Academic Profiles of Science Students:
An Analysis of Longitudinal Data on Virginia Students

Michelle Davis Klopfer

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Curriculum and Instruction

John G. Wells, Chair
Thomas O. Williams
Brenda R. Brand
Brian R. Murphy

February18th 2020
Blacksburg, Virginia

Keywords: science education, STEM, longitudinal data, standards, assessment

Academic Profiles of Science Students:
An Analysis of Longitudinal Data on Virginia Students

Michelle Davis Klopfer

ABSTRACT

In recent decades, United States public school education has moved toward standards-based curricula. However, performance on standardized tests may not be representative of subject literacy or workforce preparedness. This misalignment may be particularly true in the sciences, where low science literacy and gender-related workforce shortfalls are evident. This study was an exploration of how well standardized test scores and other academic metrics reflected progression to a science major, by gender. This exploratory study used longitudinal data from the Virginia Department of Education, prepared by the Virginia Longitudinal Data System, for students who graduated from Virginia public schools from 2004-2016 (N=1,089,389). Students' standardized assessment scores, science course grades, demographics, and post-secondary major were analyzed using correlation analysis, logistic regression, principal component analysis, and hypothesis testing.

Overall, 9% of high school completers enrolled in a post-secondary science major, with approximately half of those students attending 4-year schools. Seventy percent of science majors were female; females were most prevalent in health-related majors and least prevalent in physical sciences. Logistic regression identified the following factors significantly related to enrolling in a post-secondary science major: gender, high school science grades, and the high school's percent of students who majored in science. A student's status as economically disadvantaged or an underrepresented minority was significantly related to enrolling in a 2-year science major. In comparisons among academic metrics, standardized test scores and science grades were uncorrelated, and science grades differed significantly among demographic

subgroups. Overall, demographic and school-level factors were more closely related to majoring in science than were academic factors. For both genders and for biological, physical, and health sciences, the percent of students majoring in science doubled from 2005-2015.

Standardized test scores and course grades measured different aspects of learning, and higher science grades were related to majoring in science. However, the designation of "science major" is so broad as to be uninformative in a research context; more specificity would be needed to develop academic profiles. From these findings, one can conclude that demographic and cultural factors – rather than academic factors – were more closely related to whether students pursued a science pathway.

Academic Profiles of Science Students:
An Analysis of Longitudinal Data on Virginia Students

Michelle Davis Klopfer

GENERAL AUDIENCE ABSTRACT

In recent decades, United States public school education has moved toward standards-based curricula. However, performance on standardized tests may not represent subject knowledge or job preparedness, particularly in the science fields. This study was an exploration of how well standardized test scores and other academic measured were related to majoring in science, for male and female students. This exploratory study used data from the Virginia Department of Education, prepared by the Virginia Longitudinal Data System, for students who graduated from Virginia public schools from 2004-2016. Students' standardized test scores, science course grades, demographics, and college major were analyzed. Overall, 9% of high school completers enrolled in a science major after high school, with approximately half of those students attending 4-year schools. Seventy percent of science majors were female; females were most prevalent in health-related majors and least prevalent in physical sciences. The following factors were significantly related to enrolling in a science major: gender, high school science grades, and the high school's percent of students who majored in science. A student's status as economically disadvantaged or an underrepresented minority was significantly related to enrolling in a 2-year science major. In comparisons among academic measures, standardized test scores and science grades were not related to each other, and science grades differed among demographic groups. Overall, demographic and school-level factors were more closely related to majoring in science than were academic factors. For both genders and for biological, physical, and health sciences, the percent of students majoring in science doubled from 2005-2015. Standardized test scores and course grades measured different aspects of learning, and higher

science grades were related to majoring in science. However, the designation of “science major” is so broad as to be uninformative in a research context; more specificity would be needed to develop academic profiles. From these findings, one can conclude that demographic and cultural factors – rather than academic factors – were more closely related to whether students pursued a science pathway.

ACKNOWLEDGEMENTS

First, I would like to sincerely thank Dr. John Wells for his guidance, support, and patience during this process. I would also like to thank Dr. Thomas Williams and Dr. Brenda Brand for challenging me to think about my study in different ways. Dr. Brian Murphy first introduced me to the pedagogical path, and I am so appreciative that he helped and mentored me through the whole journey. This study would not have been possible without Dr. David Knight and Dr. Isabel Bradburn, who welcomed me onto their research team and helped me navigate the data.

Finally, I would like to thank my family and friends, who helped keep me sane. My husband, children, and parents were all encouraging and supportive, and I could not have done it without them. My parents have referred to me as a “gradual” student for many years, but those days are finally over. Unless I go back for another degree…

Table of Contents

List of Tables:

List of Figures:

Chapter 1 – Introduction

Background and Justification

After World War II, the US prided itself on being the global center for innovation and development, built by an educated citizenry. National spending on education increased with the Space Race, and student achievement climbed (Graham, 2013). However, the nation's focus turned to other issues in the 1970s, with education-related issues losing both importance and funding. When the Reagan-era report on the state of US education was released in 1983 (National Commission on Excellence in Education, 1983), it served as a wake-up call for both the public and the educational system. The report identified the US as "a nation at risk," with low and declining student test scores, poorly trained teachers, and millions of functionally illiterate adults (Graham, 2013). The authors of the report blamed the public educational system for this problem, specifically the use of an "incoherent, outdated patchwork quilt" of a learning curriculum (National Commission on Excellence in Education, 1983, p. 15).

Many of the ensuing educational reforms in the US attempted to fix the "patchwork quilt" curriculum, and the initial focus was on improving educational quality for the fields of science, technology, engineering, and mathematics (STEM; Bybee & Fuchs, 2006). Professional and educational organizations in each of these fields developed discipline-specific learning standards (AAAS, 1989, 1993; ITEEA, 2007; NBPTS, 2016). These standards were a compilation of the most important content, concepts, and techniques that K-12 students should know for each field, with the goal of providing students with a consistent and rigorous education in STEM fields.

These STEM standards formed the basis for the next educational reforms: standards-based curricula (Ravitch, 2016; Spring, 2014). Subject-specific standards were developed that represented a progression of skills and knowledge through K-12, with each grade's standards building upon the standards from previous grades (Bruner, 1960; VDOE, 2017). Additional government regulation at this time, through the No Child Left Behind Act (US Department of Education, 2002), required that schools monitor and report student progress. Periodic standardized assessments of student learning became increasingly prevalent in K-12 education. States that did not have their own standards-based curriculum began implementing the national Common Core Curriculum in 2009.

However, Virginia had already developed their Standards of Learning (SOL) curriculum in 1998 (VDOE, 2013), after state educators observed low scores by Virginia students on national and international assessments. The subject-specific SOLs were designed to be unambiguous and rigorous; they include standards for K-12 instruction in reading, writing, mathematics, science, history, and social studies (VDOE, 2013). SOL assessments in elementary school and middle school focus mainly on reading and mathematics, and high school SOL assessments are course specific (VDOE, 2017).

Since the implementation of the SOL curriculum in Virginia, student achievement on SOL assessments has steadily increased. As a result, accreditation rates at Virginia schools have also increased, as accreditation occurs when at least 70% of students achieve passing scores in reading, math, history, and science (VDOE, 2013). Accreditation increased from 6% of schools in 1999, to 64% in 2002, to 95% in 2005 (VDOE, 2013). With rising assessment scores and accreditation rates, the SOL curriculum has been viewed as a success.

Need for the Study

Although increasing SOL assessment scores may indicate improvements in student achievement, the authors of *A Nation at Risk* (1983) emphasized employment-related measures of success, noting that "knowledge, learning, information, and skilled intelligence are the new raw materials of international commerce" (p. 10). More recently, a 2012 US government task force reported a similar goal for education: "A robust and capable STEM workforce is crucial to United States competitiveness… There are, however, indications that not enough citizens are being educated for careers in STEM or STEM-related fields" (Federal Coordination in STEM Education Task Force, 2012, p. 2). Thirteen of the fifteen fastest-growing occupations in the US are in STEM fields (Bureau of Labor Statistics, 2015), and there is currently a shortfall of qualified STEM career entrants. It is estimated that 1 million additional students will be needed to meet the immediate demand in STEM-related careers (Holdren & Lander, 2012).

The current shortfall in STEM career entrants is a result of multiple factors. Only 25-36% of college students choose a STEM field for their initial college major (Morgan, Gelbgiser, & Weeden, 2013; Rask, 2010; Shaw & Barbuti, 2010), with approximately 40% of those STEM majors selecting science-focused disciplines (Mau, 2016). Fewer than half of STEM students persist through college to graduate with a degree in a STEM field (Graham et al., 2013). With few students entering and completing STEM-focused post-secondary education, STEM jobs will remain unfilled.

Many of the fields and occupations that show the greatest projected need for future employees (Bureau of Labor Statistics, 2015) also have some of the largest gender disparities in college major (Ganley, George, Cimpian, & Makowski, 2018). Although women currently comprise more than half of all US college students, women are 20% of the undergraduate students in engineering and computer science, 40% of the students in physical sciences, and 45% of the students in math and statistics (Mann & DiPrete, 2013; NPR, 2014). In life science fields, however, females outnumber males, comprising 55% of biology students and 80% of the students in the health professions (NPR, 2014). Of the fifteen fastest-growing occupations in the

US (for 2014-2024), eight are in healthcare, two are in technology, and two are in math/analytics (Bureau of Labor Statistics, 2015). The substantial gender differences in choice of college major may contribute to difficulties in meeting workforce needs in these rapidly growing careers.

Given the importance of filling STEM career openings, much research has been conducted related to the STEM pipeline from K-12 into a STEM career. However, many of the previous studies have taken a “snapshot” approach, investigating educational outcomes for a single subject or during a relatively narrow time period (Deary, Strand, Smith, & Fernandes, 2007; Freeman et al., 2014; Jones, Ruff, & Osborne, 2015; Schunk & Pajares, 2005). Education is not a series of independent and disconnected events, though. Educational experiences in different grades and subjects are linked, forming patterns that characterize the learning process (Geary, 2011; Krapp & Prenzel, 2011; Siegler et al., 2012). Therefore, a more holistic and longitudinal view of the STEM pipeline is needed.

To investigate the longitudinal progression toward STEM educational outcomes, researchers could track individual students throughout the educational system, monitoring educational metrics and outcomes for multiple years. Alternatively, researchers could track students backward from a known educational outcome, such as a post-secondary degree, to model the academic factors that preceded the observed outcome. The recent proliferation of data collection has made such longitudinal studies of individuals much more feasible (Baker, 2010; Virginia University Research Consortium on Early Childhood, 2015). In Virginia, an individual’s K-12 data can be connected with data from other sources, including higher education, employment, and social services (VLDS, 2017). A longitudinal study of education-related data from a large sample could be used to explore the academic pathways toward a STEM career, helping clarify some of the factors related to the STEM workforce shortage.

Although some work has been done to investigate the pathways through engineering and math education (Riegle-Crumb & King, 2010; Virginia University Research Consortium on Early Childhood, 2015; VLDS, 2014), little research has explored the academic milestones and metrics along the pathway to a science degree. As in the other STEM fields, relatively few students major in science and only half of those students obtain a post-secondary science degree (Graham et al., 2013; Mau, 2016; Morgan et al., 2013; Rask, 2010; Shaw & Barbuti, 2010). In the science disciplines in particular, persistence to graduation was linked closely with academic proficiency (Mau, 2003; 2016), so it is crucial to understand the academic profiles of science graduates in order to increase the number of trained entrants for science careers. Science fields also exhibit some of the greatest gender differences in choice of major, with females comprising only 40% of physics majors, but 80% of students in the health sciences (Mann & DiPrete, 2013; NPR, 2014). The gender disparities in major selection may contribute to workforce shortfalls, especially for fast-growing fields like health services (Bureau of Labor Statistics, 2015).

Purpose of the Study

The purpose of this study was to explore the gender-specific academic patterns that precede successful progression toward science careers, with the goal of reducing the STEM workforce shortfall. Existing longitudinal data on Virginia students were used to analyze relationships among performance on science-focused standardized tests, enrollment patterns in science courses, grades in high school science courses, and enrollment in post-secondary science programs. This longitudinal approach permitted the tracking of anonymized students through much of their educational careers. Gender-specific patterns of academic indicators were developed to clarify male/female differences in science pathways. Through development of gender-specific academic profiles of Virginia students who major in science fields, the best explanatory metrics were identified. Furthermore, the explanatory suitability of Virginia's current metrics of science progress – scores on the science SOL assessments – was evaluated.

Collectively, these explorations of the science pathways provide the mechanisms for clarifying some of the precursors to the shortage of prepared STEM career entrants. Specifically, investigating the academic factors related to the choice of science major may explain the low entrance rates for post-secondary science majors. Moreover, large gender differences in choice of science field exacerbate the shortfall of qualified career entrants. Comparing patterns of academic characteristics for male and female students could help identify gender differences related to what students select as a major. The findings of this exploratory study may allow educators to modify future courses or data collection in order to increase successful matriculation of male and female students into science fields.

This research also directly addressed the research needs of the Virginia Longitudinal Data System (VLDS) and the Virginia Department of Education (VDOE). VLDS is interested in studying "factors or conditions that have the greatest impact on educational achievement" and "factors or conditions that predict [workforce] success" (VLDS, 2017b). Similarly, VDOE is interested in studies of "the impact of curriculum, courses, and/or programs on student achievement, high school graduation, postsecondary readiness/success, and workforce outcomes" (VLDS, 2017c). This study focused on exploring the relationships among course enrollment, student achievement, and postsecondary readiness. VDOE is also interested in investigating how "factors and interventions associated with better outcomes (e.g., behavior, achievement, persistence in education) for students…differ among student subgroups" (VLDS, 2017c); in this study, academic outcomes were studied for male and female subgroups, as well as for the subgroups of post-secondary attendees and non-attendees.

Research Questions

How well do SOL assessment scores and other academic metrics reflect the progression to a post-secondary science major for male and female students in Virginia?

1. What are the academic profiles of Virginia students, by gender, who initially selected a post-secondary science major?
2. How do science-related educational metrics of high school completers compare with metrics of:
    a. students entering science programs at 2-year schools, and
    b. students entering science programs at 4-year schools?
3. To what extent are gender-specific patterns in academic profiles reflective of the progression toward a post-secondary science major for Virginia students?

Chapter 2 – Literature Review

The Premise of Schooling

This research is grounded in the premise of schooling: that formal education helps shape skills and knowledge, where "schooling" itself is the component of education that is associated with human-contrived institutions (Hamilton, 1989; Thelin, 2011). Schools have existed in various forms for centuries and have been adapted to fit the political goals of the era (Ravitch, 2016; Stromquist & Monkman, 2014). Schooling methods have changed dramatically over time, from rote memorization and elocution to problem-based learning and online discussion boards (Pinar, 2014). The content and skills in the schooling curricula have also changed over time, but the concept of a curriculum has remained relatively constant, as a pathway to a core body of knowledge and skills.

Schooling is clearly not the only factor (and maybe not even the dominant factor) that affects what a person is interested in or skilled in; numerous social, environmental, and personal forces also educate us and shape who we become (Thelin, 2011). However, formal schooling in the US is a relatively consistent experience among different people in different parts of the country. Most relevant to this research, the characteristics of the US schooling system have the potential to affect learning for millions of students (Ravitch, 2016). The content, skills, and assessments that comprise a school curriculum affect a student's literacy (Holbrook & Rannikmae, 2009), post-secondary performance (Adelman, 2006), and career success (Conley, 2010).

Although the content and pedagogical methods have changed over time, most schooling systems have attempted to balance two main goals of schooling: 1) the Jeffersonian ideal of developing literate citizens (Millar, 2006) and 2) the pragmatic need for training a competent workforce (Bybee & Fuchs, 2006). The balance between these schooling objectives has shifted frequently, depending on the specific needs of the time (Hamilton, 1989; Ravitch, 2016). However, by many metrics, the US educational system has been unsuccessful in achieving either of these goals in recent decades.

Schooling in the United States

After World War II, America found itself at the center of the global economy, due in large part to the technological developments made during the war. More students were staying in school for education and training, and the nation enjoyed a period of prosperity. This educated citizenry endeavored to achieve other self-imposed challenges in the 1960s, particularly the Space Race. To achieve these goals, the government devoted significant funding to education, and student achievement increased (Graham, 2013). Students were staying in school for more years than at any other time in history, with approximately 70% of students finishing high school, as compared to only 29% in 1930 (Simon & Grant, 1965). College enrollment rates increased dramatically in the 1950s and 1960s, from 14% men and 5% of women in 1950 to 32% of men and 16% of women in 1970 (Snyder, 1993). The US continued to be a strong global presence both economically and technologically. However, the end of the Space Race and the end of the Cold War removed much of the external pressure to excel in technological development and innovation. As the US struggled to deal with other political and social issues in the 1970s, the nation's forgotten educational system stagnated, and student achievement began declining.

A 1983 government report on the state of US education brought the educational system back to the center of national discussions (National Commission on Excellence in Education, 1983). The Reagan-era report began boldly, with "Our Nation is at risk. Our once unchallenged preeminence in commerce, industry, science, and technological innovation is being overtaken by competitors throughout the world" (p. 9). The authors listed multiple metrics that described the US's failure to develop literate citizens: the lowest literacy score among industrialized nations on international tests, a 13% illiteracy rate in 17-year-olds, and steady declines in SAT scores and science achievement from 1963-1980. Similarly, the report indicated that schools were also failing to train a workforce: "Business and military leaders complain that they are required to spend millions of dollars on costly remedial education and training programs in such basic skills as reading, writing, spelling, and computation" (National Commission on Excellence in Education, 1983, pp. 11-12). The authors of the *Nation at Risk* report placed the blame squarely on the US public education system, stating that "its educational institutions seem to have lost sight of the basic purposes of schooling" (p. 9).

The authors of the *Nation at Risk* report noted that US public schools lacked consistency, and instruction amounted to an "incoherent, outdated patchwork quilt" wherein each teacher selected the content and concepts that he or she taught (National Commission on Excellence in Education, 1983, p. 15). Students' educational experiences, therefore, differed greatly and relied heavily on their teachers. The educational reforms following the *Nation at Risk* report focused primarily on increasing the consistency of schooling.

The decrease in literacy in the fields of science, technology, engineering, and mathematics (STEM) had been identified in the *Nation at Risk* report, so these subjects were among the first targets for improvements in educational quality and consistency through the development of discipline-specific standards (Bybee & Fuchs, 2006). For each of these subjects, professional and educational organizations developed learning standards that were a compilation of the most important content, concepts, and techniques that students should know to be literate in each field (AAAS, 1989, 1993; ITEEA, 2007; NBPTS, 2016). The goal of these standards was to clearly define rigorous requirements that would serve as a foundation for college or career entry and thereby increase instructional consistency among classrooms. However, the use of these new standards was still at the teacher's or school district's discretion, so the goal of large-scale consistency was not yet achieved.

To move schools away from having a "cafeteria-style curriculum" (National Commission on Excellence in Education, 1983, p. 17), states began developing entire curricula based on the idea of learning standards. If the standards created by the subject-area experts represented the endpoint of subject literacy or career/college readiness, then the standards-based curriculum delineated the grade-by-grade pathway to that outcome. The grade-specific standards include topics of increasing complexity as students advance through school (Bruner, 1960; CCSS Initiative, 2018b). These standards-based curricula further increased the consistency of the educational experience, as teachers now had roadmaps for the entire K-12 process showing how each standard would be taught.

Starting in 2009, the Common Core State Standards (CCSS) provided a national blueprint that identified what public-school students should know and be able to do by each grade (Spring, 2014). The CCSS focused on K-12 mathematics and English language arts/literacy, and they "were created to ensure that all students graduate from high school with the skills and knowledge necessary to succeed in college, career, and life, regardless of where they live" (CCSS Initiative, 2018). Forty-two states adopted the Common Core State Standards as their educational foundation (CCSS Initiative, 2018), although the majority of these states are now attempting to withdraw from the CCSS consortium (Education Next, 2016). States that already had existing rigorous educational standards in place prior to CCSS implementation could petition to continue with their current system. Virginia opted to continue its Standards of Learning (SOL) curriculum, rather than adopt CCSS (VDOE, 2010).

During this time period, a parallel educational reform movement was occurring, due in large part to the No Child Left Behind (NCLB) Act of 2001. The authors of NCLB noted that substantial achievement gaps existed among subgroups of public-school students, particularly when viewed in the contexts of socioeconomic status, race, or gender (McRenolds, 2006; Uline & Johnson, 2005). Schools were tasked with taking steps to reduce these gaps and provide a consistent, high-quality education for all students, regardless of demographic or geographic factors. NCLB mandated that schools monitor student learning through periodic standardized tests (Ravitch, 2014).

The reporting requirements of NCLB meshed well with the standards-based curricula, and the era of standardized assessments began. In addition to in-class assessments of learning, students also complete state-level or national tests that are aligned with the curricular standards. In Virginia, students take SOL assessments annually for mathematics and reading, and complete periodic or end-of-course SOL assessments in science and history/social science (VDOE, 2017). Many such assessments are "high stakes" and determine whether the student passes the course or grade. A 2013 study estimated that students spent approximately 4 weeks of school time per year on standardized assessments (Nelson, 2013), but that amount of time has decreased in recent years after public outcry.

Standards-based assessments have been criticized for their lack of authenticity and context; life rarely provides multiple-choice answers to questions. The standardized, test-based format of these assessments makes it difficult to assess students' abilities to perform tasks and procedures or to think creatively. Assessments also emphasize the knowledge and skills of the individual student, overlooking the importance of working collaboratively within a team. Finally, standards-based assessments are often one-chance, high-stakes tests; students do not have the opportunity to practice persistence by learning from mistakes and correcting errors. These assessments are effective at testing knowledge, but may fall short in assessing the 21st-century skills necessary to be a literate citizen who is capable of succeeding in college or a career (Bybee & Fuchs, 2006).

Evaluating Student Outcomes in Standards-Based Curricula

Now that the US educational system's standards-based curricular reforms have been in place for a few years, it is time to start evaluating to what extent these changes have affected student outcomes, particularly the outcomes related to literacy and workforce preparation. In Virginia, only 6% of the state's schools met the accreditation standards in 1999 (i.e., at least 70% passing rates in reading, math, history, and science; VDOE, 2013). By 2002, 64% of Virginia's schools met accreditation standards, and 95% of schools were accredited by 2005. These gains represent significant increases in student achievement on the SOL assessments.

However, increasing SOL scores is not a goal of schooling; a successful educational system develops broad literacy and prepares students to succeed in post-secondary education or the workforce. Analyses of the national CCSS have found few improvements in broader student outcomes under that standards-based curriculum. Loveless (2014, 2016) found no relationship between gains on the National Assessment of Educational Progress (NAEP) and curricular similarity to CCSS. Similarly, Schmidt and Houang (2012) saw no difference in NAEP gains in states that more fully implemented CCSS as compared to states that did not. Thus far, there is little empirical support for the CCSS improving educational metrics for students (Xu & Cepa, 2015); the standards-based curriculum is not adequately supporting the schooling goal of developing student literacy.

Furthermore, the current educational system is not achieving the other goal of schooling: preparing students to enter (and succeed in) post-secondary education or a career. Although more students are entering four-year colleges than ever before, only 60% of those students complete a degree (US Dept. of Education, 2018). Of the students who did not persist to a degree, lack of academic preparation was one of the more common reasons given (Chen, 2013). In particular, post-secondary students struggle with courses in the STEM fields, and poor performance in STEM courses is associated with an increased probability of dropping out of college (Chen, 2013). In addition, standards-based curricula are also not sufficiently preparing students to enter the workforce after school. Today's careers frequently require creativity, problem solving, and collaboration, but learning standards and standards-based assessments often emphasize content and individual achievement.

The standards-based educational systems state that the increases in student assessment scores are proof of successful programs. However, the given national data indicate that a broader evaluation is needed, one that specifically addresses the major goals of schooling – literacy and college/career readiness. While these goals are viewed as the successful outcomes of the educational system, students may follow very different pathways toward achieving these goals. Furthermore, such pathways may differ substantially among demographic groups or for different STEM majors or fields. Therefore, a more holistic, longitudinal exploration of the academic process is necessary if we are to investigate the pathways toward STEM careers, rather than the single endpoint of STEM career entry.

STEM Career Pathways

The pathway into any career is the result of a series of choices and decisions made during childhood, adolescence, and early adulthood (Wang & Degol, 2013). These choices are influenced by an individual's expectations for success and his or her associated value of that success. Both expectation and value are shaped by cultural norms and personal experiences, although aptitude and affective factors also influence an individual's perceptions (Wang & Degol, 2013). Therefore, an individual's experiences with STEM-related activities affect his or her interest, self-efficacy, and long-term goals, which subsequently influence educational and career choices. Given it is the series of experiences, rather than a single moment, that influences educational and career pathways, it is important that such experiences be explored as longitudinal factors related to high school achievement, choice of college major, and persistence to a college degree.

In the STEM fields, a number of experiential factors affect achievement and interest of high school students. Differences in STEM achievement due to socioeconomic factors, race/ethnicity, and gender are evident in elementary, middle school, and high school (Quinn & Cooc, 2015), and boys typically received slightly higher grades in math and science courses than did girls (National Center for Education Statistics, 2012). In addition, female students were less likely than males to retain interest in a STEM career during high school. The percentage of males interested in a STEM career remained stable during high school (from 39.5% to 39.7%), while the much lower rate for females decreased during high school (from 15.7% to 12.7%; Sadler, Sonnert, Hazari, & Tai, 2012). A student's high school experiences then influence selection of a college major, with choice of a STEM major being most closely related to a student's achievement in 12th-grade mathematics, exposure to math and science courses, and math self-efficacy (Wang & Degol, 2013). Math self-efficacy is consistently lower for females than males, although that difference has decreased over time (Sax et al., 2015). Achievement and interest are both built from prior experiences and self-efficacy, framed in the social context of the students' cultural experiences (Lent, Brown, & Hackett, 1994). Achievement is quite similar for male and female students, but the lens through which the achievement is viewed may differ substantially by gender throughout the pathway toward STEM careers.

One of the major goals along the STEM pathway is graduation with a degree in a STEM field, leading to entry into a STEM career. Not surprisingly, persistence to a STEM degree was related most closely to GPA in STEM courses, although numbers of high school science and math courses were also significantly associated with graduating in a STEM field (Maltese & Tai, 2011). In another study, performance in high school science and math courses and positive science self-efficacy were correlated with college persistence (Shaw & Barbuti, 2010). Slight gender differences in math achievement persisted in college, but "researchers tend to agree that intellectual aptitude, at least by itself, is not an overriding factor in the underrepresentation of females in math-intensive fields" (Wang & Degol, 2013, p. 308). The experience of schooling (including course enrollment, achievement, and persistence) appears to be much more influential in affecting STEM-pathway outcomes; this relationship is particular evident for the science disciplines.

Science Career Pathways

A longitudinal study of science pathways is appropriate for a number of reasons. First, scientific literacy is crucial in our world, where being an educated citizen requires a basic knowledge of topics as diverse as climate change, genetic modification of foods, and ecosystem sustainability (Holbrook & Rannikmae, 2009; Millar, 2006). In *The Next Generation Science*

Standards (AAAS, 1993), experts identified what all students need to know to achieve this level of science literacy. However, accurately assessing this learning (particularly in standards-based assessments) is challenging and often incomplete. Therefore, this research study will focus on the pathways to one component of the STEM fields: science.

In addition to the need for science literacy, many scientific fields have large workforce demands. Of the fifteen fastest-growing occupations in the US (for 2014-2024), eight are in healthcare, and therefore require substantial preparation in the sciences (Bureau of Labor Statistics, 2015). Furthermore, many of the fields and occupations that show the greatest projected need for future employees (Bureau of Labor Statistics, 2015) also have some of the largest gender disparities in college major. Women currently comprise 40% of the students in physical sciences, 55% of biology students, and 80% of the students in the health professions (Mann & DiPrete, 2013; NPR, 2014). The gender differences in college major may contribute to difficulties in meeting workforce needs in these rapidly growing careers.

Another important reason to study science pathways is that researchers have found close links between proficiency gained during schooling and subsequent college graduation in science fields (Mau, 2003; 2016). A better understanding of academic profiles of science students at multiple points along the science pathway would therefore help clarify factors affecting persistence. Although significant links between performance and persistence have been found, some educators are concerned that effective science education does not fit well within the constraints of most standards-based curricula, which may focus more on content than on the problem-solving skills necessary in scientific fields (Bennett, 2014). Given there are substantive links between academic experiences and persistence in these high-demand science careers, the investigation of academic factors affecting the science pathways, for both males and females, is critical for understanding the schooling process for scientific disciplines.

Factors Affecting Science Pathways

While we often view entry into a science career as the successful outcome of the science pathway, there are many points and factors along the pathway that have been studied by researchers. Studies of elementary and middle school students in the US have identified slight achievement gaps in science, with female test scores 0.23SD, 0.25SD, and 0.18SD lower than males in Grades 3, 5, and 8, respectively (Quinn & Cooc, 2015). With the exception of Asian students in Grade 8, all other minority races performed lower than white students on science tests in Grades 3, 5, and 8 (Quinn & Cooc, 2015). But these early differences in science achievement do not appear to affect student enjoyment of science; Ainley & Ainley (2011) found that science enjoyment was not dependent on high levels of science knowledge in elementary and middle school students. Furthermore, a student's early enjoyment of and interest in science was a good predictor of whether that student engaged further with science topics in later years (Ainley & Ainley, 2011). The early educational years appear to be the opportunity to build interest in science, without focusing as heavily on science achievement.

As students move through middle school and into high school, they begin to identify (or not identify) with science fields (Jones et al., 2015), and this self-identification is only partially shaped by science achievement. In many cases, communities and families play key roles as students develop their career goals and personal identities in high school, particularly with respect to science careers (Aschbacher, Li, & Roth, 2010). Science enjoyment is still an important factor, and teaching methods like active learning have been shown to promote both enjoyment of and performance in the science classroom (Freeman et al., 2014).

When students enroll in post-secondary education, they choose whether or not to major in a scientific field. According to a study by Hutchinson-Anderson, Johnson, and Craig (2015), students' academic experiences in high school greatly influenced this choice of major. Students who took more AP science courses or were comfortable with a larger number of laboratory techniques were more likely to study science in college. Furthermore, Hutchinson-Anderson et al. (2015) found that the choice to major in science was also linked to students' exposure to science careers during high school. It is of note that even after choosing to major in a science field, a student does not necessary self-identify as "a science person" (Hazari, Sadler, & Sonnert, 2013), and female and minority students were less likely than male or white students to identify as such. Similarly, white male students were the demographic group most likely to persist in post-secondary school to degree completion (Mau, 2016). Clearly, the overall progression through the science pathway is shaped by multiple factors, including academic experiences and aptitude, enjoyment and interest, and cultural and social influences. A well-designed longitudinal study is needed to more fully understand the role that these factors play in directing students in science career pathways.

The Potential of Longitudinal Studies

Standards-based curricula are often structured as spiral curricula, with content and topics for each year building on what students learned in previous years (Newcomb, Murphy, & Berkson, 2002). Academic experiences and metrics are intentionally interconnected among years and among subjects, and these connections help students internalize and apply what they have learned. Since the educational progression through the science pathway encompasses many years and life stages, it is important to investigate this process by using longitudinal data from a span of time to better understand the factors affecting this progression. The current era of assessment and data collection makes these types of analyses possible (Daniel, 2015). As part of student records, multiple metrics related to performance, enrollment, demographics, and school characteristics are collected throughout the student's educational career. Analyses of such data provide the potential to discern patterns and important relationships among factors (Williamson, 2016).

A number of studies have been conducted on various facets of the educational process, using longitudinal data. Geary (2011) used cognitive metrics collected in 1st grade as predictors of mathematics achievement in 5th grade, and Siegler et al. (2012) found correlations between elementary students' understanding of fractions and their overall mathematics achievement in high school. Krapp and Prenzel (2011) tracked how students' interest in science changed over time, and Riegle-Crumb and King (2010) examined some of the academic and affective precursors related to college major choice, exploring differences among demographic groups.

Other studies have used longitudinal data to investigate delayed effects from specific interventions. For example, researchers found that students who attended public preschool were more likely to be promoted on time to 1st, 3rd, and 8th grade than were students whose preschool attendance was not known (Virginia University Research Consortium on Early Childhood, 2015). A small number of studies have attempted to link datasets from multiple life stages, such as a study of the teacher pipeline that tracked teachers from their college degrees to their teaching classroom assignments, subjects, and school demographics (VLDS, 2014).

These datasets of longitudinal data allow researchers to study large numbers of students throughout (and beyond) their school years. Furthermore, the large sample size makes it possible to identify statistically significant differences among subgroups, allowing any differential effects due to socioeconomic status, gender, or race/ethnicity to become evident. Virginia's longitudinal data are a valuable resource for use in modeling and assessing the relationships between schooling and student progression along science pathways for Virginia students.

Research Focus

Many of the previously discussed studies investigated components of the complex relationships among achievement, interest, and schooling. The researchers demonstrated that schooling had a significant effect on student success: the teachers, curriculum, teaching methods, and school climate affected course grades, test scores, persistence, and interest levels (MacNeil, Prater, & Busch, 2009; Thapa, Cohen, Guffey, & Higgins-D'Alessandro, 2013). However, most researchers only studied students for a short time period, in one or two grades, for a single subject, or for a small number of academic or affective constructs. A more holistic investigation of the relationships among standards-based education, science achievement, and science interest has not been conducted for Virginia students.

The current view of "success" of Virginia's SOL curriculum is largely limited to an evaluation of school accreditation rates calculated from SOL assessment pass/fail rates. While significant gains have occurred in accreditation rates and SOL assessment scores, increasing test scores is not the goal of schooling. Rather, schooling should help develop literate citizens who are prepared to succeed in college or careers. Therefore, an alternative evaluation of the collective schooling experience can come from looking backward from known student outcomes, such as post-secondary school entry, to investigate the academic precursors to those outcomes. Such an approach would allow for an investigation of academic pathways for all students, and in particular for different demographic subgroups, an important facet of the issue given the substantial gender differences in STEM career pathways.

Although researchers have investigated the effects of science-related interventions on short-term student outcomes, little research has been done to investigate science achievement or interest throughout the schooling experience. This study will address the research gap by utilizing a large longitudinal dataset of Virginia students, in an attempt to quantify relationships among factors that may be related to science achievement and selection of a post-secondary major, including assessment scores, course enrollment, course grades, and demographic variables. Use of a longitudinal approach provides a more holistic exploration of the data related to success and persistence in science, with particular emphasis on Virginia's SOL assessment data.

Chapter 3 – Method

Introduction

An exploratory analysis was conducted to investigate academic pathways in science fields. Existing datasets within the Virginia Longitudinal Data System were explored, with the goal of developing gender-specific academic profiles for Virginia high school students entering post-secondary science programs. These analyses incorporated a wide range of metrics, including assessment scores, grades, and enrollment patterns, to identify the metrics that are most closely related to progression along science pathways. This exploratory study involved quantifying unknown relationships among factors and testing for differences among subgroups. The data sources, study population and sample of that population, specific variables of interest, and analysis procedures are described in the following sections.

Research Questions

How well do SOL assessment scores and other academic metrics reflect the progression to a post-secondary science major for male and female students in Virginia?

1. What are the academic profiles of Virginia students, by gender, who initially selected a post-secondary science major?
2. How do science-related educational metrics of high school completers compare with metrics of:
    a. students entering science programs at 2-year schools, and
    b. students entering science programs at 4-year schools?
3. To what extent are gender-specific patterns in academic profiles reflective of the progression toward a post-secondary science major for Virginia students?

Data Sources

Virginia Longitudinal Data System. The data used in this study were housed by the Virginia Longitudinal Data System (VLDS). The goal of the state-run VLDS is to facilitate analyses that connect data from multiple state agencies, as such analyses can help identify relationships among factors at different life stages. A double-deidentification process makes it possible to link data on individuals from multiple datasets, while still protecting the privacy and anonymity of each person (VLDS, 2017). Participating agencies include the Virginia Department of Education (VDOE), the State Council of Higher Education for Virginia (SCHEV), the Virginia Employment Commission, the Virginia Department of Social Services, the Virginia Community College System, the Virginia Department for Aging and Rehabilitative Services, the Virginia Department of Health Professions, and the Office of Children's Services (VLDS, 2017).

Virginia Department of Education. Since this study focused on educational issues, there was heavy reliance on data collected by the VDOE. Many of the VDOE data were collected in conjunction with the state SOL assessments, which began in 1998 (VDOE, 2013). In 2017, Virginia's public-school students in K-12 completed science-focused SOL tests in grades 5 and 8, and at the end of Earth Science, Biology, and Chemistry courses (VDOE, 2017). Although students' scores on state SOL assessments formed the core of the VDOE data, student files in the VDOE dataset also included a wealth of other information. Their student records included demographic information (gender, race, ethnicity, and economically disadvantaged status), academic program/track enrollment, and high school completion. Their course enrollment and grades were recorded, including participation in any Advanced Placement (AP) classes. Additional standardized assessments, such as the PSAT, SAT, and ACT, were also part of many student records. Finally, the VDOE dataset included data from the National Student

Clearinghouse for students who entered post-secondary institutions, including the name, location, and type of the institution and the initial major field of study.

Study Population and Sample Selection

The study population consisted of students who were enrolled in Virginia public schools and completed high school from 2004-2016. Although this was a longitudinal study, it was not necessary for data to be available for a student for the entire time period, as each data metric was analyzed using only the students for whom data were available for that metric or combination of metrics. For reference, more than 1.2 million students were enrolled in K-12 in public schools in Virginia in 2016-2017 (VDOE, 2017b), or approximately 92,000 students per grade level.

For an individual's record to be included in the study, the VLDS dataset must have contained data for at least one academic metric of interest. This data pool was further limited for specific research questions, such as analyses for specific demographic groups and analyses of post-secondary science majors. If data on the grouping metric were unavailable in a student record (e.g., the student's gender or post-secondary major was not listed), that record was omitted from that analysis only.

Data Manipulations

Student-level data were used from the following VLDS databases: Student Records, State Assessment Results, ACT Test Results, AP Test Results, SAT Test Results, National Student Clearinghouse, and Course Enrollment Table. Based on the DOE Student Record table, three binary variables were created to characterize students' demographics, as related to gender, under-represented minority (URM) status, and economically disadvantaged status. Although demographic information is not static over time, the information reported during the year of high school completion was used. Students were characterized as URM if race was listed as American

Indian or Alaska Native, Black, Hispanic, Native Hawaiian or Pacific Islander, or Non-Hispanic two or more races. Students were characterized as economically disadvantaged by the DOE if they were eligible for free/reduced meals, received Temporary Assistance for Needy Families, were eligible for Medicaid, identified as migrant, or experienced homelessness.

The Classification of Instructional Programs (CIP) codes were used to classify post-secondary majors into scientific fields. Biological Sciences (CIP=26) and Physical Sciences (CIP=40) were clearly designated in CIP codes. An "Other Sciences" grouping was developed for this study to capture additional fields and majors in science, including Natural Resources (CIP=3), Health Professions (CIP=51), and the following additional majors, many of which were in the Multidisciplinary category of instructional programs (CIP=30):

- 30.01 Biological and Physical Sciences
- 30.06 Systems Science and Theory
- 30.10 Biopsychology
- 30.15 Science, Technology, and Society
- 30.18 Natural Sciences
- 30.25 Cognitive Science
- 30.27 Human Biology
- 30.32 Marine Sciences
- 30.33 Sustainability Studies
- 31.05 Kinesiology and Exercise Science
- 42.27 Research and Experimental Psychology

For SOL assessment data, only data from science-specific tests were retained. These included assessments for grade 5, grade 8, Earth Science, Biology, and Chemistry. SOL testing materials and protocols changed in 2012/2013, so separate variables were used to identify the different tests. If students took any SOL test more than once, the highest score was used in analyses. Scores on science SAT tests (Chemistry, Ecology/Biology, Molecular Biology, and Physics), ACT tests (Science), and AP tests (Biology, Chemistry, Environmental Science, Physics B, Physics EM, and Physics M) were also included in analyses; a student's highest score for each test was used. Categorization into 2-year or 4-year post-secondary school was based on First Institution Type, with types 1 and 2 corresponding to 4-year schools, and type 4 corresponding to 2-year schools.

Graduation year was used to limit course-taking data to only courses taken within four years of high school completion. Courses were further limited to science courses, using the School Courses for the Exchange of Data (SCED) code (SCED Subject = 3). Grade designations for ungraded courses (e.g., pass, fail, non-graded, etc.) were dropped. If the listed numeric grade was less than 40, the grade was set at 40. If students took a course more than once, the highest course grade was used in analyses. Letter grades were converted to numeric values (Table 1, based on Rauschenberg, 2014):

Table 1. *Course Grade Conversions from Letter Grades to Numeric Grades*

Letter Grade	Numeric Grade
A+	99
A	97
A-	94
B+	91.5
B	89
B-	86
C+	83.5
C	81
C-	78
D+	75.5
D	73.5
D-	71
F	62.5

Variables of Interest

In this study, the focus was on variables that directly related to science and post-secondary path, including science assessment scores, science course grades, and post-secondary major. In conjunction with demographic data, these science-specific metrics were used to build academic profiles of science students and to identify differences among student subgroups. Specifically, the following variables from the VLDS dataset were analyzed or used in developing subgroups for analyses:

- SOL assessment scores: grade-5 science, grade-8 science, Earth Science, Biology, and Chemistry
- Other assessment scores: SAT Chemistry, SAT Ecology/Biology, SAT Molecular Biology, SAT Physics, the science component of the ACT, AP Biology, AP Chemistry, AP Environmental Biology, AP Physics B, AP Physics EM, AP Physics M
- Grades for high school science courses
- High school name and code
- Initial post-secondary major
- Initial post-secondary institution name, state, and type
- Gender, URM status, and economically disadvantaged status

Analysis Methods

The quantitative analysis methods of correlation analysis, hypothesis testing, logistic regression, and principal components analysis were used to quantify and describe relationships among student outcomes. In addition, descriptive statistics were calculated for all variables, for all subgroups studied. Data setup and analyses were conducted using R (R Core Team, 2019); maps were produced using ArcGIS® (www.esri.com). Analysis methods and procedures were aligned with the research questions and with the data variables (Table 2).

Table 2. *Alignment Among Research Questions, Data, and Analyses*

Research Question	Data	Analyses
RQ1 – academic profiles of science majors	College major Science assessment scores (SOL and other) High school science grades Demographics	Descriptive statistics Correlation analyses Logistic regression
RQ2 – science majors compared with other students	College major and degree Science assessment scores (SOL and other) High school science grades Demographics	Descriptive statistics Hypothesis testing (*t*-test)
RQ3 – synthesis of patterns	Results from RQ1 and RQ2	Principal components analysis Synthesize patterns and relationships among metrics and subgroups Identify key variables that are significant markers

Descriptive statistics. One of the benefits of analyzing this large dataset was the ability to summarize data in different ways to aid interpretation. For this study, descriptive statistics (mean, standard deviation, and sample size) of data were calculated for each student subgroup investigated. Descriptive statistics were only reported if the cell sample size was greater than 30 students. When metrics included a spatial component, maps were created using ArcGIS® software by Esri (www.esri.com).

Correlation analyses. A major goal of this exploratory study was to investigate the relationships among different factors related to science education. Therefore, correlation analyses were conducted to measure the strength and direction of the relationship between two variables. Specifically, the Pearson correlation (r_{xy}) was used when analyzing linear, normally distributed variables:

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\,\sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

where n is the sample size, and x_i and y_i are the individual sample points (Howell, 2011). Matrices of pairwise correlations and p-values were produced for high school completers and for high schools. Correlation coefficients were only reported if the cell sample size was greater than 30 students. Boxplots were created to aid in visualizing patterns in the large number of correlation coefficients calculated. Analyses were conducted in R using the Hmisc package (Harrell, et al., 2019).

Hypothesis testing. Hypothesis tests were used to identify significant differences in variables between groups. Two-sample, two-tailed *t*-tests were used to compare two means; this test included the assumptions that the variable was normally distributed and that the groups were independent (Howell, 2011). In this study, *t*-tests were used for statistically comparing 22 academic metrics (Table 3) between the following pairs of groups:

- Female high school completers vs. male high school completers
- URM high school completers vs. non-URM high school completers
- Economically disadvantaged high school completers vs. non-economically disadvantaged high school completers
- Students enrolling in science at 2-year schools vs. high school completers
- Students enrolling in science at 4-year schools vs. high school completers

Table 3. *Academic Variables Compared Using T-Tests*

Category	Variable
Grades	Mean high school science grade
SOL Scores	Grade 5 science 1 (2006-2012)
	Grade 5 science 2 (2013-2017)
	Grade 8 science 1 (2006-2012)
	Grade 8 science 2 (2013-2017)
	Earth Science 1 (2006-2012)
	Earth Science 2 (2006-2012)
	Biology 1 (2006-2012)
	Biology 2 (2006-2012)
	Chemistry 1 (2006-2012)
	Chemistry 2 (2006-2012)
Assessments	SAT Chemistry
	SAT Ecology/Biology
	SAT Molecular Biology
	SAT Physics
	ACT Science
	AP Biology
	AP Chemistry
	AP Environmental Science
	AP Physics B
	AP Physics EM
	AP Physics M

Logistic regression. Logistic regression quantifies relationships between the dependent binary variable and one or more independent variables (Tabachnick & Fidell, 2007). In this study, the dependent binary variable was whether or not the student enrolled in a post-secondary science major. Separate logistic regressions were conducted for all science majors, science majors at 2-year schools, and science majors at 4-year schools to identify what variables were most closely related to each outcome. Furthermore, additional logistic regressions were conducted for female and male students separately, as related to post-secondary science majors. Stepwise logistic regressions, based on AIC, were conducted in R using the packages MASS (Venables & Ripley, 2002) and naniar (Tierney, Cook, McBain, & Fay, 2019).

Principal components analysis. To visualize groupings and separation among post-secondary majors, principal components analysis (PCA) was used. Data were summarized for each CIP grouping of majors; groups with fewer than 10 observations were omitted. Data were then standardized ($\bar{x}$ = 0, SD = 1) prior to analysis, and the highly significant variables from logistic regression analyses were selected as the axes for PCA. Analyses were conducted in R using the packages ggbiplot (Vu, 2011), FactoMineR (Le, Josse, & Husson, 2008), and corrplot (Wei & Simko, 2017).

Synthesis. Individual results from Research Questions 1 and 2 provided insight into individual components of the research problem. However, these individual analyses must be viewed more holistically in order to directly relate them to the overarching problem. Therefore, Research Question 3 involved a non-statistical meta-analysis: a synthesis of individual results to determine the extent to which the observed academic patterns reflect progression toward a science major. Results of hypothesis tests and regression analyses were used to identify gender-specific patterns and relationships among academic metrics. Key variables that functioned as significant markers of academic progress were identified for males and females. In addition, occupational projections for scientific and health professions (Virginia Employment Commission, 2018) were compared to the number of students majoring in related post-secondary science programs. From these two sets of data, estimates of annual surplus or shortfall of trained occupation entrants were calculated. When viewed holistically, the findings related to academic profiles, post-secondary science path, and occupational alignment help explain the extent to which demographic patterns in academic metrics are reflective of students' progression along a science pathway toward science-focused careers.

Limitations of the Study

There are several limitations associated with this study design. First, although these large datasets are powerful tools for gaining insight into educational processes and outcomes, the quality of the data relies on external stakeholders, such as state agencies and schools. The data used in this study were checked for systematic errors and clear mistakes, but some errors may remain in the dataset.

Secondly, the assessment scores and course grades were used for a purpose in this study that they were not intended to fulfill. SOL tests and grades are assessments designed to inform students and educators about student achievement, not as factors in statistical analyses. However, the VLDS program was initiated under the assumption that such analyses are possible and valid. Course grades, in particular, should be viewed with caution, since course grades do not necessarily follow a standard format. Grading systems may not be consistent among courses, schools, or teachers. Therefore, higher degrees of variability and noise would be expected related to this data type, and grade-related results may be difficult to interpret.

Thirdly, each datapoint represents a snapshot in time; for socioeconomic data, that may misrepresent a student's lived experiences. Whereas an individual's gender and race are relatively stable over time, socioeconomic status could change as a family's economic situation changes. In this study, the student's socioeconomic status in the year of high school completion was the only year considered, and additional students were classified as economically disadvantaged at previous points in school but not during that year. Furthermore, being classified as low income over multiple years can have a cumulative effect on educational pathways (Michelmore & Dynarski, 2017). Therefore, the effects of economically disadvantaged status are likely underestimated in this study.

Because of data availability, only Virginia public-school students who completed high school were included in analyses. The results may not be generalizable to other states, particularly because Virginia's educational curriculum is unique and does not follow the national Common Core State Standards curriculum. Furthermore, data on Virginia students who were only homeschooled or attended only private schools were not included in the study. Approximately 101,000 students in Virginia attend private schools (US Department of Education, 2014) and 40,000 are homeschooled or have a religious exemption (VDOE, 2017c); therefore, Virginia's public schools currently enroll approximately 90% of the state's school-age children.

Finally, this study includes analyses of only some of the factors potentially related to progression to a science major. Evaluating all potential factors is beyond the scope of this study, even though other factors – both academic and non-academic – undoubtedly influence academic success in science fields. Also, this study is an exploration of enrollment in science, not persistence in science. These are different phenomena with different influences. Future studies should explore the factors related to post-secondary persistence and entrance in science careers.

Summary

This study was an exploratory analysis of the academic profiles of post-secondary science majors in Virginia schools, as well as a comparison of science-related academic metrics among demographic and post-secondary subgroups. The study used existing data from the Virginia Longitudinal Data System, including science SOL assessment scores, other science assessment scores, science course grades, post-secondary major and school, and demographic variables. The analysis methods of correlation analysis and logistic regression were used to model academic variables most closely related to majoring in science at 2-year schools or 4-year schools and by gender. In addition, *t*-tests were used to statistically compare academic metrics between educational and demographic subgroups, and principal components analysis aided in the visualization and synthesis of patterns in the results.

Chapter 4 – Results

Introduction

This exploratory study included a large number of variables, sub-groups, research questions, and analyses. To help improve understanding of the connections among the various findings, the presentation of results will follow the structure depicted in Figure 1.

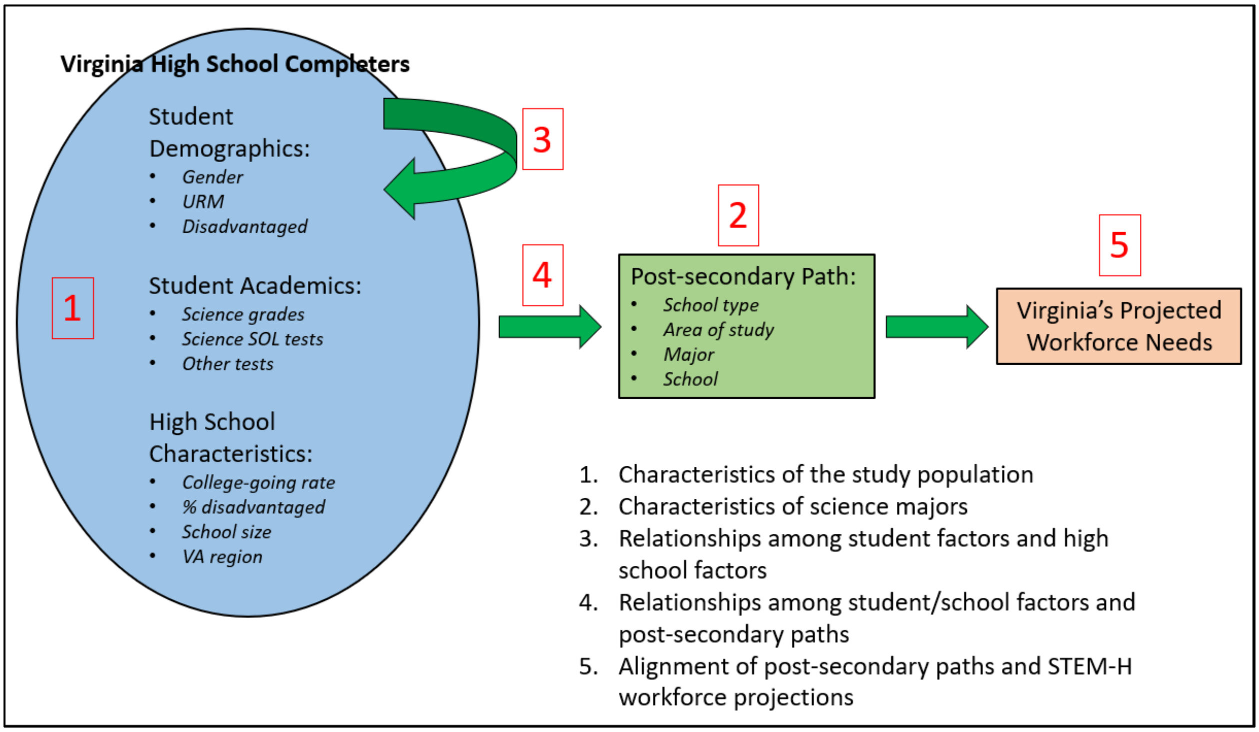

Figure 1. Overview of the structure of Chapter 4 – Results.

1. Characteristics of the Study Population

Demographic characteristics. The study population included Virginia public school students who graduated from 2004-2016, for whom DOE data were present in the VLDS system. In total, data from more than one million students were used in this study (Table 4). Of these high school completers, the gender ratio was approximately even, roughly one-third were under-represented minorities (URM), and more than one-quarter qualified as economically disadvantaged during grade 12 (Table 4).

Table 4. *Demographic Characteristics of the Study Population*

Population Segment	Number	Percentage
Total	1,089,389	---
Sex		
Female	547,046	50.2%
Male	542,343	49.8%
Under-represented Minority (URM) Status [a]		
URM	374,022	34.3%
Not URM	715,367	65.7%
Economic Status [b]		
Economically Disadvantaged	291,114	26.7%
Not Economically Disadvantaged	798,275	73.3%

[a] Included American Indian or Alaska Native, Black, Hispanic, Native Hawaiian or Pacific Islander, and Non-Hispanic two or more races.
[b] Eligible for free/reduced meals, received Temporary Assistance for Needy Families (TANF), eligible for Medicaid, identified as migrant, or experienced homelessness.

Post-secondary enrollment. Statewide, one-third of high school completers enrolled directly in a 4-year school (i.e., college or university) after high school, whereas approximately one-fourth enrolled in a 2-year school, such as a community college or technical school (Table 5). More than one-third did not enter post-secondary school. Regional trends were evident related to post-secondary education paths, with greater proportions of students from southwestern Virginia entering 2-year schools (Figure 2), more students from northern Virginia entering 4-year schools (Figure 3), and more students from central Virginia and the Shenandoah Valley region not entering post-secondary school (Figure 4). Information from these three maps was combined in Figure 5, which shows the mean years of post-secondary path, a weighted average of the percent of 0-, 2-, and 4-year-bound students.

Table 5. *Post-secondary Enrollment Characteristics of Study Population*

Post-Secondary Path	Number	Percentage
4-year school	384,640	35.3%
2-year school	283,872	26.1%
Neither 2-year or 4-year school	420,877	38.6%

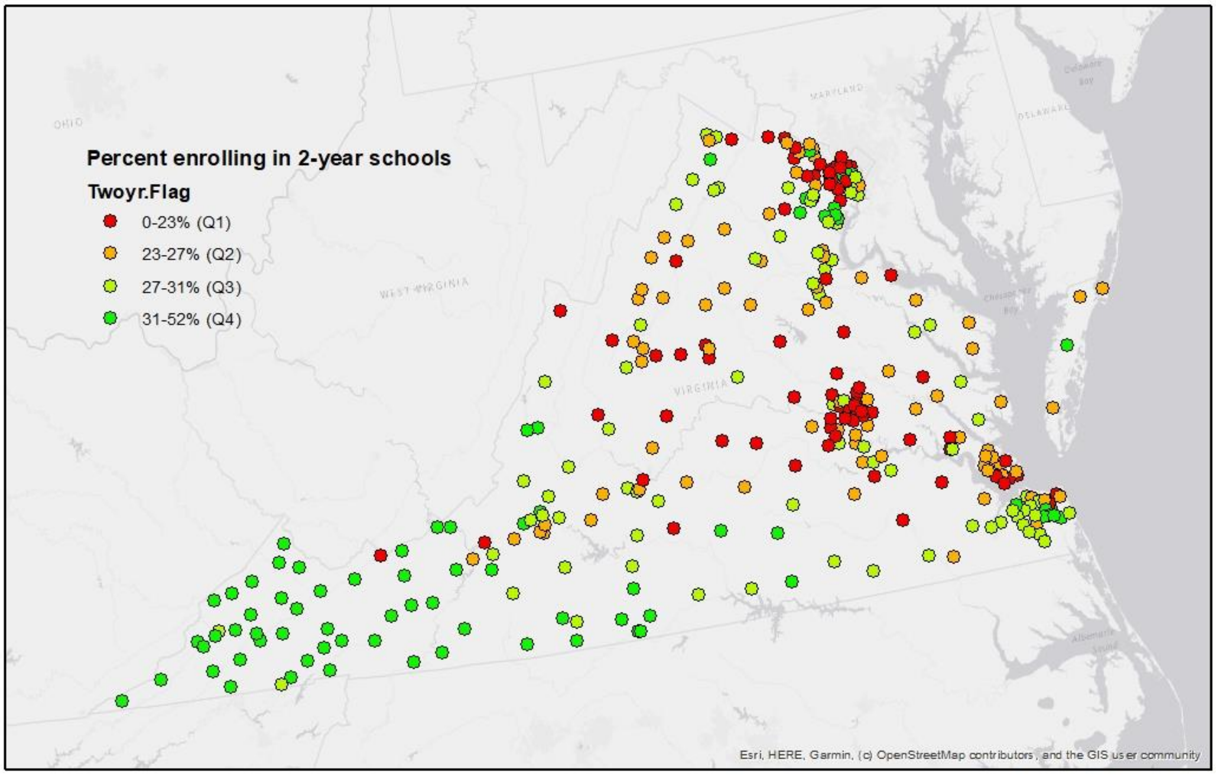

Figure 2. Percent of students enrolling in 2-year post-secondary schools, by high school.

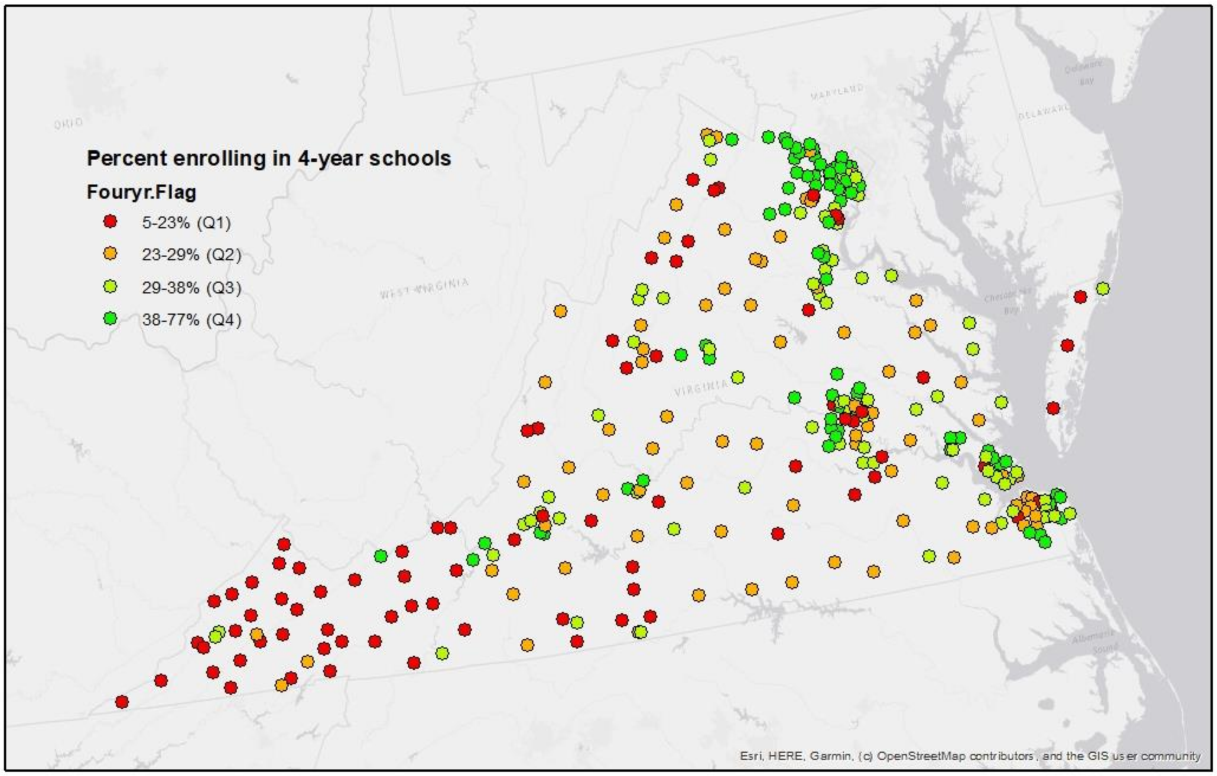

Figure 3. Percent of students enrolling in 4-year post-secondary schools, by high school.

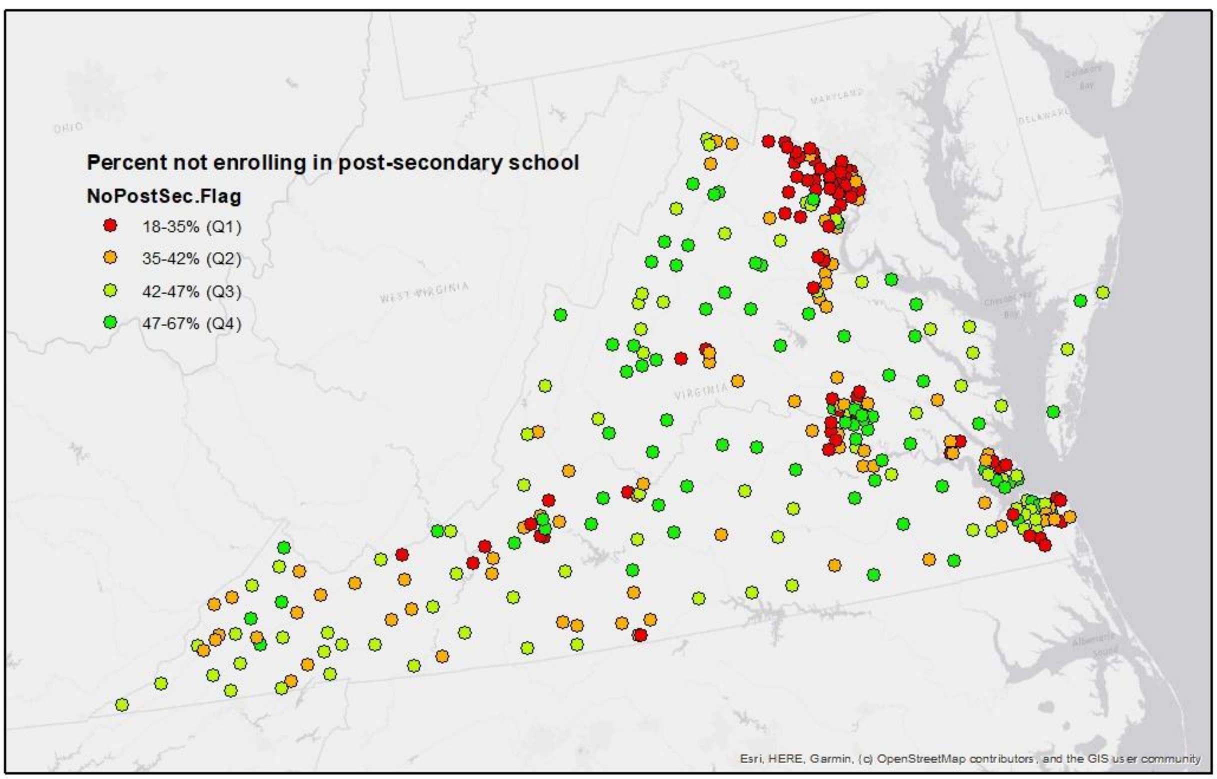

Figure 4. Percent of students not enrolling in post-secondary schools, by high school.

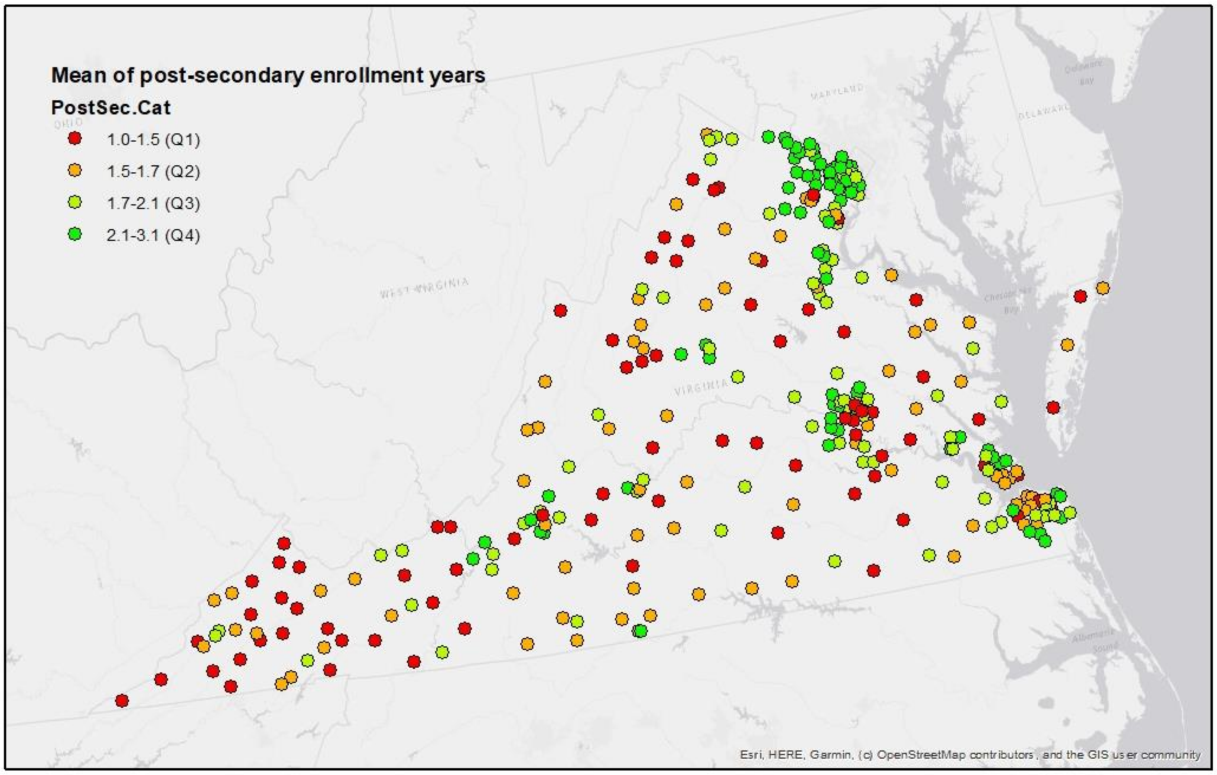

Figure 5. Weighted average of years of post-secondary school enrollment, by high school.

The percent of high school completers who enrolled in post-secondary school, for all majors, decreased slightly from 2005-2015 for both 2-year and 4-year schools (*Figure 6*).

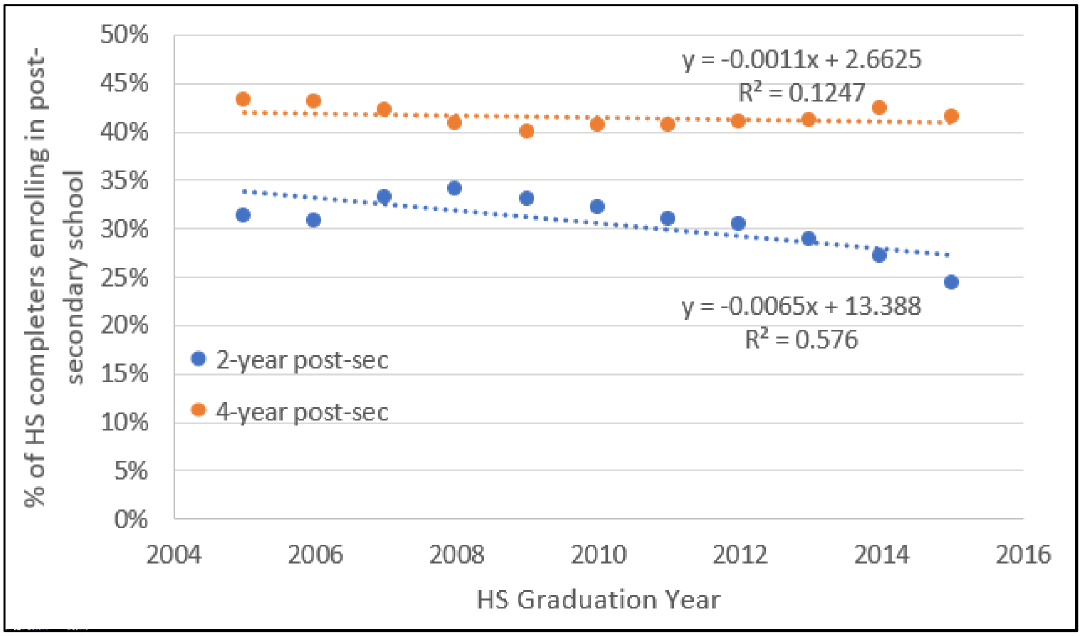

Figure 6. Percent of high school completers enrolling in post-secondary school, by type of post-secondary school.

Academic metrics. The mean, standard deviation, and sample sizes of 22 academic metrics for high school completers are listed in Appendix 1 (Tables A1.1 – A1.4). Each metric is reported for the study population of high school completers and for the following subgroups of high school completers: female students, male students, URM students, non-URM students, economically disadvantaged students, and non-economically disadvantaged students.

2. Characteristics of Science Majors

Post-secondary enrollment in science. Of the study population of high school completers, approximately 4% initially enrolled in a science major at a 2-year school and approximately 5% entered science at a 4-year school (Figure 7). Science students at 2-year schools were predominantly in the “Other” science category, including the health professions and multi-disciplinary studies (Table 6). Science students at 4-year schools enrolled predominantly in biological sciences and health professions, with physical sciences accounting for fewer science students (Table 6).

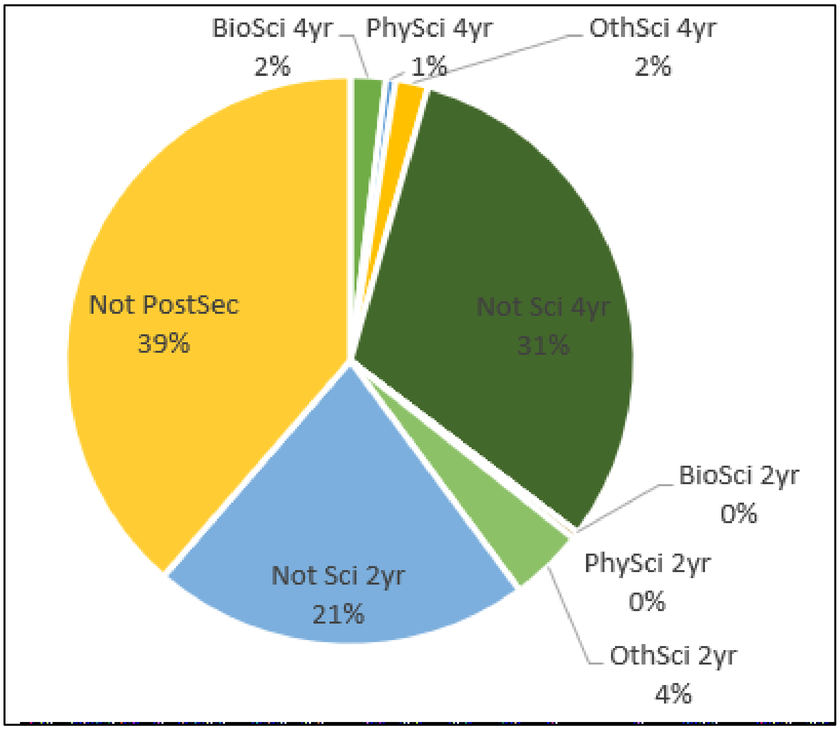

Figure 7. Post-secondary enrollment characteristics of study population, including type of science program.

Table 6. *Post-secondary Enrollment of Science Majors*

Science Field	2-Year Schools		4-Year Schools		2-Yr and 4-Yr Schools	
	Number	Percent	Number	Percent	Number	Percent
Biological Sciences	45	0%	21,994	46%	22,039	23%
Physical Sciences	4,238	9%	5,939	12%	10,177	10%
Other Sciences	45,540	91%	20,162	42%	65,702	67%
All Sciences	49,823		48,095		97,918	

Demographic characteristics of science majors. Females substantially outnumbered male students in biological, physical, and other science categories at 2-year schools (Table 7) and also outnumbered males in biological and other sciences at 4-year schools (Table 8). Proportions of URM students and economically disadvantaged students were higher in 2-year science programs than in 4-year science programs. For reference, 34% of the study population was URM and 27% was economically disadvantaged.

Table 7. *Demographic Characteristics of Science Majors Enrolling at 2-Year Schools*

Population Segment	Biological Sciences	Physical Sciences	Other Sciences	All Sciences
Females	30 (67%)	2,647 (62%)	32,787 (72%)	35,464 (71%)
Males	15 (33%)	1,591 (38%)	12,753 (28%)	14,359 (29%)
URM	18 (40%)	2,121 (50%)	18,087 (40%)	20,226 (41%)
Not URM	27 (60%)	2,117 (50%)	27,453 (60%)	29,597 (59%)
Econo. Disad.	11 (24%)	1,185 (28%)	16,783 (37%)	17,979 (36%)
Not Econo. Disad.	34 (76%)	3,053 (72%)	28,757 (63%)	31,844 (64%)

Table 8. *Demographic Characteristics of Science Majors Enrolling at 4-Year Schools*

Population Segment	Biological Sciences	Physical Sciences	Other Sciences	All Sciences
Females	14,834 (67%)	2,658 (45%)	15,416 (76%)	32,908 (68%)
Males	7,160 (33%)	3,281 (55%)	4,746 (24%)	15,187 (32%)
URM	6,510 (30%)	1,293 (22%)	6,090 (30%)	13,893 (29%)
Not URM	15,484 (70%)	4,646 (78%)	14,072 (70%)	34,202 (71%)
Econo. Disad.	3,828 (17%)	791 (13%)	3,492 (17%)	8,111 (17%)
Not Econo. Disad.	18,166 (83%)	5,148 (87%)	16,670 (83%)	39,984 (83%)

Academic metrics of science majors. The mean, standard deviation, and sample sizes of 22 academic metrics for science majors in 2-year schools (Tables A1.5 – A1.8) and science majors in 4-year schools (Tables A1.9 – A1.12) are listed in Appendix 1. Each metric is reported for the population of 2-year or 4-year science students and for the following subgroups of 2-year and 4-year students: female students, male students, URM students, non-URM students, economically disadvantaged students, non-economically disadvantaged students, biological science majors, physical science majors, and other science majors.

Enrollment in science programs at 2-year post-secondary schools. Approximately one-third of science students at 2-year post-secondary schools enrolled in the multidisciplinary major of Biological and Physical Science (CIP = 30.01; Figure 8); this major may serve as a stepping stone to entry into science programs at 4-year schools. The next most frequent science majors at 2-year schools were all in health fields: Health Diagnostics; Nursing; and Mental Health (Table 9). Students enrolled in science at many community colleges, with Tidewater Community College and Northern Virginia Community College having the highest number of science students enroll (Table 10).

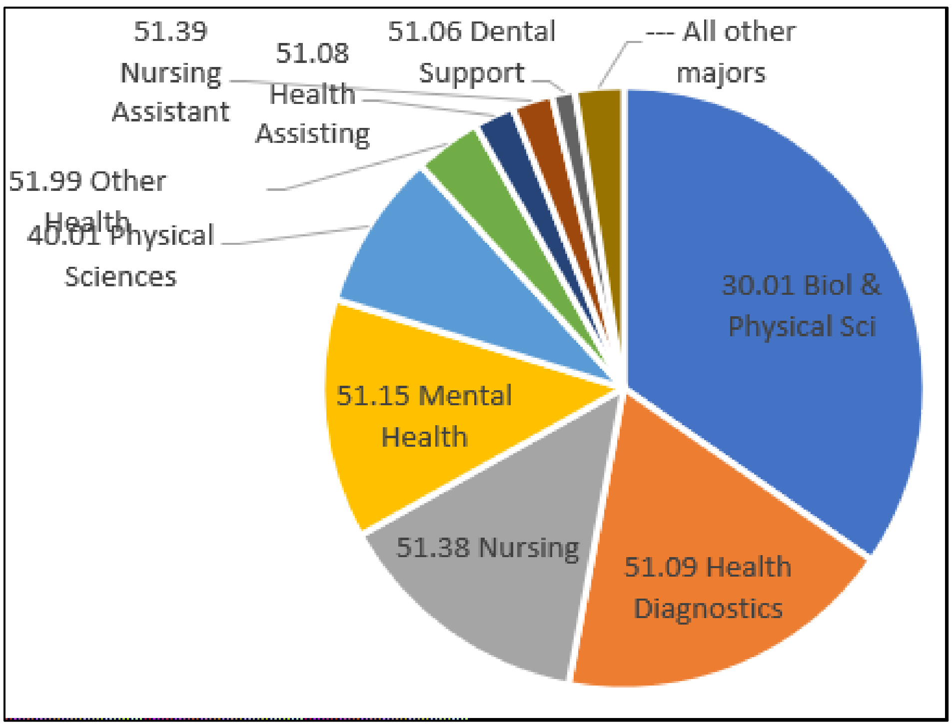

Figure 8. Enrollment in 2-year post-secondary schools, by science major.

Table 9. *Science Student Enrollment by Major: 2-Year Schools*

CIP Code	Major Name	Number	Percentage
3.01	Natural Resources	149	0%
26.01	Biology	38	0%
30.01	Biol & Physical Sci	17,262	35%
40.01	Physical Sciences	4,223	8%
51.00	Health Sciences	36	0%
51.06	Dental Support	619	1%
51.07	Health Admin	529	1%
51.08	Health Assisting	1,083	2%
51.09	Health Diagnostics	9,109	18%
51.10	Lab Science	348	1%
51.11	Health Prep	30	0%
51.15	Mental Health	6,411	13%
51.18	Opt. Support	34	0%
51.23	Rehabilitation	21	0%
51.35	Therapy	54	0%
51.38	Nursing	6,955	14%
51.39	Nursing Assistant	1,077	2%
51.99	Other Health	1,788	4%
---	All other majors	57	0%

Table 10. *Science Student Enrollment by School: 2-Year Schools in Virginia*

School Name	Number	Percentage
Tidewater Community College	9,827	20%
Northern Virginia Community College	6,492	13%
J Sargeant Reynolds Community College	5,152	10%
Richard Bland College of William and Mary	4,213	9%
Thomas Nelson Community College	4,102	8%
Virginia Western Community College	2,963	6%
John Tyler Community College	1,752	4%
Germanna Community College	1,737	4%
Southside Virginia Community College	1,544	3%
Lord Fairfax Community College	1,526	3%
Mountain Empire Community College	1,168	2%
Blue Ridge Community College	1,156	2%
Southwest Virginia Community College	1,055	2%
Piedmont Virginia Community College	1,026	2%
Wytheville Community College	936	2%
Danville Community College	892	2%
Virginia Highlands Community College	815	2%
Rappahannock Community College	781	2%
Patrick Henry Community College	762	2%
Other Virginia schools	1,448	3%

Enrollment in science programs at 4-year post-secondary schools. Forty percent of science students at 4-year post-secondary schools initially enrolled in General Biology (CIP = 26.01; Figure 9), which includes the specific majors of General Biology/Biological Sciences and General Biomedical Sciences. The next most common science majors at 4-year schools were Nursing (12%) and Chemistry (7%; Table 11). Enrollment for the remaining 41% of science students was dispersed among a large number of science majors and fields (Table 11).

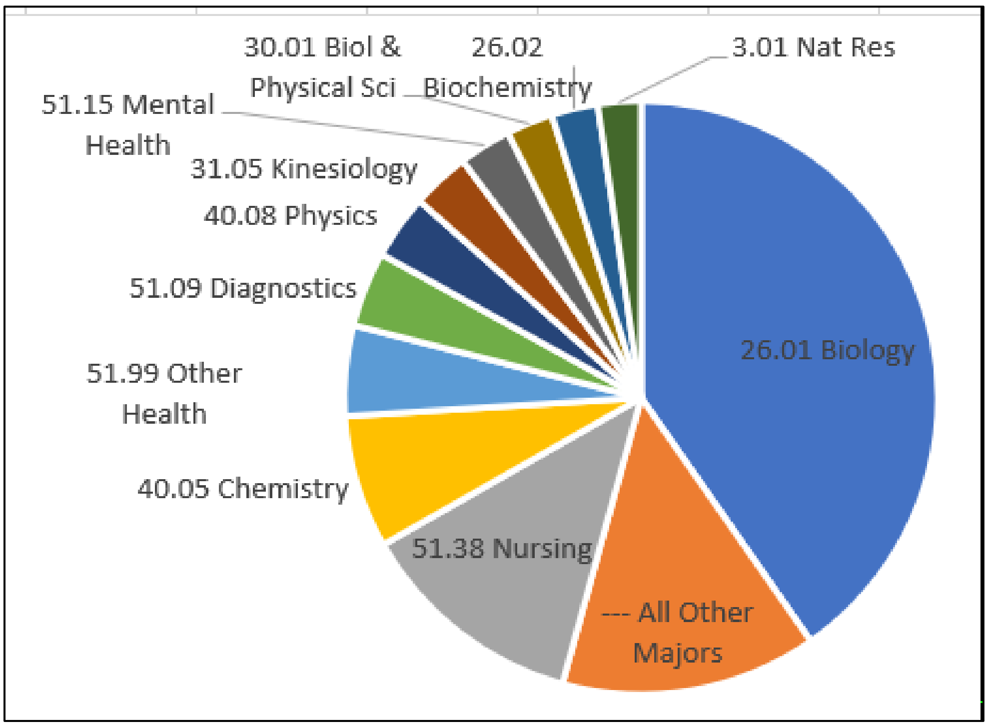

Figure 9. Enrollment in 4-year post-secondary schools, by type of science major.

Table 11. *Science Student Enrollment by Major: 4-Year Schools*

CIP Code	Major Name	Number	Percentage
3.01	Natural Resources	1,125	2%
3.05	Forestry	444	1%
26.01	Biology	19,388	40%
26.02	Biochemistry	1,219	3%
26.09	Physiology	343	1%
26.15	Neurobiology	318	1%
30.01	Biol & Physical Sci	1,220	3%
30.15	Science & Technology	380	1%
31.05	Kinesiology	1,521	3%
40.05	Chemistry	3,486	7%
40.06	Geology	468	1%
40.08	Physics	1,693	4%
51.00	Health Sciences	295	1%
51.02	Comm. Disorders	658	1%
51.09	Diagnostics	1,974	4%
51.11	Health Prep	692	1%
51.15	Mental Health	1,377	3%
51.22	Public Health	367	1%
51.38	Nursing	6,003	12%
51.99	Other Health	2,370	5%
---	All Other Majors	2,754	6%

The vast majority of Virginia students entering 4-year schools for science enrolled in a post-secondary school in Virginia (Table 12), with only 12% of students going out of state. Students who stayed in Virginia were dispersed among a large number of 4-year schools, and James Madison University, Virginia Commonwealth University, and Virginia Tech enrolled the largest numbers of science students (Figure 10 and Table 13). Post-secondary school enrollments by type of science major (biological, physical, or other science) are listed in Appendix 2.

Table 12. *Science Student Enrollment by State, for 4-year Post-secondary Schools*

State	Number	Percentage
Virginia	42,195	87.7%
North Carolina	867	1.8%
Florida	538	1.1%
Pennsylvania	520	1.1%
West Virginia	503	1.0%
South Carolina	448	0.9%
Tennessee	310	0.6%
Alabama	205	0.4%
Ohio	203	0.4%
New York	198	0.4%
Texas	181	0.4%
District of Columbia	145	0.3%
California	137	0.3%
Kentucky	124	0.3%
Colorado	120	0.2%
Georgia	109	0.2%
Other states	1,292	2.7%

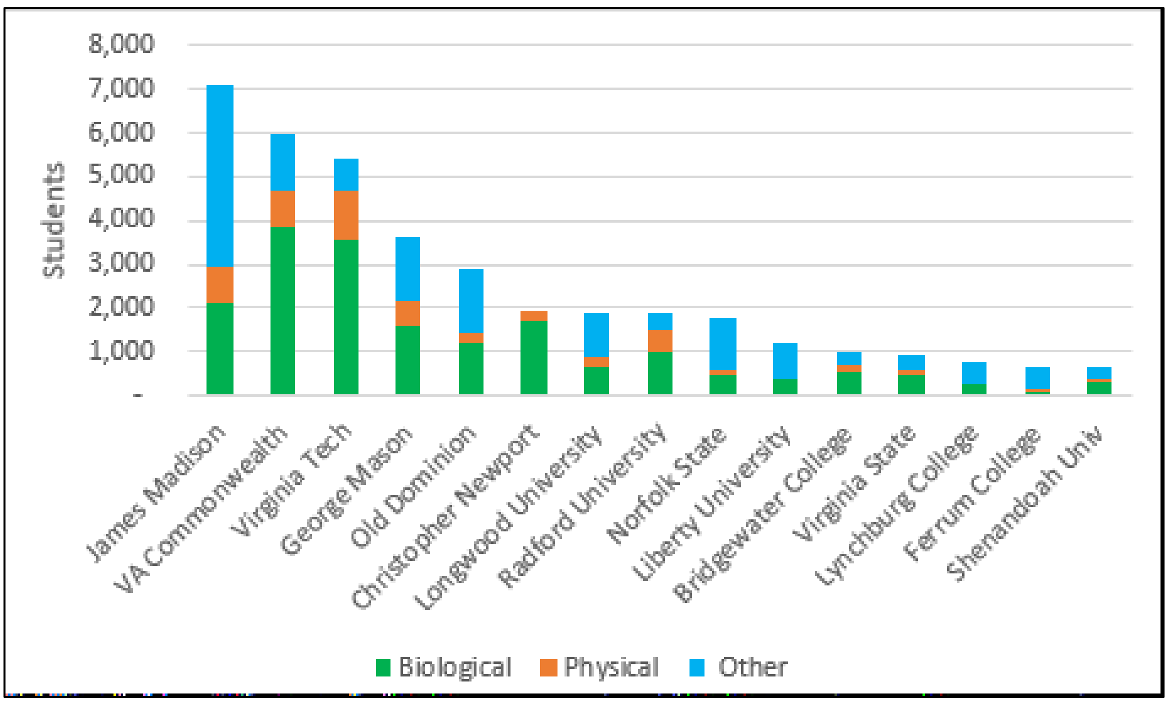

Figure 10. Enrollment in 4-year Virginia post-secondary schools, by type of science major.

Table 13. *Science Student Enrollment by School: 4-Year Schools in Virginia*

School Name	Number	Percentage
James Madison University	7,098	17%
Virginia Commonwealth University	5,956	14%
Virginia Tech	5,407	13%
George Mason University	3,611	9%
Old Dominion University	2,886	7%
Christopher Newport University	1,914	5%
Longwood University	1,910	5%
Radford University	1,903	5%
Norfolk State University	1,795	4%
Liberty University	1,208	3%
Bridgewater College	996	2%
Virginia State University	940	2%
Lynchburg College	756	2%
Ferrum College	663	2%
Shenandoah University	629	1%
Hampton University	616	1%
Jefferson College of Health Sciences	571	1%
University of Virginia-Main Campus	568	1%
The University of Virginia's College at Wise	520	1%
Other Virginia schools	2,248	5%

3. Relationships Among Student Factors and High School Factors

Academic factors. Correlations among assessment scores and course grades (and the associated p-values) are listed in Appendix 3 (Table A3.1). Figure 11 was created to help visualize patterns in the large matrix of correlation coefficients. It becomes evident that all science-focused test scores (i.e., SOL, SAT, ACT, and AP tests) are positively correlated with each other (dark blue, orange, and yellow boxplots in Figure 11). Similarly, students' grades in high school science courses are also positively correlated, although with a much wider range (green boxplot in Figure 11). However, scores on SOL, SAT, ACT, and AP assessments were essentially uncorrelated with grades in high school science courses (grey and light blue boxplots in Figure 11).

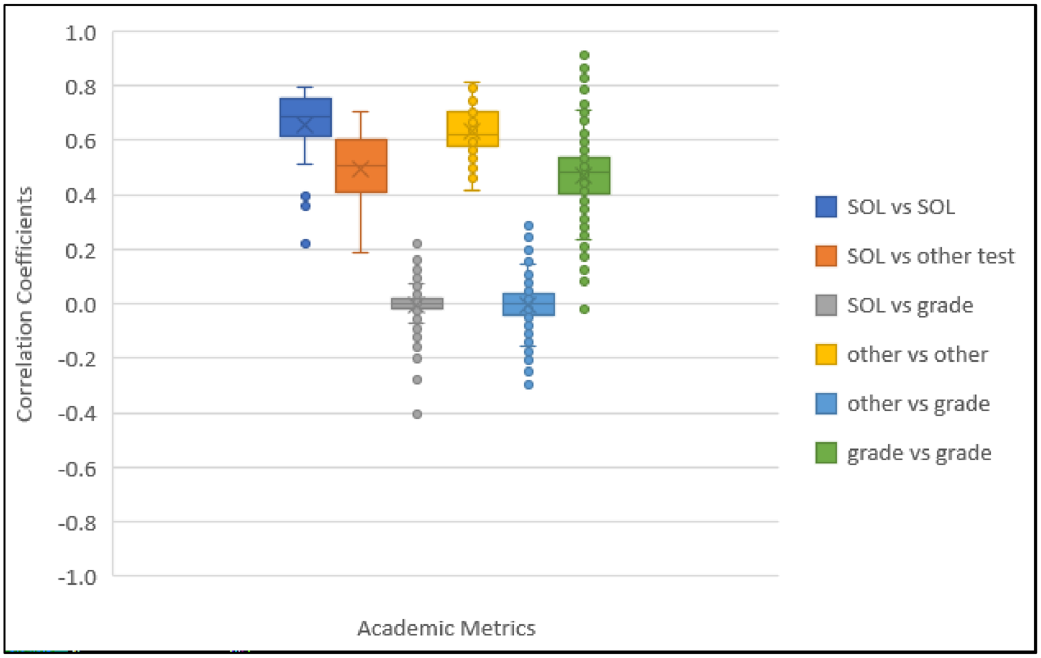

Figure 11. Patterns in correlation coefficients among academic metrics in science, based on student-level data.

Demographic and academic factors. Differences in academic metrics (Appendix 1) among demographic groups were identified using t-tests (Table 14). Mean science grade differed significantly ($p<0.001$) between male and female students (Figure 12), URM and non-URM students (Figure 13), and economically disadvantaged and non-economically disadvantaged students (Figure 14). Female students, non-URM students, and non-economically disadvantaged students received significantly higher science course grades.

Table 14. *T-Test Significance (p-value) of Demographic Differences by Academic Metric*

Academic Metric	Gender	URM	Disadvantaged Status
Mean Science Grade	<0.001***	<0.001***	<0.001***
SOL Grade 5 (1)	0.03*	0.36	0.60
SOL Grade 5 (2)	0.33	0.07	0.06
SOL Grade 8 (1)	0.13	0.51	0.96
SOL Grade 8 (2)	0.80	0.07	0.46
SOL Earth Sci (1)	0.26	0.20	0.51
SOL Earth Sci (2)	0.91	0.20	0.54
SOL Biology (1)	0.11	0.74	0.01**
SOL Biology (2)	0.30	0.12	0.80
SOL Chemistry (1)	0.04*	0.05*	0.00**
SOL Chemistry (2)	0.46	0.05*	0.25
SAT Chemistry	0.85	0.54	0.98
SAT Ecology	0.99	0.40	0.81
SAT Mol Bio	0.16	0.95	0.77
SAT Physics	0.92	0.92	0.96
ACT Science	0.59	0.67	0.23
AP Biology	0.54	0.10	0.58
AP Chemistry	0.56	0.79	0.15
AP Env Sci	0.91	0.57	0.86
AP Physics B	0.35	0.03*	0.31
AP Physics EM	0.36	0.14	0.76
AP Physics M	0.18	0.69	0.66

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

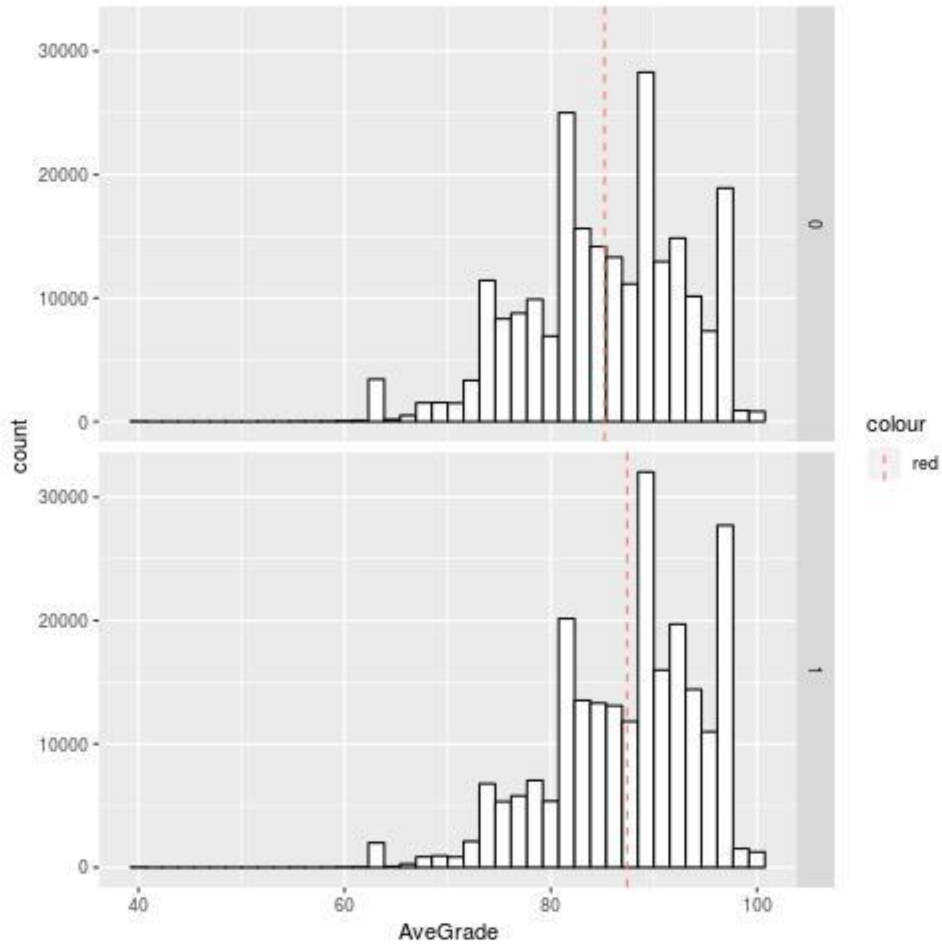

Figure 12. Frequency distributions of mean science course grades for male high school completers (top) and female high school completers (bottom). The red dashed line indicates the group mean.

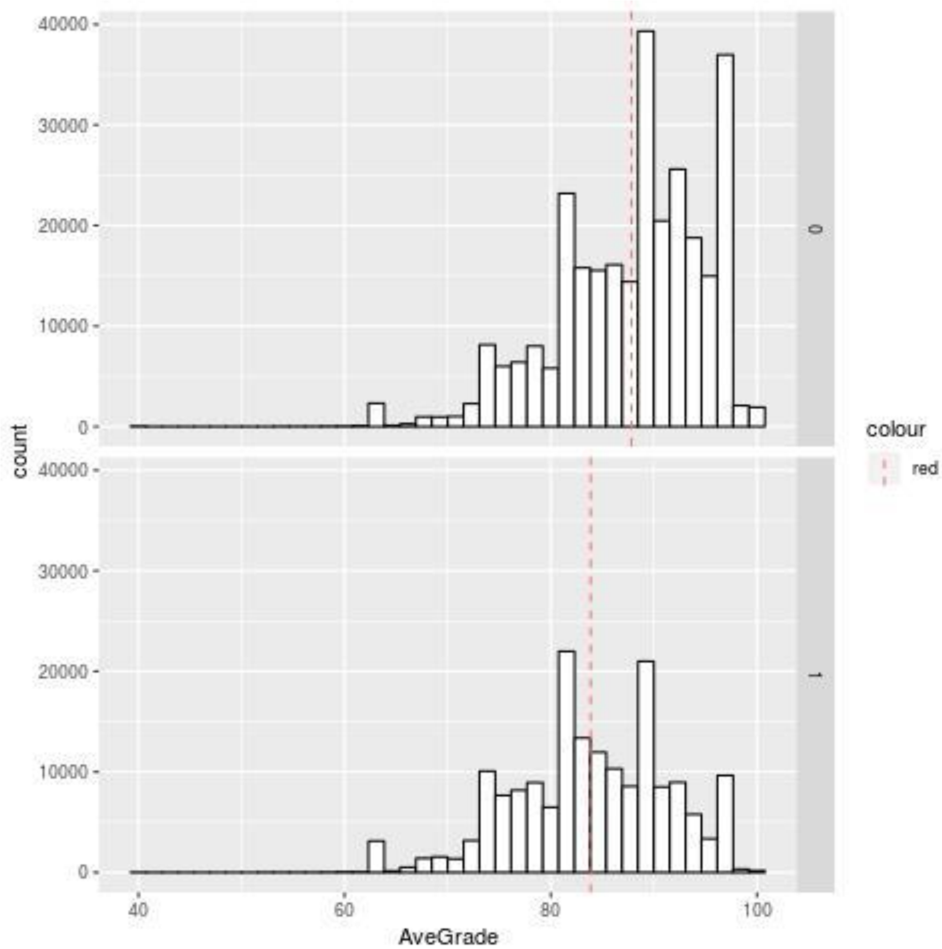

Figure 13. Frequency distributions of mean science course grades for non-URM high school completers (top) and URM high school completers (bottom). The red dashed line indicates the group mean.

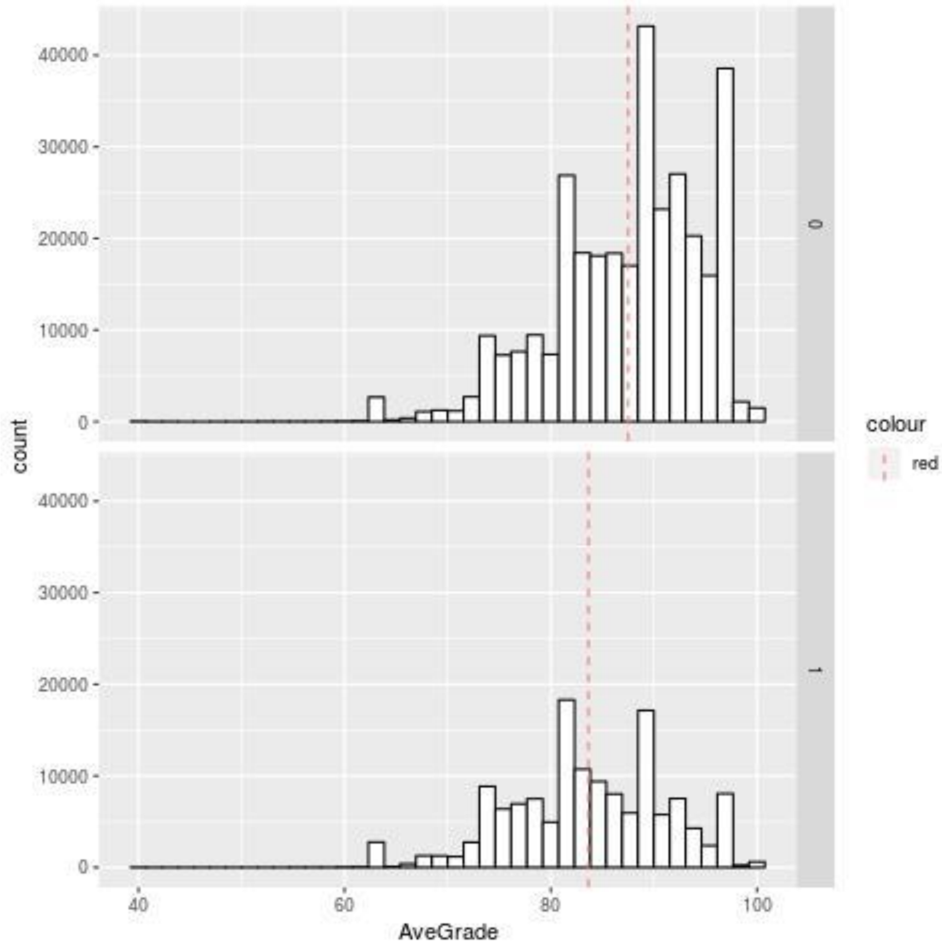

Figure 14. Frequency distributions of mean science course grades for non-economically disadvantaged high school completers (top) and economically disadvantaged high school completers (bottom). The red dashed line indicates the group mean.

School-level and academic factors. Student-level data provided additional insights into science profiles and pathways when combined at the high school level. No regional patterns were evident in mean science SOL scores (Figure 15), but regional patterns were present for percent of economically disadvantaged students. Schools with high proportions of economically disadvantaged students were much more common in the southern and western parts of Virginia (red dots in Figure 16).

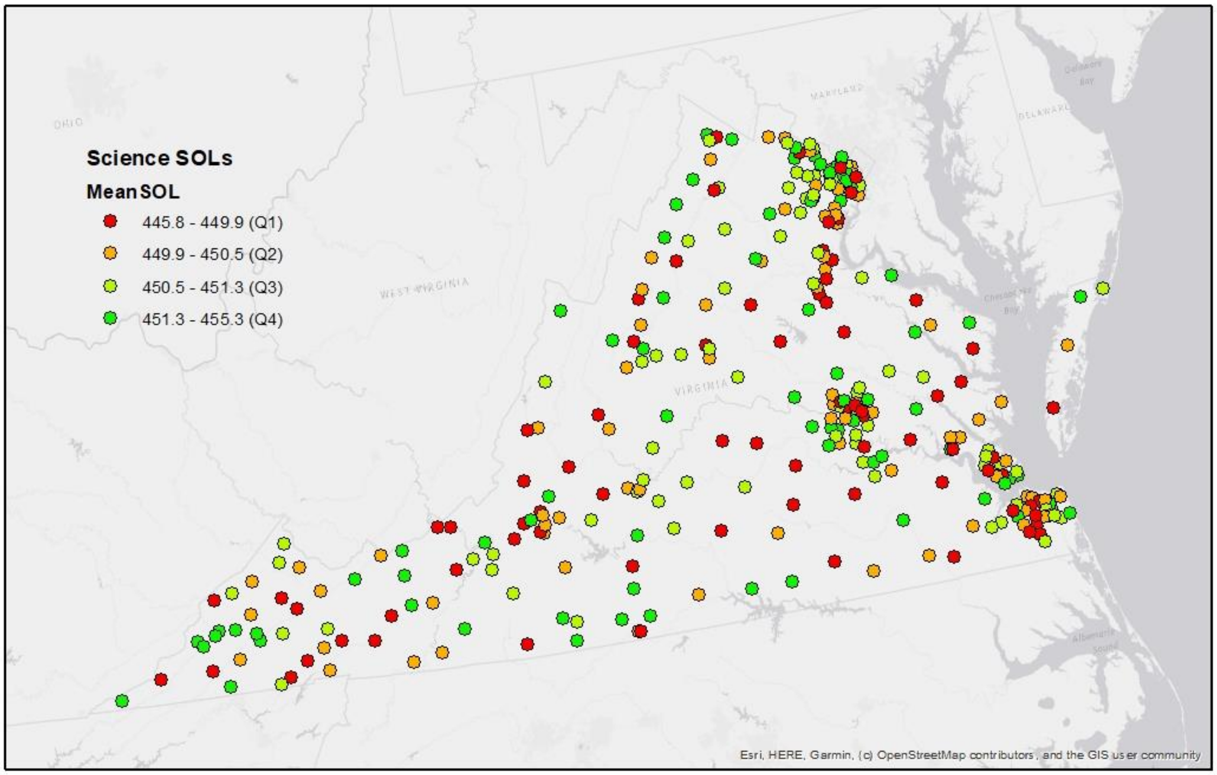

Figure 15. Mean of science SOL assessments, by high school.

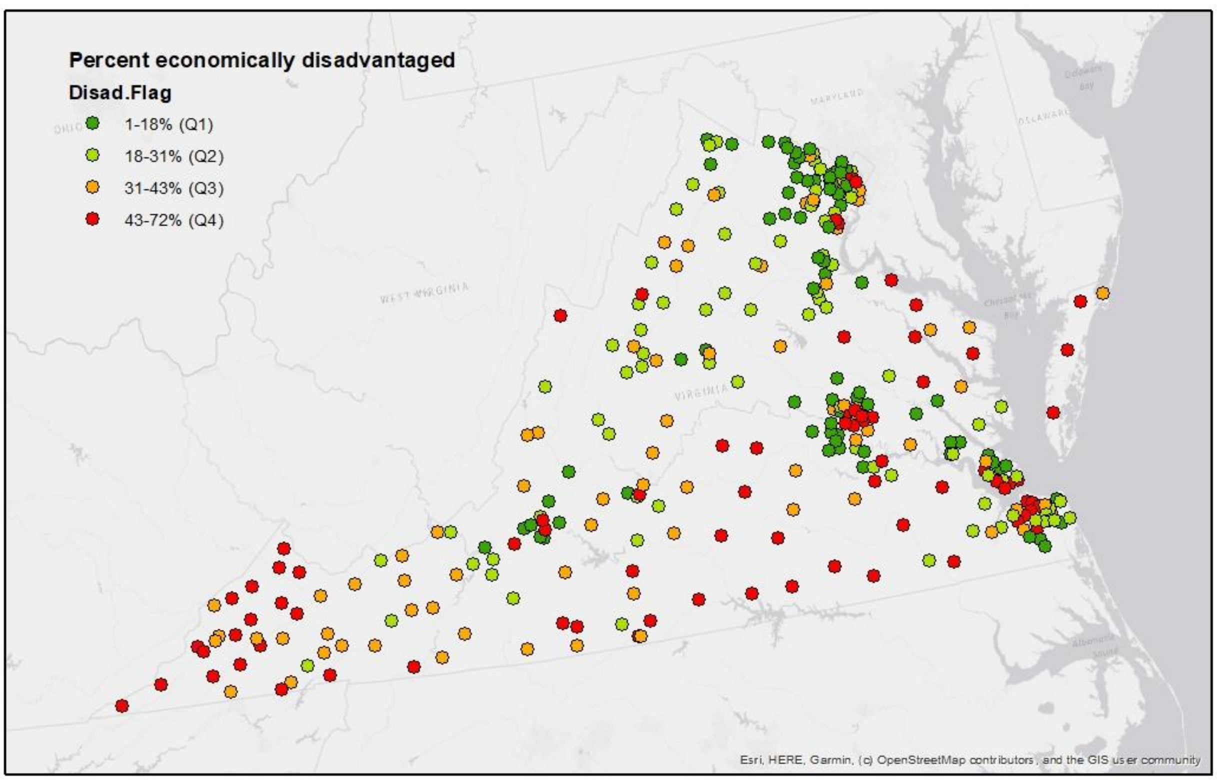

Figure 16. Percent of economically disadvantaged students, by high school.

The percent of economically disadvantaged students and the percent of URM students were both slightly negatively correlated with metrics of science performance (SOL scores, other test scores, and course grades); school size and academic metrics were uncorrelated (Figure 17). Correlation coefficients and p-values for high school-level data are listed in Appendix 3, Table A3.2.

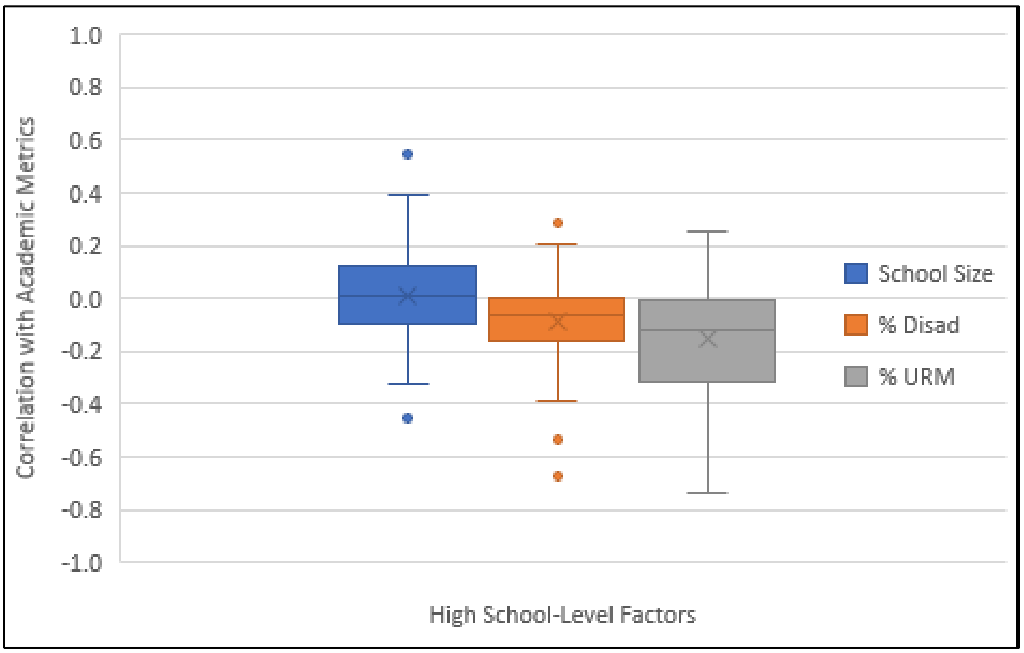

Figure 17. Patterns in correlation coefficients with academic metrics in science, based on school-level data.

4. Relationships Among Student/School Factors and Post-Secondary Paths

Spatial patterns in post-secondary science enrollment. Statewide, 9% of students enrolled in a science major in a post-secondary school, with half of those entering 2-year schools and half entering 4-year schools (Table 15). However, science-bound students were not evenly distributed from high schools; spatial patterns were evident. High schools in the southern and western parts of Virginia had higher rates of students entering science fields than did high schools in northern Virginia (Figure 18). When science majors at 2-year and 4-year schools are viewed separately, we see that most of the science majors from 2-year schools are coming from the southwestern part of the state, while 4-year science students are coming from northern Virginia (Figure 19 and Figure 20). This follows the general 2-year- and 4-year-going patterns for all majors (Figure 2 and Figure 3).

Table 15. *Post-secondary Enrollment Characteristics of Study Population*

Post-Secondary Path	Any Major	Science Major
2-year school	26.1%	4.6%
4-year school	35.3%	4.4%
Neither 2-year or 4-year school	38.6%	---

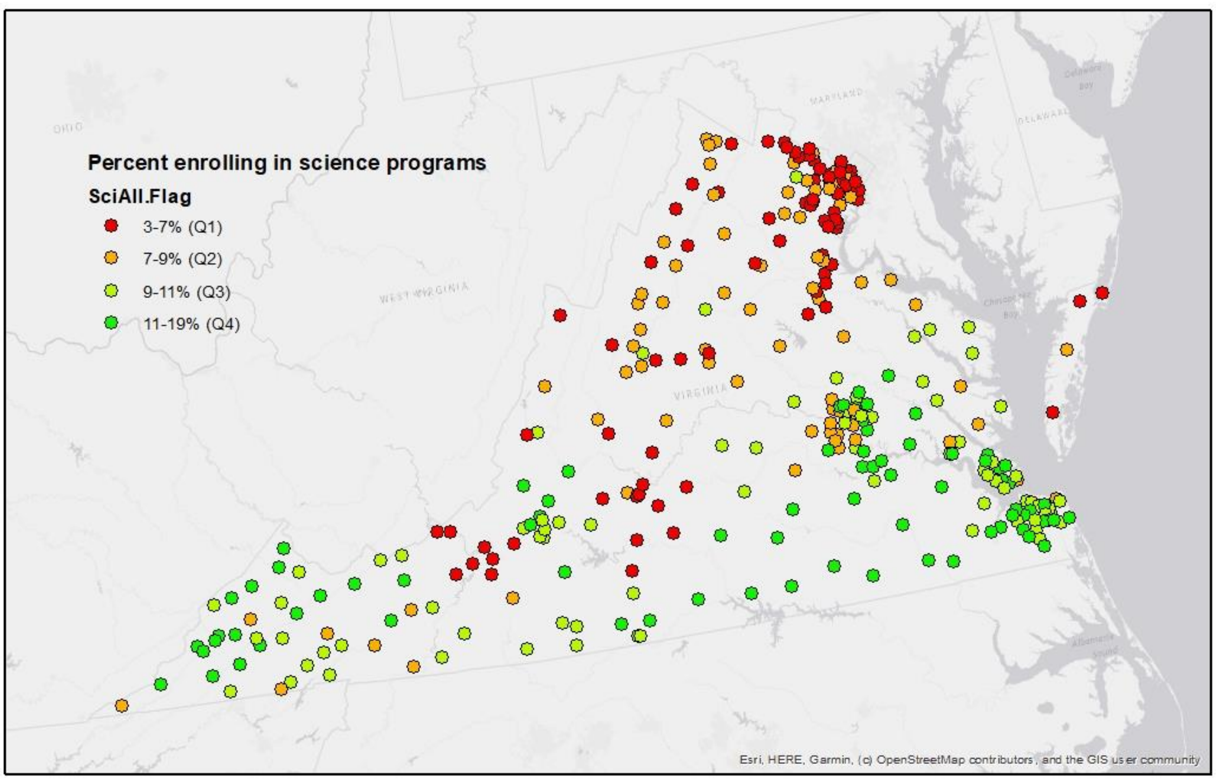

Figure 18. Percent of students enrolling in science in post-secondary schools, by high school.

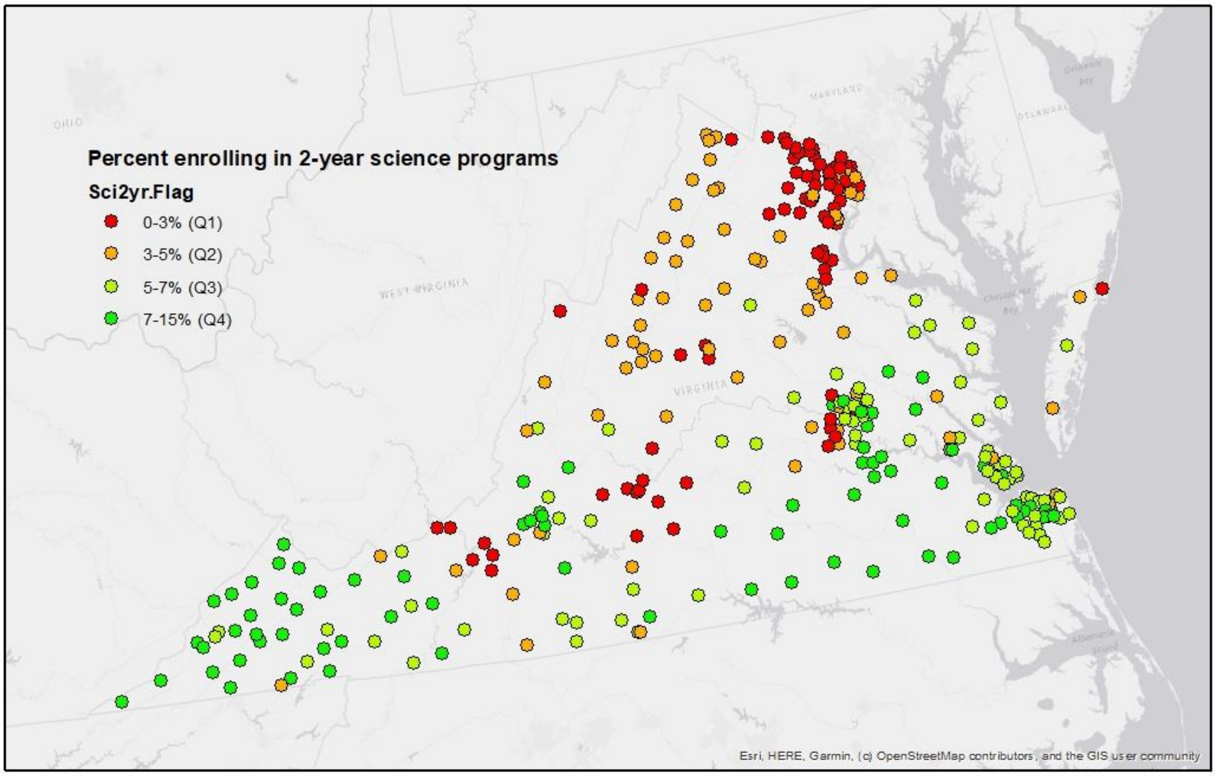

Figure 19. Percent of students enrolling in science programs in 2-year post-secondary schools, by high school.

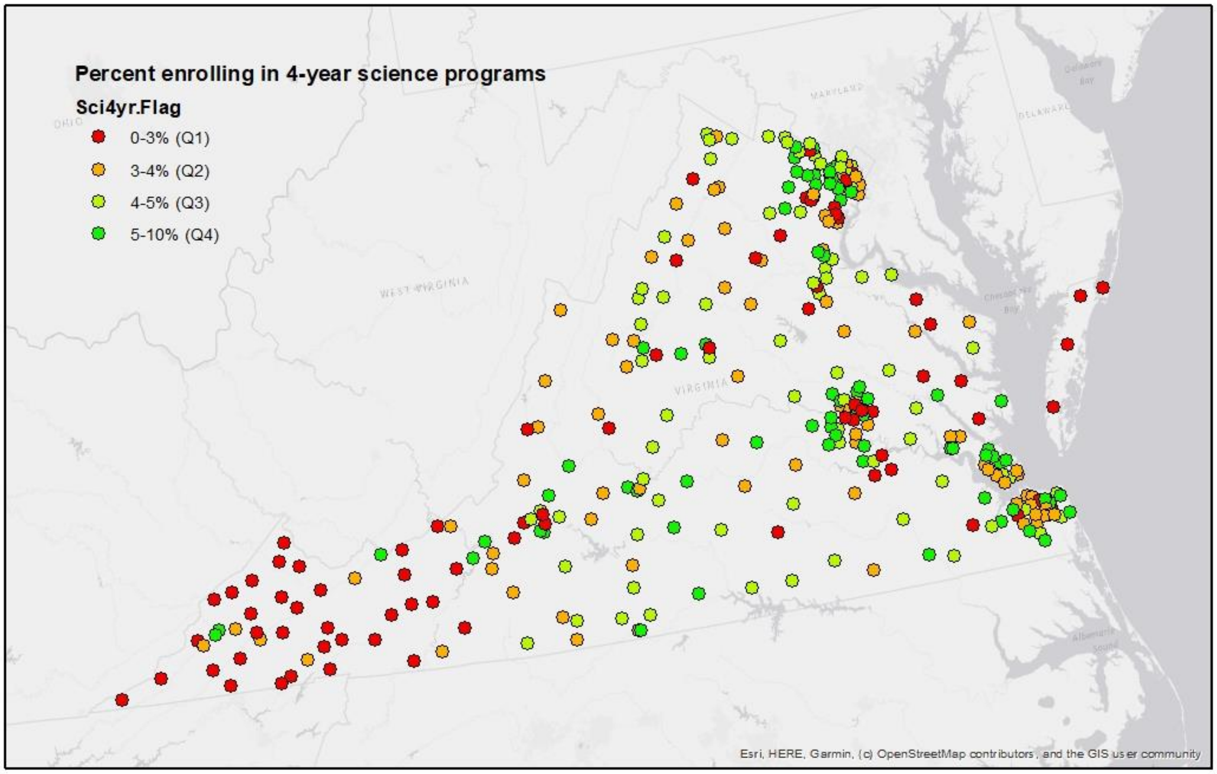

Figure 20. Percent of students enrolling in science programs in 4-year post-secondary schools, by high school.

High schools also differed in percent of students entering each type of science field, with a greater percent of students in northern and southeastern Virginia enrolling in biological science and physical science majors (Figure 21 and Figure 22), and other science majors being more common in southwestern Virginia (Figure 23).

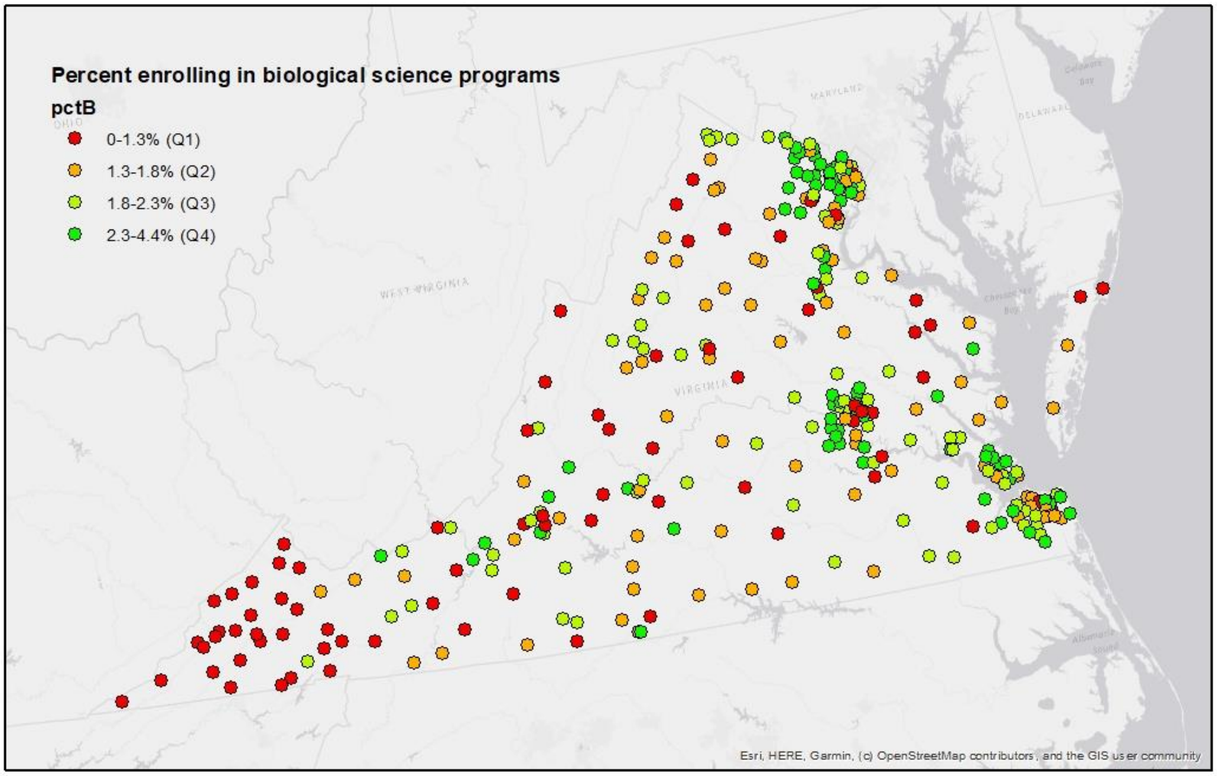

Figure 21. Percent of students enrolling in post-secondary biological science programs.

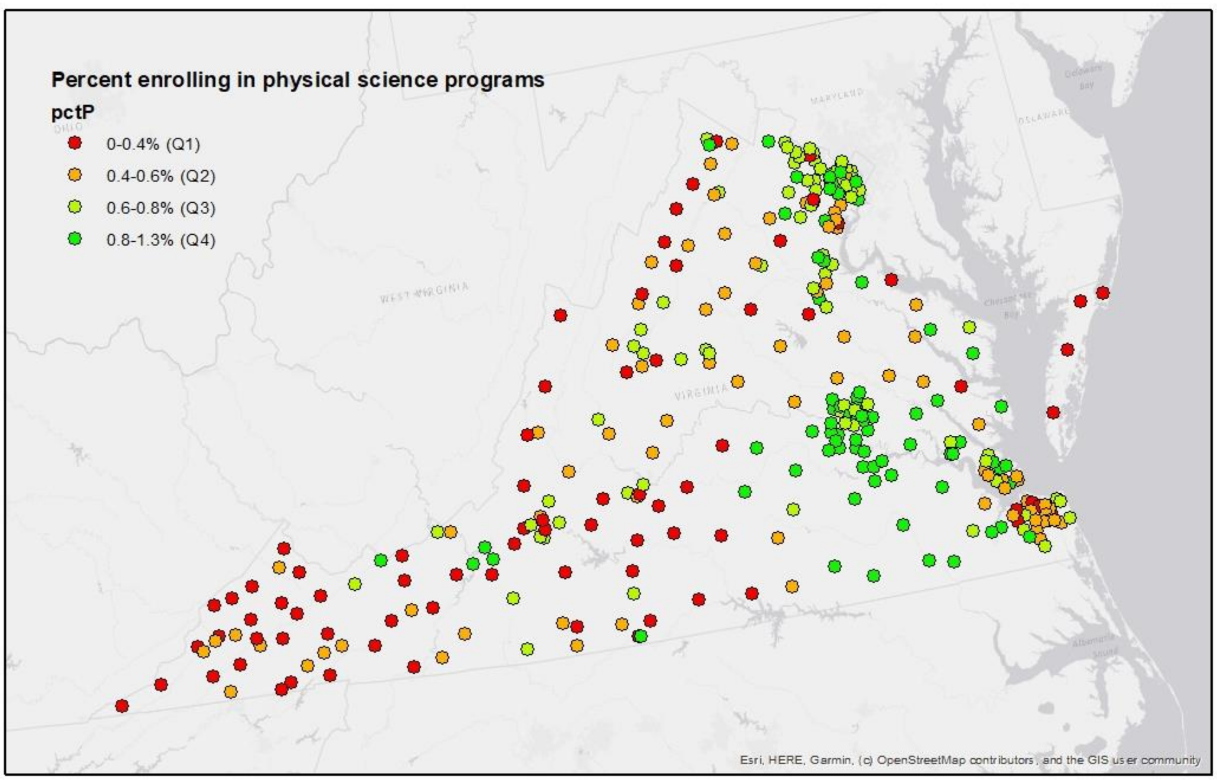

Figure 22. Percent of students enrolling in post-secondary physical science programs.

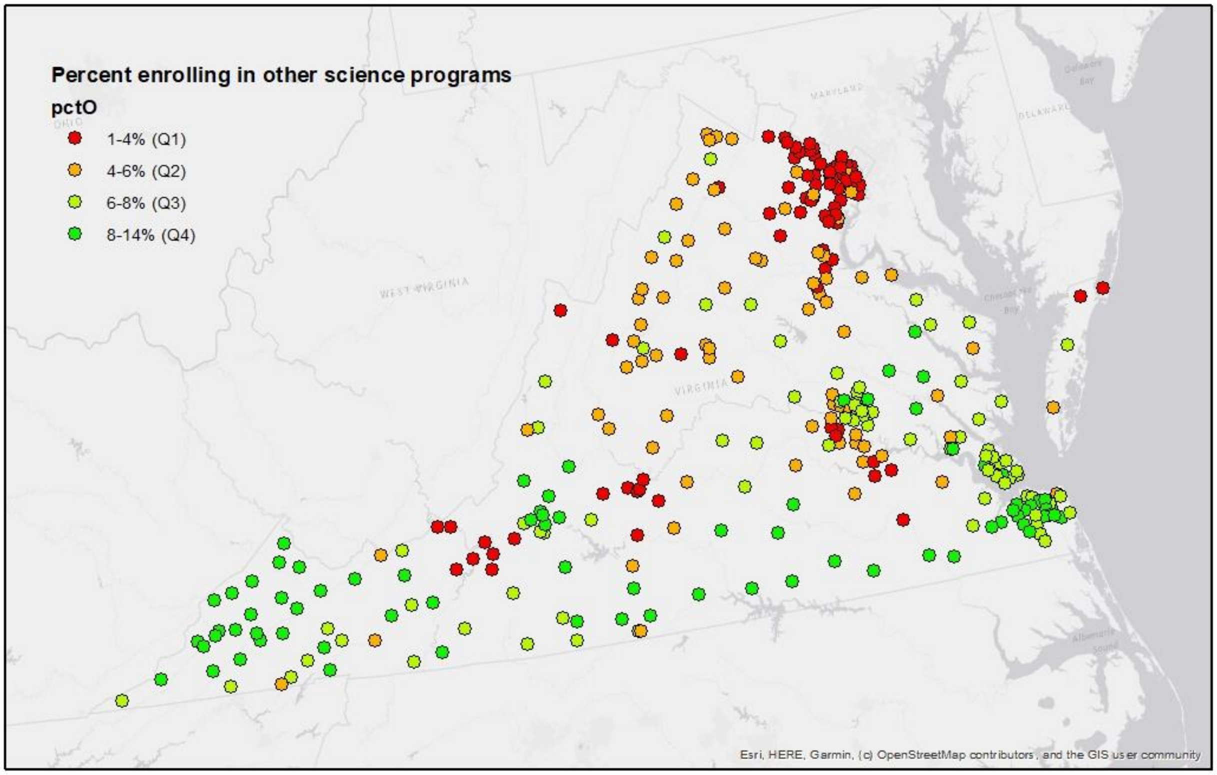

Figure 23. Percent of students enrolling in other post-secondary science programs.

This observed spatial pattern appears to be a combination of preference for type of post-secondary school (i.e., 2-year vs. 4-year) and preference for type of science major. Of students enrolling in four-year schools only, there were regional "pockets" of high or low rates of enrollment in biological sciences (Figure 24) and other sciences (Figure 25). Enrollment in the physical sciences did not demonstrate clear regional patterns (Figure 26).

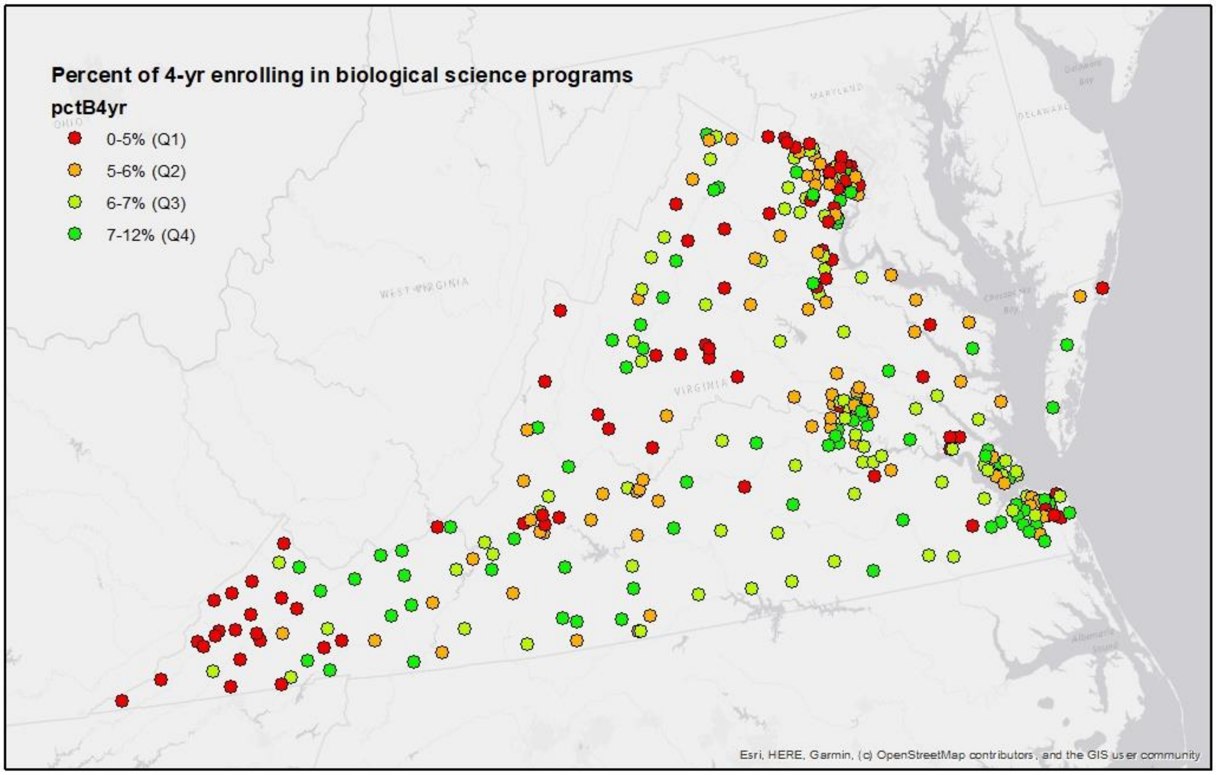

Figure 24. Percent of students enrolling in 4-year schools who majored in biological sciences.

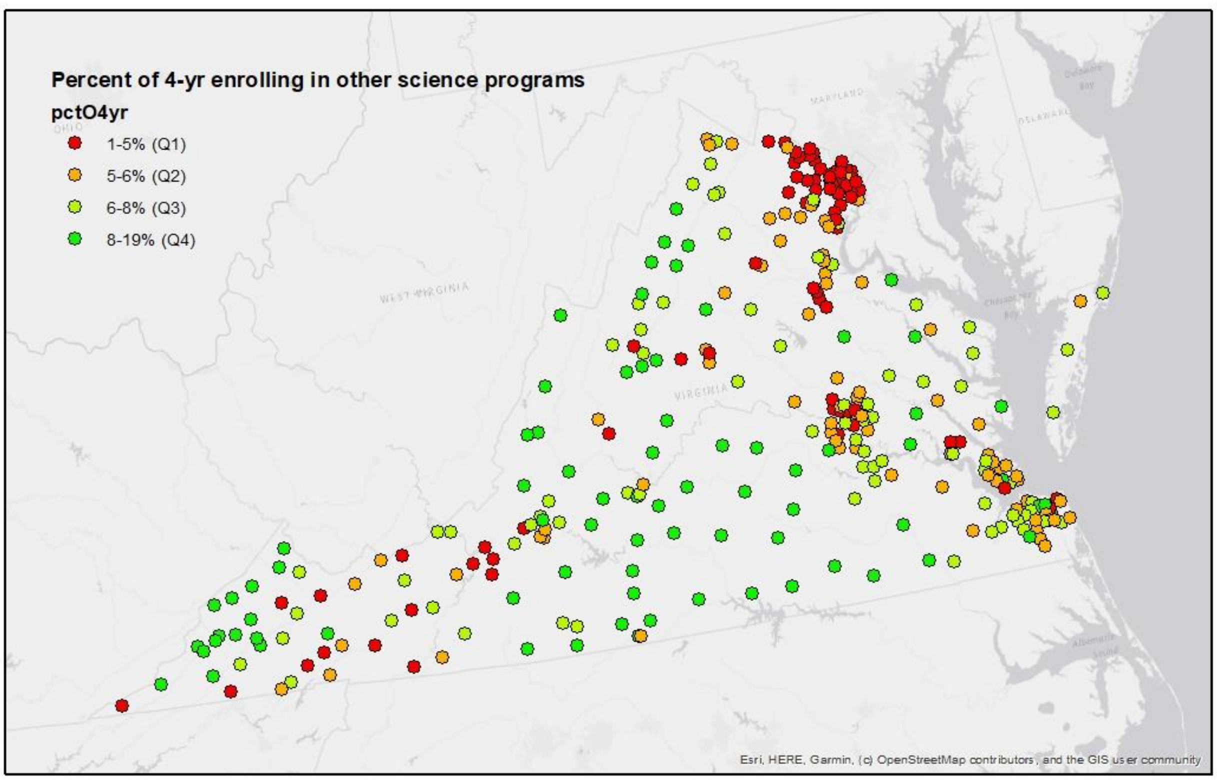

Figure 25. Percent of students enrolling in 4-year schools who majored in other sciences.

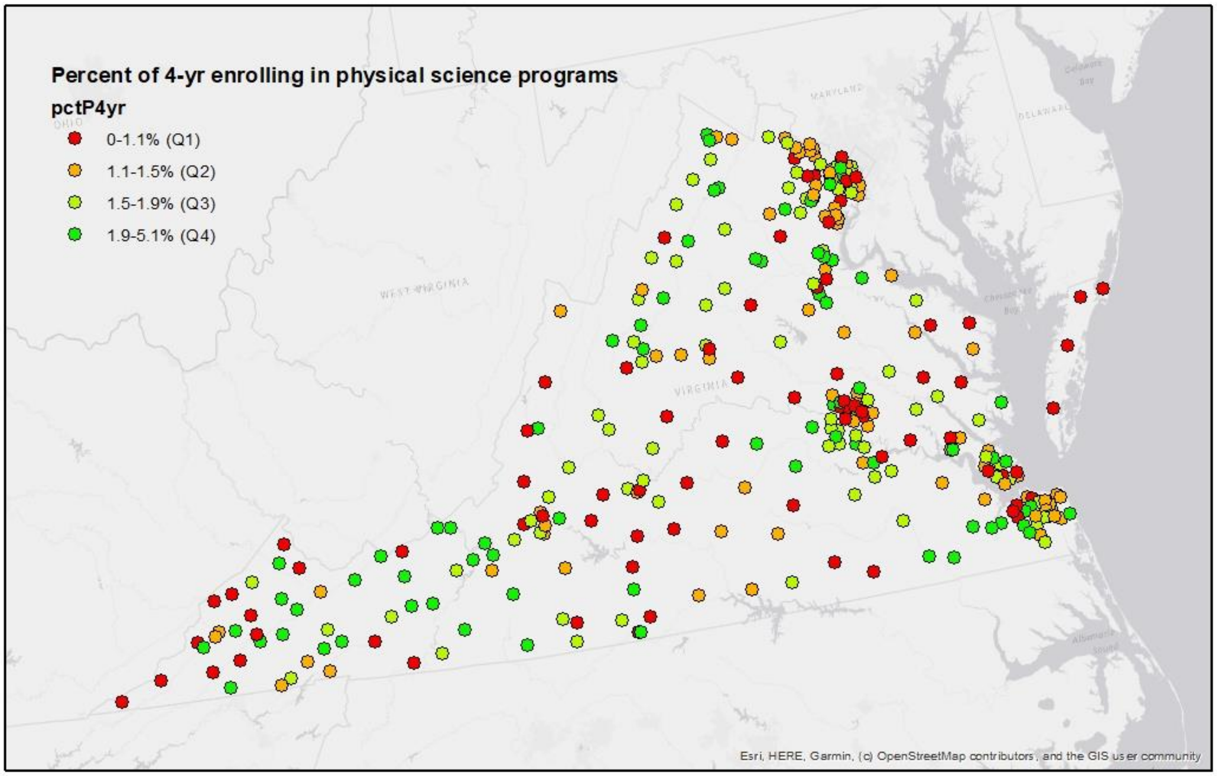

Figure 26. Percent of students enrolling in 4-year schools who majored in physical sciences.

Regional patterns in post-secondary enrollment. Substantial differences in post-secondary enrollment existed across Virginia. For both 2-year and 4-year schools combined, Southside had the largest percentage of post-secondary students entering science and health majors (32%; Table 16), as compared to Northern Virginia, with the lowest percentage of science/health majors (14%). These two regions also had the highest and lowest percentages of students enrolling in all the STEM-H fields combined (50% and 32%, respectively; Table 16 and Figure 27).

Table 16. *Post-secondary Enrollment by Virginia Region and Major Area*

Major Area	Agriculture	Business	Liberal Arts	Science/Health	Eng/CS/Math	Technology	Other
Southside	1%	8%	41%	32%	6%	12%	1%
Central	1%	12%	41%	28%	8%	6%	5%
Southwest	1%	4%	53%	24%	3%	13%	2%
Tidewater	0%	12%	41%	22%	8%	8%	9%
N. Neck	0%	7%	53%	21%	8%	6%	3%
Western	1%	8%	47%	21%	6%	11%	6%
Valley	1%	8%	54%	19%	7%	7%	4%
Northern	0%	13%	49%	14%	13%	5%	5%

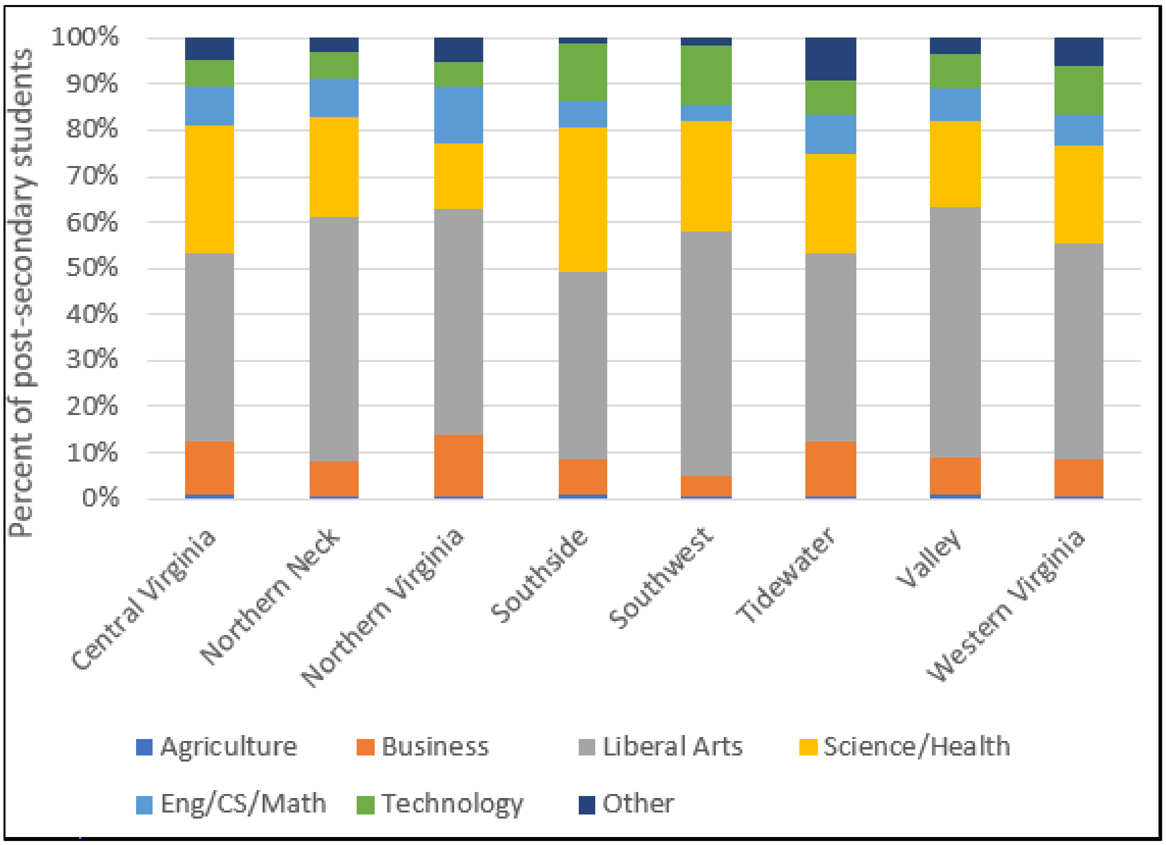

Figure 27. Post-secondary enrollment by major area, by Virginia region.

When narrowing the focus to only 4-year schools, the picture changes. The largest number of science majors enrolling in 4-year schools came from Northern Virginia (Figure 28), and the 4-year schools with the highest enrollment of science majors were: James Madison University, Virginia Commonwealth University, Virginia Tech, George Mason University, and

Old Dominion University (Figure 28). However, regions differed greatly in the percent of students who enrolled in these and other 4-year schools (Figure 29), and the schools in the "other VA" category differed among regions. Other post-secondary schools that received more than 10% of a region's 4-year science majors included: Longwood University (Southside, 17%), University of Virginia at Wise (Southwest, 24%), Radford University (Southwest, 16%, and Western, 11%), Norfolk State University (Tidewater, 13%), and Jefferson College of Health Sciences (Western, 11%).

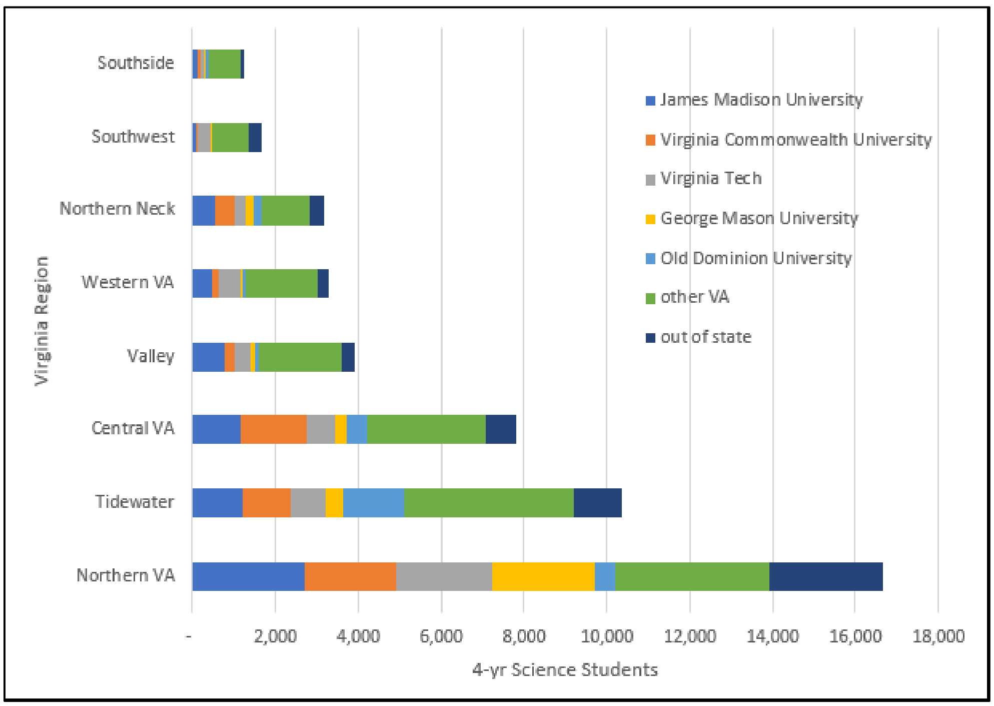

Figure 28. Frequency of enrollment at 4-year post-secondary schools for science majors, by Virginia region.

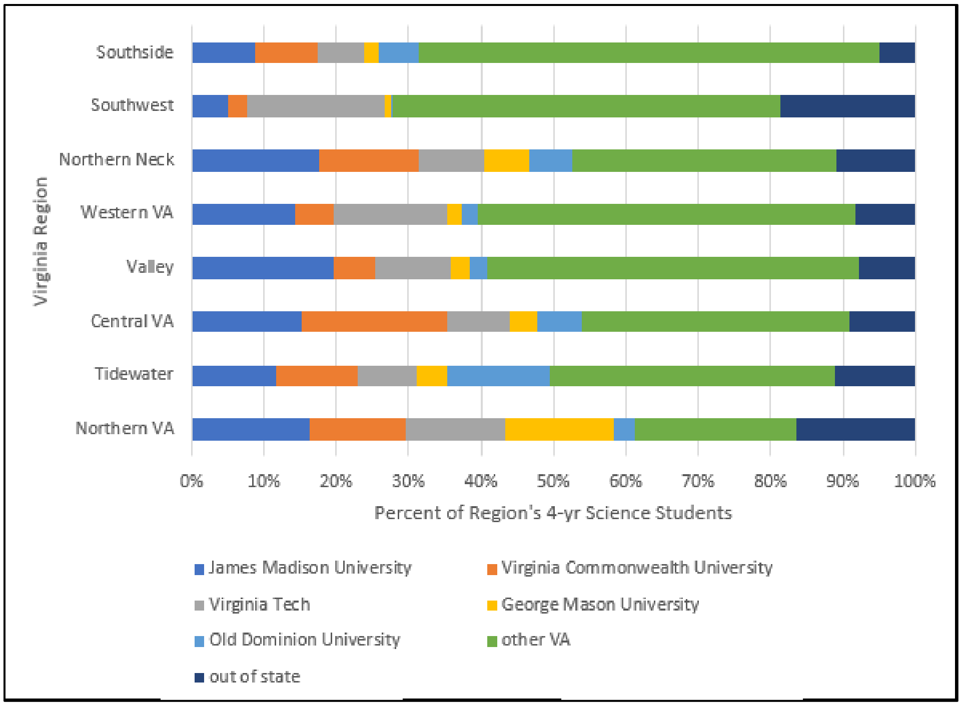

Figure 29. Relative frequency of enrollment at 4-year post-secondary schools for Virginia science majors, by Virginia region.

Temporal patterns in post-secondary science enrollment. The percent of high school completers who enrolled in post-secondary school decreased slightly from 2005-2015 (Figure 6). However, the proportion of those post-secondary students who enrolled in science approximately doubled during that time period for both male and female students (Figure 30), as well as for each of the major science fields (Figure 31).

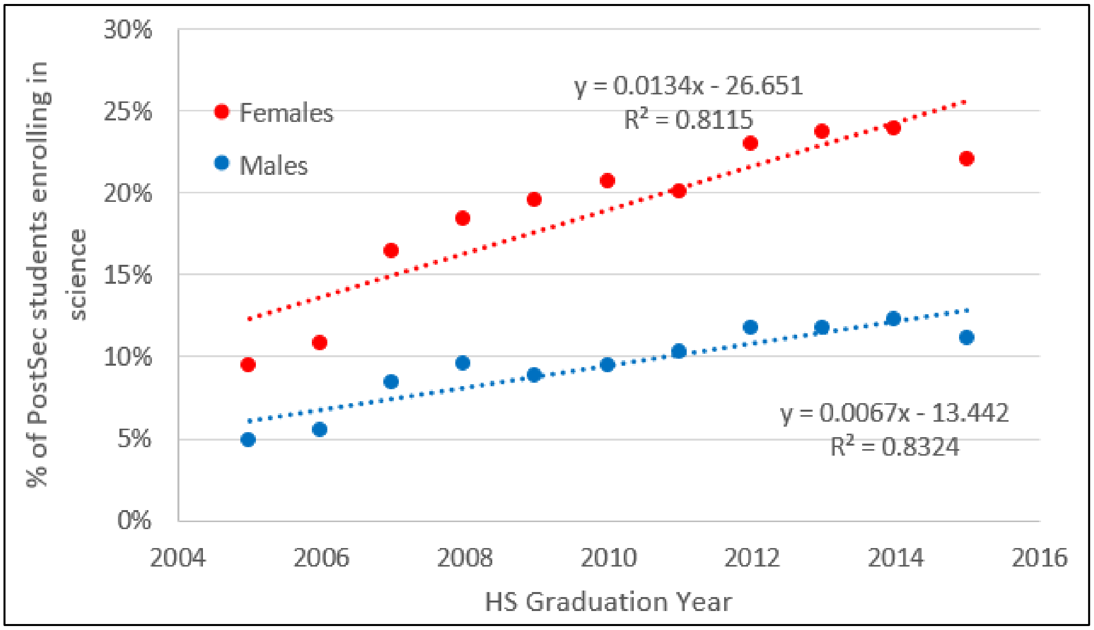

Figure 30. Changes in percent of post-secondary students enrolling in science programs, by gender.

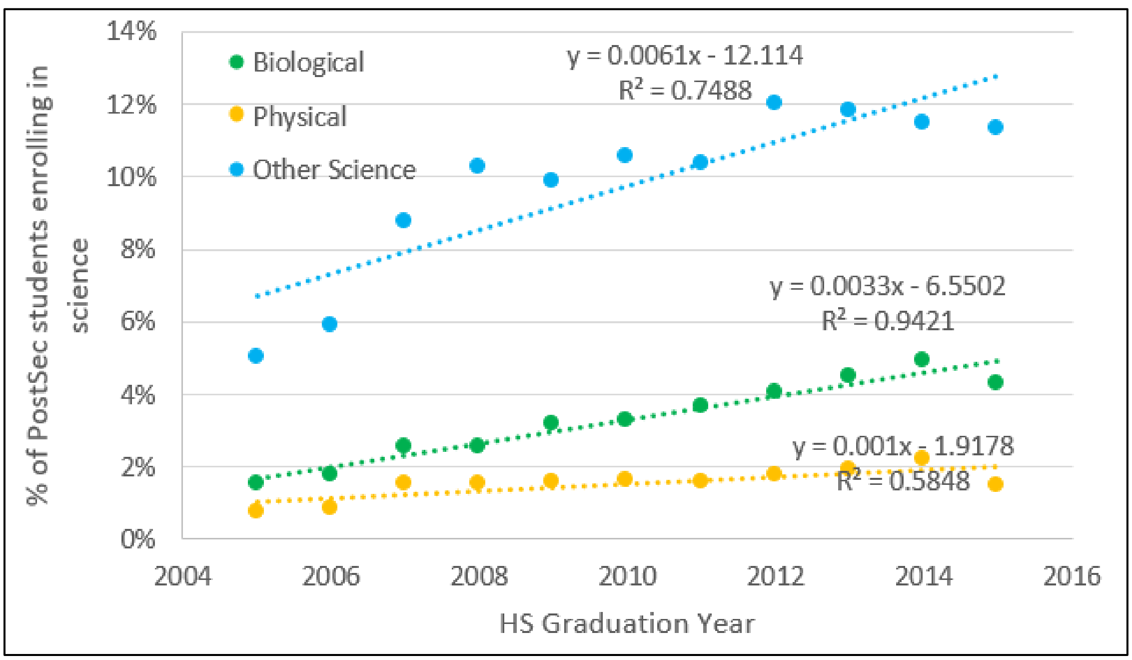

Figure 31. Changes in percent of post-secondary students enrolling in science programs, by science field.

Spatiotemporal patterns in post-secondary science enrollment. The temporal trends in science-going rates were also affected by spatial factors, as regional differences were observed. Relative to the number of students bound for post-secondary school, the rates of enrolling in science showed higher growth around Norfolk and Newport News, in the southeastern part of the state, as compared to Northern Virginia (Figure 32). Trends in the rates of enrolling in different science fields also differed across Virginia, with faster growth in biological science enrollment in the southeastern part of the state (Figure 33) and faster growth in physical science enrollment around Richmond (Figure 34). High schools with faster growth in enrollment in other sciences were dispersed throughout the state (Figure 35).

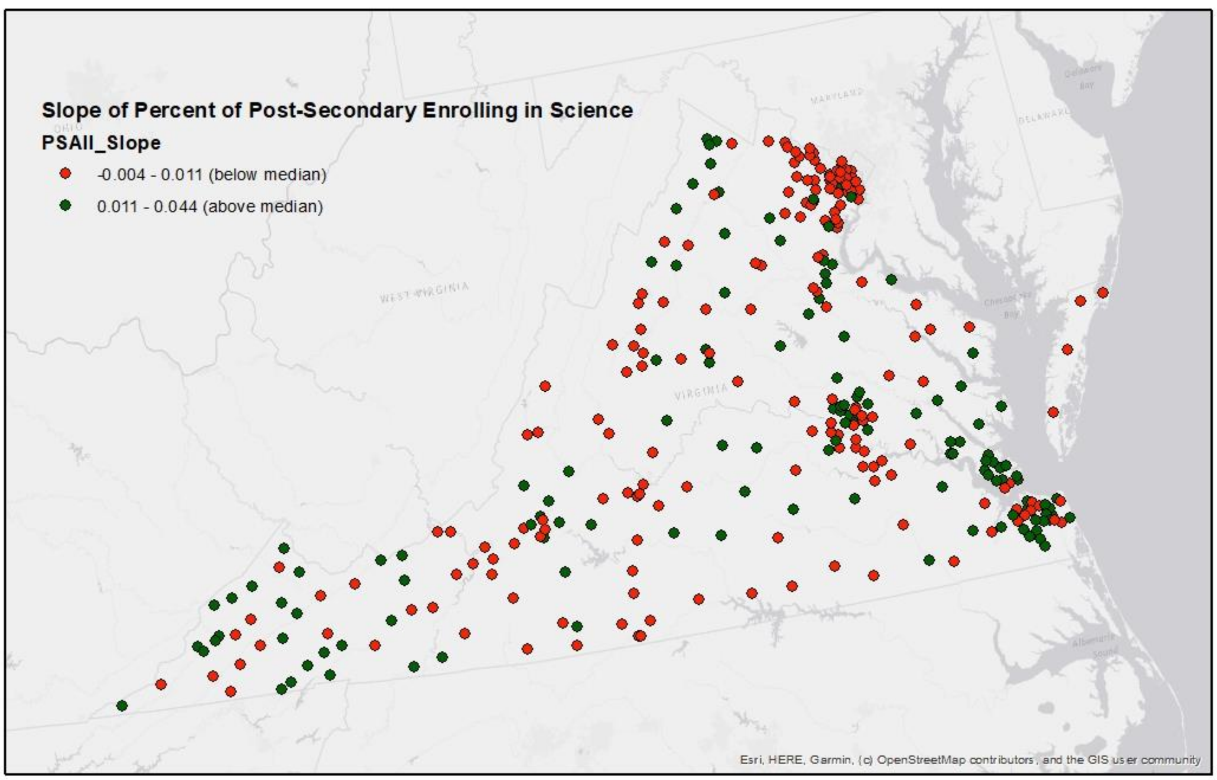

Figure 32. Slope of linear regression of the percent of students enrolling in post-secondary school who selected a science major, by high school from 2005-2015.

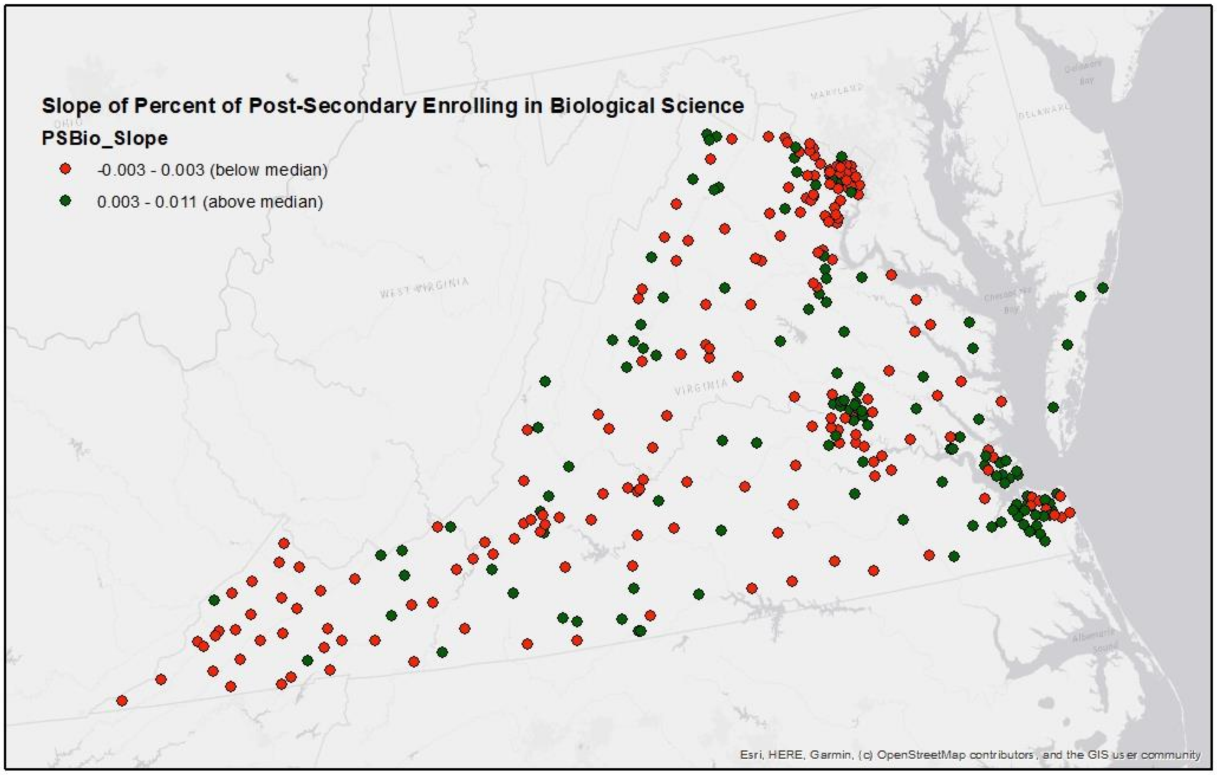

Figure 33. Slope of linear regression of the percent of students enrolling in post-secondary school who selected a biological science major, by high school from 2005-2015.

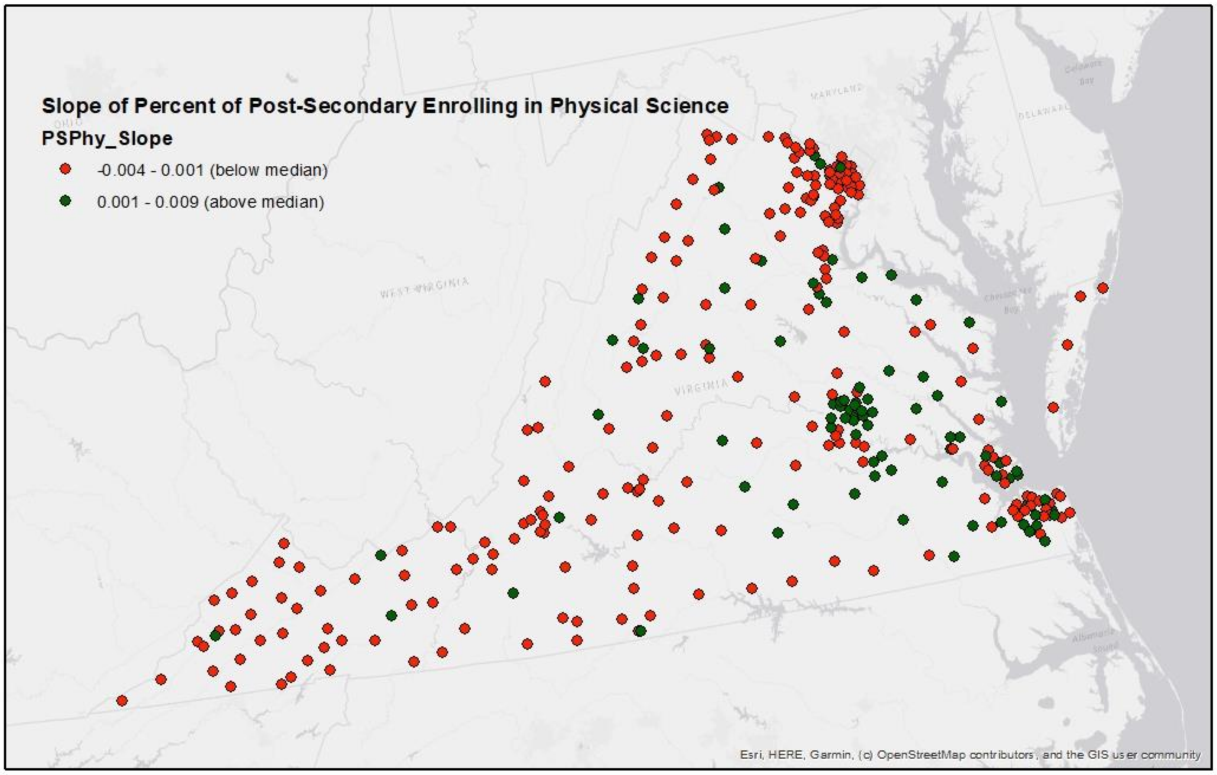

Figure 34. Slope of linear regression of the percent of students enrolling in post-secondary school who selected a physical science major, by high school from 2005-2015.

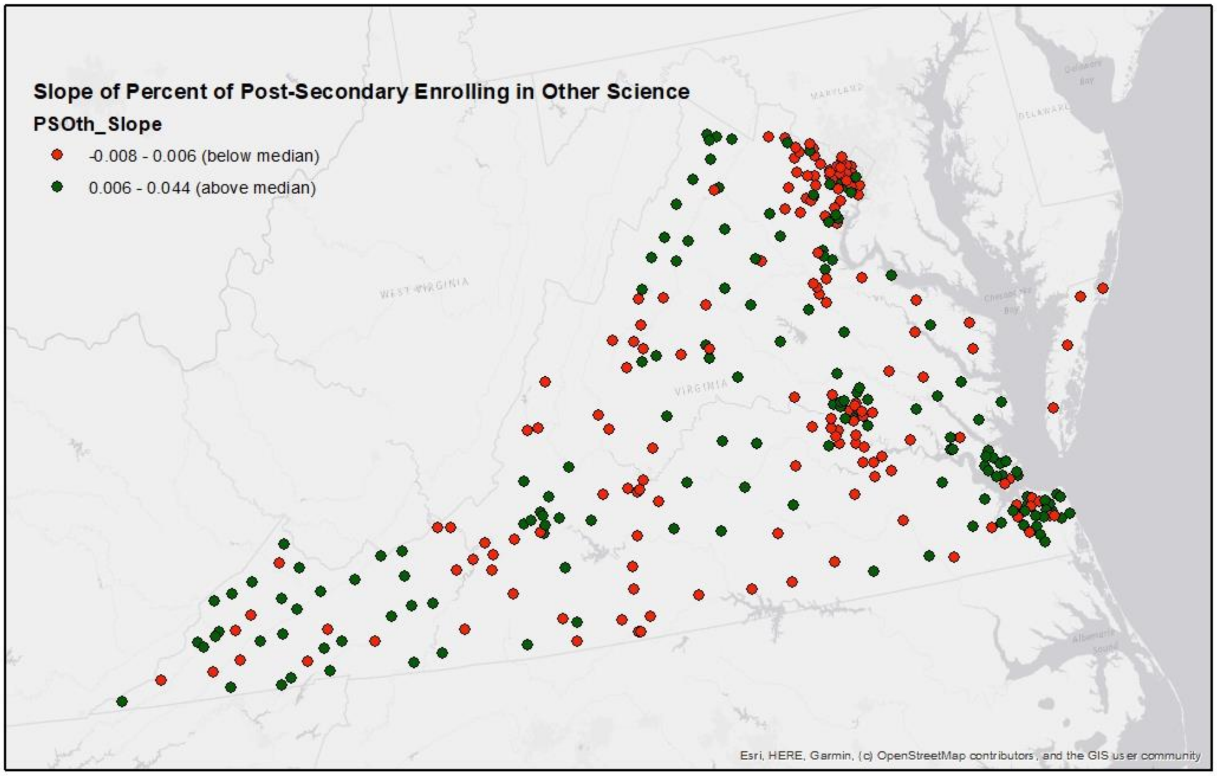

Figure 35. Slope of linear regression of the percent of students enrolling in post-secondary school who selected a major in an "other" science major field, by high school from 2005-2015.

Logistic regression of academic and demographic factors. Stepwise logistic regression required complete cases, but data were incomplete for the majority of students (Table 17). Data from 14,680 students were used for logistic regression, and data from 1,074,709 incomplete cases were omitted from stepwise model selection.

Table 17. *Data Missingness for Stepwise Logistic Regression*

Variable	Percent Missing
SOL Grade 5	66%
SOL Grade 8	70%
SOL Earth Sci	64%
SOL Biology	59%
SOL Chemistry	74%
Average science grade	57%

Stepwise regression for all science majors (vs. all other high school completers) identified the highly significant variables of gender, mean science grade, and the high school's percent of students majoring in science (Table 18). For science majors at 2-year schools, the student variables of gender, economically disadvantaged status, and mean science grade, and the high school variables of percent entering science and percent entering 4-year post-secondary schools were all highly significant (Table 19). Similarly, for science majors at 4-year schools, the student variables of gender, economically disadvantaged status, and mean science grade, and the high school variable of percent economically disadvantaged were all highly significant (Table 20).

Table 18. *Results of Stepwise Logistic Regression for All Science Majors (2-year and 4-year)*

Variable	P-Value	Estimate	Odds Ratio
Female	< 0.0001 ***	0.859	2.360
Disadvantaged	0.16	-0.089	0.915
SOL Grade 8	0.05	0.001	1.001
SOL Earth Sci	0.09	0.002	1.002
SOL Biology	0.03 *	-0.002	0.998
Ave. science grade	< 0.0001 ***	0.028	1.028
HS % entering science	< 0.0001 ***	11.942	153,656
HS % entering 4-year	0.10	-0.372	0.690

*** p<0.001, * p<0.05

Table 19. *Results of Stepwise Logistic Regression for Students Enrolling in Science Programs at 2-year Post-secondary Schools*

Variable	P-Value	Estimate	Odds Ratio
URM	0.03 *	-0.187	0.829
Female	< 0.0001 ***	0.989	2.688
Disadvantaged	0.0001 ***	0.337	1.401
SOL Biology	0.06	-0.002	0.998
SOL Chemistry	0.009 **	0.003	1.003
Ave. science grade	0.0003 ***	-0.019	0.981
HS % entering science	< 0.0001 ***	18.625	122,674,200
HS % entering 4-year	< 0.0001 ***	-2.393	0.091

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

Table 20. *Results of Stepwise Logistic Regression for Students Enrolling in Science Programs at 4-year Post-secondary Schools*

Variable	P-Value	Estimate	Odds Ratio
URM	0.08	0.152	1.165
Female	< 0.0001 ***	0.671	1.956
Disadvantaged	< 0.0001 ***	-0.569	0.566
SOL Grade 8	0.07	0.001	1.001
Ave. science grade	< 0.0001 ***	0.074	1.077
HS % entering science	0.02 *	3.272	26.364
HS % URM	0.002 **	0.779	2.180
HS % disadvantaged	0.0004 ***	-1.221	0.295

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

Given that gender was such a significant factor in all the regressions with females and males pooled, additional logistic regressions were conducted for males and females separately. For both gender-specific regressions, mean science grade and the high school's percent entering science were highly significant (Table 21 and Table 22), although grades appeared to be more influential for male students, whereas the effect of high school science percent was greater for female science students.

Table 21. *Results of Stepwise Logistic Regression for Female Students Enrolling in Post-secondary Science Programs*

Variable	P-Value	Estimate	Odds Ratio
SOL Earth Sci	0.02 *	0.003	1.003
SOL Biology	0.08	-0.002	0.998
Ave. science grade	< 0.0001 ***	0.021	1.021
HS % entering science	< 0.0001 ***	12.579	290,513
HS % entering 4-year	0.02 *	-0.653	0.520

*** p<0.001, * p<0.05

Table 22. *Results of Stepwise Logistic Regression for Male Students Enrolling in Post-secondary Science Programs*

Variable	P-Value	Estimate	Odds Ratio
Disadvantaged	0.007 **	-0.313	0.732
SOL Grade 8	0.09	0.001	1.001
Ave. science grade	< 0.0001 ***	0.034	1.041
HS % entering science	< 0.0001 ***	10.415	33,365

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

A large number of variables and multiple subgroups were used for logistic regression, so Table 23 was created to help identify patterns and consistently significant variables. Gender and mean science grade were highly significant in all regressions conducted, and the high school-level variable of percent of students entering science was also highly significant in the majority of regressions. Economically disadvantaged status (both at the student level and high school level) appeared to be a factor that separated science students into 2-year and 4-year post-secondary groups. Overall, science SOL scores were not significant factors in these logistic regressions.

Table 23. Summary of Significance of Variables in Stepwise Logistic Regression

Variable	All Science	2-Year Science	4-Year Science	Female	Male
URM	-	*	-	-	-
Female	***	***	***	NA	NA
Disadvantaged	-	***	***	-	**
SOL Grade 5	-	-	-	-	-
SOL Grade 8	-	-	-	-	-
SOL Earth Sci	-	-	-	*	-
SOL Biology	*	-	-	-	-
SOL Chemistry	-	**	-	-	-
Ave. science grade	***	***	***	***	***
HS % entering science	***	***	*	***	***
HS % URM	-	-	**	-	-
HS % disadvantaged	-	-	***	-	-
HS % entering 2-year	-	-	-	-	-
HS % entering 4-year	-	***	-	*	-

*** p<0.001, ** p<0.01, * p<0.05, - p>0.05

Principal components analyses of academic and demographic factors. Using the highly significant variables from logistic regression, principal components analyses (PCA) were conducted for all science majors (Figure 36), science majors at 2-year schools (Figure 37), and science majors at 4-year schools (Figure 38). The biplots created from these analyses help illustrate the similarities and differences within and among science majors. For example, the biplot of all science majors (Figure 36) demonstrate the gender differences between physical sciences and health sciences, where the group of health science majors is shifted toward the higher values in the Female.Flag variable (where 1=female and 0=male). Also, the biological sciences were all relatively consistent along the AveGrade variable of mean science grade, but the health sciences show a large range in this variable, from high grades in H.Medicine (pre-med) majors to low grades in H.Alternative (alternative medicines).

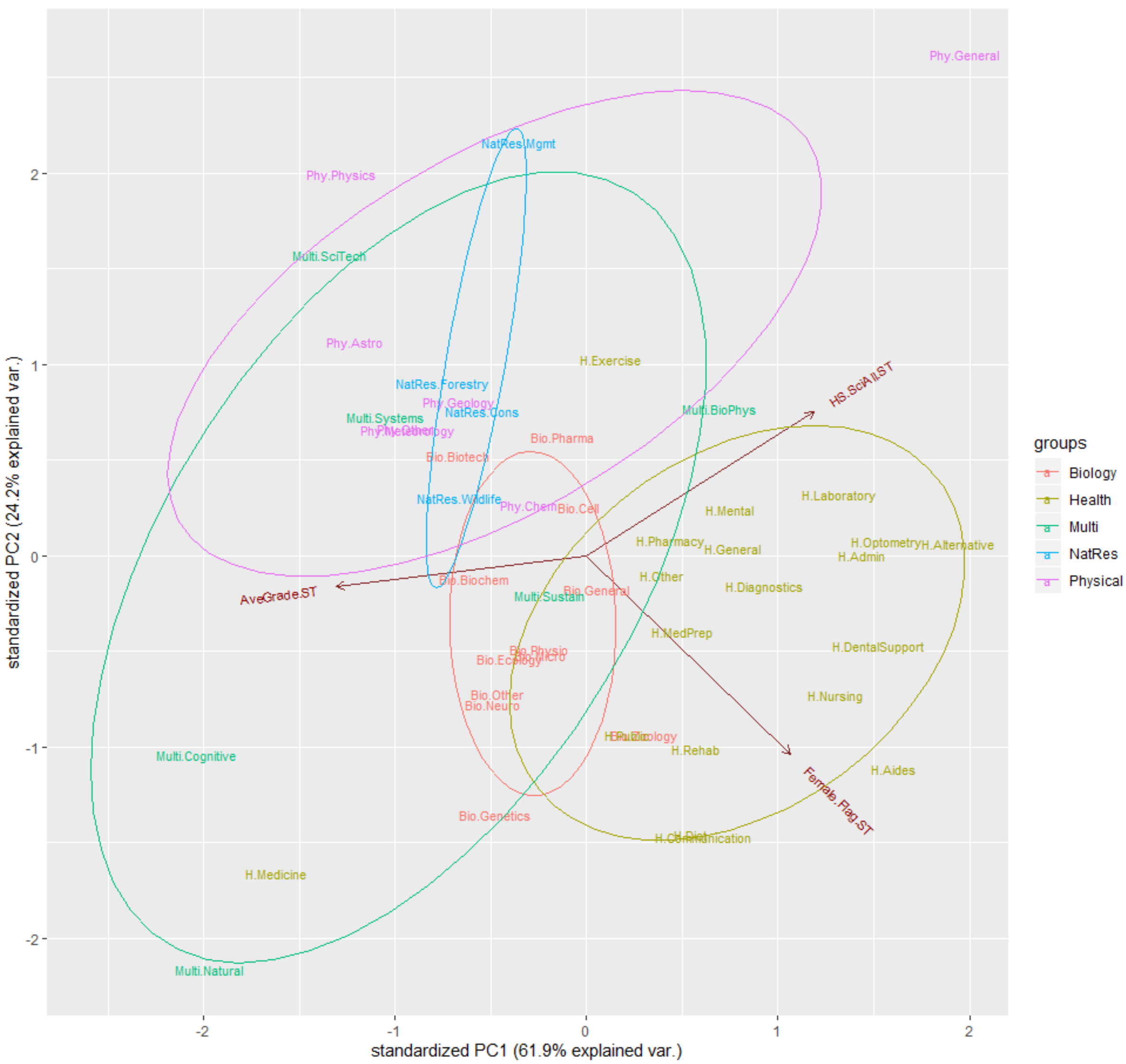

Figure 36. Biplot from principal components analysis of science majors, based on highly significant factors from logistic regression.

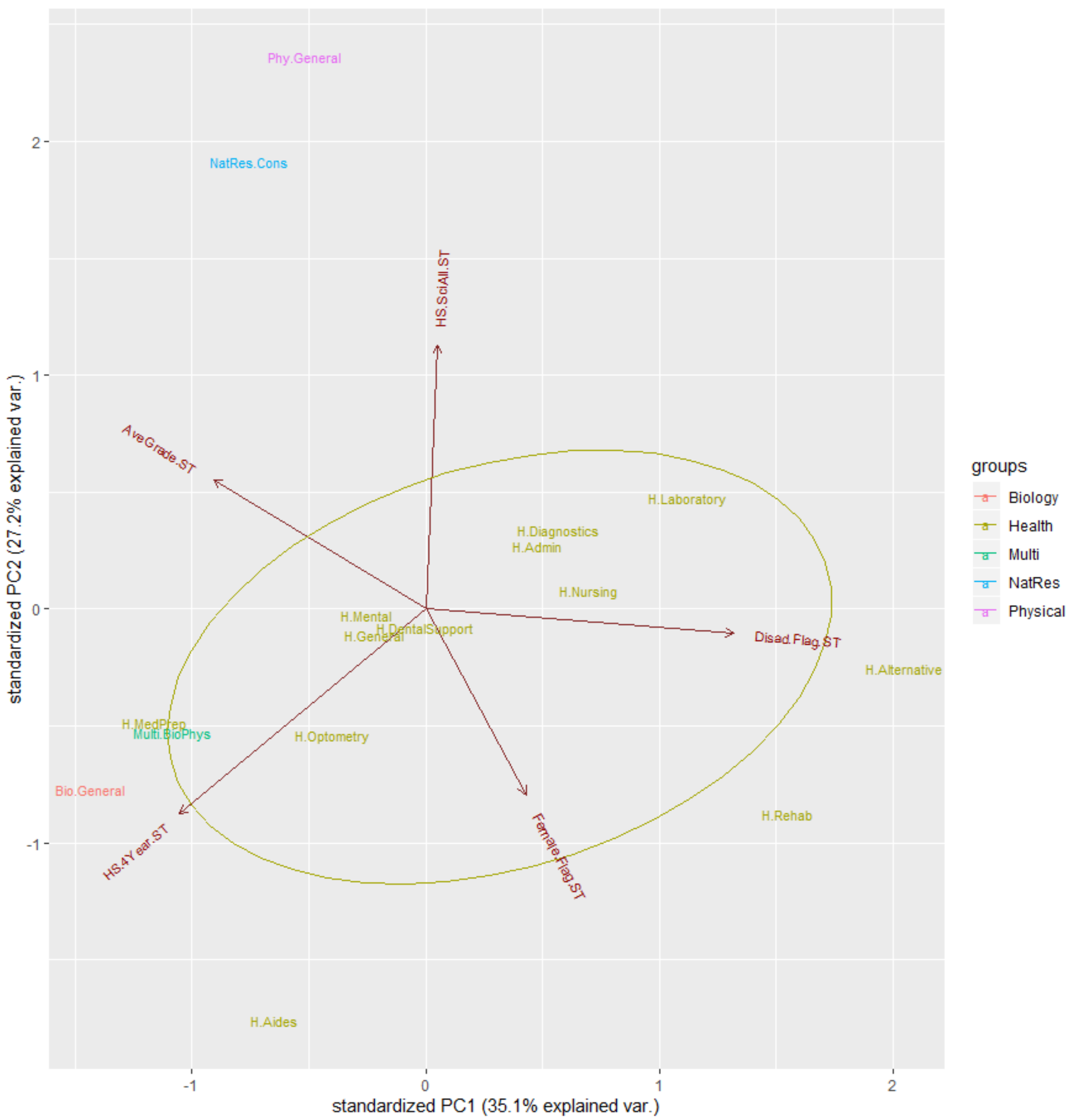

Figure 37. Biplot from principal components analysis of science majors at 2-year schools, based on highly significant factors from logistic regression.

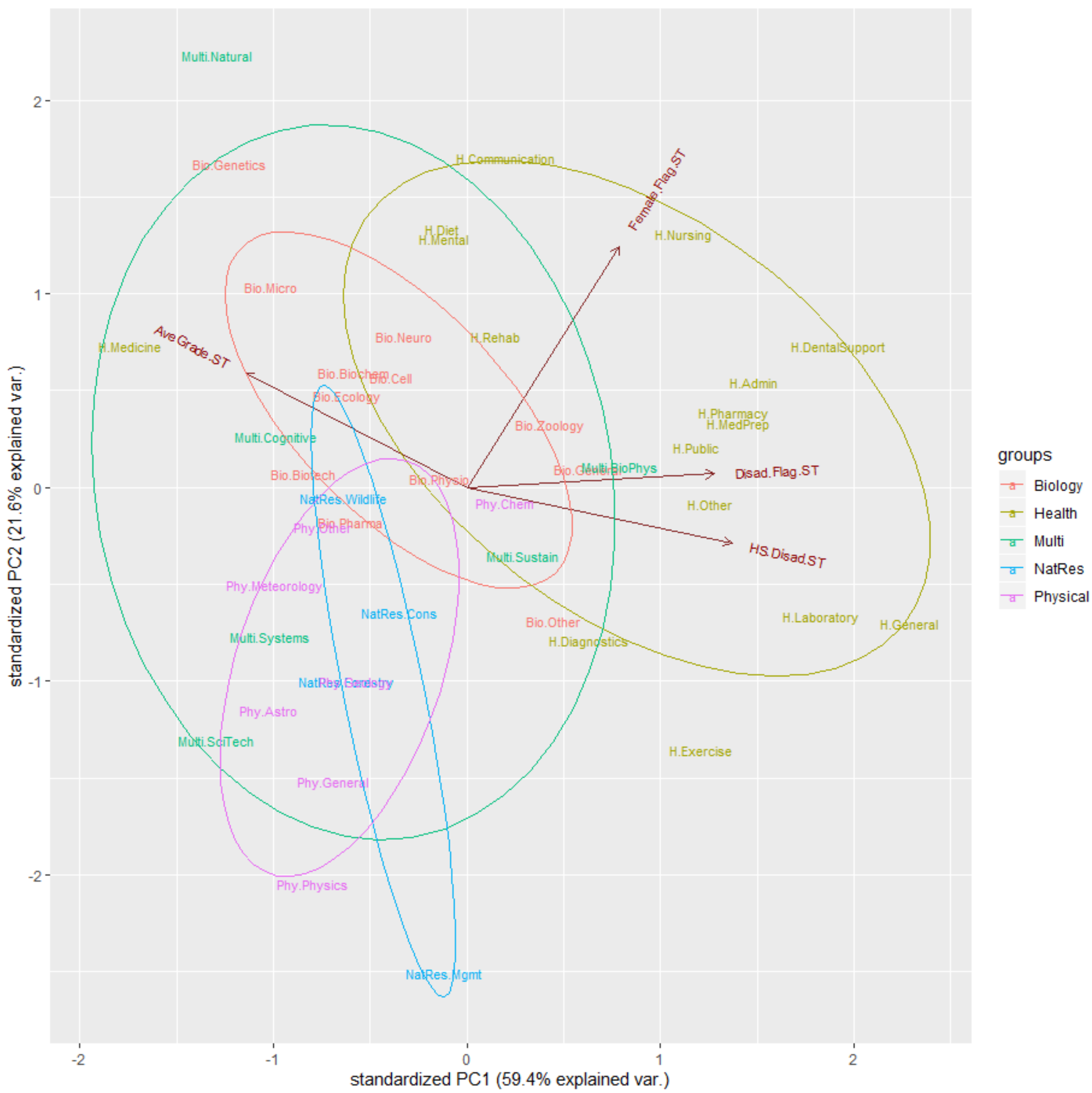

Figure 38. Biplot from principal components analysis of science majors at 4-year schools, based on highly significant factors from logistic regression.

PCA biplots for female (Figure 39) and male (Figure 40) science students were based on the same highly significant variables from logistic regressions: mean science grade and percent of students at the student's high school who enrolled in science. Male and female science students showed very similar patterns among and within science major groups.

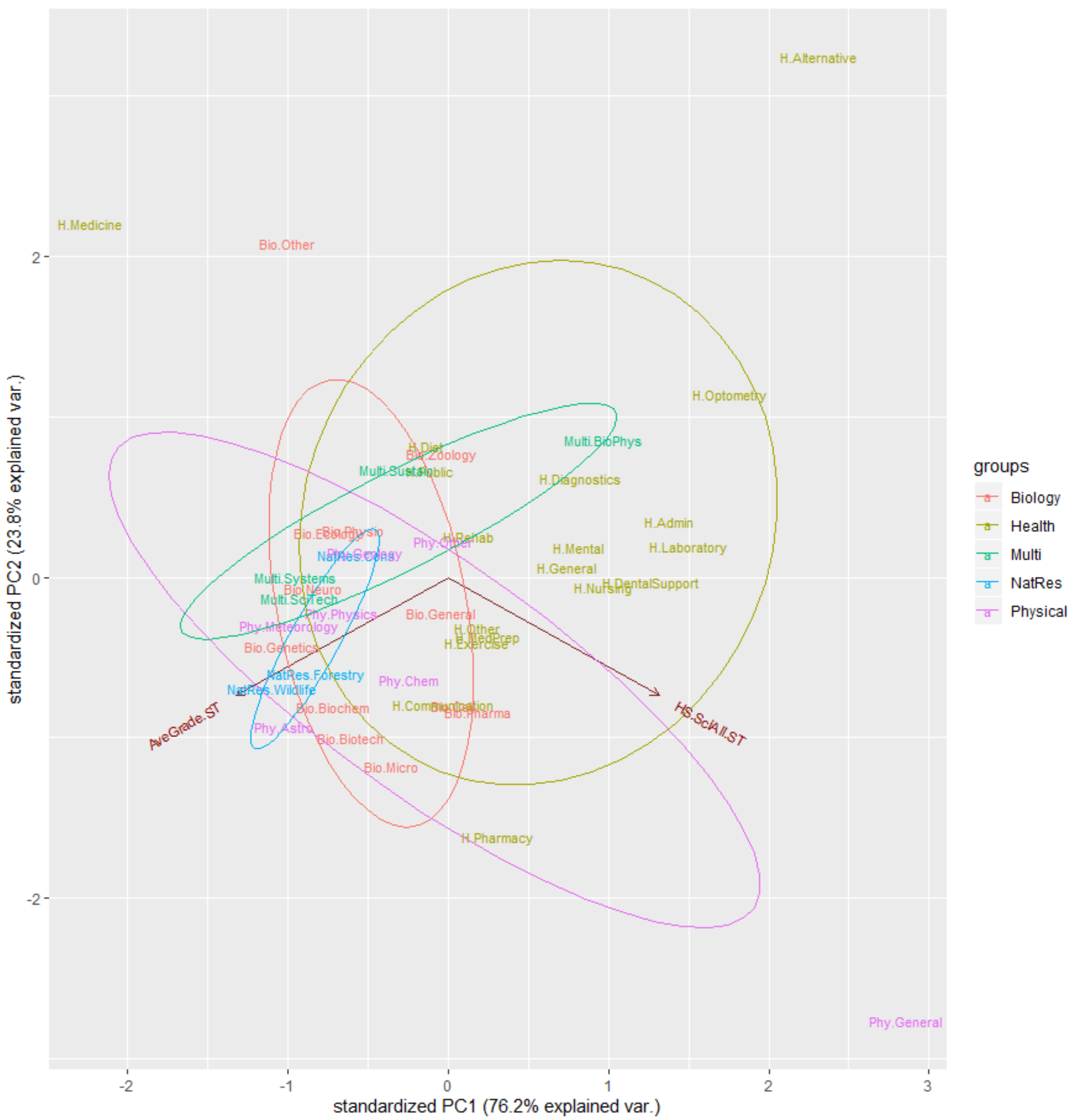

Figure 39. Biplot from principal components analysis of female science majors, based on highly significant factors from logistic regression.

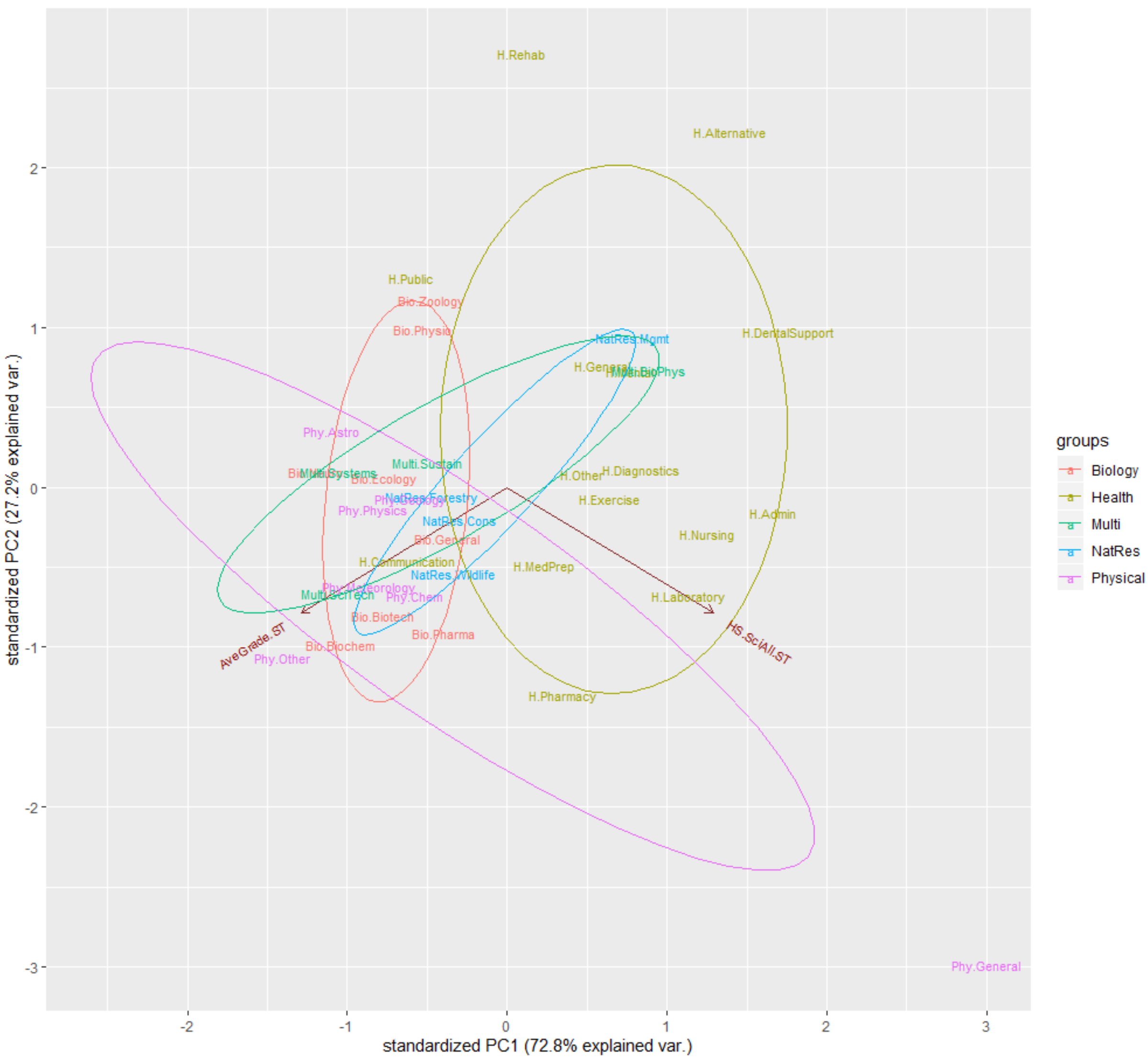

Figure 40. Biplot from principal components analysis of male science majors, based on highly significant factors from logistic regression.

Post-secondary path of high science achievers. Students scoring in the top 5% of students on their Biology SOL or Chemistry SOL scores did not differ from the overall population in likelihood of selecting a post-secondary major in science (Figure 41 and Table 24). In comparison, students with mean science grade in the top 5% of students were somewhat more likely to major in science (23% vs. 20%) or engineering/computer science/math (13% vs. 9%).

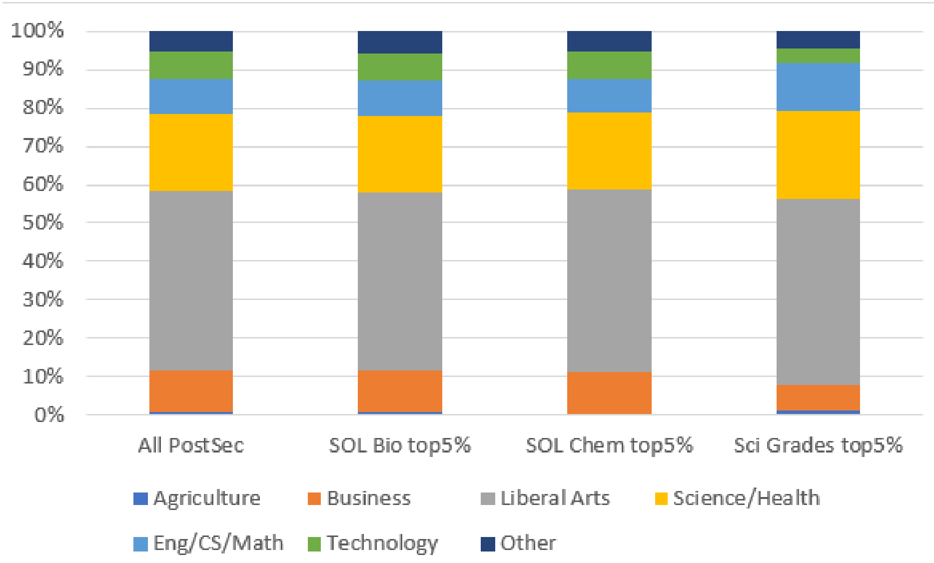

Figure 41. Post-secondary majors of students scoring in top 5% of Biology SOL, Chemistry SOL, or mean science grade, as compared to the overall population.

Table 24. Post-secondary Majors of High Science Achievers

Major Area	All Post-Sec Students	Top 5% SOL Biology	Top 5% SOL Chemistry	Top 5% Science Grades
Agriculture	1%	1%	0%	1%
Business	11%	11%	11%	7%
Liberal Arts	47%	46%	48%	48%
Science/Health	20%	20%	20%	23%
Eng/CS/Math	9%	9%	9%	13%
Technology	7%	7%	7%	4%
Other	6%	6%	5%	4%

Comparison of post-secondary major fields. A PCA was conducted on all post-secondary majors to visualize how science majors fit into this larger picture. The student variable of gender and the high school variables of percent economically disadvantaged and percent enrolling in 4-year post-secondary school were used in the PCA (Figure 42); these factors were consistently significant in logistic regressions related to science majors. In the biplot, the groups of Science/Health and Liberal Arts overlapped substantially. However, the different STEM fields had little overlap, based on these three axes.

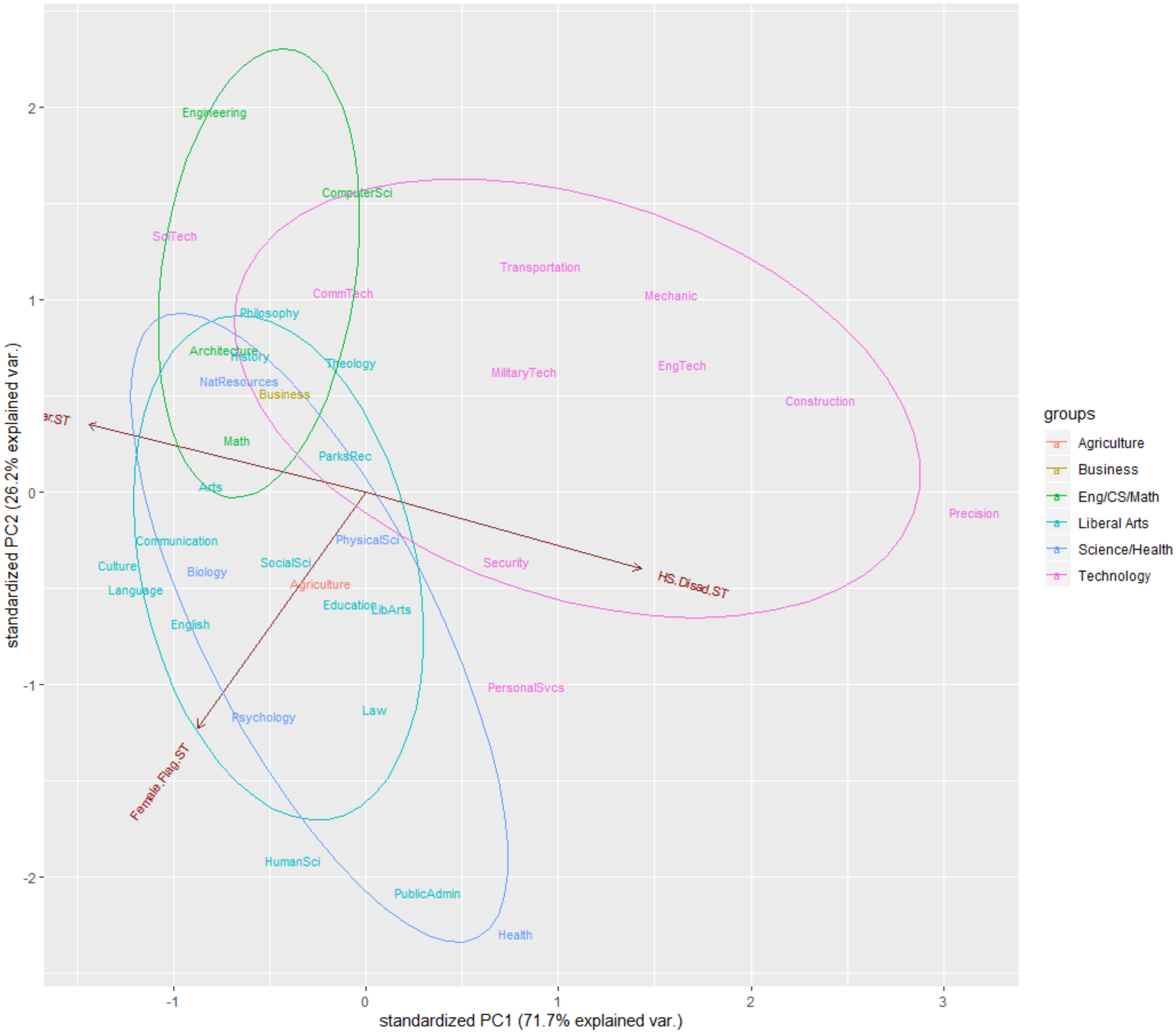

Figure 42. Biplot from principal components analysis of all majors, based on gender and the high school variables of percent economically disadvantaged and percent enrolling in 4-year post-secondary school.

5. Alignment of Post-Secondary Paths and Science Workforce Projections

Virginia occupational projections and post-secondary enrollment. Although post-secondary majors and occupations do not have a one-to-one relationship, attempts were made to categorize and align post-secondary science majors at 2-year and 4-year schools with occupations listed in the Virginia Employment Commission (2018) occupational projections (Table 25). The calculations of annual surplus or shortfall numbers assumed that all students who initially majored in a field would complete a degree and enter that occupation; the actual number of students following this path would be much lower. According to these estimates, there will be an excess of life scientists, physical scientists, and science technicians. In contrast, most of the health-related fields will have a shortfall of career entrants, due in large part to the fast growth expected in healthcare occupations (Virginia Employment Commission, 2018).

Table 25. *Employment Projections by Occupation for Virginia (2016-2026), as Related to Post-Secondary Enrollment in Science*

Occupation	Estimated Jobs 2016[a]	Projected Jobs 2026[a]	Annual Change[a]	Annual # of Majors[b]	Annual Surplus (or Shortfall)[b]
Life Scientists	5,403	6,172	77	1,898	1,821
Physical Scientists	8,005	8,805	80	530	450
Science Technicians	8,287	9,061	77	1,670	1,593
Health Practitioners	128,157	151,488	2,333	1,271	(1,062)
Health Technologists	78,657	91,713	1,306	778	(528)
Other Health Technicians	5,264	5,912	65	86	21
Nursing and Health Aides	51,803	65,767	1,396	1,112	(284)
Physical Therapists	5,078	6,824	175	6	(169)
Other Healthcare Support	36,577	46,482	990	181	(809)

a: Data from Virginia Employment Commission (2018)
b: Results from this study

Summary of Key Findings

The previous sections contained a large number of results and findings from this study. This section highlights the key findings relevant to each research question, which will form the basis for discussion in Chapter 5.

Research Question 1: What are the academic profiles of Virginia students, by gender, who initially selected a post-secondary science major?

- Approximately 8% of high school completers enrolled in a post-secondary science program, with half of those at 2-year schools and half at 4-year schools.

- Students enrolling in science were predominantly female (around 70% of science students).
- Nearly all 4-year science majors (88%) enrolled in a post-secondary school in Virginia.
- Logistic regressions identified gender, mean science grade, and the high school's percent of students enrolling in science as significant factors in whether or not students enroll in a post-secondary science program.
- The split between 2-year and 4-year science programs was most closely related to an individual's status as economically disadvantaged or URM and the high school-level metrics of percent disadvantaged, percent URM, and percent attending 4-year schools.
- Principal components analysis illustrated the wide range of science pathways that exist.

Research Question 2: How do science-related educational metrics of high school completers compare with metrics of a.) students entering science programs at 2-year schools, and b.) students entering science programs at 4-year schools?

- Science-focused standardized assessments (SOLs, SAT, ACT, and AP) were positively correlated with each other. Science course grades were not correlated with standardized assessment scores.
- Mean science grade differed significantly among student subgroups, with females scoring higher than males, non-URM students scoring higher than URM students, and non-economically disadvantaged students scoring higher than economically disadvantaged students.
- Similarly, students entering 4-year science programs received higher grades than students entering 2-year science programs, who outscored high school completers.
- SOL scores did not differ significantly among student subgroups.

- The percent of economically disadvantaged students at a high school was negatively correlated with most science-related metrics.
- Demographic and high school-level factors were more closely related to science pathways than were SOL scores.

Research Question 3: To what extent are gender-specific patterns in academic profiles reflective of the progression toward a post-secondary science major for Virginia students?

- Gender was the driving factor in many of the analyses related to academic pathways into science.
- Other demographic factors – both at the individual level and the school level – were related to specific pathways, such as the split between 2-year and 4-year science programs.
- Regional patterns in post-secondary science pathways (both major and type of school) were evident, with more students in southern and western Virginia enrolling in science.
- Temporal trends showed slightly decreasing post-secondary enrollment in all fields from 2005-2015, but the percent of students majoring in science doubled during that time for male and female students, as well as for biological, physical, and other science categories.

Chapter 5 – Discussion

Introduction

Discussion in this chapter will progress from a micro-level evaluation of data to an individual-level evaluation of pathways, culminating in a macro-level evaluation of larger patterns. First, the section on Academic and Demographic Metrics with focus on the data. This section aligns with Research Question #2, regarding observed differences in academic metrics among student subgroups. The strengths and weaknesses of the data types will be discussed, with an evaluation of the usability of the VLDS data to address education-related questions. The next section, Academic Profiles of Science Majors, will focus on the students and is aligned with Research Question #1. In this section, the factors that are related to whether or not students enroll in post-secondary science programs will be discussed. Key predictive factors will be evaluated, including SOL assessment scores. Next, the focus will shift to the bigger picture in the section Patterns in Post-secondary Science Pathways. This section aligns with Research Question #3 and includes an evaluation of the commonalities, trends, and patterns in metrics and pathways related to science. This synthesis will occur at multiple levels and through different lenses as demographic, regional, and temporal patterns are evaluated. The science-specific findings will be viewed within the wider context of STEM disciplines. The findings from each of the individual research questions will then be synthesized in the Conclusions section, to address the overarching research question. Finally, the implications to stakeholders will be discussed, including how these findings relate to the STEM workforce and the goals of schooling.

Academic and Demographic Metrics

Although this study focused on student pathways into science fields, it is important to first discuss the data that were used in this exploratory study. This study showed that the VLDS data from the DOE could be used in a longitudinal evaluation of student metrics. However, we must have a deeper understanding of the strengths and weaknesses of the VLDS data before developing conclusions from those data about students and science pathways. Therefore, the different types of VLDS data will be discussed here, with particular emphasis on the benefits and drawbacks of using each data type, as found in this study and as supported by the literature.

Demographic data. First, demographic data formed a core portion of the VLDS data about students. Data on gender, economically disadvantaged status, race, and numerous other metrics were available for nearly all Virginia students. This broad coverage enables researchers to divide students into relevant subgroups and investigate outcomes for specific demographic groups. However, each datapoint represents a single snapshot in time, which can be problematic in longitudinal studies. For example, a student who first qualified as economically disadvantaged in grade 12 would have had vastly different life experiences than another student who had been economically disadvantaged since 1st grade. Using a single point in time to determine subgroups can exclude students or introduce bias, but other approaches add complexity and make interpretation difficult. If a student transfers to a new high school in 11th grade, what school district most influenced his or her educational experience? If a student identified as female in grade 6 and as male in grade 10, what gender category best describes that student? While issues such as these occur in relatively few students in the large dataset, it is important to consider how they could affect results and the interpretation of results. Evaluating demographic differences in academic experiences and outcomes is critically important for ensuring that academic programs are meeting the needs of all student subgroups, so it is crucial that researchers are able to accurately assign students to subgroups using VLDS data. Based on the experiences in this study, one can conclude that the demographic information from DOE that were available from VLDS were suitable for accurate assignment to student subgroups.

Initial post-secondary path. A second type of data used in the study involves post-secondary pathways for students, including post-secondary school, school type, and initial major. These data were present for a large proportion of students in the dataset. However, a missing data point is problematic: does it indicate that the student did not attend post-secondary school, or just that the data are missing? It is not possible to determine from the data which of these options is correct. Furthermore, the DOE's National Student Clearinghouse data provide information on the initial school and initial major only, ignoring transfers from 2-year schools to 4-year schools and changes in major. More than a third of students change major during their post-secondary education (Astorne-Figari & Speer, 2019), and approximately 12% of community college students transferred to another school (Juszkiewicz, 2017). Therefore, these data provide an incomplete picture of post-secondary pathways, unless paired with additional data on persistence in post-secondary schools. Overall, the VLDS data on initial post-secondary path will underestimate the number of students who enroll after high school, but the degree of underestimation is unknown.

Course grades. Grades in high school courses were a fascinating data type in this study. Course-taking data were available for fewer students than were demographic or post-secondary data, with course data available for only 40% of the sample. Any sampling biases in obtaining those data (i.e., by region, high school, or demographic factors) could significantly affect results and interpretation related to course-taking data and grades. These data also showed little consistency in grading schemes, with course grades reported as letter grades, numeric grades, or in categories like pass/fail. While these grading schemes may be reflective of high school policies or teacher policies, it adds complexity and uncertainty and makes comparisons more difficult.

Although the grading schemes complicated comparisons among subgroups, the science course grades yielded some interesting results related to demographic factors. Firstly, male students had significantly lower mean science grades than female students. These findings would lead to three potential interpretations: 1) gender-based achievement gaps exist in classroom science performance, 2) consistent science grading biases exist, based on gender, and/or 3) female students have higher grades in high school courses overall. Other researchers have found that males and females demonstrated the same achievement levels in STEM-related tasks (Jungert, Hubbard, Dedic, & Rosenfield, 2019) and in all major subjects (Duckworth & Seligman, 2006). Results are mixed related to gender-based grading biases, where Krawczyk (2018) found a bias toward higher grades for female students. In contrast, Shumow and Schmidt (2013) found no gender differences in grades, but male and female students differed in motivation and attitude in science classes. Duckworth and Seligman (2006) found that girls earned higher grades than boys in all major subjects, throughout elementary, middle, and high school. Based on previous studies, it is likely that the higher female grades in science observed in this study follow the pattern of high overall grades for girls, rather than any significant difference in achievement or any substantial grading bias. The underlying cause or motivation for overall higher grades for female students is unknown, but the outcome is consistent among subjects.

Similarly, economically disadvantaged students had lower grades than non-economically disadvantaged students, and URM students had lower grades than non-URM students. The same interpretations could apply here, as well: 1) racial and SES-based achievement gaps are present, 2) grading biases exist, and/or 3) non-disadvantaged and non-URM students have higher course grades overall. Morgan et al. (2016) found that achievement gaps based on SES existed in science, were often present at the start of elementary school, and persisted until at least the end of 8^{th} grade. When evaluating grading bias based on race, Van Ewijk (2011) found no evidence for a direct grading bias, but identified that teachers sometimes had lower expectations or unfavorable attitudes toward students of a different race, which could indirectly affect students' grades or performance. For Virginia students, there was no evidence of achievement gaps by race or SES, based on performance on SOL assessments. However, these assessments may not be sufficient for identifying small differences among students, as will be discussed in the following section.

Given the non-uniform distribution of economically disadvantaged students among high schools and regions, an additional explanation is possible: grade inflation in affluent schools. Marcus (2018) found that from 1998-2016, GPA at private schools increased 8%, suburban school grades increased 3%, and city school grades increased only 0.6%, with the author noting, with concern, that observed differences in GPA were closely aligned with wealth. Science grades were found to be an influential factor related to post-secondary science pathways, so it is important to understand any potential biases in these data.

Although rarely included in longitudinal analyses, the grade data available from VLDS provided a unique insight into the educational process that other academic metrics did not capture. Science course grades functioned like an index, incorporating an unknown mix of information related to science interest and aptitude, overall academic achievement, societal forces associated with demographic factors, teacher grading schemes, and characteristics of the schools. The "black box" of student grades is worth unpacking: a thorough study of the VLDS grade data would help identify the relative contributions of each of these academic, demographic, and structural factors to student grades. Until student grades can be broken into their component factors, these data can serve as indicators – particularly for entering science fields – but we cannot thoroughly understand what the data show about the educational system.

SOL assessments. Measuring a different aspect of learning than grade data, the SOL assessments had relatively thorough coverage in the VLDS. Most student records included scores for at least one science SOL assessment. Unfortunately, the methodology and questions for the tests changed midway through the time period, so the time series needed to be divided in half, thereby greatly reducing the analytic power of the data. Assessment changes are necessary periodically to ensure a high-quality test, but a period of dual testing would make it possible to convert scores between the two time periods, extending the usefulness of the data. Without such a connection, the potential of the SOL data to serve as a "long-term dataset" was functionally reduced to only a few years in length.

Unlike the grade data that showed differences among demographic subgroups, the SOL science test results were not significantly different among subgroups of gender, URM status, economically disadvantaged status, or Virginia region. The lack of apparent biases among student subgroups could be viewed as a strength of the SOL assessments. However, the SOL assessment scores were not correlated with science course grades, indicating that the two metrics are measuring different aspects of science learning. The SOL test scores were positively correlated with other science-focused standardized assessments (i.e., SAT, ACT, and AP).

Although SOL test scores inform educators of students' skill at test taking and their grasp of test-focused knowledge, SOL assessment scores in science were not related to in-school performance or likelihood of enrolling in post-secondary science programs. Students did not define their future career paths based on assessment scores. However, the strong correlation between SOL scores and performance on other standardized tests (e.g., SAT, ACT, and AP) demonstrated an alternative benefit of these tests: the numerous SOL assessments taken throughout school may serve as a predictive proxy of student performance on other tests. SOL tests in science provide students with a preview of future science assessments, beyond Virginia's SOL curriculum. Although SOL tests and grades were not educationally aligned, the SOL tests did align with other assessments. While SOL assessments may not provide guidance related to post-secondary path, one can conclude that the tests help students progress along the post-secondary pathway by improving performance on college-entrance exams.

Differences in metrics. The majority of science-focused academic metrics were not significantly different among student subgroups. However, mean science course grade showed significant differences among groups: female students outscored male students; non-URM students outscored URM students; and non-economically disadvantaged students outscored economically disadvantaged students in high school science courses. Grades also differed by post-secondary path, where students enrolling in 4-year science programs had significantly higher science grades than students enrolling in 2-year science programs who, in turn, had significantly higher science grades than high school completers. SOL assessment scores, in comparison, were not significantly different among demographic groups or groups with different science-focused post-secondary pathways.

Given the different patterns demonstrated by SOL assessment scores and course grades, these two tools are assessing different aspects of the learning process. A major criticism of standardized testing is that it does not accurately assess the types of learning needed to succeed, particularly in the STEM fields that rely heavily on problem solving, creativity, iterative thinking, and collaboration (Bybee & Fuchs, 2006). Regardless of the underlying cause of the difference, high school science grades were more closely related than SOL scores to post-secondary pathways in science. Furthermore, grades were able to identify differences among student subgroups that were not identified in the SOL data. Regardless of whether these grade differences are related to achievement differences or institutional biases, they identify that Virginia schools are not meeting the needs of all student subgroups, particularly URM students and economically disadvantaged students.

Academic Profiles of Science Majors

The previous section focused on the academic and demographic data used in the study. In this section, the focus will shift to the students, through an exploration of the factors related to student pathways into science fields. Throughout this discussion, it is important to recognize that the exploratory analyses conducted in this study cannot show causation, only correlation. Educational and career-related pathways involve numerous influencing factors, well beyond the scope of this study. With the diversity of scientific fields of study, there are a correspondingly large number of pathways into those fields. Herein, some of the more prevalent pathways and associated factors will be examined.

Gender. One of the reasons for initiating this study was to investigate factors that preceded the large gender differences in choice of science field. Therefore, it is not surprising that gender was the dominant factor associated with different science pathways. In the logistic regressions conducted, gender was a highly significant factor for whether or not students enrolled in science programs in 2-year post-secondary schools, 4-year post-secondary schools, and for science programs in any post-secondary school. Gender was also related to what type of science field the student enrolled in, with female students more likely to enroll in biological and health-related sciences. Even within the subcategories of science major, gender was a major factor. For example, in the Physical Science field, females were more likely to major in Chemistry than Physics; in Biological Sciences, females more commonly enrolled in Genetics than in Biotechnology (Figure 36).

Both within and among post-secondary major groupings, gender is one of the dominant factors related to selection of post-secondary major. Many researchers have investigated the gender-specific factors that are related to the choice of college major, particularly for the STEM fields. Zafar (2013) found that males cared more about monetary outcomes in the workplace, which affected their choice of college major. Jungert et al. (2019) identified the role that self-efficacy played in selection of post-secondary major, particularly for females, who had lower self-efficacy for STEM fields. Ganley et al. (2018) found that female students selected a college major based on their perception of the gender bias against women in each field, a factor that emerged as the dominant predictor for the unbalanced distribution of males and females by college major.

In this study, females were more likely than males to enroll in nearly all of the scientific fields, except physical sciences. Applying the findings of previous researchers, one could conclude that Virginia's male students are opting out of science fields for more lucrative careers in engineering or business. Furthermore, the prevalence of female students in biological and health professions may lead female students to perceive less gender bias in those fields than in other disciplines. If money and gender biases are as influential as previous research has shown, then efforts to balance the sex ratio in science majors should focus on informing male students that surgeons earn more than engineers, while also introducing female students to women who are successful in fields such as chemistry. Conversely, it is also important to recognize the truths in student perceptions related to gender and career pathways: business is often more lucrative than biology, and strong gender biases and discrimination still exist in many scientific fields. A systemic change is needed to truly affect these factors that influence gender-specific pathways into science.

Socioeconomic status and race. Although neither race nor economically disadvantaged status was significantly related to the likelihood of majoring in science or not majoring in science, both of these factors were significantly related to the division of students between 2-year and 4-year post-secondary schools. Economically disadvantaged students and URM students were both more likely to attend 2-year schools than were their non-economically disadvantaged or non-URM classmates. This split into 2-year/4-year groups then determined the initial majors and pathways available to students, with the majority of 2-year students enrolling in health professions and science technician programs. No significant differences by race or SES were observed on the SOL assessments, so performance and achievement among these demographic groups were not significantly different. However, economic and racial conditions appear to be affecting post-secondary options of many Virginia students. This is corroborated in the literature through studies such as Niu (2017), who found that students of low socioeconomic status have multiple disadvantages in the pursuit of a STEM major, often through low preparedness for post-secondary school. Furthermore, URM students who were also economically disadvantaged had additional obstacles along their path toward a science or STEM major (Saw, Chang, & Chan, 2018).

Post-secondary science programs in 2-year schools already have high levels of diversity, with higher proportions of URM students and economically disadvantaged students than the overall high school population. However, this diversity did not extend to 4-year science programs, which were predominantly affluent and white. This identifies a clear opportunity to broaden diversity in STEM fields – a large number of URM and economically disadvantaged students are already interested in science fields, but they may not have access to all the post-secondary educational options of their peers. Diversity in science programs could be increased by strengthening the connections between 2-year and 4-year programs, while providing targeted financial and social support to disadvantaged and URM students in the science pathway.

Grades. More than any factor except gender, mean high school grade in science courses was closely related to whether students enrolled in science fields after high school. Grades also separated students into different majors within some science disciplines. Although students in all majors in biological sciences and natural resources had approximately the same mean science grades, course grades differed substantially among health-related majors. For example, students in medical preparation (i.e., pre-med) had the highest science grades, while students majoring in optometry and alternative medicine had the lowest science grades (Figure 36).

The influence of grades on post-secondary path was also observed for the high science achievers. Students who scored in the top 5% on Chemistry or Biology SOL assessments were no more likely to enroll in a science field than the overall population of students bound for post-secondary school, but students who earned the highest grades were more likely to enroll in science/health majors in post-secondary school (23% vs. 20%; Table 24.). From this, one could conclude that students construct their self-concept more from course grades than from standardized assessment scores; such self-identification can influence selection of college major (Hazari, et al., 2013). Schools should therefore recognize the importance of grades in affecting post-secondary pathways. For example, providing tutoring assistance to help students improve course grades could have the larger benefit of broadening post-secondary options.

High school characteristics. Pathways to post-secondary schools and careers are not solely shaped by individual-level factors. Rather, an individual's path is partially influenced by his or her social network of family, friends, and community members. Therefore, the composition and characteristics of the high school can substantially affect student pathways into science fields. A significant factor related to whether a student would enroll in a post-secondary science program was the proportion of science-bound students in his or her high school. This metric may reflect the quality of the science or STEM programs at the high school or a broader community-level emphasis on science or STEM careers. Aschbacher et al. (2010) also noted that schools and educators play key roles as students develop career aspirations and personal identities related to science. Regardless of the underlying cause, students were more likely to enter science-related fields if their high school peers were also enrolling in science.

Other school-level demographic factors also affected post-secondary pathways. At schools with a high proportion of economically disadvantaged students or a low proportion of students enrolling in 4-year schools, an individual student was more likely to enter a 2-year science program than a 4-year science program. The community college pathway was more common for economically disadvantaged students (Juszkiewicz, 2017), a pattern also seen in Massachusetts high schools (Papay, Murnane, & Willett, 2015).

High school culture, such as the proportion of students who attend 4-year schools, changes gradually through either bottom-up or top-down forces. In a bottom-up change of community culture, the interests and achievements of peer groups shape the experiences of the rest of the student body. For example, a nationally ranked robotics team or a successful student inventor can increase interest in STEM classes, majors, and careers. Alternatively, top-down forces can support school-wide initiatives, unique classroom opportunities, or outstanding teachers. These top-down factors can affect a large number of students, potentially shaping school culture in future years. But changes to school culture alone are not sufficient to affect post-secondary pathways of students; high school culture must also be viewed in the context of economic obstacles. Changes to school culture may be constrained by the economic circumstances of the individual and/or the community. To expand post-secondary opportunities for the greatest number of students, a supportive high school culture and sufficient resources are both necessary.

Post-secondary school. Almost 90% of Virginia high school students who enrolled in science at 4-year schools stayed in Virginia for post-secondary school. However, those students were dispersed among a large number of schools; no single college or university dominated science enrollment. Similarly, students also selected a wide range of majors in scientific disciplines. Virginia’s community colleges, colleges, and universities are meeting the post-secondary needs of most of Virginia’s science students, and Virginia schools offer a diverse array of science programs. Furthermore, the public-school system is adequately preparing students to be competitive in enrollment in post-secondary science programs in Virginia.

Conclusions regarding academic profiles. Overall, there is no single profile of science students; the field of science itself is so broad and diverse that there are numerous pathways into science majors. Specific majors (e.g., a physics major at a 4-year school) will have more discrete academic profiles than will overall “science” majors, but variability in academic profiles will still be present for all academic endpoints. The findings of this study should not be viewed as deterministic predictions, where students who achieve certain grades or scores in science will then major in science in post-secondary school. Rather, the findings demonstrated the relative importance of some academic and non-academic factors along the pathway toward a science degree. The academic experiences and milestones of male and female students were very similar, with the two genders performing nearly identically on all standardized tests in science, from grade 5 to grade 12. In spite of similar academic aptitude and achievement in science, there were large gender differences in post-secondary major. One can therefore conclude that societal and non-academic factors play a larger role in selection of a science major than do academic factors. However, by viewing multiple academic and demographic metrics concurrently, researchers can use the VLDS education-related data as indicators of gender-specific post-secondary paths into science.

Patterns in Post-Secondary Science Pathways

This exploratory study included many variables, analyses, and results. In this section, individual findings will be synthesized, with discussion of broader patterns and relationships specific to pathway selection. Furthermore, the study results will be viewed through different lenses (i.e., demographic, academic, non-academic) and at different scales (i.e., student, high school, demographic group, region). This multi-level synthesis of results will help provide a deeper understanding of the factors related to the pathways to post-secondary science majors.

Demographic patterns. Gender differences formed the dominant patterns observed in the data. No significant achievement gaps in assessments were observed, but female students had significantly higher grades in high school science classes. Also, female students were more likely to enter a science field in post-secondary school, with the greatest prevalence of female students enrolling in biological sciences and other sciences (primarily health-related fields). In spite of their different endpoints of post-secondary major, male and female students were influenced by the same academic and high school-level factors at approximately the same degrees, according to logistic regression and PCA results. However, Ganley et al. (2018) found that female students' perception of gender bias in different careers was the primary predictor of gender ratio for STEM majors. Specifically, their findings align well with the gender-specific patterns observed in this research, indicating that culture, more than individual aptitude or academic experiences, greatly influenced selection of college major. Reducing differences in the ratio of males to females in science-related careers will rely on understanding – and eventually changing – perceived and actual gender biases in science careers.

Additional patterns were identified for economically disadvantaged students and URM students. Again, no achievement gaps were present, based on SOL assessments or other science assessments, but both URM students and economically disadvantaged students received lower grades in science courses than did other students. In a previous study, Van Ewijk (2011) found no evidence for a direct grading bias based on race, but identified that teachers may indirectly affect grades by having different expectations for different subgroups of students. Furthermore, URM students and economically disadvantaged students had a greater likelihood of attending 2-year post-secondary schools, such as community colleges. One can conclude that lower grades in high school classes due to grading biases would reduce the range of post-secondary options for URM and economically disadvantaged students in Virginia, potentially limiting them to 2-year science programs. A thorough analysis of the grade data – and its links with demographic factors – would help clarify the underlying causes of the lower science course grades for at-risk subgroups of the population.

Regional patterns in Virginia. High school-level factors (including percent of students who were economically disadvantaged, percent of students who enrolled in science majors, and percent of students who enrolled in 4-year schools) affected individual students' post-secondary pathways into science. Although variation among individual high schools existed, many metrics exhibited strong regional patterns in Virginia. The rural southwestern part of the state had higher rates of economically disadvantaged students, and those students were more likely to attend 2-year post-secondary schools. In comparison, the affluent areas in northern Virginia had the highest rates of 4-year post-secondary enrollment. Similar patterns were seen in Massachusetts, where spatial patterns in socioeconomics correlated with patterns in educational outcomes (Papay et al., 2015). Based on these findings, statewide analyses and evaluations of Virginia schools provide only one part of the educational picture by identifying the range of outcomes and each school's current place in that distribution. However, grouping all Virginia schools together can provide a misleading view of academic progress; the schools and communities are influenced by widely different factors. Therefore, it is also important to compare each high school to schools of similar size with comparable demographic composition and cultures. Identifying similarities and differences among schools within the same region, or even within the same county, can provide insight into specific actions and factors that positively or negatively affect educational outcomes, including progression toward a science degree. Just as school groupings are developed for high school athletics, similar within-group comparisons would allow for more appropriate academic contrasts, as well.

While the patterns of socioeconomic status – and the associated 2-year and 4-year enrollment rates – are well known, the regional patterns related to science-going rates are novel to this study. Overall, high schools in the southern half of the state produced the highest proportions of students who enrolled in post-secondary science programs (Figure 18). This spatial relationship was driven by two factors: many high schools in southwestern Virginia sent high proportions of students to 2-year science programs, and relatively few students in northern Virginia opted to major in any science field. The regional differences in science preference, regardless of 2-year or 4-year path, point to the underlying culture of these regions and experiences of the students in those regions. For life science majors, personal links to the outdoors may help explain observed patterns. In a study of activity patterns, Matz et al. (2014) found that people in rural areas were outdoors nearly twice as much as people in urban areas (9.8% and 5.8% of the day, respectively). During the crucial developmental period of childhood, children experiencing natural settings in rural areas may be more likely to identify with biological systems – and to build self-efficacy related to those fields. Such effects could persist throughout schooling, leading to the greater prevalence of students in rural areas enrolling in the life sciences.

Temporal and spatiotemporal patterns. Educational pathways of students reflect a dynamic system, influenced by numerous external factors. Overall enrollment in community colleges has steadily declined since the Recession-caused peak in 2009, and 4-year schools have experienced flat enrollment during that period (Juszkiewicz, 2017). In Virginia, science majors have comprised an increasingly large portion of those post-secondary students, with the percent of science majors approximately doubling from 2005-2015 for biological, physical, and other science fields (Figure 31). Some of the hotspots for increasing rates of science majors are the areas of Richmond, Newport News, and Norfolk (Figure 33). Whether the result of peer influences, great science teachers, local educational initiatives, community culture, or some other factor, the growth of science-bound students in these cities outpaces growth in other parts of Virginia.

Patterns in STEM fields. Academic profiles and pathways to science majors differed among science fields, indicating that characterizing science majors by a single profile is not realistic. Furthermore, the disciplines of science, technology, engineering, and math are often grouped together as the STEM fields. Given the wide range of pathways evident for science alone, looking at profiles for technology, engineering, and math would further broaden the profiles of potential students, such that the entire range of academic and demographic metrics would likely fall within at least one of the STEM fields. When viewed in the PCA plot of all majors (Figure 42), the STEM majors do not group together or remain distinct from business, agriculture, or liberal arts. Rather, the plot illustrates the wide variety within the STEM fields relative to academic and demographic factors. While this diversity in pathways is a strength (there is a major that could appeal to almost everyone), it also shows that the STEM grouping itself is somewhat artificial, based more on political initiatives than on real similarities among the major fields.

Conclusions regarding pathway patterns. Although there are diverse pathways into science fields, gender-specific patterns did reflect progression toward a post-secondary science major. However, patterns in academic performance – particularly standardized assessment scores – did not provide sufficient information related to science pathways. High school science grades and the high school-level metrics of SES and college-going rate further refined the gender-specific models of post-secondary pathways into science for Virginia students. These exploratory analyses using the VLDS educational data helped reveal some previously unidentified patterns and relationships related to science pathways.

Conclusions

- Research Question #1: What are the academic profiles of Virginia students, by gender, who initially selected a post-secondary science major?
    - Context: Science is a broad field, with a large number of science pathways and a correspondingly wide range of academic profiles. Enrolling in a post-secondary

science program was not restricted to students with specific academic qualifications. Rather, the profiles associated with science pathways were more closely related to demographics and school culture, with mean science grade being the only academic factor related to likelihood of enrolling in science.

  - Conclusions:
    - An academic profile of a "science major" is so broad as to be essentially meaningless.
    - Societal and non-academic factors play a larger role than academic factors in the choice to enroll in a post-secondary science program.

- Research Question #2: How do science-related educational metrics of high school completers compare with metrics of a.) students entering science programs at 2-year schools, and b.) students entering science programs at 4-year schools?
  - Context: Scores on SOL assessments did not differ among student subgroups, but grades in high school science classes were significantly different by gender, SES, race, and post-secondary path. SOL scores and grades were uncorrelated.
  - Conclusions:
    - There was no evidence of achievement gaps (based on SOL scores), so differences in grading could result from biases or differences in motivation.
    - SOL assessments and course grades are measuring different aspects of science learning.

        - Academic rigor ranged widely for post-secondary science programs. For any high school completer, some science program is accessible to them, regardless of grades or assessment scores in science.
- Research Question #3: To what extent are gender-specific patterns in academic profiles reflective of the progression toward a post-secondary science major for Virginia students?
    - Context: Demographic data, particularly gender, were driving factors in models of progression toward science majors. School-level and regional influences were also evident. However, academic factors were relatively minor influencers for post-secondary paths toward science.
    - Conclusions:
        - Male and female students were influenced by the same academic and non-academic factors at approximately the same degrees, but they selected significantly different post-secondary paths related to science.
        - Culture – more than science aptitude or academic experiences – influenced student choice of whether to enroll in a post-secondary science program.

Overall Research Question: How well do SOL assessment scores and other academic metrics reflect the progression to a post-secondary science major for male and female students in Virginia?

The mean science grade in high school courses was closely related to enrolling in a post-secondary program in science. SOL assessment scores, in comparison, were not. The SOL assessment scores did not sufficiently reflect post-secondary science pathways; these tests measured preparation, but did not provide direction for students. In comparison, average science grade was closely related to the progression toward a science major for both male and female students. Rather than academic profiles, demographic profiles that incorporated high school-level information best reflected the progression to a post-secondary science major. Specifically, the individual factors of gender and economically disadvantaged status and the high school's percent economically disadvantaged, science-going, and 4-year-going rates were all closely related to a post-secondary major in science. All student subgroups performed similarly on SOL assessments, implying that the large gender differences observed in choice of post-secondary science major were affected more by cultural and social influences than by individual aptitude in science.

The DOE data available from the VLDS were suitable for addressing education-related research questions, providing useful and thorough information on student characteristics and experiences. However, the connections among the different academic variables and educational outcomes were often tenuous. SOL assessment scores, in particular, provided little information about student pathways to science. SOL scores were good proxies for performance on science components of SAT, ACT, and AP tests. But grades, not SOL scores, contributed to students' science self-identity and were related to post-secondary science pathway. The percent of students enrolling in science programs doubled during the study period, so we can conclude that Virginia's SOL-based curriculum is maintaining or developing student interest in science fields. However, performance on SOL assessments contributes little to student interest in science.

Implications

For high school educators and guidance counselors. Educators who interact with high school students can greatly influence students' future pathways through the content and examples they discuss and the advice that they provide. Therefore, it is important for educators to recognize the dramatic differences in science pathways between male and female students, even though both genders have similar SOL assessment scores and similar schooling experiences. The differences in chosen post-secondary pathway are largely the result of cultural influences, both in and out of school. Furthermore, many of the occupations with the greatest current shortfall – especially the health professions – also have highly skewed sex ratios. Educators can target career-based messages to address gender-specific concerns and values, making both sexes aware of the potential benefits of different careers. Specifically, male students typically value lucrative career paths, and female students favor fields in which they perceive less gender bias against women. Emphasizing demographic diversity – particularly gender diversity – in various science fields may help improve female students' perceptions of gender biases, thereby increasing the likelihood of them selecting that field (Ganley et al., 2018). Similarly, male students may benefit from hearing about the salaries of different career options (Zafar, 2013). In-class examples and experiences highlighting these ideas could help students explore additional career options in science.

Furthermore, educators and guidance counselors can emphasize the wide range of academic rigor in science pathways. Poor performance in school may limit a student's options in science, but it does not preclude a science career. Some of the most promising job opportunities are in the "hidden STEM" careers, technician-level occupations that typically require a certification from a 2-year program (Rothwell, 2013). Students should be aware that a career in science is not limited to "being a scientist," and a wealth of job opportunities exist in science-related fields. Regardless of high school grades or test scores, there is a post-secondary program in science that all high school completers could qualify for academically. High school educators would greatly benefit their students by introducing them to the breadth of science occupations that are available.

High school educators and administrators can also help students move toward science careers by encouraging a school culture that supports science and post-secondary education. School culture was found to be an important factor influencing science pathways of Virginia students, with the percent of students enrolling in science and the percent enrolling in 4-year schools significantly related to likelihood of majoring in science. Whether through top-down initiatives to improve science classrooms or to recruit highly qualified science teachers, or through bottom-up efforts to support student science clubs, such efforts can positively affect school culture and student outcomes for multiple years. Such initiatives, however, require resources. Another aspect of school culture – proportion of students who were economically disadvantaged – also affected post-secondary pathways into science, steering students away from 4-year schools. Supporting disadvantaged students and their schools with additional resources would help broaden the educational opportunities available to those students.

For DOE and VLDS. The educational data available from VLDS made it possible to link student records together across years and make comparisons among student subgroups, high schools, and regions. But for those comparisons to be valid, the data must be collected consistently, with only minimal changes to methodology over time. When larger changes are required, such as a restructuring of SOL assessments, both methods should be used in tandem for a period of time, to allow for conversion between old and new data. As DOE and VLDS keep adding years of data to the existing datasets, the data become increasingly powerful for answering research questions…if the time series of data has not been split by methodological changes.

Summarizing data at the state level or making statewide comparisons may provide good "soundbite" metrics, but such state-level calculations may be somewhat misleading for educational data and should not be the only way of ranking school performance. High schools are divided into Groups for sports, based on school enrollment, to allow fair competitions among schools. Similarly, academic comparisons should also occur among demographically and regionally comparable schools. Future research is needed to identify appropriate groupings for schools to ensure fair academic comparisons.

For the STEM workforce. The pathways into science majors should, ideally, lead the student to successful employment in a science career, and many of the science-related occupations in Virginia have increasing numbers of job openings, particularly in the health professions. Many of the careers associated with 2-year programs (e.g., health technologists, health aides, and healthcare support professions) may have an insufficient number of trained workers to fill these positions. These fast-changing "hidden STEM" careers are often overlooked in career awareness initiatives in middle schools and high schools, but many of these occupations will be in high demand in the near future (Rothwell, 2013). The projected number of majors entering each area is undoubtedly an overestimate, since it is based on all students who initially declared a science major completing that program. In reality, approximately 25% of students complete 2-year programs (Juszkiewicz, 2017) and 50% of STEM majors graduate from 4-year schools (Graham et al., 2013). About 40% of college students change their major at least once (Astorne-Figari, & Speer, 2019). Even students who complete their degrees in a science field may not enter a science occupation, particularly in the biological sciences; approximately 50% of graduates get jobs in fields other than their major (Xie, & Shauman, 2004). Combining these estimates, only about 5-10% of students who initially selected a science major may actually enter a career in science. Given those numbers, 4-year science graduates will not be overabundant for the estimated job market, but the shortfall for many of the health professions will be even greater.

This study focused on the factors related to enrolling in a post-secondary science program. That is only one milestone on the pathway to a science career. Only by extending the investigation to post-secondary experiences can the goals of schooling (i.e., literacy and job training) be assessed thoroughly. Student performance on the science SOL assessments and in science course grades could provide proxies for scientific literacy; both measure basic levels of science knowledge. Additional instruments for measuring scientific literacy are available that could supplement the SOL and grade information. The other goal of public schooling – training a workforce – does not quite fit with science careers. Most occupations in scientific fields require additional education beyond high school in a 2-year or 4-year program (at minimum). Therefore, high schools should instead be training students to succeed in post-secondary science programs, rather than to directly enter science careers. The effectiveness of Virginia's science schooling could be measured in the performance and persistence in post-secondary science programs, on the path to a career in science.

Future research. Exploratory data analysis is common for large, longitudinal datasets. This approach can identify patterns and trends in the data, but cannot usually extract the underlying causes or direct effects of those patterns. Further research is often needed to clarify findings from exploratory analysis. Building on the findings from this study, two main areas of research are needed: 1) high school data and 2) post-secondary experiences.

A deeper investigation of the high school data related to science would help clarify some of the findings of this study. First, an in-depth investigation of SOL assessment data is needed.

SOL assessment data did not show any differences among student subgroups. Furthermore, SOL scores were not correlated with grade data, but were positively correlated with other tests. This would lead one to question whether the science SOL assessments are measuring science learning or test-taking skill. Future research linking SOL scores (and high school grades) with post-secondary performance and persistence would help explain the patterns observed in SOL assessment scores. Similarly, grade data showed patterns that were difficult to interpret. Are science grade differences among student subgroups the result of demographic biases, overall grade differences, actual performance differences, or different grading schemes? Future research should attempt to unpack the grade data and associated demographic factors to explore underlying causes of differences in science grades. Finally, student performance in other subjects may relate to the likelihood of majoring in science. For example, students with high math achievement may be more likely to enroll in physical science fields, or students with high overall grade point averages may be more likely to attend 4-year schools. A student's broader academic experiences may therefore affect his or her pathways into science.

Enrolling in science is only one of the initial steps along the pathway to a science career; a student's post-secondary performance and persistence are also important. Future research should link high school data with performance in post-secondary science courses to evaluate the effectiveness of the SOL curriculum at preparing students for further studies. Additional investigations into post-secondary persistence should explore relationships among demographic factors, academic factors (high school and college), college major, and persistence to degree. This study identified a high percentage of students entering 2-year science programs; following these students into 4-year schools or into the workforce would help clarify these frequently overlooked pathways into science careers.

References

AAAS (American Association for the Advancement of Science). (1989). *Science for All Americans*. Retrieved from: http://www.project2061.org/publications/sfaa/online/intro.htm

AAAS. (1993). *Benchmarks for science literacy.* New York: Oxford University Press.

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college*. Washington, D.C.: US Department of Education.

Ainley, M., & Ainley, J. (2011). Student engagement with science in early adolescence: The contribution of enjoyment to students' continuing interest in learning about science. *Contemporary Educational Psychology, 36*(1), 4-12.

Aschbacher, P. R., Li, E., & Roth, E. J. (2010). Is science me? High school students' identities, participation and aspirations in science, engineering, and medicine. *Journal of Research in Science Teaching, 47*(5), 564-582.

Astorne-Figari, C., & Speer, J. D. (2019). Are changes of major major changes? The roles of grades, gender, and preferences in college major switching. *Economics of Education Review, 70*, 75-93.

Bahr, P. R., Fagioli, L. P., Hetts, J., Hayward, C., Willett, T., Lamoree, D., ... & Baker, R. B. (2019). Improving placement accuracy in California's community colleges using multiple measures of high school achievement. *Community College Review, 47*(2), 178-211.

Baker, R. S. J. D. (2010). Data mining for education. *International Encyclopedia of Education, 7*(3), 112-118.

Bennett, A. (2014). Project-based science: a pathway to problem-solving skills. *Children's Technology and Engineering, 2014*(Dec), 20–23.

Bureau of Labor Statistics. (2015). *Employment projections.* Retrieved from https://www.bls.gov/data/

Bruner, J. (1960). *The Process of Education*. Cambridge, MA: Harvard University Press.

Bybee, R. W., & Fuchs, B. (2006). Preparing the 21st century workforce: a new reform in science and technology education. *Journal of Research in Science Teaching, 43*(4), 349–352.

Chen, X. (2013). STEM Attrition: College Students' Paths into and out of STEM Fields. Statistical Analysis Report. NCES 2014-001. National Center for Education Statistics.

CCSS (Common Core State Standards) Initiative. (2018). *About the standards*. Retrieved from http://www.corestandards.org/about-the-standards/

CCSS Initiative. (2018b). *Key shifts in mathematics*. Retrieved from http://www.corestandards.org/other-resources/key-shifts-in-mathematics/

Conley, D. T. (2010). *College and career ready: Helping all students succeed beyond high school.* John Wiley & Sons.

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology, 46*(5), 904-920.

Deary, I. J., Strand, S., Smith, P., & Fernandes, C. (2007). Intelligence and educational achievement. *Intelligence, 35*(1), 13-21.

Duckworth, A. L., & Seligman, M. E. (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. *Journal of Educational Psychology, 98*(1), 198.

Education Next. (2016). States curb Common Core opposition by leaving testing consortia. *Education Next, 16*(4). Retrieved from http://educationnext.org/states-curb-common-core-opposition-by-leaving-testing-consortia/

Federal Coordination in STEM Education Task Force. (2012). Coordinating federal science, technology, engineering, and mathematics (STEM) education investments: Progress report. Washington, DC: National Science and Technology Council.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences, 111*(23), 8410-8415.

Ganley, C. M., George, C. E., Cimpian, J. R., & Makowski, M. B. (2018). Gender equity in college majors: Looking beyond the STEM/non-STEM dichotomy for answers regarding female participation. *American Educational Research Journal, 55*(3), 453-487.

Geary, D. C. (2011). Cognitive predictors of achievement growth in mathematics: a 5-year longitudinal study. *Developmental Psychology, 47*(6), 1539.

Graham, E. (2013). "A Nation at Risk" turns 30: Where did it take us? *NEA Today, April 25*. Retrieved from http://neatoday.org/2013/04/25/a-nation-at-risk-turns-30-where-did-it-take-us-2/

Graham, M. J., Frederick, J., Byars-Winston, A., Hunter, A. B., & Handelsman, J. (2013). Increasing persistence of college students in STEM. *Science, 341*(6153), 1455-1456.

Hamilton, D. (1989). *Towards a Theory of Schooling* (Routledge Revivals). Routledge.

Harrell, Frank E. Jr, with contributions from Charles Dupont and many others. (2019). Hmisc: Harrell Miscellaneous. R package version 4.2-0. https://CRAN.R-project.org/package=Hmisc

Hazari, Z., Sadler, P. M., & Sonnert, G. (2013). The science identity of college students: Exploring the intersection of gender, race, and ethnicity. *Journal of College Science Teaching, 42*(5), 82-91.

Holbrook, J., & Rannikmae, M. (2009). The meaning of scientific literacy. *International Journal of Environmental and Science Education, 4*(3), 275-288.

Holdren, J. P., & Lander, E. (2012). Report to the President—Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics. *President's Council of Advisors on Science and Technology*.

Howell, D. C. (2011). *Statistical Methods for Psychology* (8th ed.). Belmont, CA: Wadsworth.

Hutchinson-Anderson, K., Johnson, K. & Craig, P. A. (2015). Students' perceptions of factors influencing their desire to major or not major in science. *Journal of College Science Teaching 45*(2), 78–85.

ITEEA (International Technology Education Association). (2007). *Standards for technological literacy: Content for the study of technology*. Retrieved from https://www.iteea.org/File.aspx?id=67767

Jones, B. D., Ruff, C., & Osborne, J. W. (2015). Fostering students' identification with mathematics and science. In K. A. Renninger, M. Nieswandt, & S. Hidi (Eds.*), Interest and K-16 mathematics and science learning, in and out of school*. Washington, DC: American Educational Research Association.

Jungert, T., Hubbard, K., Dedic, H., & Rosenfield, S. (2019). Systemizing and the gender gap: examining academic achievement and perseverance in STEM. *European Journal of Psychology of Education, 34*(2), 479-500.

Juszkiewicz, J. (2017). Trends in community college enrollment and completion data, 2017.

Krapp, A., & Prenzel, M. (2011). Research on interest in science: Theories, methods, and findings. *International Journal of Science Education, 33*(1), 27-50.

Krawczyk, M. (2018). Do gender and physical attractiveness affect college grades?. Assessment & Evaluation in Higher Education, 43(1), 151-161.

Le, S., Josse, J., & Husson, F. (2008). FactoMineR: An R Package for Multivariate Analysis. *Journal of Statistical Software*, *25*(1), 1-18. 10.18637/jss.v025.i01

Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior, 45*(1), 79-122.

Loveless, T. (2014). *The 2014 Brown Center report on American education*. Washington, DC: Brookings Institution.

Loveless, T. (2016). *The 2016 Brown Center report on American education.* Washington, DC: Brookings Institution.

MacNeil, A. J., Prater, D. L., & Busch, S. (2009). The effects of school culture and climate on student achievement. *International Journal of Leadership in Education, 12*(1), 73-84.

Maltese, A. V., & Tai, R. H. (2011). Pipeline persistence: Examining the association of educational experiences with earned degrees in STEM among US students. *Science Education, 95*(5), 877-907.

Mann, A., & DiPrete, T. A. (2013). Trends in gender segregation in the choice of science and engineering majors. *Social Science Research, 42*(6), 1519-1541.

Marcus, J. (2018). The Newest Advantage of Being Rich in America? Higher Grades. *The Education Digest, 83*(6), 12-17.

Matz, C. J., Stieb, D. M., Davis, K., Egyed, M., Rose, A., Chou, B., & Brion, O. (2014). Effects of age, season, gender and urban-rural status on time-activity: Canadian Human Activity Pattern Survey 2 (CHAPS 2). *International Journal of Environmental Research and Public Health, 11*(2), 2108-2124.

Mau, W. C. (2003). Factors that influence persistence in science and engineering career aspirations. *The Career Development Quarterly, 51*(3), 234-243.

Mau, W. C. J. (2016). Characteristics of US students that pursued a STEM major and factors that predicted their persistence in degree completion. *Universal Journal of Educational Research, 4*(6), 1495-1500.

McReynolds, K. (2006). The No Child Left Behind Act raises growing concerns. *Encounter: Education for Meaning and Social Justice, 19*(2), 33-36.

Michelmore, K., & Dynarski, S. (2017). The gap within the gap: Using longitudinal data to understand income differences in educational outcomes. *AERA Open, 3*(1), 2332858417692958.

Millar, R. (2006). Twenty first century science: Insights from the design and implementation of a scientific literacy approach in school science. *International Journal of Science Education, 28*(13), 1499-1521.

Morgan, P. L., Farkas, G., Hillemeier, M. M., & Maczuga, S. (2016). Science achievement gaps begin very early, persist, and are largely explained by modifiable factors. *Educational Researcher, 45*(1), 18-35.

Morgan, S. L., Gelbgiser, D., & Weeden, K. A. (2013). Feeding the pipeline: Gender, occupational plans, and college major selection. *Social Science Research, 42*(4), 989-1005.

National Commission on Excellence in Education. (1983). *A nation at risk: The imperative for educational reform.* Washington, DC: Author.

National Center for Education Statistics (2012). *Higher education: Gaps in access and persistence study. Table E-42-2.* Retrieved from http:// nces.ed.gov/pubs2012/2012046/tables/e-42-2.asp

NBPTS (National Board for Professional Teaching Standards). (2016). *What teachers should know and be able to do.* Retrieved from http://accomplishedteacher.org/

Nelson, H. (2013). *Testing more, teaching less.* American Federation of Teachers.

Newcomb, T. J., Murphy, B. R., & Berkson, J. M. (2002). Circular threads in fisheries education: Employing integrated themes throughout a student's academic career. *Fisheries 27*(11), 16-20.

Niu, L. (2017). Family socioeconomic status and choice of STEM major in college: An analysis of a national sample. *College Student Journal, 51*(2), 298-312.

NPR. (2014). Who studies what? Men, women, and college majors. Retrieved from http://www.npr.org/sections/money/2014/10/28/359419934/who-studies-what-men-women-and-college-majors

Papay, J. P., Murnane, R. J., & Willett, J. B. (2015). Income-based inequality in educational outcomes: Learning from state longitudinal data systems. *Educational Evaluation and Policy Analysis, 37*(1_suppl), 29S-52S.

Pinar, W. (2014). *Curriculum: Toward new identities*. Routledge.

Quinn, D. M., & Cooc, N. (2015). Science achievement gaps by gender and race/ethnicity in elementary and middle school: Trends and predictors. *Educational Researcher, 44*(6), 336-346.

R Core Team (2019). R: A language and environment for statistical computing.

Rask, K. (2010). Attrition in STEM fields at a liberal arts college: The importance of grades and pre-collegiate preferences. *Economics of Education Review, 29*(6), 892-900.

Rauschenberg, S. (2014). How consistent are course grades? An examination of differential grading. *Education Policy Analysis Archives*, *22*, 1-38.

Ravitch, D. (2014). *Reign of error: the hoax of the privatization movement and the danger to America's public schools*. New York, NY: Vintage Books.

Ravitch, D. (2016). *The death and life of the great American school system: How testing and choice are undermining education.* Basic Books.

Riegle-Crumb, C., & King, B. (2010). Questioning a white male advantage in STEM: Examining disparities in college major by gender and race/ethnicity. *Educational Researcher, 39*(9), 656-664.

Rothwell, J. (2013). The hidden STEM economy. Washington: Brookings Institution.

Sadler, P. M., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. *Science Education, 96*(3), 411-427.

Saw, G., Chang, C. N., & Chan, H. Y. (2018). Cross-sectional and longitudinal disparities in STEM career aspirations at the intersection of gender, race/ethnicity, and socioeconomic status. *Educational Researcher, 47*(8), 525-531.

Sax, L. J., Kanny, M. A., Riggers-Piehl, T. A., Whang, H., & Paulson, L. N. (2015). "But I'm not good at math": The changing salience of mathematical self-concept in shaping women's and men's STEM aspirations. *Research in Higher Education, 56*(8), 813-842.

Schmidt, W. H., & Houang, R. T. (2012). Curricular coherence and the Common Core State Standards for mathematics. *Educational Researcher, 41*, 294–308.

Schunk, D. H., & Pajares, F. (2005). Competence perceptions and academic functioning. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 141-163) New York: Guilford.

Shaw, E. J., & Barbuti, S. (2010). Patterns of persistence in intended college major with a focus on STEM majors. *NACADA Journal, 30*(2), 19-34.

Shumow, L., & Schmidt, J. A. (2013). Academic grades and motivation in high school science classrooms among male and female students: Associations with teachers' characteristics. *Journal of Education Research, 7*(1).

Siegler, R. S., Duncan, G. J., Davis-Kean, P. E., Duckworth, K., Claessens, A., Engel, M., Susperreguy, M. I., & Chen, M. (2012). Early predictors of high school mathematics achievement. *Psychological Science, 23*(7), 691–697.

Simon, K. A., & Grant, W. V. (1965). *Digest of educational statistics.* Office of Education, Bulletin 1965, No. 4.

Snyder, T. D. (1993). *120 years of American education: A statistical portrait.* U.S. Department of Education, Center for Education Statistics.

Sokatch, A. (2006). Peer influences on the college-going decisions of low socioeconomic status urban youth. *Education and Urban Society, 39*(1), 128-146.

Spring, J. (2014). *American education* (16th ed.). New York, NY: McGraw-Hill.

Stromquist, N. P., & Monkman, K. (Eds.). (2014). *Globalization and education: Integration and contestation across cultures*. R&L Education.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics.* Allyn & Bacon/Pearson Education.

Thapa, A., Cohen, J., Guffey, S., & Higgins-D'Alessandro, A. (2013). A review of school climate research. *Review of Educational Research, 83*(3), 357-385.

Thelin, J. R. (2011). *A history of American higher education*. JHU Press.

Tierney, N., Cook, D., McBain, M., & Fay, C. (2019). naniar: Data Structures, Summaries, and Visualisations for Missing Data. R package version 0.4.2. https://CRAN.R-project.org/package=naniar

Uline, C. L., & Johnson, J. F. (2005): Closing achievement gaps: What will it take? *Theory into Practice, 44*(1), 1-3.

US Department of Education. (2002). No child left behind act. Washington, DC: US Department of Education.

US Department of Education, National Center for Education Statistics. (2014). *Private school universe survey (PSS), 2013-2014*. Retrieved from https://nces.ed.gov/surveys/pss/tables/table_2013_15.asp

U.S. Department of Education, National Center for Education Statistics. (2018). *The Condition of Education 2018 (NCES 2018-144).* Retrieved from https://nces.ed.gov/fastfacts/display.asp?id=40

Van Ewijk, R. (2011). Same work, lower grade? Student ethnicity and teachers' subjective assessments. *Economics of Education Review, 30*(5), 1045-1058.

VDOE (Virginia Department of Education). (2010). *Virginia Standards of Learning & Common Core State Standards.* Retrieved from http://www.doe.virginia.gov/testing/common_core/index.shtml

VDOE. (2013). *2013 annual report, Appendix A. Historical overview of the Standards of Learning Program*. Retrieved from http://www.doe.virginia.gov/boe/reports/annual_reports/2013_appendix_a_sol_history.pdf

VDOE. (2017). *Standards of Learning (SOL) & testing*. Retrieved from http://www.doe.virginia.gov/testing/

VDOE. (2017b). *Fall membership reports*. Retrieved from http://www.pen.k12.va.us/statistics_reports/enrollment/fall_membership/report_data.shtml

VDOE. (2017c). *Home schooled students & religious exemptions*. Retrieved from http://www.pen.k12.va.us/statistics_reports/enrollment/home_school_religious_exempt/index.shtml

Venables, W. N. & Ripley, B. D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York.

Virginia Employment Commission. (2018). Long and short-term occupational projections. Retrieved from: https://virginiaworks.com/occupational-projections

Virginia University Research Consortium on Early Childhood. (2015). *Predicting on-time promotion to and literacy achievement in eighth grade in relation to public prekindergarten in Virginia*. Richmond, VA: Virginia Early Childhood Foundation. Retrieved from https://vlds.virginia.gov/media/1033/impacts-of-public-preschool-participation-in-virginia.pdf

VLDS (Virginia Longitudinal Data System). (2014). *Examining the teacher pipeline in Virginia: an analysis of current VLDS data.* Retrieved from https://vlds.virginia.gov/media/1017/2014_examining_va_teacher_pipeline-vlds_website.pdf

VLDS. (2017). *About VLDS*. Retrieved from https://vlds.virginia.gov/about-vlds

VLDS. (2017b). *New windows of insight.* Retrieved from https://vlds.virginia.gov/insights

VLDS. (2017c). *Agency specific research agenda.* Retrieved from https://vlds.virginia.gov/insights/agency-research-agendas/

Vu, V. Q. (2011). ggbiplot: A ggplot2 based biplot. R package version 0.55. http://github.com/vqv/ggbiplot

Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*(4), 304-340.

Wei, T., & Simko, V. (2017). R package "corrplot": Visualization of a Correlation Matrix (Version 0.84). Available from https://github.com/taiyun/corrplot

Williamson, B. (2016). Digital education governance: data visualization, predictive analytics, and “real-time” policy instruments. *Journal of Education Policy, 31*(2), 123-141.

Xie, Y., & Shauman, K. A. (2004). Women in science: Career processes and outcomes. *Social Forces, 82*(4), 1669-1671.

Xu, Z., & Cepa, K. (2015). *Getting College and Career Ready during State Transition toward the Common Core State Standards.* Working Paper 127. National Center for Analysis of Longitudinal Data in Education Research (CALDER).

Zafar, B. (2013). College major choice and the gender gap. *Journal of Human Resources, 48*(3), 545-595.

Appendix A -- Academic Metrics

High School Completers

Metrics shown include mean, standard deviation in parentheses, and sample size in italics for each academic metric.

Table A.1. *Mean Science Grade and Scores for Science SOL Assessments in Grades 5 and 8 for High School Completers*

Population Segment	Mean Science Grade	Grade 5 (2006-12)	Grade 5 (2013-17)	Grade 8 (2006-12)	Grade 8 (2013-17)
All Students	86.3 (7.69)	464.4 (62.6)	443.6 (65.9)	482.5 (65.0)	435.8 (53.4)
	464,295	*331,292*	*37,876*	*164,612*	*157.895*
Females	87.4 (7.36)	464.1 (62.6)	443.9 (66.1)	482.3 (65.0)	435.9 (53.3)
	233,098	*166,282*	*18,941*	*82,733*	*79,305*
Males	85.2 (7.86)	464.6 (62.5)	443.3 (65.6)	482.8 (65.0)	435.8 (53.6)
	231,197	*165,010*	*18,935*	*81,879*	*78,590*
URM	83.9 (7.64)	464.2 (62.9)	442.8 (66.0)	482.4 (65.3)	435.5 (53.3)
	176,685	*113,399*	*13,048*	*56,564*	*53,907*
Not URM	87.8 (7.33)	464.4 (62.4)	444.0 (65.8)	482.6 (64.8)	436.0 (53.5)
	287,610	*217,893*	*24,828*	*108,048*	*103,988*
Econo. Disad.	83.7 (7.80)	464.3 (62.7)	442.6 (65.8)	482.6 (65.0)	435.7 (53.5)
	142,881	*88,279*	*10,130*	*43,853*	*42,149*
Not Econo. Disad.	87.5 (7.34)	464.4 (62.5)	444.0 (65.9)	482.5 (65.0)	435.9 (53.4)
	321,414	*243,013*	*27,746*	*120,759*	*115,746*

Table A.2. *Scores for High School Science SOL Assessments for High School Completers*

Population Segment	Earth Sci (2006-12)	Earth Sci (2012-17)	Biology (2006-12)	Biology (2012-17)	Chemistry (2006-12)	Chemistry (2012-17)
All Students	457.3 (54.2)	438.0 (43.3)	453.9 (47.9)	442.7 (47.6)	456.7(47.8)	448.0 (48.3)
	252,655	*143,444*	*278,386*	*172,668*	*166,024*	*115,036*
Females	457.1 (54.2)	438.0 (43.2)	453.8 (47.8)	442.5 (47.5)	456.4 (47.7)	447.9 (48.3)
	126,731	*71,961*	*139,620*	*86,443*	*83,237*	*57,602*
Males	457.4 (54.1)	437.9 (43.3)	454.1 (47.9)	442.8 (47.6)	456.9 (47.9)	448.1 (48.4)
	125,924	*71,483*	*138,766*	*86,225*	*82,797*	*57,434*
URM	457.1 (54.1)	437.8 (43.3)	454.0 (47.9)	442.4 (47.3)	457.0 (48.0)	447.6 (48.1)
	86,571	*49,110*	*95,746*	*59,083*	*57,143*	*39,245*
Not URM	457.4 (54.2)	438.1 (43.3)	453.9 (47.8)	42.8 (47.7)	456.5 (47.7)	448.2 (48.5)
	166,084	*94,334*	*182.640*	*113,585*	*108,881*	*75,791*
Econo. Disad.	457.4 (54.3)	438.1 (43.4)	454.3 (47.9)	442.6 (47.5)	457.2 (48.0)	447.7 (48.6)
	67,438	*38,154*	*74,501*	*45,870*	*44,505*	*30,512*
Not Econo. Disad.	457.2 (54.1)	437.9 (43.2)	453.8 (47.9)	442.7 (47.6)	456.5 (47.7)	448.1 (48.2)
	185,217	*105,290*	*203,885*	*126,798*	*121,519*	*84,524*

Table A.3. *Scores for SAT and ACT Assessments for High School Completers*

Population Segment	SAT Chem	SAT EcoBio	SAT MolBio	SAT Phys	ACT Science
All Students	65.97 (9.72) *7,934*	62.15 (9.44) *3,576*	66.06 (8.83) *4,041*	65.96 (8.74) *4,700*	21.95 (5.23) *78,781*
Females	65.95 (9.70) *4,001*	62.15 (9.49) *1,772*	66.26 (8.61) *2,045*	65.94 (8.76) *2,357*	21.94 (5.23) *39,554*
Males	65.99 (9.75) *3,933*	62.15 (9.40) *1,804*	65.87 (9.06) *1,996*	65.97 (8.73) *2,343*	21.96 (5.23) *39,227*
URM	65.88 (9.72) *2,708*	62.34 (9.33) *1,220*	66.08 (8.92) *1,371*	65.94 (8.67) *1,614*	21.96 (5.22) *27,241*
Not URM	66.02 (9.73) *5,226*	62.06 (9.50) *2,356*	66.06 (8.79) *2,670*	65.97 (8.78) *3,086*	21.94 (5.24) *51,540*
Econo. Disad.	65.97 (9.63) *2,164*	62.09 (9.76) *973*	66.13 (8.76) *1,075*	65.97 (8.89) *1,225*	21.91 (5.25) *21,157*
Not Econo. Disad.	65.97 (9.76) *5,770*	62.18 (9.32) *2,603*	66.04 (8.86) *2,966*	65.95 (8.69) *3,475*	21.96 (5.23) *57,624*

Table A.4. *Scores on AP Science Assessments for High School Completers*

Population Segment	AP Biology	AP Chemistry	AP EnvSci	AP PhysicsB	AP PhysicsEM	AP PhysicsM
All Students	2.78 (1.25)	2.78 (1.37)	2.55 (1.31)	2.58 (1.26)	3.47 (1.46)	3.23 (1.38)
	30,036	*20,275*	*26,451*	*6,908*	*2,744*	*7,675*
Females	2.78 (1.26)	2.77 (1.37)	2.55 (1.31)	2.60 (1.25)	3.50 (1.45)	3.26 (1.37)
	14,935	*10,150*	*13,285*	*3,469*	1,379	*3,856*
Males	2.78 (1.25)	2.78 (1.36)	2.55 (1.30)	2.57 (1.26)	3.45 (1.47)	3.21 (1.39)
	15,101	*10,125*	*13,166*	*3,439*	*1,365*	*3819*
URM	2.76 (1.26)	2.77 (1.36)	2.55 (1.31)	2.63 (1.26)	3.41 (1.46)	3.23 (1.37)
	10,233	6,772	*9,147*	*2,369*	*917*	*2,595*
Not URM	2.79 (1.25)	2.78 (1.37)	2.55 (1.31)	2.56 (1.26)	3.50 (1.46)	3.24 (1.38)
	19,803	*13,503*	*17,304*	*4,539*	*1,827*	*5,080*
Econo. Disad.	2.77 (1.26)	2.75 (1.37)	2.55 (1.32)	2.61 (1.28)	3.46 (1.46)	3.25 (1.37)
	8,050	5,371	*7,178*	*1,785*	714	*2,002*
Not Econo.	2.78 (1.25)	2.79 (1.37)	2.55 (1.30)	2.58 (1.25)	3.48 (1.46)	3.23 (1.38)
Disad.	*21,986*	*14,904*	*19,273*	*5,123*	*2,030*	*5,673*

Science Majors at 2-Year Schools

Metrics shown include mean, standard deviation in parentheses, and sample size in italics for each academic metric.

Table A.5. *Mean Science Grade and Scores for Science SOL Assessments in Grades 5 and 8 for Science Majors at 2-year Schools*

Population Segment	Mean Science Grade	Grade 5 (2006-12)	Grade 5 (2013-17)	Grade 8 (2006-12)	Grade 8 (2013-17)
All Students	85.5 (7.08)	464.53 (62.59)	444.08 (66.37)	482.64 (64.34)	435.78 (53.62)
	21,846	*86,503*	*9,778*	*42,839*	*41,247*
Females	85.9 (6.99)	464.05 (62.53)	443.91 (66.83)	482.63 (64.23)	435.98 (53.53)
	15,510	*44,247*	*4,939*	*21,944*	*21,122*
Males	84.7 (7.23)	465.04 (62.65)	444.25 (65.90)	482.67 (64.47)	435.57 (53.70)
	6,336	*42,256*	*4,839*	*20,895*	*20,125*
URM	84.1 (6.84)	464.55 (63.15)	443.55 (65.86)	482.59 (64.45)	436.14 (53.93)
	9,603	*31,478*	*3,553*	*15,661*	*14,896*
Not URM	86.6 (7.06)	464.52 (62.26)	444.38 (66.66)	482.68 (64.28)	435.58 (53.44)
	12,243	*55,025*	*6,225*	*27,178*	*26,351*
Econo. Disad.	84.6 (7.15)	464.09 (63.01)	442.51 (65.87)	481.84 (64.08)	436.16 (53.57)
	8,757	*26,316*	*2,979*	*12,983*	*12,571*
Not Econo. Disad.	86.1 (6.97)	464.73 (62.40)	444.76 (66.58)	482.99 (64.46)	435.62 (53.64)
	13,089	*60,187*	*6,799*	*29,856*	*28,676*
Biological Sciences	NA	NA	NA	NA	N/A
Physical Sciences	86.3 (6.50)	463.68 (61.92)	440.03 (69.76)	483.07 (67.19)	434.83 (54.74)
	2,119	*1,287*	*143*	*638*	*578*
Other Sciences	85.4 (7.13)	464.07 (62.75)	442.51 (67.04)	481.74 (65.70)	436.33 (53.35)
	19,699	*13,851*	*1,578*	*6,834*	*6,611*

Table A.6. *Scores for High School Science SOL Assessments for Science Majors at 2-year Schools*

Population Segment	Earth Sci (2006-12)	Earth Sci (2012-17)	Biology (2006-12)	Biology (2012-17)	Chemistry (2006-12)	Chemistry (2012-17)
All Students	457.11 (54.01)	437.86 (43.36)	454.05 (47.94)	442.74 (47.48)	456.71 (48.10)	447.91 (48.55)
	66,000	*37,295*	*72,514*	*45,175*	*43,338*	*29,971*
Females	457.05 (54.12)	437.86 (43.49)	453.79 (47.86)	442.73 (47.45)	456.43 (47.88)	447.96 (48.67)
	33,791	*19,040*	*37,124*	*23,128*	*22,180*	*15,347*
Males	457.17 (53.90)	437.86 (43.23)	454.32 (48.02)	442.74 (47.51)	457.00 (48.32)	447.85 (48.43)
	32,209	*18,255*	*35,390*	*22,047*	*21,158*	*14,624*
URM	456.74 (53.88)	437.52 (43.27)	453.87 (48.03)	442.77 (47.05)	457.57 (48.27)	447.21 (48.44)
	24,064	*13,565*	*26,659*	*16,336*	*15,860*	*10,856*
Not URM	457.32 (54.09)	438.06 (43.41)	454.15 (47.89)	442.72 (47.72)	456.21 (47.99)	448.31 (48.61)
	41,936	*23,730*	*45,855*	*28,839*	*27,478*	*19,115*
Econo. Disad.	457.48 (54.31)	437.92 (43.81)	454.37 (47.96)	442.69 (47.47)	457.83 (48.37)	447.54 (48.78)
	20,033	*11,375*	*22,176*	*13,763*	*13,165*	*9,045*
Not Econo. Disad.	456.95 (53.88)	437.84 (43.16)	453.91 (47.93)	442.76 (47.48)	456.22 (47.97)	448.07 (48.45)
	45,967	*25,920*	*50,338*	*31,412*	*30,173*	*20,926*
Biological Sciences	N/A	N/A	N/A	N/A	N/A	N/A
Physical Sciences	454.27 (54.74)	437.58 (44.09)	453.80 (50.41)	442.52 (48.28)	457.43 (48.54)	449.98 (51.02)
	984	*569*	*1,110*	*654*	*660*	*445*
Other Sciences	457.33 (53.91)	438.63 (43.50)	454.03 (48.11)	442.67 (47.16)	455.95 (47.45)	448.03 (48.30)
	10,707	*5,968*	*11,745*	*7,212*	*6,932*	*4,881*

Table A.7. *Scores for SAT and ACT Assessments for Science Majors at 2-year Schools*

Population Segment	SAT Chem	SAT EcoBio	SAT MolBio	SAT Phys	ACT Science
All Students	66.19 (9.59) *2,082*	61.79 (9.51) *887*	66.37 (8.83) *1,052*	65.88 (9.03) *1,224*	21.94 (5.26) *20,539*
Females	66.20 (9.55) *1,067*	61.61 (9.65) *430*	66.82 (8.54) *561*	65.84 (9.17) *619*	21.91 (5.27) *10,544*
Males	66.18 (9.63) *1,015*	61.95 (9.39) *457*	65.84 (9.13) *491*	65.92 (8.88) *605*	21.98 (5.25) *9,995*
URM	66.19 (9.63) *789*	62.34 (9.53) *327*	66.29 (8.91) *374*	65.68 (9.24) *446*	22.01 (5.26) *7,538*
Not URM	66.19 (9.57) *1,293*	61.46 (9.50) *560*	66.41 (8.79) *678*	65.99 (8.91) *778*	21.91 (5.26) *13,001*
Econo. Disad.	65.86 (9.81) *641*	61.78 (9.63) *275*	66.39 (8.94) *321*	65.67 (9.29) *362*	21.83 (5.30) *6,216*
Not Econo. Disad.	66.34 (9.49) *1,441*	61.79 (9.47) *612*	66.36 (8.79) *731*	65.97 (8.92) *862*	22.00 (5.24) *14,323*
Biological Sciences	N/A	N/A	N/A	N/A	N/A
Physical Sciences	N/A	N/A	N/A	N/A	22.34 (5.13) *308*
Other Sciences	65.73 (9.36) *338*	61.80 (10.23) *125*	66.32 (8.23) *183*	65.92 (9.77) *172*	21.98 (5.26) *3,227*

Table A.8. *Scores on AP Science Assessments for Science Majors at 2-year Schools*

Population Segment	AP Biology	AP Chemistry	AP EnvSci	AP PhysicsB	AP PhysicsEM	AP PhysicsM
All Students	2.75 (1.25) *7,844*	2.78 (1.37) *5,290*	2.56 (1.31) *6,809*	2.62 (1.27) *1,772*	3.44 (1.46) *750*	3.25 (1.39) *2,038*
Females	2.74 (1.26) *4,019*	2.77 (1.38) *2,679*	2.55 (1.31) *3,453*	2.62 (1.25) *889*	3.55 (1.45) *378*	3.33 (1.37) *1,037*
Males	2.77 (1.24) *3,825*	2.79 (1.37) *2,611*	2.58 (1.30) *3,356*	2.62 (1.29) *883*	3.33 (1.48) *372*	3.17 (1.41) *1,001*
URM	2.73 (1.26) *2,886*	2.79 (1.36) *1,888*	2.57 (1.31) *2,522*	2.69 (1.28) *663*	3.44 (1.45) *288*	3.27 (1.40) *743*
Not URM	2.77 (1.24) *4,958*	2.77 (1.38) *3,402*	2.56 (1.31) *4,287*	2.58 (1.26) *1,109*	3.44 (1.47) *462*	3.24 (1.39) *1,295*
Econo. Disad.	2.74 (1.26) *2,434*	2.74 (1.38) *1,589*	2.57 (1.32) *2,039*	2.64 (1.30) *534*	3.45 (1.48) *242*	3.31 (1.38) *631*
Not Econo. Disad.	2.76 (1.24) *5,410*	2.80 (1.37) *3,701*	2.56 (1.30) *4,770*	2.61 (1.26) *1,238*	3.44 (1.46) *508*	3.23 (1.40) *1,407*
Biological Sciences	N/A	N/A	N/A	N/A	N/A	N/A
Physical Sciences	2.88 (1.31) *111*	2.67 (1.37) *78*	2.54 (1.30) *99*	N/A	N/A	N/A
Other Sciences	2.76 (1.25) *1,343*	2.74 (1.39) *844*	2.61 (1.33) *1,083*	2.56 (1.29) *271*	3.50 (1.37) *124*	3.36 (1.38) *319*

Science Majors at 4-Year Schools

Metrics shown include mean, standard deviation in parentheses, and sample size in italics for each academic metric.

Table A.9. *Mean Science Grade and Scores for Science SOL Assessments in Grades 5 and 8 for Science Majors at 4-year Schools*

Population Segment	Mean Science Grade	Grade 5 (2006-12)	Grade 5 (2013-17)	Grade 8 (2006-12)	Grade 8 (2013-17)
All Students	90.5 (5.40)	464.60 (62.76)	444.12 (65.64)	482.31 (65.33)	436.00 (53.30)
	27,138	*117,374*	*13,277*	*58,286*	*55,462*
Females	90.7 (5.28)	464.30 (62.74)	444.46 (65.67)	481.78 (65.47)	436.08 (53.23)
	18,677	*64,893*	*7,309*	*32,195*	*30,843*
Males	89.9 (5.61)	464.98 (62.77)	443.70 (65.60)	482.96 (65.16)	435.90 (53.38)
	8,461	*52,481*	*5,968*	*26,091*	*24,619*
URM	88.5 (5.76)	464.20 (63.19)	443.14 (66.32)	481.50 (65.97)	435.39 (53.09)
	8,394	*30,868*	*3,495*	*15,331*	*14,501*
Not URM	91.3 (4.98)	464.74 (62.60)	444.46 (65.39)	482.60 (65.10)	436.21 (53.37)
	18,744	*86,506*	*9,782*	*42,955*	*40,961*
Econo. Disad.	88.9 (5.99)	464.82 (62.84)	444.95 (66.07)	483.11 (64.60)	435.65 (53.45)
	4,951	*15,933*	*1,830*	*7,878*	*7,534*
Not Econo. Disad.	90.8 (5.19)	464.57 (62.75)	443.98 (65.57)	482.18 (65.44)	436.05 (53.27)
	22,187	*101,441*	*11,447*	*50,408*	*47,928*
Biological Sciences	90.5 (5.41)	464.55 (61.99)	445.93 (64.04)	482.08 (65.55)	437.35 (53.20)
	12,155	*6,718*	*758*	*3,354*	*3,136*
Physical Sciences	91.2 (5.27)	465.44 (63.77)	449.86 (66.09)	483.90 (65.66)	438.71 (52.38)
	3,206	*1,794*	*225*	*847*	*880*
Other Sciences	90.2 (5.40)	463.13 (65.33)	443.72 (63.31)	481.07 (67.93)	436.60 (54.11)
	11,777	*6,145*	*688*	*2,954*	*2,970*

Table A.10. *Scores for High School Science SOL Assessments for Science Majors at 4-year Schools*

Population Segment	Earth Sci (2006-12)	Earth Sci (2012-17)	Biology (2006-12)	Biology (2012-17)	Chemistry (2006-12)	Chemistry (2012-17)
All Students	457.63 (54.29)	438.00 (43.31)	453.89 (47.82)	442.75 (47.70)	456.64 (47.75)	448.04 (48.17)
	89,458	*50,589*	*98,655*	*60,844*	*58,753*	*40,865*
Females	457.58 (54.39)	438.00 (43.21)	453.66 (47.70)	442.71 (47.80)	456.31 (47.90)	447.80 (48.24)
	49,342	*27,994*	*54,293*	*33,594*	*32,374*	*22,548*
Males	457.69 (54.17)	437.99 (43.43)	454.16 (47.97)	442.81 (47.58)	457.06 (47.56)	448.32 (48.08)
	40,116	*22,595*	*44,362*	*27,250*	*26,379*	*18,317*
URM	457.69 (54.17)	437.48 (43.22)	453.76 (47.93)	442.50 (47.52)	456.70 (47.67)	448.41 (48.45)
	40,116	*13,204*	*26,089*	*15,851*	*15,530*	*10,631*
Not URM	457.44 (54.35)	438.18 (43.34)	453.93 (47.79)	442.84 (47.76)	456.63 (47.78)	447.90 (48.06)
	23,593	*37,385*	*72,566*	*44,993*	*43,223*	*30,234*
Econo. Disad.	457.70 (54.27)	437.68 (43.45)	454.28 (47.57)	442.86 (47.66)	456.58 (47.45)	448.08 (49.10)
	65,865	*6,741*	*13,494*	*8,091*	*8,060*	*5,579*
Not Econo.	457.61 (54.81)	438.04 (43.29)	453.82 (47.87)	442.74 (47.70)	456.65 (47.80)	448.03 (48.02)
Disad.	*12,193*	*43,848*	*85,161*	*52,753*	*50,693*	*35,286*
Biological	457.63 (54.21)	438.36 (43.86)	454.09 (48.10)	442.22 (48.22)	456.22 (48.03)	447.42 (48.27)
Sciences	*77,265*	*2,866*	*5,694*	*3,468*	*3,419*	*2,353*
Physical	458.00 (53.01)	437.22 (42.90)	455.08 (46.11)	441.62 (47.75)	455.82 (46.23)	444.57 (46.68)
Sciences	*1,375*	*765*	*1,518*	*927*	*930*	*638*
Other Sciences	456.64 (54.20)	438.98 (43.27)	453.09 (48.39)	444.52 (49.04)	456.67 (49.04)	449.54 (49.18)
	4,612	*2,684*	*5,198*	*3,271*	*3,034*	*2,176*

Table A.11. *Scores for SAT and ACT Assessments for Science Majors at 4-year Schools*

Population Segment	SAT Chem	SAT EcoBio	SAT MolBio	SAT Phys	ACT Science
All Students	66.04 (9.72) *2,790*	62.24 (9.64) *1,242*	66.22 (8.93) *1,460*	66.11 (8.70) *1,674*	21.95 (5.25) *27,859*
Females	66.07 (9.72) *1,543*	61.97 (9.80) *695*	66.57 (8.57) *794*	66.11 (8.74) *922*	21.93 (5.24) *15,364*
Males	65.99 (9.73) *1,247*	62.58 (9.45) *547*	65.80 (9.34) *666*	66.12 (8.66) *752*	21.97 (5.26) *12,495*
URM	65.54 (9.76) *715*	62.31 (9.17) *325*	65.68 (9.49) *384*	66.23 (8.50) *438*	21.88 (5.23) *7,372*
Not URM	66.21 (9.71) *2,075*	62.21 (9.81) *917*	66.41 (8.72) *1,076*	66.07 (8.77) *1,236*	21.97 (5.26) *20,487*
Econo. Disad.	65.70 (9.32) *388*	61.63 (10.51) *173*	66.25 (8.97) *204*	65.94 (8.76) *216*	21.90 (5.22) *3,829*
Not Econo. Disad.	66.09 (9.79) *2,402*	62.34 (9.50) *1,069*	66.21 (8.93) *1,256*	66.14 (8.69) *1,458*	21.96 (5.25) *24,030*
Biological Sciences	66.77 (9.37) *162*	61.09 (9.96) *82*	65.88 (8.22) *77*	66.82 (8.56) *115*	22.04 (5.36) *1,656*
Physical Sciences	64.77 (8.67) *48*	N/A	N/A	N/A	22.02 (5.50) *442*
Other Sciences	67.05 (9.56) *149*	62.36 (9.09) *64*	67.90 (9.22) *71*	64.84 (9.04) *95*	22.04 (5.19) *1,486*

Table A.12. *Scores on AP Science Assessments for Science Majors at 4-year Schools*

Population Segment	AP Biology	AP Chemistry	AP EnvSci	AP PhysicsB	AP PhysicsEM	AP PhysicsM
All Students	2.80 (1.25) *10,649*	2.77 (1.37) *7,219*	2.55 (1.30) *9,319*	2.56 (1.26) *2,510*	3.51 (1.45) *964*	3.25 (1.37) *2,703*
Females	2.79 (1.26) *5,810*	2.76 (1.37) *3,990*	2.56 (1.30) *5,164*	2.61 (1.28) *1,415*	3.52 (1.43) *545*	3.27 (1.36) *1,490*
Males	2.81 (1.25) *4,839*	2.78 (1.37) *3,229*	2.55 (1.30) *4,155*	2.50 (1.24) *1,095*	3.49 (1.48) *419*	3.22 (1.40) *1,213*
URM	2.79 (1.24) *2,761*	2.72 (1.36) *1,875*	2.58 (1.29) *2,473*	2.60 (1.26) *675*	3.41 (1.41) *232*	3.20 (1.37) *687*
Not URM	2.80 (1.26) *7,888*	2.78 (1.38) *5,344*	2.54 (1.30) *6,846*	2.55 (1.26) *1,835*	3.54 (1.46) *732*	3.26 (1.38) *2,016*
Econo. Disad.	2.86 (1.24) *1,432*	2.75 (1.36) *986*	2.60 (1.27) *1,328*	2.62 (1.27) *325*	3.43 (1.38) *119*	3.13 (1.39) *355*
Not Econo. Disad.	2.79 (1.26) *9,217*	2.77 (1.37) *6,233*	2.55 (1.30) *7,991*	2.55 (1.26) *2,185*	3.52 (1.46) *845*	3.26 (1.37) *2,348*
Biological Sciences	2.76 (1.23) *634*	2.86 (1.37) *410*	2.51 (1.34) *505*	2.69 (1.39) *154*	3.60 (1.35) *58*	3.36 (1.43) *163*
Physical Sciences	2.87 (1.24) *166*	2.81 (1.30) *105*	2.55 (1.31) *143*	N/A	N/A	3.32 (1.47) *41*
Other Sciences	2.77 (1.28) *566*	2.82 (1.38) *370*	2.56 (1.31) *526*	2.74 (1.33) *136*	3.60 (1.38) *52*	3.44 (1.30) *142*

Appendix B -- Post-Secondary Science Enrollment

Table B.1. *Biological Science Student Enrollment at 4-Year Schools in Virginia*

School Name	Number	Percentage
Virginia Commonwealth University	3,857	20%
Virginia Tech	3,560	18%
James Madison University	2,134	11%
Christopher Newport University	1,700	9%
George Mason University	1,610	8%
Old Dominion University	1,190	6%
Radford University	1,003	5%
Longwood University	644	3%
Bridgewater College	512	3%
Virginia State University	497	3%
Norfolk State University	469	2%
Liberty University	372	2%
Shenandoah University	300	2%
Lynchburg College	235	1%
Virginia Union University	219	1%
Hampton University	215	1%
Virginia Military Institute	211	1%
Other Virginia schools	900	5%

Table B.2. *Physical Science Student Enrollment at 4-Year Schools in Virginia*

School Name	Number	Percentage
Virginia Tech	1,102	21%
Virginia Commonwealth University	813	15%
James Madison University	805	15%
George Mason University	532	10%
Radford University	466	9%
Old Dominion University	241	5%
Longwood University	227	4%
Christopher Newport University	214	4%
Bridgewater College	212	4%
Norfolk State University	145	3%
Virginia State University	96	2%
Virginia Military Institute	92	2%
Shenandoah University	82	2%
Other Virginia schools	251	5%

Table B.3. *Other Science Student Enrollment at 4-Year Schools in Virginia*

School Name	Number	Percentage
James Madison University	4,159	24%
George Mason University	1,469	8%
Old Dominion University	1,455	8%
Virginia Commonwealth University	1,286	7%
Norfolk State University	1,181	7%
Longwood University	1,039	6%
Liberty University	825	5%
Virginia Tech	745	4%
University of Virginia-Main Campus	541	3%
Ferrum College	525	3%
Jefferson College of Health Sciences	519	3%
The University of Virginia's College at Wise	510	3%
Lynchburg College	485	3%
Radford University	434	3%
Hampton University	365	2%
Virginia State University	347	2%
Bridgewater College	272	2%
Shenandoah University	247	1%
Other Virginia schools	885	5%

Appendix C -- Correlations Among Variables

High School Completers

For the following tables, the correlation coefficient is shown above the diagonal, and the p-value is shown below the diagonal.

Table C.1. *Correlation Coefficients and P-Values Between Academic Metrics for Virginia High School Completers*

Variable	SOL5.1	SOL5.2	SOL8.1	SOL8.2	SOLESci.1	SOLESci.2	SOLBio.1	SOLBio.2	SOLChem.1	SOLChem.2
SOL.Score.gr5.1	---	0.562	0.686	0.704	0.696	0.658	0.704	0.640	0.555	0.514
SOL.Score.gr5.2	0.001	---	.	0.761	.	0.665	.	0.689	.	.
SOL.Score.gr8.1	0.000	.	---	0.780	0.746	0.752	0.758	0.757	0.620	0.612
SOL.Score.gr8.2	0.000	0.000	0.000	---	.	0.788	.	0.795	.	0.685
SOL.Score.ESci.1	0.000	.	0.000	.	---	0.392	0.748	0.750	0.590	0.587
SOL.Score.ESci.2	0.000	0.000	0.000	0.000	0.000	---	0.745	0.756	0.628	0.623
SOL.Score.Bio.1	0.000	.	0.000	.	0.000	0.000	---	0.360	0.654	0.693
SOL.Score.Bio.2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	---	0.678	0.686
SOL.Score.Chem.1	0.000	.	0.000	.	0.000	0.000	0.000	0.000	---	0.223
SOL.Score.Chem.2	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000	0.001	---
SAT.Chem	0.000	.	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000
SAT.EcoBio	0.000	.	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000
SAT.MolBio	0.000	.	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000
SAT.Phys	0.000	.	0.000	.	0.000	0.000	0.000	0.003	0.000	0.000
ACT.Science	0.000	.	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000
AP.Bio	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AP.Chem	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AP.EnvSci	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AP.PhysB	0.000	.	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000
AP.PhysEM	0.000	.	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
AP.PhysM	0.000	.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table C.1 (cont).

Variable	SAT.Chem	SAT.EcoBio	SAT.MolBio	SAT.Phys	ACT.Science	AP.Bio	AP.Chem	AP.EnvSci	AP.PhysB	AP.PhysEM	AP.PhysM
SOL.Score.gr5.1	0.330	0.493	0.386	0.348	0.548	0.410	0.365	0.489	0.353	0.267	0.275
SOL.Score.gr5.2	.	.	.	.	.	.	.	.	.	.	.
SOL.Score.gr8.1	0.413	0.514	0.505	0.391	0.633	0.533	0.449	0.585	0.412	0.386	0.367
SOL.Score.gr8.2	.	.	.	.	.	0.621	0.557	0.641	.	0.394	0.430
SOL.Score.ESci.1	0.325	0.607	0.450	0.306	0.605	0.509	0.408	0.602	0.442	0.188	0.294
SOL.Score.ESci.2	0.333	0.491	0.448	0.424	0.603	0.562	0.430	0.656	0.496	0.210	0.261
SOL.Score.Bio.1	0.430	0.600	0.541	0.405	0.648	0.594	0.487	0.626	0.425	0.317	0.383
SOL.Score.Bio.2	0.512	0.705	0.604	0.352	0.631	0.642	0.545	0.642	0.609	0.347	0.432
SOL.Score.Chem.1	0.575	0.566	0.552	0.495	0.610	0.606	0.628	0.587	0.496	0.462	0.479
SOL.Score.Chem.2	0.578	0.613	0.542	0.537	0.647	0.647	0.650	0.599	0.563	0.550	0.528
SAT.Chem	---	0.812	0.795	0.764	0.611	0.637	0.791	0.532	0.596	0.530	0.561
SAT.EcoBio	0.000	---	0.720	0.729	0.605	0.728	0.610	0.647	0.495	0.639	0.560
SAT.MolBio	0.000	0.000	---	0.691	0.618	0.744	0.673	0.652	0.506	0.618	0.593
SAT.Phys	0.000	0.000	0.000	---	0.593	0.632	0.691	0.515	0.708	0.667	0.712
ACT.Science	0.000	0.000	0.000	0.000	---	0.604	0.577	0.596	0.523	0.416	0.462
AP.Bio	0.000	0.000	0.000	0.000	0.000	---	0.685	0.676	0.592	0.506	0.605
AP.Chem	0.000	0.000	0.000	0.000	0.000	0.000	---	0.603	0.701	0.591	0.655
AP.EnvSci	0.000	0.000	0.000	0.000	0.000	0.000	0.000	---	0.585	0.519	0.555
AP.PhysB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	---	0.727	0.709
AP.PhysEM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	---	0.792
AP.PhysM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	---

High Schools

For the following tables, the correlation coefficient is shown above the diagonal, and the p-value is shown below the diagonal.

Table C.2. *Correlation Coefficients and P-Values Between Mean Academic and Demographic Metrics for Virginia High Schools*

Variable	count	Disad.Flag	SR.URMFlag	SOL.Score.gr5.1	SOL.Score.gr5.2	SOL.Score.gr8.1	SOL.Score.gr8.2
count	---	-0.425	0.107	0.151	-0.056	0.078	0.139
Disad.Flag	0.000	---	0.495	-0.019	-0.028	0.055	-0.011
SR.URMFlag	0.047	0.000	---	-0.070	-0.032	0.027	-0.044
SOL.Score.gr5.1	0.005	0.726	0.194	---	-0.223	0.404	0.271
SOL.Score.gr5.2	0.300	0.601	0.549	0.000	---	-0.260	0.153
SOL.Score.gr8.1	0.150	0.308	0.617	0.000	0.000	---	0.276
SOL.Score.gr8.2	0.010	0.845	0.414	0.000	0.005	0.000	---
SOL.Score.ESci.1	0.356	0.811	0.464	0.000	0.224	0.039	0.960
SOL.Score.ESci.2	0.038	0.583	0.154	0.000	0.633	0.000	0.000
SOL.Score.Bio.1	0.844	0.980	0.951	0.000	0.923	0.000	0.000
SOL.Score.Bio.2	0.164	0.154	0.459	0.000	0.085	0.518	0.000
SOL.Score.Chem.1	0.243	0.001	0.270	0.000	0.355	0.224	0.035
SOL.Score.Chem.2	0.311	0.495	0.609	0.001	0.006	0.021	0.256
SAT.Chem	0.006	0.228	0.870	0.418	0.220	0.006	0.615
SAT.EcoBio	0.033	0.604	0.950	0.772	0.324	0.732	0.718
SAT.MolBio	0.359	0.655	0.217	0.691	0.995	0.029	0.000
SAT.Phys	0.020	0.249	0.625	0.000	0.063	0.001	0.175
ACT.Science	0.004	0.000	0.534	0.008	0.001	0.472	0.007
AP.Bio	0.003	0.019	0.001	0.000	0.685	0.004	0.454
AP.Chem	0.040	0.954	0.202	0.020	0.468	0.000	0.007
AP.EnvSci	0.098	0.512	0.115	0.061	0.399	0.000	0.558
AP.PhysB	0.862	0.183	0.375	0.462	0.722	0.028	0.024
AP.PhysEM	0.086	0.170	0.706	0.682	0.293	0.846	0.963
AP.PhysM	0.857	0.183	0.024	0.422	0.016	0.721	0.643

Table C.2 (cont.)

Variable	SOL.Score. ESci.1	SOL.Score. ESci.2	SOL.Score. Bio.1	SOL.Score. Bio.2	SOL.Score. Chem.1	SOL.Score. Chem.2	SAT. Chem	SAT. EcoBio
count	-0.050	0.112	0.011	0.075	-0.063	0.055	0.149	-0.119
Disad.Flag	-0.013	0.030	-0.001	-0.077	0.183	-0.037	-0.066	0.029
SR.URMFlag	0.040	-0.077	-0.003	-0.040	0.060	-0.028	0.009	0.004
SOL.Score.gr5.1	0.346	0.223	0.318	0.362	0.271	0.176	-0.044	0.016
SOL.Score.gr5.2	-0.066	-0.026	-0.005	-0.093	-0.050	0.148	-0.067	0.055
SOL.Score.gr8.1	0.112	0.350	0.427	-0.035	0.066	-0.124	0.149	0.019
SOL.Score.gr8.2	0.003	0.597	0.263	0.254	0.114	-0.061	-0.028	0.020
SOL.Score.ESci.1	---	-0.240	0.415	-0.072	0.373	-0.100	-0.120	0.082
SOL.Score.ESci.2	0.000	---	0.104	0.259	-0.073	-0.009	-0.004	-0.163
SOL.Score.Bio.1	0.000	0.054	---	-0.152	0.410	-0.188	0.095	0.129
SOL.Score.Bio.2	0.181	0.000	0.005	---	0.061	0.445	-0.064	0.125
SOL.Score.Chem.1	0.000	0.179	0.000	0.260	---	-0.006	0.050	0.129
SOL.Score.Chem.2	0.065	0.871	0.000	0.000	0.919	---	-0.079	0.103
SAT.Chem	0.028	0.935	0.081	0.246	0.366	0.152	---	0.077
SAT.EcoBio	0.140	0.003	0.021	0.025	0.020	0.064	0.168	---
SAT.MolBio	0.054	0.422	0.024	0.005	0.480	0.926	0.000	0.581
SAT.Phys	0.510	0.827	0.000	0.355	0.262	0.170	0.000	0.572
ACT.Science	0.011	0.001	0.003	0.259	0.000	0.000	0.008	0.278
AP.Bio	0.839	0.974	0.057	0.725	0.086	0.029	0.283	0.002
AP.Chem	0.236	0.543	0.635	0.466	0.831	0.012	0.000	0.007
AP.EnvSci	0.000	0.967	0.907	0.468	0.365	0.000	0.063	0.002
AP.PhysB	0.024	0.531	0.555	0.691	0.219	0.079	0.016	0.006
AP.PhysEM	0.673	0.197	0.099	0.526	0.042	0.176	0.008	0.844
AP.PhysM	0.883	0.237	0.785	0.204	0.983	0.394	0.994	0.131

Table C.2 (cont.)

Variable	SAT.MolBio	SAT.Phys	ACT.Science	AP.Bio	AP.Chem	AP.EnvSci	AP.PhysB	AP.PhysEM	AP.PhysM
count	0.051	0.129	0.156	0.162	0.112	0.090	-0.010	-0.096	-0.010
Disad.Flag	0.025	-0.064	-0.203	-0.127	-0.003	-0.036	-0.073	0.077	0.073
SR.URMFlag	0.068	0.027	-0.034	-0.182	0.069	-0.086	-0.049	0.021	0.123
SOL.Score.gr5.1	0.022	0.243	-0.142	0.242	0.126	0.102	-0.041	-0.023	-0.044
SOL.Score.gr5.2	0.000	-0.103	0.181	0.022	-0.039	-0.046	-0.020	-0.059	0.132
SOL.Score.gr8.1	0.121	0.178	-0.039	0.156	0.236	0.253	0.121	0.011	0.020
SOL.Score.gr8.2	-0.206	0.075	-0.146	-0.041	0.145	-0.032	-0.124	0.003	0.025
SOL.Score.ESci.1	-0.107	0.037	-0.137	0.011	-0.064	-0.277	-0.124	0.024	0.008
SOL.Score.ESci.2	-0.045	0.012	-0.180	-0.002	0.033	0.002	0.035	0.072	-0.065
SOL.Score.Bio.1	0.124	0.244	-0.161	0.104	-0.026	-0.006	-0.033	0.093	-0.015
SOL.Score.Bio.2	-0.154	-0.051	-0.061	0.019	0.040	0.039	0.022	0.036	-0.069
SOL.Score.Chem.1	-0.039	0.062	-0.374	0.093	0.012	0.049	-0.068	0.114	-0.001
SOL.Score.Chem.2	-0.005	-0.076	0.241	0.119	0.135	0.288	-0.096	-0.076	-0.047
SAT.Chem	0.258	0.247	0.146	0.059	0.373	0.102	0.133	0.149	0.000
SAT.EcoBio	0.031	0.032	-0.061	0.174	0.150	0.174	0.153	0.011	0.085
SAT.MolBio	---	0.272	0.079	0.244	0.139	0.132	0.224	0.015	-0.074
SAT.Phys	0.000	---	0.037	0.107	0.153	0.060	0.248	0.090	0.146
ACT.Science	0.153	0.500	---	0.153	0.135	0.065	-0.030	-0.106	0.046
AP.Bio	0.000	0.053	0.005	---	0.186	0.344	0.361	-0.008	0.005
AP.Chem	0.012	0.006	0.013	0.001	---	0.370	0.163	0.183	0.276
AP.EnvSci	0.017	0.278	0.230	0.000	0.000	---	0.144	0.091	0.238
AP.PhysB	0.000	0.000	0.587	0.000	0.003	0.009	---	0.021	0.072
AP.PhysEM	0.784	0.111	0.059	0.887	0.001	0.104	0.715	---	0.367
AP.PhysM	0.180	0.009	0.398	0.924	0.000	0.000	0.194	0.000	---