systemic inequities by honoring and viewing students cultural, linguistic knowledge and experiences as assets that can be used to promote critical thinking, engagement and ultimately achievement. Thus, Culturally Responsive Teaching seeks to change how teachers view students by shifting the narrative from a deficit perspective to one that recognizes students' experiences and culture as a valuable source of knowledge and an asset in their learning.

Hammond (2014) argues that teachers who recognize students culture, language and experiences, hold higher expectations, are less likely to resort to punitive discipline practices and more likely to practice culturally responsive teaching practices. Furthermore the research on teacher beliefs suggests that teachers who hold high expectations have a positive influence on student self perceptions which in turn positively influence goal-setting, effort, persistence and academic achievement (Cherry, 1987). Thus, Culturally Responsive Teaching practices are a promising approach to not only change how Teachers see and teach REM students but also how students see themselves in relation to the content. Considering the results of this study in relation to the research on Culturally Responsive Teaching provides some direction for how policy-makers can support healthy school ecologies that promote the academic success of REM students in STEM.

Theoretical Implications

The research into improving participation and achievement among REM students in STEM has predominantly centered on input/output models that are based on a human capital view of education. Human Capital theory suggests that the amount of knowledge and skills that an individual acquires determines their effectiveness, efficiency, and thereby value in the job market. When applied to Teachers, this suggests that higher levels of education, training will result in better outcomes. As mentioned before, there is sparse evidence to support this hypothesis. On the student side, Cultural Capital theory has been the predominant theoretical framework used to explain disparities in educational outcomes month REM students. Cultural Capital Theory asserts that differences in educational outcomes reflect differences in students access and acquisition of social connections that support their ability to succeed in schools (Kingston, 2001). As such, students with high-levels of social connections do better than those who do not have access the such connections. This theoretical framework positions students, households and communities as lacking or not having the ability to access capital necessary to help them be successful in schools. As such, Cultural Capital theory frames disparities in educational outcomes and rooted in student deficits that schools have little to no influence over.

The results of this study are inconsistent with either of these two theoretical perspectives. Human Capital theory predicts that level of education, certification and years of experience might be the the data did not support this hypothesis. On the other hand, Cultural Capital Theory would predict that those student characteristics most closely tied to cultural capital, namely SES would be the strongest predictor of student outcomes. While SES was indeed one of the strongest predictors, for REM students, Teacher Efficacy was about as strong across REM students. Thus neither Human Capital nor Cultural Capital Theories were supported by this study.

Directions for Future Research

The REM STEM model is a conceptual improvement over that offered by the leaky pipeline metaphor that has been used to describe the attrition of underrepresented groups in pursuing STEM degrees. It offers a research-based heuristic that tracks STEM outcomes as being influenced by various structural and individual factors that have been found to impact individual preparedness in STEM and entrance into STEM Majors. In this study, the REM STEM model was adapted to better reflect the hierarchical nature of the school context and organized around Tagiuri's School Climate Taxonomy. The results of this study indeed revealed that inputs such as school and individual student features known to influence educational outcomes were heavily mediated by social processes related to teacher beliefs in this case Teacher Self-Efficacy. Self-Efficacy Theory predicts that teachers who believe in their ability to bring about the academic success of their students would be more likely to be successful in doing so. Furthermore, the more success they experience as effective teachers, the stronger the effect is especially when these beliefs are shared by groups of teachers. The results of this study are consistent with the pattern predicted with Self-Efficacy Theory and also lead to further questions about how teacher beliefs such as Teacher Self-efficacy might bring about academic success and how the context might influence and support Teacher Self-Efficacy of REM Students. In the following section, I propose an ecological perspective rooted in Culturally Responsive and Critical perspectives to theorize about how Teacher Preparation can be designed to support the educational success of REM Students.

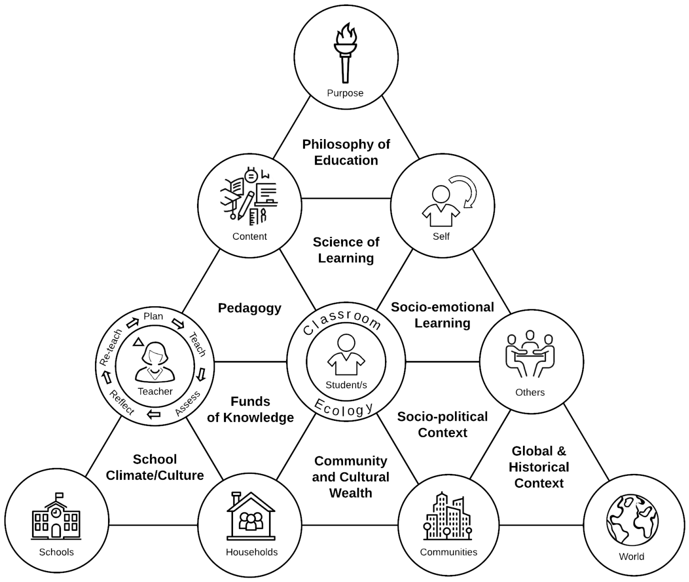
Critical Social Justice Framework

Empirical studies including this one are heavily reliant on input/output frameworks that can often obfuscate the social context and relationships that produce the outcome. This study utilized an adaptation of the REM STEM model and despite the results supporting the predictions of the conceptual model the implications for policy and practice are left open. If *Teacher Self-Efficacy* is as important as the most powerful predictors of academic success for REM students then how can Teacher Preparation Programs support the development of Teacher Self-Efficacy and what practices can be help foster Teachers sense of Self-Efficacy when it comes to bringing about the academic success of REM students in STEM.

The Critical Social Justice (CSJ) Teaching Framework depicted in Figure 5 below was co-developed by the author and colleagues at Claremont Graduate University's Teacher Education Program (Partida, Bermúdez & Hatkoff, 2019).

Figure 5

Critical Social Justice Teaching Model


Purpose
Philosophy of Education
Content
Self
Science of Learning
Pedagogy
Socio-emotional Learning
Plan
Teach
Assess
Reflect
Re-teach
Teacher
Classroom
Student/s
Ecology
Others
Funds of Knowledge
Socio-political Context
School Climate/Culture
Community and Cultural Wealth
Global & Historical Context
Schools
Households
Communities
World

The CSJ Teaching Model represents an ecological view of teaching that is characterized by various inter and intra personal relationships that shape the classroom ecology and are also influenced by society and culture at large. The term Critical Social Justice is adapted from the work of Sensoy & DiAngelo (2017) and comprises the follow core tenants:

1. Recognize society is stratified along social group lines, inequality is deeply and structurally embedded, and those inequalities are reproduced within schooling.
2. Actively seek & make change that disrupts inhumane, unjust, and inequitable patterns and practices.
3. Affirm & Empower students (households, communities, colleagues, & yourself) to harness the resources needed to navigate an unjust world with empathy, savvy, and agency.
4. Dismantle systems and practices of oppression & reimagine love-soaked, empowering ecologies.

Thus, the CSJ Framework is a tool that is used to organize the knowledge, skills and habits mind that help teachers enact and reflect on their teaching practice through an ecological perspective and with the aim of disrupting systemic inequities present in classroom, schools and society at large. Within this framework, each triangle represents a set of relationships that is unpacked through a Critical Social Justice lens and contributes to the overall classroom ecology and ultimately the school experience of the students within the classroom. The CSJ Teaching competencies included in Appendix L provide detailed descriptions of teacher practices aimed at disrupting systemic inequities in schools and classrooms. This framework and competencies supports the development of teachers sense of self-efficacy by explicitly and openly acknowledging the various factors that contribute to health of their classroom ecology and provides various points of entry for making improvements. While not all factors are within a teacher's sphere of influence, they can nevertheless become aware of how these factors relate to and shape the relationships that are namely their relationships with students, their curriculum and the students relationship with each other.

The CSJ Framework is not specific to any content area; however, the results of this study support the idea that teacher beliefs, especially with regard to their ability to bring about the success of REM students matter. When Teachers believe that they have the ability to bring about the academic success of their students they are more likely to hold high expectations and encourage students by communicating belief in students abitiy and supporting their academic success accordingly. Lisa Delpit characterizes teachers that embody an ethic of high expectations and care as "Warm Demanders" Delpit (2013). Warm demanders are teachers who get to know and build relationships with students and in turn create classroom ecologies that promote critical thinking, high academic standards and a strong relationships between students and the teacher as well as students with each other. According to Delpit (2013), warm demanders "expect a great deal of their students, convince them of their own brilliance, and help them to reach their potential in a disciplined and structured environment." This approach is particularly important for REM students who are negatively impacted by lack of access to high quality rigorous curriculum, low expectations due to racial and cultural stereotypes, as internalized stereotypes about their ability to be successful in rigorous mathematics or science classrooms. Thus the warm demander can be further characterized as a teacher presence or disposition with 1) a high level of personal warmth: care, rapport, trust, and 2) a high level of active demandingness:

personal concern for the student as a foundation for excellence and academic effort (Delpit, 2012). Given the strength in the relationship between Teacher Efficacy and Mathematics Achievement that was found in this study, further studies could examine the degree to which teaching dispositions vary in relation to teacher Self-Efficacy. Connecting the beliefs of teachers to their practices in the classroom would offer additional evidence and direction to broaden participation and improve educational outcomes in STEM education.

Culturally Responsive Teacher Efficacy

Disparities in educational outcomes in STEM have been identified for as long as educational statistics have been collected. Various explanations have been proposed ranging from deficit perspectives about REM student ability, culture, and access to high quality teachers and curriculum. Ecological perspectives opens the door for policy and interventions that target school s and more specifically school culture. A focus on school culture requires schools to first recognize the ways that REM students can be harmed by school policies and practices that reproduce inequities through what Valenzuela (1999) refers to as subtractive schooling. According to Valenzuela (1999) subtractive schooling divests youth of important social and cultural resources, leaving them progressively more vulnerable to academic failure and alienation from schools. Furthermore, the ways that schools perpetuate this harm are not always explicitly stated but reflected in the unwritten, unvoiced, unofficial (and often unintended) lessons students learn in school about the knowledge, behaviors, values, and perspectives that are or are not valid and privileged, typically as determined by dominant, hegemonic culture. (Delpit 2006; McLaren, 2006). According to Tye (2000), subtractive schooling practices reflect the “deep structure” of schooling or societies set of assumptions about what schools are for and how education should properly be conducted, whether those assumptions support or undermine students and communities. These assumptions are particularly harmful to REM students when they serve to reinforce harmful stereotypes and deficit perspectives that in turn influence the policies, practices that shape the school and classroom ecologies.

Critical perspectives can help advance the stated goals of current policy efforts through a transformational approach to teacher and school culture. Instead of focusing on individual teacher quality measures that have only a loose association with student achievement, a critical perspective looks at systems of inequity that shape how teachers view and support REM students through an ethic of care, rigor and compassion. The research about the impact that Culturally Relevant Pedagogy has on the educational outcomes of REM students is piling (Hammond, 2015). There is also a growing consensus that collective Teacher Efficacy among the strongest predictor of student achievement above and beyond individual and external factors such as ability and socio-economic status (Donohoo, Hattie & Eells, 2018). Thus, what is emerging from these two lines of research is what I am calling is Culturally Responsive Teacher Efficacy and by extension Collective Culturally Responsive Teacher Efficacy. As such Culturally Responsive Teaching can be characterized at the individual and school-level. At the individual level, it includes a Teacher's self-beliefs about their ability to promote the academic success of culturally and linguistically diverse students. At the school level, it is a function of the both the explicit and implicit social structures within the school that influence, shape teacher's collective beliefs. Lastly, this combination opens up several lines of inquiry for examination of how schools can build and sustain healthy school ecologies that promote the academic success of REM students in general and more specifically in STEM.

Broadening participation in STEM for historically underrepresented groups will require a shift in the standard pipeline model of STEM education. The factors that have led to persistent inequities in STEM educational outcomes can be traced back to harmful practices and policies still present in schools and classrooms today (Sensoy & DiAngelo, 2017). Shifting the narrative from one that places sole responsibility on teachers to be “more effective” to a more holistic perspective that reckons with the structural and systemic symptoms of persistent inequity. By recognizing the ways that schools perpetuate inequities and actively seeking to disrupt this, schools can be places where teachers are part of healthy school and classroom ecologies designed to bring about the academic success of REM students. Thus the focus of further studies and interventions should be to find better ways of nurturing and sustain Collective Culturally Responsive Teacher Self-Efficacy.

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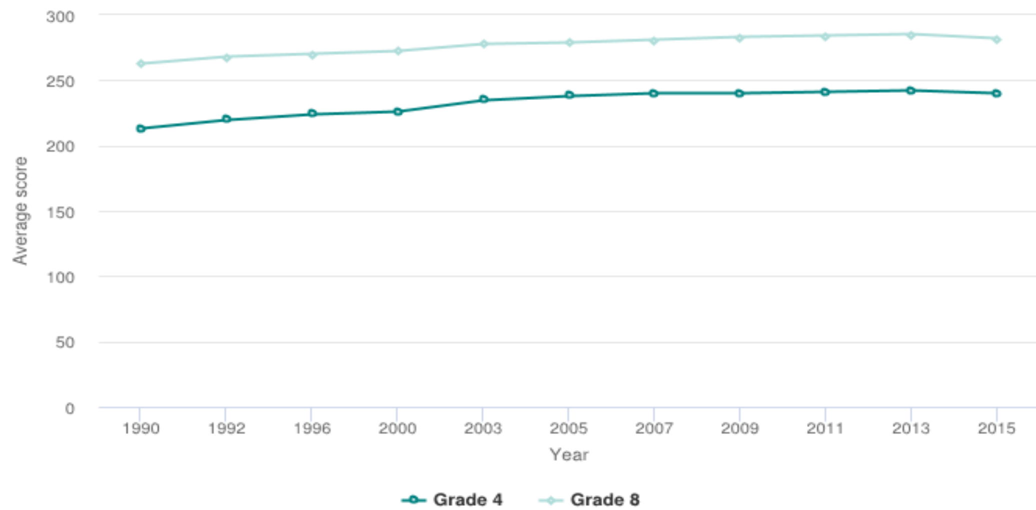
Appendix

Appendix A

A. Average NAEP mathematics scores of students in grades 4 and 8: 1990–2015



NAEP = National Assessment of Educational Progress.

Note(s): NAEP mathematics assessment scores range from 0 to 500 for grades 4 and 8.

Source(s): National Science Foundation, National Center for Science and Engineering Statistics, special tabulations (2016) of NAEP 1990, 1992, 1996, 2000, 2003, 2005, 2007, 2009, 2011, 2013, and 2015 mathematics assessments, National Center for Education Statistics. See Appendix Table 1-1.

Science and Engineering Indicators 2018

Source: National Science Board. (2018). [Figure 1-1]. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://www.nsf.gov/statistics/indicators/data/figures.

Appendix B

B. Students in grades 4, 8, and 12 scoring at or above the main NAEP's proficient level in mathematics for their grade, by student grade and characteristics: 1990–2015

(Average score)

Grade and race or ethnicity	Socioeconomic status[a]		Sex	
	Eligible for free or reduced-price lunch	Not eligible for free or reduced-price lunch	Male	Female
All students in grade 4				
White	237	255	249	247
Black	221	237	223	225
Hispanic[b]	227	244	231	229
Asian or Pacific Islander	241	266	259	255
American Indian or Alaska Native	223	239	228	226
More than one race	233	256	246	244
All students in grade 8				
White	276	298	292	291
Black	256	273	259	262
Hispanic[b]	266	282	270	270
Asian or Pacific Islander	291	316	305	306
American Indian or Alaska Native	260	280	265	270
More than one race	271	296	285	285
All students in grade 12				
White	145	164	161	159
Black	124	140	129	131
Hispanic[b]	135	144	141	136
Asian or Pacific Islander	157	177	171	169
American Indian or Alaska Native	133	s	141	s
More than one race	144	165	158	157

Source: National Science Board. (2018). [Table 1-2]. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://www.nsf.gov/statistics/indicators/data/tables.

Appendix C

C. Average scores of students in grades 4, 8, and 12 on the main NAEP science assessment, by socioeconomic status and sex within race or ethnicity: 2015

TABLE 1-3

Average scores of students in grades 4, 8, and 12 on the main NAEP science assessment, by socioeconomic status and sex within race or ethnicity: 2015

(Average score)

Grade and race or ethnicity	Socioeconomic status[a]		Sex	
	Eligible for free or reduced-price lunch	Not eligible for free or reduced-price lunch	Male	Female
All students in grade 4				
White	154	172	166	165
Black	129	148	132	134
Hispanic[b]	134	157	139	139
Asian or Pacific Islander	150	178	168	166
American Indian or Alaska Native	134	158	139	140
More than one race	147	171	157	159
All students in grade 8				
White	153	171	167	164
Black	127	146	131	132
Hispanic[b]	135	154	142	137
Asian or Pacific Islander	148	174	165	164
American Indian or Alaska Native	134	155	142	136
More than one race	146	170	161	158
All students in grade 12				
White	146	164	162	159
Black	119	136	127	123
Hispanic[b]	132	145	140	133
Asian or Pacific Islander	150	177	167	165
American Indian or Alaska Native	s	s	s	s
More than one race	145	162	160	151

Source: National Science Board. (2018). [Table 1-3]. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://www.nsf.gov/statistics/indicators/data/tables.

Appendix D

M. Highest-level mathematics course enrollment of high school completers, by socioeconomic status within race or ethnicity: 2013

TABLE 1-4

Average scores of students in grade 8 on the main NAEP technology and engineering literacy assessment, by socioeconomic status and sex within race or ethnicity: 2014

(Average score)

Race or ethnicity	Socioeconomic status[a]		Sex	
	Eligible for free or reduced-price lunch	Not eligible for free or reduced-price lunch	Male	Female
White	145	166	158	162
Black	122	144	126	131
Hispanic[b]	133	152	137	139
Asian or Pacific Islander	144	171	159	159
American Indian or Alaska Native	137	s	s	s
More than one race	143	163	149	160

s = suppressed for reasons of confidentiality and/or reliability.

NAEP = National Assessment of Educational Progress.

[a] NAEP uses eligibility for the federal National School Lunch Program (NSLP) as a measure of socioeconomic status. NSLP is a federally assisted meal program that provides low-cost or free lunches to eligible students. It is often referred to as the free or reduced-price lunch program.

[b] Hispanic may be any race. American Indian or Alaska Native, Asian or Pacific Islander, black, white, and more than one race refer to individuals who are not of Hispanic origin.

Note(s)

Main NAEP technology and engineering literacy assessment scores range from 0 to 300.

Source(s)

National Science Foundation, National Center for Science and Engineering Statistics, special tabulations (2016) of main NAEP 2014 technology and engineering literacy assessment, National Center for Education Statistics.

Science and Engineering Indicators 2018

Source: National Science Board. (2018). [Table 1-14]. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://www.nsf.gov/statistics/indicators/data/tables.

Appendix E

E. Science course enrollement of high school completers, by student and family characteristics: 2013

TABLE 1-16

Science course enrollment of high school completers, by student and family characteristics: 2013

(Percent)

Student and family characteristic	General science	AP/IB or advanced science	No biology	General biology	AP/IB or advanced biology	No chemistry	General chemistry	AP/IB or advanced chemistry	No physics	General physics	AP/IB or advanced physics
All students	78.6	21.3	2.5	86.1	11.5	24.4	67.9	7.7	58.5	36.4	5.1
Sex											
Male	80.2	19.7	2.7	87.7	9.7	27.1	65.4	7.5	56.7	36.8	6.6
Female	77.1	22.8	2.2	84.5	13.2	21.9	70.2	7.9	60.3	36.0	3.7
Race or ethnicity											
White	76.6	23.3	2.4	85.3	12.4	23.9	67.3	8.8	58.3	36.3	5.4
Black	85.4	14.4	1.2	89.8	9.0	23.8	72.8	3.4	62.8	34.8	2.4
Hispanic[a]	84.0	15.9	2.9	89.2	7.9	27.1	68.1	4.8	59.6	36.9	3.5
Asian	48.5	51.5	3.8	66.1	30.1	10.1	65.2	24.7	32.9	47.4	19.8
Other[b]	91.5	7.7	2.7	91.2	6.1	33.0	63.2	3.7	74.5	25.1	0.4
Two or more races	81.1	18.9	2.9	86.9	10.3	28.1	65.6	6.4	62.0	33.2	4.7
SES[c]											
Lowest fifth	89.1	10.6	3.3	90.3	6.4	34.1	62.4	3.5	68.1	30.1	1.9
Middle three-fifths	81.2	18.6	2.1	87.5	10.4	25.8	68.0	6.2	60.8	35.2	4.0

Source: National Science Board. (2018). [Table 1-16]. Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://www.nsf.gov/statistics/indicators/data/tables.

Appendix F

F. Percentage of fall 2009 ninth-graders who were pursuing or planning to pursue selected postsecondary degree, among those who were taking or planning to take postsecondary classes, by student, family, and school characteristics: 2013

Characteristic	Bachelor's degree program	Associate's degree program	Diploma program for occupational training	No specific program	Other/ don't know
Total	**41.8**	**33.7**	**5.0**	**6.5**	**13.0**
Sex					
Female	41.8	33.8	4.5	6.8	13.1
Male	41.7	33.6	5.5	6.3	12.9
Race/ethnicity					
Asian, non-Hispanic	52.4	30.3	‡	6.2	9.9
Black, non-Hispanic	32.3	35.3	5.3	6.2	20.8
Hispanic or Latino	25.1	41.4	6.6	8.4	18.4
White, non-Hispanic	50.1	30.6	4.3	5.8	9.1
More than one race, non-Hispanic	37.8	35.3	4.6 !	8.4	13.9
All other races, non-Hispanic	24.6	28.5	18.8 !	‡	24.7 !
Socioeconomic status quintile					
Lowest fifth	22.6	37.4	9.5	6.9	23.6
Middle three fifths	36.2	38.1	5.1	7.6	13.0
Highest fifth	65.9	21.5	2.0	4.0	6.6
Parent's highest education					
Less than high school	15.3	36.3	11.8	9.1	27.5
High school	26.7	39.9	7.5	8.9	17.0
Associate's degree	33.4	40.8	5.3	6.3	14.2
Bachelor's degree	53.2	29.8	2.3	5.5	9.2
Master's degree or higher	67.1	20.3	2.2	4.0	6.5
Mathematics achievement quintile (2012)					
Lowest fifth	15.3	40.2	13.6	9.2	21.7
Middle three fifths	35.2	38.5	5.1	7.3	13.9
Highest fifth	67.1	20.9	0.9	3.8	7.3
School sector					
Public, 2009 and 2012	38.7	35.5	5.3	6.9	13.7
Private, 2009 and 2012	69.9	17.8	2.2 !	3.2	6.8
Changed sectors, 2009 to 2012	61.9	20.3	‡	5.2 !	10.2

! Interpret data with caution. Estimate is unstable because the standard error represents more than 30 percent (but less than 50 percent) of the estimate.

‡ Does not meet NCES reporting standards. The standard error represents 50 percent or more of the estimate, and/or the numerator is less than 3, and/or the denominator is less than 30.

NOTE: This table represents 50.4 percent of the fall 2009 ninth-grade cohort (those who were taking or planning to take postsecondary classes in 2013).

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09), First Follow-up and 2013 Update Public-Use File.

Source: Dalton, B., Ingels, S.J., and Fritch, L. (2016). [Table 11]. High School Longitudinal Study of 2009 (HSLS:09) 2013 Update and High School Transcript Study: A First Look at Fall 2009 Ninth-Graders in 2013 (NCES 2015-037rev). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved [09/2019] from http://nces.ed.gov/pubsearch.

Appendix G

G. Percentage of fall 2009 ninth-graders considering a science, technology, engineering, or math (STEM) major (among those with an identified major), by level of program and student, family, and school characteristics: 2013

Characteristic	Overall	Postsecondary program: Bachelor's degree program	Associate's degree program	Other program[1]
Total	**23.3**	**31.9**	**17.4**	**15.3**
Sex				
Female	14.5	23.6	7.9	6.5
Male	33.3	41.4	28.2	25.3
Race/ethnicity				
Asian, non-Hispanic	41.9	52.5	26.9	28.8
Black, non-Hispanic	15.5	22.9	12.3	11.1
Hispanic or Latino	19.8	27.9	16.2	17.6
White, non-Hispanic	24.8	31.9	17.9	15.8
More than one race, non-Hispanic	22.7	32.7	19.6	10.1 !
All other races, non-Hispanic	25.3 !	43.6 !	‡	‡
Socioeconomic status quintile				
Lowest fifth	16.8	28.6	15.1	11.6
Middle three fifths	21.7	29.6	17.1	16.0
Highest fifth	30.3	35.4	20.4	19.2
Parent's highest education				
Less than high school	18.0	31.8 !	16.6	14.1 !
High school	18.2	27.4	14.5	14.8
Associate's degree	19.7	29.6	15.2	12.6 !
Bachelor's degree	27.5	31.5	23.3	20.7
Master's degree or higher	30.3	36.4	18.6	14.4
Mathematics achievement quintile (2012)				
Lowest fifth	11.8	17.1	10.2	11.8
Middle three fifths	17.1	20.9	15.5	14.0
Highest fifth	39.9	44.5	30.9	26.5
School sector				
Public, 2009 and 2012	23.2	32.7	17.3	15.4
Private, 2009 and 2012	25.2	28.6	19.1	13.7
Changed sectors, 2009 to 2012	20.1	23.9 !	14.4 !	12.9 !

! Interpret data with caution. Estimate is unstable because the standard error represents more than 30 percent (but less than 50 percent) of the estimate.

‡ Does not meet NCES reporting standards. The standard error represents 50 percent or more of the estimate, and/or the numerator is less than 3, and/or the denominator is less than 30.

[1] Other programs include "certificate or diploma program (occupational training)," "no program, just taking courses," "other," and "don't know."

NOTE: About 10 percent of fall 2009 ninth-graders who were taking or planning to take postsecondary classes in 2013 indicated that they did not have a major they were considering.

SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09), First Follow-up and 2013 Update Public-Use File.

Source: Dalton, B., Ingels, S.J., and Fritch, L. (2016). [Table 12]. High School Longitudinal Study of 2009 (HSLS:09) 2013 Update and High School Transcript Study: A First Look at Fall 2009 Ninth-Graders in 2013 (NCES 2015-037rev). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved [09/2019] from http://nces.ed.gov/pubsearch.

Appendix H

H. Percentage of 2003−04 beginning bachelor's and associate's degree students who entered but subsequently left STEM fields, by demographic, precollege academic, and postsecondary enrollment characteristics: 2003−2009

Demographic, precollege academic, and postsecondary enrollment characteristics	STEM entrants among beginning bachelor's degree students: Left PSE without a degree or certificate[1]	STEM entrants among beginning bachelor's degree students: Switched major to a non-STEM field	STEM entrants among beginning associate's degree students: Left PSE without a degree or certificate[1]	STEM entrants among beginning associate's degree students: Switched major to a non-STEM field
Total	**20.2**	**28.1**	**36.5**	**32.8**
Sex				
Male	23.7	25.5	38.0	28.8
Female	14.2	32.4	32.7	42.6
Race/ethnicity[2]				
White	19.8	28.1	35.8	30.3
Black	29.3	36.0	41.5	36.3
Hispanic	23.1	26.4	39.9	37.6
Asian	9.8	22.6	26.2	28.1
All other races	20.5	25.4	33.4 !	48.9
Highest education of parents				
High school or less	30.1	28.8	35.8	34.2
Some college	22.1	27.2	42.1	31.5
Bachelor's degree or higher	16.6	27.9	31.6	32.8
Income level in 2003–04[3]				
Lowest 25 percent	29.2	28.6	45.9	25.1
Lower middle 25 percent	21.6	28.4	27.9	38.8
Upper middle 25 percent	18.2	27.5	29.6	34.1
Highest 25 percent	15.4	28.0	42.6	34.1
Highest mathematics in high school[4]				
Skipped	46.9	27.1 !	46.6	28.1
None of the following	40.6	17.4 !	47.1	24.3
Algebra II/trigonometry	26.7	32.5	31.0	38.9
Pre-calculus	19.6	32.1	27.3	32.6
Calculus	12.0	23.7	28.7	37.1 !
High school GPA[5]				
Skipped	33.2	26.9	40.5	30.8
Less than 2.50	45.8	25.3 !	41.8	36.3
2.50–2.99	24.6	32.9	37.5	30.4
3.00–3.49	22.1	32.5	36.2	31.3
3.50 or higher	14.1	25.5	21.8	30.8
Selectivity of institution first attended[6]				
Very selective	11.5	26.1	‡	‡
Moderately selective	18.2	30.3	‡	‡
Minimally selective/open admission	38.4	26.4	‡	‡

See notes at end of table.

Demographic, precollege academic, and postsecondary enrollment characteristics	STEM entrants among beginning bachelor's degree students: Left PSE without a degree or certificate[1]	STEM entrants among beginning bachelor's degree students: Switched major to a non-STEM field	STEM entrants among beginning associate's degree students: Left PSE without a degree or certificate[1]	STEM entrants among beginning associate's degree students: Switched major to a non-STEM field
Level and control of institution first attended				
Public 4-year	19.8	30.5	28.7	39.2
Private nonprofit 4-year	17.5	24.0	‡	‡
For-profit 4-year	56.8	‡	34.3	16.9 !
Public 2-year	‡	‡	36.8	33.9
Private 2-year	‡	‡	39.9	30.5 !
Other	‡	‡	‡	‡
Ever received a Pell Grant through 2009				
No	17.7	27.1	41.2	29.1
Yes	24.6	29.7	31.8	36.5

! Interpret data with caution. Estimate is unstable because the standard error represents more than 30 percent of the estimate.

‡ Reporting standards not met.

[1] "PSE" refers to postsecondary education. "Students who left PSE without a degree or certificate" are also referred to as students who dropped out of college or college dropouts in the text.

[2] Black includes African American, Hispanic includes Latino, and "All other races" includes American Indian, Alaska Native, Native Hawaiian, other Pacific Islanders, and individuals who indicated Two or more races or Other.

[3] The total income in 2002 for independent students or parents of dependent students.

[4] Information for this variable is only available for students under age 24. Those age 24 or above (about 16 percent of the study sample) were included in the "skip" category.

[5] Information for this variable is only available for students under age 24 who received a high school diploma. Those age 24 or above or without a high school diploma (about 21 percent of the study sample) were included in the "skip" category.

[6] The selectivity of institution was developed only for public and private nonprofit 4-year institutions using the following criteria: whether the institution was open admission (had no minimal requirements); the number of applicants; the number of students admitted; the 25th and 75th percentiles of ACT and/or SAT scores; and whether test scores were required for admission. For more information, see Cunningham, A.F. (2006). *Changes in Patterns of Prices and Financial Aid* (NCES 2006-153). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. In this table, for-profit 4-year institutions and private 2-year and less-than-2-year institutions are included in the category of "minimally selective/open admission."

NOTE: STEM (science, technology, engineering, and mathematics) includes mathematics, physical sciences, biological/life sciences, engineering/engineering technologies, science technologies, and computer/information sciences. Estimates include students enrolled in Title IV eligible postsecondary institutions in the 50 states, the District of Columbia, and Puerto Rico. Standard error tables are available at http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2014001.

SOURCE: U.S. Department of Education, National Center for Education Statistics, 2003/04 Beginning Postsecondary Students Longitudinal Study, Second Follow-up (BPS:04/09) and Postsecondary Education Transcript Study of 2009 (PETS:09).

Source: Chen, X. (2013). [Table 2] STEM Attrition: College Students' Paths Into and Out of STEM Fields (NCES 2014-001). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Appendix I

N. Number and percentage distribution of teachers in public and private elementary and secondary schools, by selected teacher characteristics: Selected years, 1987–88 through 2015–16

[Standard errors appear in parentheses]

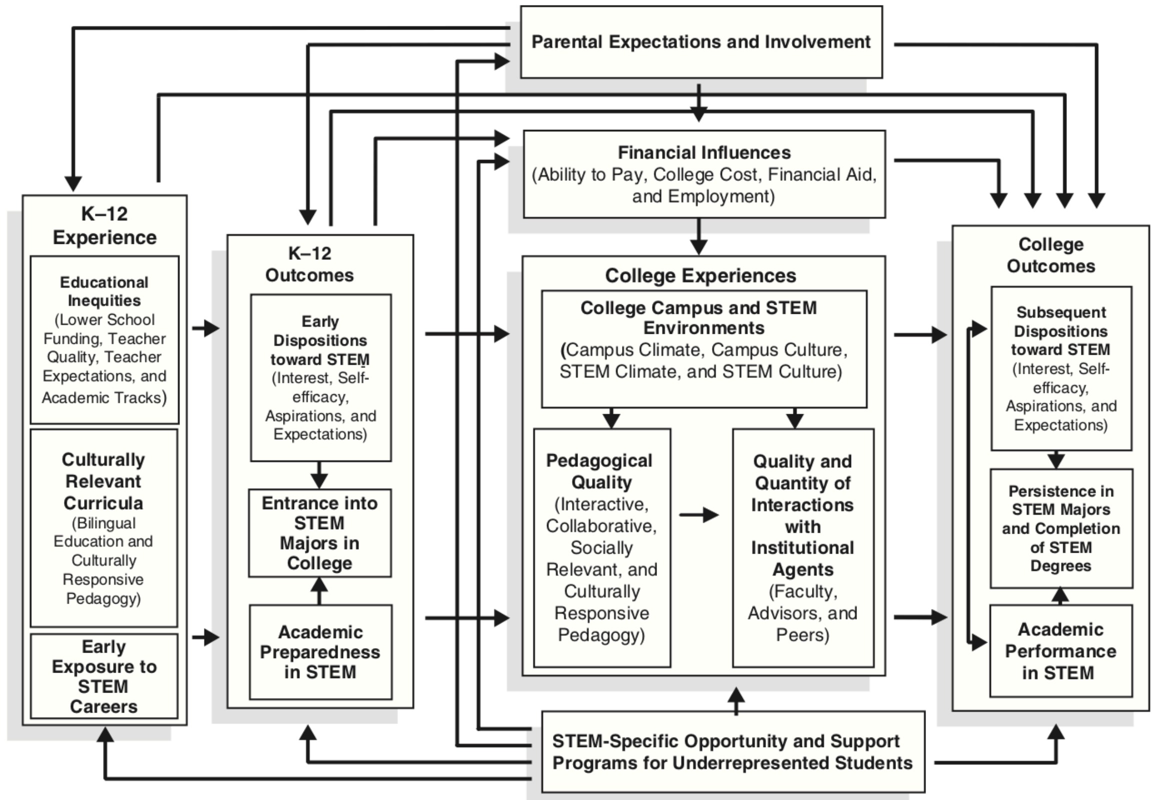
Selected teacher characteristic	Number of teachers (in thousands)						
	1987–88	1990–91	1999–2000	2003–04	2007–08	2011–12	2015–16
1	2	3	4	5	6	7	8
Public schools							
Total	**2,323 (13.2)**	**2,559 (20.7)**	**3,002 (19.4)**	**3,251 (29.2)**	**3,405 (44.0)**	**3,385 (41.4)**	**3,827 (49.5)**
Sex							
Male	685 (6.8)	719 (11.2)	754 (10.7)	813 (13.3)	821 (20.4)	802 (22.2)	897 (18.1)
Female	1,638 (10.1)	1,840 (14.7)	2,248 (16.0)	2,438 (23.5)	2,584 (34.6)	2,584 (30.5)	2,930 (39.1)
Race/ethnicity							
White[1]	2,018 (12.6)	2,214 (20.0)	2,532 (17.2)	2,702 (30.1)	2,829 (38.7)	2,773 (30.5)	3,067 (41.9)
Black[1]	191 (4.6)	212 (6.4)	228 (6.0)	257 (11.0)	239 (15.8)	231 (12.1)	256 (8.8)
Hispanic[1]	69 (2.6)	87 (4.5)	169 (6.4)	202 (11.3)	240 (16.6)	264 (13.4)	338 (9.2)
Asian[1,2]	21 (1.1)	27 (1.7)	48 (2.7)	42 (2.5)	42 (7.2)	61 (7.3)	86 (3.9)
Pacific Islander	— (†)	— (†)	— (†)	6 (0.8)	6 (1.3)	5 (1.4)	9 (1.1)
American Indian/Alaska Native[1]	24 (1.3)	20 (1.4)	26 (1.9)	17 (1.2)	17 (1.9)	17 (2.9)	17 (1.5)
Two or more races	— (†)	— (†)	— (†)	24 (2.2)	31 (2.9)	35 (3.7)	54 (2.8)
Age							
Under 30	313 (5.0)	257 (5.7)	509 (9.2)	540 (27.4)	612 (22.4)	518 (15.9)	574 (11.4)
30 to 39	823 (7.7)	684 (10.8)	661 (9.8)	798 (14.5)	898 (16.8)	979 (19.3)	1,090 (17.0)
40 to 49	762 (7.4)	1,034 (13.3)	953 (10.3)	840 (14.3)	808 (19.2)	849 (19.2)	1,050 (17.7)
50 to 59	357 (5.7)	477 (8.6)	786 (12.6)	942 (26.0)	879 (21.1)	783 (20.5)	823 (14.4)
60 and over	68 (2.5)	107 (4.1)	93 (4.0)	131 (4.8)	207 (10.3)	256 (13.2)	290 (7.5)
Highest degree earned							
Less than bachelor's	15 (1.0)	17 (1.2)	20 (1.3)	35 (2.5)	27 (2.1)	128 (8.6)	93 (3.7)
Bachelor's	1,214 (9.8)	1,327 (11.7)	1,560 (15.8)	1,651 (22.8)	1,612 (28.8)	1,350 (21.1)	1,550 (23.4)
Master's	932 (8.5)	1,077 (13.5)	1,257 (13.9)	1,331 (21.7)	1,517 (27.8)	1,614 (29.1)	1,812 (26.3)
Education specialist[3]	146 (3.4)	118 (5.3)	143 (5.2)	195 (6.8)	218 (8.6)	257 (9.7)	323 (8.8)
Doctor's	16 (1.2)	20 (1.7)	22 (1.8)	38 (3.5)	30 (2.7)	37 (4.0)	49 (3.1)
Years of teaching experience							
Less than 3	145 (3.2)	185 (4.8)	325 (7.7)	339 (36.6)	392 (18.1)	244 (8.5)	380 (8.8)
3 to 9	568 (6.3)	596 (9.4)	854 (12.3)	1,043 (14.1)	1,125 (19.6)	1,104 (20.6)	1,083 (17.1)
10 to 20	1,072 (8.7)	1,056 (11.8)	865 (10.1)	946 (21.5)	1,017 (24.3)	1,265 (21.0)	1,504 (23.0)
Over 20	539 (6.1)	721 (10.6)	958 (13.5)	922 (27.9)	871 (23.9)	772 (23.8)	860 (15.8)
Level of instruction[4]							
Elementary	1,292 (9.5)	1,442 (11.8)	1,602 (13.5)	1,716 (25.8)	1,725 (37.1)	1,726 (20.2)	1,908 (41.2)
General	788 (7.4)	887 (10.6)	1,042 (12.5)	1,130 (29.8)	1,100 (26.5)	1,078 (22.1)	1,166 (27.4)
Arts/music	116 (3.0)	110 (4.3)	99 (3.7)	101 (5.3)	103 (6.6)	82 (5.4)	108 (4.5)
English	60 (2.3)	72 (3.8)	66 (3.8)	70 (5.1)	104 (9.9)	92 (6.9)	138 (5.2)
ESL/bilingual	18 (1.1)	20 (1.3)	28 (1.8)	25 (3.6)	24 (3.3)	51 (6.8)	53 (3.1)
Health/physical ed	56 (2.0)	66 (3.2)	57 (3.5)	73 (5.0)	63 (6.0)	79 (8.1)	70 (3.2)
Mathematics	31 (2.0)	30 (1.9)	23 (2.4)	19 (2.3)	28 (3.8)	32 (6.5)	42 (2.6)
Science	18 (1.5)	21 (1.9)	11 (1.3)	19 (3.0)	15 (3.4)	18 (3.3)	25 (1.9)
Special education	168 (3.9)	176 (5.9)	227 (5.6)	240 (20.6)	230 (13.0)	239 (10.3)	247 (6.9)
Other elementary	37 (2.4)	60 (3.2)	49 (3.5)	40 (3.5)	58 (4.2)	55 (5.2)	59 (3.1)
Secondary	1,031 (10.5)	1,118 (16.5)	1,401 (17.7)	1,534 (26.0)	1,680 (39.0)	1,659 (37.8)	1,920 (47.2)
Arts/music	73 (2.0)	74 (2.3)	110 (3.4)	112 (4.1)	121 (6.2)	121 (5.6)	150 (5.3)
English	171 (3.2)	195 (5.1)	245 (5.1)	269 (9.0)	306 (10.0)	289 (9.9)	339 (9.1)
ESL/bilingual	6 (0.5)	10 (0.7)	16 (1.2)	18 (2.5)	21 (2.5)	20 (2.4)	25 (1.9)
Foreign language	43 (1.2)	52 (2.4)	71 (2.4)	73 (3.3)	78 (5.0)	88 (4.5)	95 (4.0)
Health/physical ed	76 (2.4)	76 (2.2)	99 (3.1)	102 (4.3)	119 (5.7)	101 (3.9)	108 (3.7)
Mathematics	139 (2.5)	155 (4.3)	207 (4.5)	213 (5.5)	252 (9.1)	250 (7.5)	281 (8.4)
Science	115 (2.9)	128 (4.0)	169 (4.0)	189 (6.8)	195 (8.3)	209 (6.1)	232 (6.5)
Social studies	118 (2.4)	124 (3.3)	163 (4.4)	178 (5.7)	209 (9.9)	197 (6.3)	232 (7.5)
Special education	100 (2.2)	113 (3.5)	113 (2.8)	174 (7.5)	165 (9.7)	191 (12.2)	207 (6.0)
Vocational/technical	166 (3.0)	160 (3.7)	161 (3.5)	169 (5.7)	164 (6.3)	147 (5.7)	172 (6.5)
Other secondary	25 (1.3)	30 (1.5)	47 (2.0)	36 (2.1)	47 (3.4)	46 (4.0)	80 (3.4)

Selected teacher characteristic	Percentage distribution of teachers						
	1987–88	1990–91	1999–2000	2003–04	2007–08	2011–12	2015–16
1	9	10	11	12	13	14	15
Public schools							
Total	**100.0 (†)**	**100.0 (†)**	**100.0 (†)**	**100.0 (†)**	**100.0 (†)**	**100.0 (†)**	**100.0 (†)**
Sex							
Male	29.5 (0.22)	28.1 (0.31)	25.1 (0.30)	25.0 (0.32)	24.1 (0.47)	23.7 (0.49)	23.4 (0.34)
Female	70.5 (0.22)	71.9 (0.31)	74.9 (0.30)	75.0 (0.32)	75.9 (0.47)	76.3 (0.49)	76.6 (0.34)
Race/ethnicity							
White[1]	86.9 (0.24)	86.5 (0.29)	84.3 (0.30)	83.1 (0.53)	83.1 (0.53)	81.9 (0.53)	80.1 (0.34)
Black[1]	8.2 (0.19)	8.3 (0.25)	7.6 (0.19)	7.9 (0.34)	7.0 (0.45)	6.8 (0.31)	6.7 (0.21)
Hispanic[1]	3.0 (0.11)	3.4 (0.17)	5.6 (0.20)	6.2 (0.34)	7.1 (0.46)	7.8 (0.37)	8.8 (0.22)
Asian[1,2]	0.9 (0.05)	1.0 (0.06)	1.6 (0.09)	1.3 (0.08)	1.2 (0.21)	1.8 (0.21)	2.3 (0.09)
Pacific Islander	— (†)	— (†)	— (†)	0.2 (0.03)	0.2 (0.04)	0.1 (0.04)	0.2 (0.03)
American Indian/Alaska Native[1]	1.0 (0.06)	0.8 (0.05)	0.9 (0.06)	0.5 (0.04)	0.5 (0.06)	0.5 (0.08)	0.4 (0.04)
Two or more races	— (†)	— (†)	— (†)	0.7 (0.07)	0.9 (0.09)	1.0 (0.11)	1.4 (0.07)
Age							
Under 30	13.5 (0.19)	10.0 (0.23)	17.0 (0.28)	16.6 (0.84)	18.0 (0.61)	15.3 (0.44)	15.0 (0.23)
30 to 39	35.4 (0.30)	26.7 (0.35)	22.0 (0.29)	24.5 (0.38)	26.4 (0.39)	28.9 (0.53)	28.5 (0.28)
40 to 49	32.8 (0.25)	40.4 (0.37)	31.8 (0.32)	25.9 (0.38)	23.7 (0.47)	25.1 (0.51)	27.4 (0.29)
50 to 59	15.4 (0.23)	18.7 (0.29)	26.2 (0.35)	29.0 (0.74)	25.8 (0.51)	23.1 (0.49)	21.5 (0.23)
60 and over	2.9 (0.11)	4.2 (0.16)	3.1 (0.13)	4.0 (0.14)	6.1 (0.29)	7.6 (0.34)	7.6 (0.17)
Highest degree earned							
Less than bachelor's	0.7 (0.04)	0.7 (0.05)	0.7 (0.04)	1.1 (0.08)	0.8 (0.06)	3.8 (0.24)	2.4 (0.10)
Bachelor's	52.3 (0.28)	51.9 (0.31)	52.0 (0.40)	50.8 (0.56)	47.4 (0.59)	39.9 (0.52)	40.5 (0.34)
Master's	40.1 (0.30)	42.1 (0.34)	41.9 (0.38)	40.9 (0.56)	44.5 (0.55)	47.7 (0.57)	47.3 (0.34)
Education specialist[3]	6.3 (0.14)	4.6 (0.20)	4.7 (0.17)	6.0 (0.19)	6.4 (0.25)	7.6 (0.27)	8.4 (0.18)
Doctor's	0.7 (0.05)	0.8 (0.07)	0.7 (0.06)	1.2 (0.11)	0.9 (0.08)	1.1 (0.11)	1.3 (0.08)
Years of teaching experience							
Less than 3	6.2 (0.14)	7.2 (0.19)	10.8 (0.24)	10.4 (1.13)	11.5 (0.48)	7.2 (0.24)	9.9 (0.19)
3 to 9	24.4 (0.22)	23.3 (0.30)	28.5 (0.37)	32.1 (0.33)	33.0 (0.52)	32.6 (0.52)	28.3 (0.30)
10 to 20	46.1 (0.27)	41.3 (0.35)	28.8 (0.33)	29.1 (0.58)	29.9 (0.57)	37.4 (0.53)	39.3 (0.31)
Over 20	23.2 (0.23)	28.2 (0.30)	31.9 (0.36)	28.4 (0.81)	25.6 (0.62)	22.8 (0.54)	22.5 (0.27)
Level of instruction[4]							
Elementary	55.6 (0.33)	56.3 (0.40)	53.3 (0.42)	52.8 (0.66)	50.7 (0.91)	51.0 (0.65)	49.8 (0.96)
General	33.9 (0.29)	34.6 (0.39)	34.7 (0.41)	34.8 (0.86)	32.3 (0.70)	31.8 (0.71)	30.5 (0.65)
Arts/music	5.0 (0.13)	4.3 (0.17)	3.3 (0.12)	3.1 (0.17)	3.0 (0.19)	2.4 (0.16)	2.8 (0.11)
English	2.6 (0.10)	2.8 (0.14)	2.2 (0.13)	2.2 (0.16)	3.0 (0.29)	2.7 (0.21)	3.6 (0.13)
ESL/bilingual	0.8 (0.05)	0.8 (0.05)	0.9 (0.06)	0.8 (0.11)	0.7 (0.10)	1.5 (0.20)	1.4 (0.08)
Health/physical ed	2.4 (0.09)	2.6 (0.12)	1.9 (0.12)	2.2 (0.15)	1.8 (0.18)	2.3 (0.23)	1.8 (0.08)
Mathematics	1.3 (0.09)	1.2 (0.08)	0.8 (0.08)	0.6 (0.07)	0.8 (0.11)	0.9 (0.19)	1.1 (0.07)
Science	0.8 (0.06)	0.8 (0.07)	0.4 (0.04)	0.6 (0.09)	0.4 (0.10)	0.5 (0.10)	0.7 (0.05)
Special education	7.2 (0.16)	6.9 (0.23)	7.6 (0.18)	7.4 (0.63)	6.7 (0.37)	7.1 (0.31)	6.4 (0.16)
Other elementary	1.6 (0.10)	2.4 (0.12)	1.6 (0.12)	1.2 (0.11)	1.7 (0.12)	1.6 (0.15)	1.5 (0.08)
Secondary	44.4 (0.33)	43.7 (0.40)	46.7 (0.42)	47.2 (0.66)	49.3 (0.91)	49.0 (0.65)	50.2 (0.96)
Arts/music	3.1 (0.09)	2.9 (0.08)	3.7 (0.11)	3.4 (0.12)	3.6 (0.18)	3.6 (0.14)	3.9 (0.13)
English	7.4 (0.12)	7.6 (0.18)	8.2 (0.15)	8.3 (0.27)	9.0 (0.27)	8.5 (0.25)	8.9 (0.20)
ESL/bilingual	0.3 (0.02)	0.4 (0.03)	0.5 (0.04)	0.6 (0.08)	0.6 (0.07)	0.6 (0.07)	0.7 (0.05)
Foreign language	1.9 (0.05)	2.0 (0.09)	2.4 (0.08)	2.3 (0.10)	2.3 (0.14)	2.6 (0.12)	2.5 (0.10)
Health/physical ed	3.3 (0.10)	3.0 (0.08)	3.3 (0.10)	3.1 (0.12)	3.5 (0.16)	3.0 (0.11)	2.8 (0.09)
Mathematics	6.0 (0.10)	6.0 (0.15)	6.9 (0.14)	6.5 (0.17)	7.4 (0.25)	7.4 (0.19)	7.3 (0.18)
Science	4.9 (0.11)	5.0 (0.15)	5.6 (0.12)	5.8 (0.20)	5.7 (0.24)	6.2 (0.16)	6.1 (0.15)
Social studies	5.1 (0.10)	4.8 (0.12)	5.4 (0.14)	5.5 (0.16)	6.1 (0.27)	5.8 (0.16)	6.1 (0.17)
Special education	4.3 (0.09)	4.4 (0.13)	3.8 (0.09)	5.4 (0.23)	4.9 (0.28)	5.7 (0.32)	5.4 (0.14)
Vocational/technical	7.1 (0.12)	6.3 (0.12)	5.4 (0.10)	5.2 (0.17)	4.8 (0.17)	4.3 (0.16)	4.5 (0.15)
Other secondary	1.1 (0.06)	1.2 (0.06)	1.6 (0.07)	1.1 (0.06)	1.4 (0.10)	1.4 (0.12)	2.1 (0.09)

Source: Snyder, T.D., de Brey, C., and Dillow, S.A. (2019). [Table 209.10] Digest of Education Statistics 2017 (NCES 2018-070). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC

Appendix J

I. Racial and Ethnic Minorities in STEM Model



Source: Museus, S. D., Palmer, R. T., Davis, R. J., & Maramba, D. C. (2011). [Figure 12]. Special Issue: Racial and Ethnic Minority Students' Success in STEM Education. ASHE Higher Education Report, 36(6), 1–140.

Appendix K

L. Critical Social Justice Teaching Competencies

CGU TEP Critical Social Justice Teaching

Domains, Relationships, Competency Strands

Domain 1: ***Philosophy of Education***		**Relationships:** ***Purpose, Self, Content***
1.1	Grow Self-Awareness	
1.2	Establish Baseline of Respect for Students & Their Learning	
1.3	Develop Familiarity & Facility with The Curriculum	
1.4	Take Responsibility for Students Learning & Engagement	
Domain 2: ***Pedagogy***		**Relationships:** ***Teacher, Students, Content***
2.1	Introduce New Content & Skills in Engaging and Meaningful Ways	
2.2	Make Productive Learning Accessible	
2.3	Use Instructional Practices to Grow Students' Knowledge, Skills, & Understanding	
2.4	Help Students Level Up with Steadily Increasing Rigor	
Domain 3: ***Science of Learning***		**Relationships:** ***Students, Content, Self***
3.1	Use Data to Inform Instruction	
3.2	Harness Instructional Cohesion	
3.3	Use Assessments to Promote Learning & Understanding	
Domain 4: ***Socio-Emotional Learning***		**Relationships:** ***Students, Self, Others***
4.1	Set & Demonstrate Expectations	
4.2	Promote and Maintain A Pro-Social, Asset-Based Classroom Ecology	
4.3	Use Knowledge of Students to Create Conditions that Give Rise to their Productive Participation & Engagement in the Classroom Ecology	
Domain 5: ***Funds of Knowledge***		**Relationships:** ***Teacher, Students, Households***
5.1	Support Productive Learning with Culturally Sustaining Practices	
5.2	Identify & Meet Students Where They Are	
5.3	Develop Productive & Inclusive Relationships with Households	
Domain 6: ***School Climate & Culture***		**Relationships:** ***Teacher, School, Households***
6.1	Maintain Professional Responsibilities	
6.2	Reconcile School & Personal Values, Beliefs, and Practices	
Domain 7: ***Community & Cultural Wealth***		**Relationships:** ***Students, Households, Communities***
7.1	Raise Consciousness of Local Community & Cultural Wealth	
Domain 8: ***Socio-Political Identity***		**Relationships:** ***Students, Others, Communities***
8.1	Raise Consciousness of Socio-Political Context	
8.2	Share Power & Tools	
Domain 9: ***Global Perspective***		**Relationships:** ***Others, Communities, The World***
9.1	Recognize and Acknowledge Bias in Curriculum & Media	
9.2	Promote Comparative, Critical, And Global Perspectives	