

## Seton Hall University eRepository @ Seton Hall

---

Seton Hall University Dissertations and Theses  
(ETDs)

Seton Hall University Dissertations and Theses

---

Summer 6-27-2019

# Leaving STEM: An Examination of the STEM to Non-STEM Major Change and How the STEM Curriculum Relates to Academic Achievement in Non-STEM Fields

Zachary M. Romash  
zromash@gmail.com

Follow this and additional works at: <https://scholarship.shu.edu/dissertations>

 Part of the [Higher Education Commons](#)

---

### Recommended Citation

Romash, Zachary M., "Leaving STEM: An Examination of the STEM to Non-STEM Major Change and How the STEM Curriculum Relates to Academic Achievement in Non-STEM Fields" (2019). *Seton Hall University Dissertations and Theses (ETDs)*. 2675.  
<https://scholarship.shu.edu/dissertations/2675>

LEAVING STEM: AN EXAMINATION OF THE STEM TO NON-STEM MAJOR CHANGE  
AND HOW THE STEM CURRICULUM RELATES TO ACADEMIC ACHIEVEMENT IN  
NON-STEM FIELDS

Zachary M. Romash

Dissertation Committee  
Robert Kelchen, Ph.D., Mentor  
Rong Chen, Ph.D., Committee Member  
Joseph Stetar, Ph.D., Committee Member

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of  
Philosophy  
Department of Higher Education, Leadership, Management and Policy

Seton Hall University  
2019

©2019 Zachary M. Romash




---

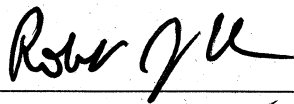
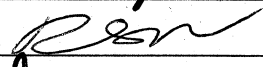
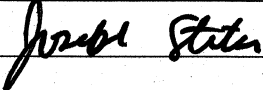
COLLEGE OF EDUCATION AND HUMAN SERVICES  
DEPARTMENT OF EDUCATION LEADERSHIP MANAGEMENT & POLICY

---

**APPROVAL FOR SUCCESSFUL DEFENSE**

**Zachary M. Romash**, has successfully defended and made the required modifications to the text of the doctoral dissertation for the. during this **Summer Semester 2019**.

**DISSERTATION COMMITTEE**  
(please sign and date beside your name)

COMMITTEE:	SIGNATURE	DATE
Mentor:		
Dr. Robert Kelchen, Ph.D		6/27/19
Dr. Rong Chen, Ph.D		6/10/2019
Dr. Joseph Stetar, Ph.D.		6/10/19

The mentor and any other committee members who wish to review revisions will sign and date this document only when revisions have been completed. Please return this form to the Office of Graduate Studies, where it will be placed in the candidate's file and submit a copy with your final dissertation to be bound as page number two.

## **ABSTRACT**

The lack of student persistence in the Science, Technology, Engineering and Mathematics (STEM) fields has been widely researched in recent years. Due to the high attrition rates in STEM fields and the shortage of STEM workers in the United States, research on STEM attrition has focused on identifying factors that cause STEM attrition and ways to increase STEM persistence. While these studies are helpful to understand STEM attrition, researchers have ignored what happens to the students who fail to persist in the STEM fields. Instead of focusing on the causes of STEM attrition, this study focused on the STEM to non-STEM major change by examining how STEM course enrollment and STEM course performance relates to various forms of academic achievement (first year retention, graduation, time to degree, cumulative GPA). The analytical sample for this study was drawn from the 2004/2009 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) and the associated 2009 Postsecondary Education Transcript Study (PETS:09) datasets with the final sample used for analysis representing students who initially enrolled in a STEM bachelor's degree program and changed to a non-STEM field or left the institution entirely. As such, the results were reflective of this group of students, and not all students in college in general. Results of the study revealed three general findings about the relationship between STEM course enrollment and STEM course academic performance and academic achievement. First, STEM credits attempted is negatively associated with first year retention. Each unit increase in STEM credits attempted reduced the odds of persistence past the first year. Secondly, performance in college level math, introductory laboratory science and STEM courses plays an important role in determining students' level of academic achievement in non-STEM fields. Lastly, females reach higher levels of academic achievement after leaving the STEM fields when compared to males.

## **Dedication**

This dissertation is dedicated to my parents – Richard and Michelle Romash. Thank you for your constant support and always believing in me. There are no words to express how grateful I am for all that you have done for me throughout my life and educational endeavors. Your words and actions taught me that anything is possible through hard work and continuous effort, and for this, I am forever grateful.

“Continuous effort – not strength or intelligence – is the key to unlocking our potential.”

(Liane Cardes).

## Table of Contents

<b>Abstract.....</b>	<b>ii</b>
<b>Dedication.....</b>	<b>iii</b>
<b>Table of Contents.....</b>	<b>iv</b>
<b>List of Tables and Figures.....</b>	<b>v</b>
<b>Chapter I: Introduction.....</b>	<b>1</b>
Problem Statement.....	1
Current Research.....	5
Deficiencies.....	7
Significance of the Study.....	8
Research Questions.....	10
<b>Chapter II: Literature Review.....</b>	<b>12</b>
Introduction.....	12
Theory.....	13
Background Variables.....	18
Pre-college Academic Achievement.....	25
Enrollment and Performance in STEM courses.....	29
Directions for Further Research.....	35
Conclusion.....	36
<b>Chapter III: Methods.....</b>	<b>37</b>
Introduction.....	37
Theoretical Framework.....	39
Measures.....	40
Source of Data.....	40
Sample.....	41
Methods.....	42
Design.....	42
Multicollinearity.....	44
Outcome Variables.....	44
Academic and Social Integration Variables.....	47
Background Variables.....	50
Weights.....	54
Limitations.....	54
Summary.....	55
<b>Chapter IV: Analysis of the Data.....</b>	<b>56</b>
Introduction.....	56
Cross-Tabulation of Independent Categorical Variables.....	58
Analysis of Research Question 1.....	61
Analysis of Research Question 2.....	69
Analysis of Research Question 3.....	75
Analysis of Research Question 4.....	81
<b>Chapter V: Conclusions and Implications.....</b>	<b>88</b>
Introduction.....	88
Key Findings & Conclusions.....	88
Recommendations for Policy, Practice & Future Research.....	92
Summary.....	96
<b>References.....</b>	<b>98</b>

## List of Tables and Figures

Table 1. Descriptive Statistics of First Year Retention.....	45
Table 2. Descriptive Statistics of Graduation.....	46
Table 3. Descriptive Statistics of Time to Degree.....	46
Table 4. Descriptive Statistics of Cumulative GPA.....	47
Table 5. Descriptive Statistics of Independent Categorical Variables.....	52
Table 6. Descriptive Statistics of Independent Continuous Variables.....	53
Table 7. Cross Tabulation Analysis of Categorical Variables by First Year Retention.....	58
Table 8. Cross Tabulation Analysis of Categorical Variables by Graduation.....	59
Table 9. Cross Tabulation Analysis of Categorical Variables by Time to Degree.....	60
Table 10. Goodness of Fit Statistics: First Year Retention (Research Question 1).....	62
Table 11. Logistic Regression Results First Year Retention (Research Question 1).....	63
Table 12. Goodness of Fit Statistics: Graduation (Research Question 1).....	64
Table 13. Logistic Regression Results Graduation (Research Question 1).....	65
Table 14. Goodness of Fit Statistics: Time to Degree (Research Question 1).....	65
Table 15. Logistic Regression Results Time to Degree (Research Question 1).....	66
Table 16. Cumulative GPA Model Summary (Research Question 1).....	67
Table 17. Cumulative GPA ANOVA (Research Question 1).....	67
Table 18. Coefficients Table: Cumulative GPA (Research Question 1).....	68
Table 19. Goodness of Fit Statistics: First Year Retention (Research Question 2).....	70
Table 20. Goodness of Fit Statistics: Graduation (Research Question 2).....	71
Table 21. Logistic Regression Results Graduation (Research Question 2).....	71
Table 22. Goodness of Fit Statistics: Time to Degree (Research Question 2).....	72
Table 23. Logistic Regression Results Time to Degree (Research Question 2).....	74
Table 24. Cumulative GPA Model Summary (Research Question 2).....	74
Table 25. Cumulative GPA ANOVA (Research Question 2).....	74
Table 26. Coefficients Table: Cumulative GPA (Research Question 2).....	75
Table 27. Goodness of Fit Statistics: First Year Retention (Research Question 3).....	76
Table 28. Goodness of Fit Statistics: Graduation (Research Question 3).....	77
Table 29. Logistic Regression Results Graduation (Research Question 3).....	78
Table 30. Goodness of Fit Statistics: Time to Degree (Research Question 3).....	78
Table 31. Logistic Regression Results Time to Degree (Research Question 3).....	79
Table 32. Cumulative GPA Model Summary (Research Question 3).....	80
Table 33. Cumulative GPA ANOVA (Research Question 3).....	80
Table 34. Coefficients Table: Cumulative GPA (Research Question 3).....	81
Table 35. Goodness of Fit Statistics: First Year Retention (Research Question 4).....	82
Table 36. Goodness of Fit Statistics: Graduation (Research Question 4).....	83
Table 37. Logistic Regression Results Graduation (Research Question 4).....	84
Table 38. Goodness of Fit Statistics: Time to Degree (Research Question 4).....	85
Table 39. Logistic Regression Results Time to Degree (Research Question 4).....	85
Table 40. Cumulative GPA Model Summary (Research Question 4).....	86
Table 41. Cumulative GPA ANOVA Research Question 4).....	86
Table 42. Coefficients Table: Cumulative GPA (Research Question 4).....	87



## CHAPTER I

### INTRODUCTION

#### **Problem Statement**

The national push to increase the number of graduates with STEM (science, technology, engineering and mathematics) degrees in the last two decades has led to a rise in the number of students that plan to major in these disciplines (Higher Education Research Institute, 2010; Chen, 2013). In 1986, the percentage of students that noted pursuing a STEM degree upon entry was less than 25%; by 2012 the number of students that planned to complete a STEM degree upon entry had risen to 39% (Higher Education Research Institute, 2010; National Science Board, 2014). Fueled by the prospect of employment, along with lucrative pay, more students aim to earn STEM degrees in college. Additionally, earning potential, combined with the increasing cost of higher education, has led students to place more value on STEM degrees compared to social science and humanities degrees (Russell & Atwater, 2005). Although the federal government has prioritized STEM education, it is ultimately up to higher education institutions to produce graduates in these fields.

Although more students are entering higher education as STEM majors, attrition rates within the majors are a concern for institutions and policy makers. Approximately one half of students that enter STEM fields do not earn a STEM degree (Chen, 2013). Of the students that leave, around 20 percent leave STEM fields by changing their majors and around 28 percent leave college completely (Chen, 2013). Compared to students that initially enroll in business, education, and social science majors, students that enter college in a STEM major are

around five percent less likely to leave college completely, but they are less likely to stay in their initial STEM major. (Arcidiacono, 2004).

Major attrition and institutional attrition are problems that are not uniquely connected to STEM fields. Bettinger (2010) in *American Universities in a Global Market* found only 43% of students who entered higher education with the desire to earn a STEM degree stayed in a STEM field. In a similar comparison, Chen's (2013) study found that of students that intended to major in the social/behavioral sciences, only 28% left their major. Other studies have found that major attrition rates for students in non-STEM fields were similar or higher than those in STEM fields (Chen, 2013). One explanation for comparable major attrition rates between STEM majors and non-STEM majors is that the STEM fields often draw high-achieving students (Bettinger, 2010). Although other fields may have similar attrition rates, STEM attrition is especially troublesome given STEM students cite poor academic performance as the reason for leaving at a higher rate than students that leave non-STEM majors (Adelman, 2006; Chen, 2013; Ost, 2010; Watkins & Mazur, 2013). Secondly, unlike most non-STEM majors, which allow students to take courses in a wide variety of disciplines, the majority of STEM leavers' coursework cannot be applied to a non-STEM major, which often results in an increase in time to degree (Sklar, 2015).

For an incoming student, a course load that allows ample time to adjust to their new environment and the higher expectations in the classroom is preferred. Research has identified that a curriculum that helps to build academic skills in the first year is linked to persistence after the first year (Hunter & Linder, 2005; Pascarella & Terenzini, 2005). According to Anderson and Kim (2006), most colleges ask students to declare their major by the spring term of their sophomore year. However, in order to stay on track with requirements, STEM students have to jump right into demanding math and science courses in the first year (Le, Robbins & Westrick,

2014; Zhang, Thorndyke, Ohland & Anderson, 2004). At most institutions, non-STEM field students can delay major coursework and focus on general education requirements (Bettinger, 2010).

As previously mentioned, the first-year curriculum for students pursuing STEM majors requires completion of specific introductory science and math sequences that develop skills that are needed throughout the degree program. The typical sequence of science courses, which was adopted in 1905 and still is the norm today, asks students to complete a year of introductory chemistry and calculus, with biology and physics in the second year (Barr, Matsui, Wanat & Gonzalez, 2010; Zhang, Thorndyke, Ohland, & Anderson, 2004). The content covered in introductory chemistry and calculus is needed to understand the more advanced coursework that follows (Gainen, 1995; Zhang et al., 2004). Because of the sequential curriculum of STEM majors, students often cannot choose when they take these introductory science and math courses. If a student does decide to wait to take introductory level STEM courses or is forced to take remedial courses, he/she faces an academic program that often takes longer than four years to complete (Bettinger, 2010).

The rigor of the first-year STEM curriculum often causes academic struggles and discontent for students. Noel-Levitz (2006) found that 45% of incoming freshman had significant difficulties with mathematics. Further, Seymour and Hewitt (1997) found that students in STEM majors noted frustration with having to take on too heavy a course load in their first year. Students often complain that science classes are too fast-paced and have an extremely competitive atmosphere (Tobias, 1990; Tobias & Lin, 1991). Along with any institutional academic progress requirements, many institutions require STEM students to meet additional GPA requirements in specific introductory courses, which further increases the

competitiveness of first-year STEM courses. Many of these courses are considered “gatekeeping” courses that are specifically meant to weed out students that may not have the ability to persist in the major (Eagan, Garcia, Hurtado, & Gasiewski, 2012; Tai, Sadler, & Loehr, 2005). Numerous studies have identified first-year chemistry, calculus and other gatekeeping courses as a factor for students to move away from a STEM major (Barr et al., 2008; Mervis, 2010; Thurmond & Cregler, 1999; Dienstag, 2008; Shaw & Barburi, 2010; Tai et al., 2005). According to Moreno & Muller (1999, p. 31), “gatekeeping [courses] expose students to a competitive environment in which formulas, symbols, and familiar language are used in new contexts.” Forcing students to take “gate-keeping” courses in their first year can hurt the institution’s chance of retaining students, as rigorous course loads, coupled with a competitive class atmosphere, often result in poor academic performance.

Alongside creating academic struggles, forcing students into a structured STEM curriculum in their first year of college can deny students the opportunity to explore different disciplines. James Powell, former president of Oberlin and Reed Colleges, cites that students that come in as a declared major “might indeed be a legitimate source of concern (and possible attrition) because they may have made a decision that is (a) premature – reflecting lack of careful planning and forethought; (b) unrealistic – resulting from lack of self-knowledge or (c) uninformed – resting on insufficient knowledge about the relationship between academic majors and future careers” (Powell, quoted in Pope, 1990, p. 80). Students also may be pressured into majors by extrinsic factors such as parental pressure or future monetary rewards (Cuseo, 2005).

Students who enroll in higher education with a declared major may not have adequately assessed their academic skills or interests.

### **Current Research**

Given the priority on STEM education in America, a large body of research exists that aims to understand the factors predicting STEM student retention. From these studies, a small body of research examining what happens to students after leaving STEM fields has emerged. After identifying students that enrolled with the intention of earning a STEM degree, researchers are able to track these students throughout their time in higher education and identify those who did not graduate with a STEM degree. The outcome most widely examined in these studies is graduation rate (Chen, 2015; Chen, 2013; Higher Education Research Institute, 2010; Huang, Taddese & Walter, 2000). These studies also disaggregate graduation rates of STEM leavers by race. With regards to race, White and Asian American students had the highest graduation rates of STEM leavers, followed by Latinos, African Americans and Native Americans. Studies have also found that women are more likely to earn a degree after leaving STEM than men (Chen, 2013; Higher Education Institute Research Institute, 2010).

Chen's (2013) study is by far the most in-depth study of STEM leavers and draws from the National Center for Educational Statistics' (NCES) Beginning Postsecondary Longitudinal Study (BPS:04/09) and the Postsecondary Education Transcript Study (PETS:09). The study tracks students that first enrolled in 2003 to 2009. The BPS provides the researchers with the ability to identify and track students that planned to pursue a STEM degree upon enrolling. The use of PETS:09 further enhances the study by providing the transcripts of students that were part of the BPS:04/09. Chen's (2013) study is the first to utilize national transcript data when

examining STEM attrition. These data sets allow the study to examine both demographic as well as pre- and post-secondary academic variables.

Using bivariate analysis, the study identified the influence of a multitude of variables (demographic, pre-college preparation, family background, STEM course taking, and performance) on STEM attrition and institutional graduation rates. This analysis aids understanding of how different variables may impact students' chances of earning a degree after leaving a STEM field. The variables that significantly influenced graduation rates of STEM leavers include parents' education level, income level, high school GPA, highest level of math taken in high school, admission selectivity, and whether or not a student was a Pell Grant recipient (Chen, 2013).

The majority of studies examining the graduation rates of STEM leavers simply calculate graduation rates, without completing any in-depth quantitative analysis. In the last section of her study, Chen (2013) conducted a multivariate analysis to provide more clarity of the bivariate analysis completed earlier in the study. The study utilizes a multinomial probit model (MNP) to “predict the probability of one event (such as switching majors) over several mutually exclusive alternatives” (Chen, 2013, p. 35). This specific model provides an understanding of the factors that are associated with the outcome of leaving STEM by switching majors or leaving STEM and never obtaining a degree, especially with regards to academic performance at the post-secondary level.

Using PETS:09 allowed Chen (2013) to explore how STEM leavers' coursework relates to academic achievement. For students that left a STEM field and eventually graduated in a non-STEM field, the amount of STEM courses taken in the first year, the type of math course taken in the first year, and performance in STEM courses were the most important variables related to

the outcome of leaving STEM by switching majors. The fewer STEM courses a student took increased the probability that a student would leave by switching their major. Also, if a student took a lower level of math in the first year (e.g., pre-calculus), they were more likely to leave by changing their major. Lastly, students that had higher grades in non-STEM courses compared to STEM courses were more likely to leave STEM fields by changing their major (Chen, 2013). Equally as important was that none of the demographic variables found to be significant in the bivariate analysis were significant for the outcome of leaving STEM by entering a non-STEM field. The MNP analysis found that leaving STEM fields negatively impacted overall GPA. The variables that increased the probability of a student leaving STEM by leaving college were gender, low-income background, attending an institution with minimal admission standards, and poor performance in STEM coursework (Chen, 2013).

Although not as definitive, qualitative studies have provided some insight into which fields STEM leavers end up in. Studies often strive to understand how students' beliefs lead to STEM attrition and what draws them to other fields. Seymour and Hewitt (1997) interviewed students that left STEM fields to pursue other majors. Through interviews, the study found that the atmosphere in non-science classes compared to science courses drew the students into other fields.

### **Deficiencies**

The previous research on how leaving a STEM field relates to educational outcomes provides a foundation for future research to better understand the impact of the first-year STEM curriculum on overall academic outcomes for STEM leavers. Other than graduation rates, previous research has yet to fully examine other important academic outcomes. Time to degree

and yearly retention rates warrant examination in order to understand the full effect of the first-year STEM curriculum on overall academic achievement.

Also, the research on students that leave STEM is overwhelmingly descriptive. Although Chen (2013) conducted a multivariate analysis, the analysis strived to better understand the results of her bivariate analysis by determining the strength of association among independent variables. Sklar (2015) provides multivariate analysis, but the study's focus is how the timing of the change of major impacts time to degree and graduation.

Chen (2013) provides a starting point as far as how first-year STEM coursework impacts graduation rates and cumulative GPA, but the study does not provide a multivariate analysis of how enrollment and performance in first-year STEM courses relate to academic achievement.

Chen (2015) states that future research should examine transcript data to identify the “gatekeeping” courses that may hinder students' academic achievement program.

Although research identifies that students struggle with the first-year STEM curriculum, the current body of research fails to provide an analysis of students' enrollment and performance in first-year STEM courses and how it relates to academic achievement after leaving the STEM fields. The limited studies that examine the relationship between first-year STEM course enrollment and performance attempt to determine how specific courses relate to academic achievement in the STEM fields and do not explore the relationship between STEM coursework and academic achievement in non-STEM fields.

### **Significance of the Study**

This study expands on previous research in a variety of ways. First, this study will look at academic outcomes that have yet to be studied. Along with graduation rates, time to degree, and GPA, this study will also examine first-year retention rates for students that enroll with the



intent to earn a STEM degree, but who ultimately do not earn a STEM degree. These variables will provide a better understanding of how students' academic program is affected by enrolling in first-year STEM courses.

Time to degree warrants examination because the STEM curriculum can limit students' major options and also prevent students from progressing in other majors (Steele, 1994). Examining time to degree will help to understand how enrolling in a large number of science and math courses impacts a student's ability to graduate in four years. Academic advisors can use this information to help students create pathways to graduating in four years even after leaving STEM fields.

Although graduation rates do shed light on the retention rates of students that leave STEM fields, first-year retention rates provide insight into when students are most at-risk of leaving STEM by leaving college entirely. Given what is known about the importance of academic performance in the first year and the fact that many student leave STEM fields due to poor academic performance, studying first-year retention rates is an outcome that gives new insight about how first-year coursework may impact students' academic program.

As Chen (2015) explains, more research is needed to determine how specific STEM courses impact a students' academic program. Using PETS:09 will allow this study to examine academic performance in specific introductory STEM courses. Through quantitative analysis, this study will determine how enrollment and performance in introductory STEM courses impact different educational outcomes. The finding of this analysis can help institutional administrators and academic advisors identify students that may be at-risk due to enrollment and performance in specific courses.

## Research Questions

1. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does the number of STEM credits attempted relate to:
  - First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
2. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in college-level math relate to:
  - First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
3. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in introductory-level laboratory science relate to:
  - First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?

4. After controlling for ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in STEM courses relate to:
  - First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?

## CHAPTER II

### LITERATURE REVIEW

#### **Introduction**

The national push to have more students earn STEM degrees in the United States and the fact that approximately 50 % of STEM entrants leave STEM fields (Chen, 2013; Chen, 2009) have led to the production of a large body of educational research that strives to understand how various factors relate to a student's chance of earning a STEM degree. By applying retention theory to the study of STEM persistence, researchers have focused on how variables shown to relate to retention (academic, demographic, social, and non-cognitive) also impact STEM degree completion. Unlike this study, the main objective of STEM attrition research is to understand the reason students leave the STEM fields. Therefore, while extremely vast, STEM attrition research provides minimal insight into how enrollment and performance in first-year STEM courses relate to students' academic achievement outside of the STEM fields.

Research on STEM attrition includes a subsection that examines the first-year STEM curriculum. Specifically, these studies seek to understand how enrollment and performance in first-year STEM course relate to STEM attrition. Using the Beginning Postsecondary Longitudinal Study 2004/2009 (BPS:04/09) and the Postsecondary Education Transcripts 2009 (PETS:2009), Chen (2013) has been able to produce the most comprehensive research on the first-year STEM curriculum to date. Chen (2013) is overwhelmingly descriptive, so her research does not consider how specific variables relate to different academic outcomes but, rather, the course taking patterns and performance of STEM leavers. By analyzing the first-year STEM curriculum, the research provides a starting point for understanding the first-year STEM curriculum and how specific courses relate to academic achievement.

Similar to STEM attrition, students' first year in postsecondary education is another highly researched topic in higher education. Given the power of first-year course performance to predict graduation, researchers have worked to identify which first-year courses predict academic achievement. Using student transcript data, researchers have identified enrollment and performance in first-year math and English courses as predictors of overall academic achievement, regardless of the intended major (Bahr, 2008; Callahan & Belcheir, 2017; Herzog, 2005). Still, these studies do not focus on the STEM leaver population and therefore do not account for the substantial curricular differences between STEM and non-STEM majors.

More research on the STEM leaver population is needed as the population may be particularly at risk due to the unique challenges the first-year STEM curriculum presents for students (Chen, 2013; Ost, 2010; Watkins & Mazur, 2013). Academic performance in the first year is critical for first-year retention, and enrollment in challenging STEM courses in the first year may create additional challenges to finding success in a new major.

While more research focusing on STEM leavers' coursework is needed, a review of the literature will be conducted to identify the variables found to be significant in predicting academic achievement. This literature review will begin with a review of various theories used to study college academic achievement. After reviewing the theories, I will summarize research on how pre-college variables relate to post-secondary academic achievement. I will conclude with studies that address how enrollment and performance in first-year STEM courses relate to educational outcomes (retention, time to degree, graduation, cumulative GPA).

## **Theory**

### **Historical Background**

As access to higher education expanded in the 1950s and 1960s, the issue of student attrition became a prominent concern for the United States and higher education institutions. Prior to the 1970s, researchers attempted to understand student attrition by focusing on students' individual characteristics, and they lacked a theoretical framework for conceptualizing the phenomenon (Aljohani, 2016; Panos & Astin, 1968; Spady, 1970). During the 1970s, researchers shifted their focus away from individual student characteristics and began arguing that the relationship between students and institutions is the key to understanding student attrition (Aljohani, 2016; Spady, 1970). This shift in focus served as the foundation for the development of the most widely recognized models used to study retention, which are reviewed in this section.

### **The Institutional Departure Model (Tinto, 1975, 1993)**

Within higher education literature, Vincent Tinto's (1975, 1993) institutional departure model is the most widely used theory for understanding persistence/retention (McCubbin, 2003; Metz, 2000; Reason, 2009; Veenstra, Dey, & Herrin, 2009). Tinto's theory, which is partly based on Durkheim's (1897) suicide model, argues that attrition is linked to formal and informal academic experiences as well as social integration (Demetriou & Schmitz-Sciborski, 2011). Students who are academically and socially integrated are more likely to be committed to their institution and thus are more likely to graduate (Tinto, 2007). Tinto's theory is often referred to as an interactionalist theory as it argues that attrition is a result of interactions between the student and the environment (Tinto, 1975; Terenzini & Pascarella, 1980). Tinto (1975) proposed that a student brings specific characteristics (i.e., demographic variables) and experiences to college. These background characteristics then interact with environmental variables from the institution to determine the level of academic and social integration (Terenzini & Pascarella,

1980; Tinto, 1975). Finally, academic integration influences students' goal commitment, and social integration influences students' commitment to the institution. When controlling for other variables, the more academically and socially integrated a student is into their institution, the greater the student will be committed to completing college and thus be less likely to become a victim of attrition (Tinto, 1975).

Tinto's model has been tested in various college settings and environments, and the majority of research that utilizes Tinto's model has found that the model explains a large percentage of the variance in student attrition (Alijohani, 2016). Using Tinto's (1975) model, Pascarella, Duby, Miller, and Rahser (1981) studied attrition at the University of Illinois and found that Tinto's model accounted for 48% of the variance in first-year attrition. Pascarella, Duby, and Iverson (1983) focused on voluntary withdrawal, as opposed to academic dismissal, and discovered that Tinto's model predicted 82% of the variance in first-year voluntary withdrawal. The Office of Institutional Research at Bowling Green State University administered a survey that measured many variables from Tinto's model in all first-year students. The variables in the survey explained 41% of the variance in first-year student retention (Gilmer, 2007). Using qualitative analysis to test Tinto's model for first-generation students, Longwell-Grice and Longwell-Grice's (2008) study confirmed the importance of academic and social integration (measured through student-faculty interactions) for retention. The amount of variance in attrition explained by Tinto's model differs among studies due to differences in the setting of the research and the populations being studied. Furthermore, the variables used to measure academic and social integration lead to differences in the amount of variance explained by Tinto's model.

The majority of studies testing Tinto's model support his theory, but some argue that Tinto's model does not accurately explain student attrition. The most common criticism of Tinto's model is that it is only applicable to the traditional student (McCubbin, 2003; Metz, 2002). In one of the first criticisms of Tinto's model, Bean and Metzner (1985) argued that social integration is not an important factor in the decision to leave postsecondary education for non-traditional students given that non-traditional students may already be integrated into their own networks outside of the institution. Focusing on Latino students, Torres and Solberg (2001) found that social integration factors were not significant and did not predict attrition. Findings such as those in Torres and Solberg (2001) have led others to argue that Tinto's model is not appropriate for the study of underrepresented minorities in higher education (McCubbin, 2003). Although some argue that Tinto's model should not be applied to certain populations, Tinto's model is still viewed as a reliable theory to guide persistence and degree completion research.

### **The Student Attrition Model (Bean, 1980, 1982)**

Bean's (1980) student attrition model has many similarities with Tinto's (1975) model; however, Bean (1980) argues that Tinto's application of Durkheim's (1897) suicide model to student attrition was misguided. Rather, Bean believed theoretical models used to study turnover in work organizations were more appropriate for studying student attrition.

According to Bean (1982), along with social and academic integration, organizational variables and outside environmental variables also influence students' decision to leave an institution. These variables, as well as external factors from the environment, influence students' attitudes toward and satisfaction with the institution, which indirectly relate to a student's decision to leave an institution (Himelhoch, Nichols, Ball, & Black, 1997). Empirical studies testing Bean's (1982) model reveal that the model predicts 44% to 48% of the variance in student



persistence (Bean, 1983; Bean & Metzner, 1985; Cabrera et al., 1992). Furthermore, the student attrition model does not lose its predictive power when studying nontraditional student populations, such as minority students (Himelhoch et al., 1997), community college students (Sandiford & Jackson, 2003) and adult learners (Bean & Metzner, 1985).

### **The Student Involvement Theory (Astin, 1984)**

Astin's (1984) student involvement theory is known as a behavioral model and argues that after controlling for background variables, the amount of students' involvement in college relates to their persistence at an institution. Astin (1984) defines involvement as "the quantity and quality of the physical and psychological energy that students invest in the college experience" (p. 307). Furthermore, Astin (1984) believed involvement was quantitative and qualitative. For example, a student's involvement could be measured by the number of hours he or she spent studying but also by the measuring the depth of the student's reflection (Astin, 1984). Although the student involvement theory was developed to better understand student development and learning, many believe that student involvement is directly related to the decision to drop out of college. Studies have confirmed the positive relationship between engagement at an institution and retention (Cruce, Shoup, Kinzie, & Gonyea, 2008; Pike, Kuh, & Massa-McKinley, 2008). Using the CIRP freshman data and the follow-up College Student Survey (CSS), Astin and Sax (1998) found that GPA and persistence were positively influenced by students' involvement at an institution.

Those critical of the student involvement theory note the challenge in measuring involvement. For example, students may be involved in multiple groups and activities at an institution; however, measuring involvement based on the number of groups a student belongs to fails to account for the intensity of the student's involvement. Another common criticism of the

student involvement theory is that it does not apply to non-traditional students, who may not become involved at the institution the same way traditional students are able to.

Although there are differences among Tinto (1975, 1993), Bean (1980, 1982), and Astin's (1984) theories, each model recognizes the importance of academic and social experiences that determine students' level of integration or the involvement of students at institutions.

### **Background Variables**

Tinto's theory of student departure suggests that students' individual characteristics determine how committed a student is to the institution and to graduating. Research has provided empirical evidence supporting Tinto's claim that background characteristics influence college persistence (Xu & Weber, 2018). Therefore, background variables are almost always included along with other variables related to social and academic integration when studying academic achievement (Adelman, 2006). This study will utilize background characteristics in the same manner as described above.

While demographic variables are commonly employed as control variables in researchers' analyses, it is important to note that background characteristics alone fail to predict academic achievement in postsecondary education (Adelman, 2006). Once additional control variables are added, demographic variables, such as race/ethnicity and gender, often play a reduced role in providing explanation for academic achievement. Adelman (2006, p. 24) notes that "student demographics and family demographics may have, at best, indirect connections with degree completion." Furthermore, the high levels of multicollinearity that exist between demographic variables mask the true predictive power of individual variables. Alone, demographic variables

do an extremely poor job of explaining 4-year degree attainment and must therefore be combined with other variables related to the students' experience.

### **Race/Ethnicity**

Improvements in access to higher education in the United States, coupled with the link between degree attainment and social mobility, have made the study of underrepresented minorities in higher education a prominent subject in educational research. Research shows that underrepresented minorities (URMs) persist at lower levels than White and Asian students (Astin & Oseguera, 2005; Ross, Kena, Rathbun, KewalRamani, Kristapovich, Manning, & Zhang, 2012). The most recent NCES data show that 65% of all bachelor's degrees were awarded to White students in the 2015–2016 academic year. Blacks and Hispanics made up 11% and 13%, respectively, followed by Asians (8%) and American Indians/two or more races (4%; Musu-Gillette, de Brey, McFarland, Hussar, Sonnenberg, & Wilkinson-Flicker, 2017). Using only demographic variables, Adelman (2006) found that being an underrepresented minority reduced the chances of earning a bachelor's degree by 17%. URMs also lag behind White and Asian American students in the STEM fields. Asian American students completed STEM programs at 44%, followed by White students at 33%. Latino, Native Americans, and Black students completed STEM programs at 22.1%, 18.8%, and 18.4%, respectively (Higher Education Research Institute, 2010). Research drawing from other national representative samples confirms that Whites and Asians are retained and complete STEM programs at almost twice the rate of underrepresented minorities (Center for Data Exchange and Analysis, 2001; Chen, 2009; Shaw & Barbuti, 2010).

Researchers have provided various explanations for the reason URMs lag behind when compared to majority students. Qualitative studies have found that underrepresented minorities

report feeling like outsiders, which many times stems from the belief that the campus views them as less talented than their White counterparts (Feagin, Vera, & Imani, 1996; Smedley, Myers, & Harrell, 1993).

Race/ethnicity often fails to explain the variance in students' academic achievement when other student behavior variables are controlled for in statistical analysis. Still, research demonstrates that race/ethnicity shapes students' views and perceptions regarding their education, which, according to Tinto's model, determines how well students are able to academically and socially integrate (Nora & Cabrera, 1996; Tinto, 2006; Xu & Webber, 2018).

### **Gender**

Along with race/ethnicity, gender is another demographic variable almost universally included as a control variable when conducting multivariate analysis in educational research. Considering only demographic variables, gender tends to be a significant predictor of degree completion (DeAngelo, Franke, Hurtado, Pryor, & Tran, 2011; DiPrete & Buchman, 2006; Ewert, 2012; Reason, 2009). Using NELS 1988, Ewert (2012) examined the effect of gender on six-year graduation rates of students who first enrolled in postsecondary education in 1994. When considering demographic and high school characteristics, women were 21% more likely to graduate than males (Ewert, 2012). Looking purely at background variables, research has also found that females make up a higher percentage of high performing high school students (Goldrick-Rab, 2006).

Like other demographic variables, gender loses its power to predict academic achievement when additional factors are included in the analysis. When academic performance variables are included in the regression models, research shows that gender fails to explain differences between men and women (Cho, 2007; DiPrete & Buchman, 2006; Ewert, 2012;

Reason, 2009). Using NELS data, Buchman and DiPrete (2006) found similar results. Their study found that when college academic performance and campus experiences were considered, the percentage of the female coefficient that remained to be explained decreased from 70% to 5%. Similar studies have found that academic performance in college explains much of the gender gap in 4-year retention rates (Cho, 2007; Reason, 2009).

Given that this study focuses on the STEM leaver population, it is critical for gender to be included as a control variable. Females are less likely to declare a STEM major upon enrollment compared to males (Bettinger, 2010; Kulturel-Konak, D'Allegro, & Dickinson, 2011; Griffith, 2010). Data from the Higher Education Research Institute's American Freshman: National Norms survey show that from 1998–2012, male students intended to major in STEM fields upon enrollment at a higher rate than women, with differences ranging from 10–15 percentage points (National Science Board, 2014). Even after controlling for SAT score and high school rank, Kulturel-Konak et al. (2011) found that women at three public institutions in Texas were 16% less likely to declare engineering and computers science majors when compared to men.

When women do declare STEM majors, they are more likely to leave these fields. National completion data from 2004–2014 reveal that only 29% of entering female STEM bachelor students earned STEM degrees, whereas 40% of entering male STEM bachelor students during this time period earned STEM degrees (Chen, 2013). Bettinger's (2010) examination of students entering public institutions in Ohio yielded similar results, as women with high standardized test scores were 11% more likely to leave STEM programs when compared to the same population of men.

Comparing the college coursework and grades of males and females provides an insight

into the reason females complete STEM degrees at lower rates. For example, when compared to males, female STEM majors tend to take courses from a wide range of disciplines, which significantly impacts STEM persistence (Mann & DiPrete, 2013). Additionally, Ost (2010) found that female students were more likely to change out of STEM programs than males due to having stronger grades in non-STEM fields. The differences in STEM achievement between genders further enforces the need to control for gender in this study.

### **Socioeconomic Status (SES)**

Among the various demographic characteristics known to be associated with academic achievement in college, socioeconomic status (occupation, family income, parental education) carries great significance in determining whether a student persists and graduates in higher education. Coming from a low SES background puts students particularly at risk of becoming victims of attrition (Moore, 2014; Tinto, 1993; Titus, 2006; Walpole, 2003). Students from low SES backgrounds also have lower educational aspirations, postsecondary education enrollment, persistence, and attainment compared to students from high SES backgrounds (Adelman, 2006; Aud, Hussar, Planty, Snyder, Bianco, Fox, Frohlich, Kemp, & Drake, 2010; Carter, 2006; Rockwell, 2011; Wirt, Choy, Rooney, Provasnik, Sen, & Tobin, 2004; Walpole, 2003). The NCES's Education Longitudinal Study (ELS:2002), which followed 15,000 students who began the 10<sup>th</sup> grade in 2002 found that graduation rates among students from the lowest quartile of SES were 14%, whereas graduation rates for students in the top quartile of SES backgrounds were 60% (Lauff & Ingels, 2015).

Regression analysis confirms that SES is a significant predictor of academic achievement in college. Using national data from the National Center for Education Statistics' 1996–2001 Beginning Postsecondary Students study (BPS:96/01), Titus (2006) studied degree completion

among students from low SES backgrounds. When controlling for student level and institutional variables, SES was a significant predictor of six-year graduation (Titus, 2006). Students in the lowest SES quartile were 25% less likely to graduate (Titus, 2006).

Coming from a low SES background is also related to lower levels of academic achievement in the STEM fields. Students from low SES backgrounds persist in STEM fields at a lower rate than those from high SES backgrounds, with differences in persistence rates dropping 5–15% for students from low SES backgrounds (Chen, 2013; Chen, 2009; Shaw & Baruti, 2010; Moore, 2014). After controlling for background and social and academic integration variables, STEM students from low SES backgrounds were significantly more likely to leave college (0.31 probability of attrition) than non-STEM students from the same SES background (0.26 probability of attrition; Moore, 2014). SES is an established predictor of academic achievement in both the STEM and non-STEM fields. SES has the strongest correlation to persistence/degree completion in higher education among demographic variables (Lotkowski, Robbins, & Noeth, 2004). Therefore, some measure of SES should be controlled for when studying college persistence/degree completion.

### **Financial Aid**

The increasing price of tuition for undergraduate education in the United States has made it increasingly more challenging for students to fund their education. In order to cover the rising cost of tuition, students often rely on financial aid. In 2017–2018, undergraduate students received an average of \$14,790 in financial aid (Baum, Ma, Pender, & Libassi, 2018). Research suggests the amount of financial aid offered is positively associated with the likelihood a student will enroll at a specific institution (Bettinger, 2004; Marx & Turner, 2019). However, research on the role financial aid plays in academic achievement is less conclusive.

Using financial aid as an independent variable, various studies have examined the significance of financial aid receipt on different forms of academic achievement. Bettinger (2004) used data from the Ohio Board of Regents to study the relationship between a student's financial aid award and first-year dropout behavior. Bettinger's first regression model, which only included the level of financial aid, found that the amount of financial aid was significant and positively associated with first-year retention. However, when additional independent variables, including socioeconomic status, academic preparedness, and academic performance, were added to the regression model, the financial aid level was no longer a significant predictor of dropout behavior (Bettinger, 2004). Herzog (2005) performed logistic regression to predict freshman persistence at a 4-year public institution and found that financial aid was not a significant predictor of first-year retention. Like Bettinger (2004), Herzog (2005) notes that first-year retention is better explained by academic preparedness and first-year academic performance. Other studies confirm that academic preparedness and first-year academic performance are better predictors of first-year retention than financial aid receipt.

When examining the relationship between degree completion and financial aid receipt, research shows both positive and negative effects. Building on a previous randomized experiment with the Wisconsin Grant Scholars, Anderson, Broton, Goldrick-Rab, and Kelchen (2018) examined the impact of need-based financial aid on college completion. While the study found financial aid to have an impact on six-year degree completion for specific cohorts, the results confirmed the inconsistent effects of financial aid programs on degree completion. Focusing on low-income students, Franke (2014) found that needs-based grants increased a student's chance of earning a degree within six years by approximately between 2.52% and 2.82% for every \$1,000 in additional need-grant aid. On the contrary, Franke (2014) found that



unsubsidized federal loans lowered a student's chances of graduating. Nguyen, Kramer, and Evans (2018) performed a meta-analysis of the causal evidence of the effect of grant aid on postsecondary persistence and degree attainment. The meta-analysis of 42 studies revealed that grant aid increases the probability of persistence and degree completion by two and three percentage points, respectively. Furthermore, the authors' research found that an additional \$1,000 in grant aid improved year-to-year persistence by 1.2 percentage points (Nguyen et al., 2018).

Looking specifically at STEM degree completion, Castleman, Long, and Mabel (2017) used data from the state of Florida to determine how financial aid receipt impacts STEM degree completion. Using regression analysis, the study found that eligibility for needs-based aid increased STEM credit completion 20–35%, which, in turn, increased STEM degree completion (Castelman et al., 2017). Although research on the relationship between financial aid is inconclusive, any study on persistence and degree completion should control for financial aid receipt given that the ability to afford tuition can affect social and academic integration (Reason, 2003).

As Tinto's (1975) model suggests, background variables play an important role in determining a student's level of social and academic integration. The review of the literature demonstrates the ways background variables interact with the environment (college) to determine levels of academic and social integration.

### **Pre-College Academic Achievement**

#### **SAT/ACT and High School GPA (HSGPA)**

Students' academic background carries far more predictive power in determining postsecondary graduation (Adelman, 2006). A student's academic background encompasses

various components. A large body of research has attempted to identify which components are most critical to academic achievement in postsecondary education.

SAT/ACT scores and high school GPA are the two most commonly used variables to predict students' chances of completing degree programs in postsecondary education. The combination of high school GPA and standardized test scores have been shown to be the most reliable pre-college academic achievement predictors for graduation and retention (Geiser & Sanelices, 2007; Tross, Harper, Osher, & Kneidiner, 2000; Zwick & Green, 2007). High school GPA and standardized test scores predict anywhere from 16–46% of the variance in academic success. The predictive power of high school GPA and standardized test scores is stronger when researchers measure academic success through first-year retention (Reason, 2009; Scogin, 2007). Tross et al. (2000) found that self-reported high school GPA and SAT/ACT score accounted for 29% of the variance in first-year retention for 844 first-year students at a 4-year institution in southeastern United States.

There is some debate regarding whether high school GPA or standardized test scores is a better predictor of postsecondary success. One reason for this debate is the high multicollinearity between the two variables (Wolfe & Johnson, 1995). The multicollinearity makes it difficult to estimate the power of each individual variable (Mertler & Vannata, 2001). Additionally, some argue that the SAT and ACT are biased against underrepresented minorities and students from low SES backgrounds (Sackett, Kuncel, Beatty, Rigdon, Shen, & Kiger, 2012; Tienken, 2012).

The rigorous first-year STEM curriculum makes academic achievement in high school especially critical for students who enter college intending to complete a STEM degree. STEM fields require students to enroll in rigorous courses, such as calculus and chemistry, in their first

year. Thus, students who are not adequately prepared by their high school coursework often struggle to succeed in first-year STEM courses, which often results in these students leaving the STEM fields.

Just as the case is with persistence/degree completion in any field, high school GPA is positively associated with a students' chances of persisting and earning a STEM degree (Bettinger, 2010; Chen, 2013; Crisp, Nora, & Taggart, 2009; Whalen & Shelley II, 2010). Chen's (2013) national study of STEM attrition found that 71.1% of STEM students who entered the STEM fields between 2003–2009 with less than a 2.5 high school GPA left STEM fields by dropping out of school or changing major by the spring of 2009. Standardized test scores also relate to a student's chance of persisting in STEM programs. Drawing data from the BPS:96/01, Chen's (2009) statistical report found that only 15% of students with standardized test scores in the lowest quartile earned an undergraduate degree in the STEM fields. Conversely, 57.7% of students in the highest quartile of test scores successfully completed undergraduate STEM programs. Whalen and Shelley II (2010) measured the six-year graduation/retention rate for first-time freshman with the intent to major in STEM at a large Midwestern research institution and found the composite ACT score to be a significant predictor of STEM persistence. For each point lower on the ACT, students' chances of graduating in the STEM fields decreased approximately 9.1 percentage points (Whalen & Shelley, 2010). Similarly, Larson, Pesch, Surapaneni, Bonitz, Wu, and Werbel (2014) used the high school and college transcripts of 311 students at a large Midwestern university to determine whether math self-efficacy in introductory science courses was a predictor of STEM graduation when controlling for pre-college academic achievement. When high school GPA and math ACT score were combined, the binary logistic

regression model was statistically significant, predicting 80.4% of the variance in STEM graduation.

Since STEM requires students to utilize math and quantitative skills, research has disaggregated standardized test scores by the math and verbal sections. Using data from three national data sets (National Longitudinal Study of the Class of 1972 [NLS-72], 1980 High School and Beyond [HS&B], and the National Longitudinal Study of 1998 [NELS-88]), Xie and Achen (2009) found that for all three cohorts in the study, a higher math test score increased the odds of earning an undergraduate degree in the STEM fields. Tyson et al. (2007) used the Florida Education and Employment Dataset to examine the impact of high school coursework and postsecondary graduation rates of the 1996–1997 cohort that graduated from Florida public high schools and colleges. Students who completed a math course in the most advanced category earned STEM degrees at a rate of 34.6%. On the other hand, students whose highest high school math achievement was in the five lowest categories, all graduated from STEM programs at a rate under 10%. Research has also identified that completing a math course more advanced than algebra II in high school may be an important benchmark in determining whether a student earns a STEM degree (Adelman, 1999; Tyson et al., 2007).

Research suggests that STEM leavers have pre-college academic backgrounds (low SAT/ACT scores, low HSGPA, low level of math completion in high school) that would not put them at risk for attrition in any field. Due to the lack of research studying what happens to students after leaving STEM, the predictive power of pre-college academic achievement after a student has left STEM (with an established academic history in college) is relatively unknown. This study will fill this gap in the literature by providing an understanding of how pre-college

academic achievement relates to postsecondary academic achievement after controlling for enrollment and performance in first-year STEM courses.

Research on pre-college academic achievement is especially helpful in predicting first-year academic achievement, but once a student begins in college, pre-college academic variables lose their power to predict persistence/degree completion. The next section will review the impact of STEM leavers' academic histories on educational outcomes.

## **Enrollment and Performance in STEM Courses on Overall Academic Achievement**

### **Enrollment in STEM Courses**

Students enter college with a set of beliefs about their academic strengths and preferences based on their high school coursework as well as societal and familial influences. Experiences and performance in first-year courses either confirm students' expectations or lead students to question their previous beliefs. It is experiences in first-year courses that often cause students to make changes to their academic program (i.e., changing major) and, in some cases, drop out (Attewell, Heil, & Resisel, 2012; Crisp et al., 2009; Huang, Taddese, & Walter, 2000). The decision to change academic programs or drop out of school after the first year is a complex process that cannot be fully explained by only examining first-year coursework. Still, since attrition rates in STEM fields and at institutions occur most frequently after the first year (Alting & Walsner, 2007; Chang et al., 2008; Seymour & Hewitt, 1997), researchers have paid particular attention to first-year coursework.

The first-year STEM curriculum can differ somewhat based on the institution and specific field within STEM, but, as previously noted, STEM curriculum requires students to complete "gatekeeping" courses, such as chemistry and calculus, in order to progress (Bettinger, 2010; Le et al., 2014; Zhang et al., 2004). Bettinger (2010) points out that as opposed to non-

STEM fields, the first-year STEM curriculum does not provide first-year students the opportunity to transition to their new academic setting or to explore different academic disciplines. Just by examining the enrollment histories of first-year STEM students, researchers have been able to confirm the difficulty of the courses but also, more importantly, the impact of enrolling in challenging courses during the first year on overall academic achievement.

Regardless of whether students plan to pursue a STEM degree, most first-year students enroll in STEM courses during their first year (Chen, 2013). Data from the BPS: 04/09 and the PETS:09 reveal that 87% of bachelor's students enrolled in STEM course(s) during their first year of college, and STEM units made up 27% of all units earned during the first-year (Chen, 2013). Students planning to pursue STEM degrees enroll in a greater percentage of STEM courses in the first year. (Bettinger, 2010; Chen, 2013). Examining incoming students at public 4-year institutions in Ohio, Bettinger (2010) found that students who enrolled in a STEM program took 52% of their first semester courses in STEM, compared to 28% for non-STEM majors.

STEM leavers earned an average of 11 STEM units (semester) during the first year, making up only 40% of all credits earned in the first year (Chen, 2013). It is important to note that STEM leavers also attempt fewer STEM credits, which may be a function of disinterest and remediation. Unlike other studies, Chen (2013, 2015) separated STEM leavers into two categories: those who left STEM and earned a degree in another major and those who left and never earned a degree. Interestingly, those who left STEM and never earned a degree actually earned .10 more STEM units in the first year as those who left STEM and eventually earned a degree in another field (11.5 vs. 11.4; Chen, 2013). This may suggest those STEM leavers who never earn a degree choose to continue in STEM, despite low levels of academic achievement.

The importance of first-year STEM coursework to overall academic achievement is magnified by multivariate analysis. Chen (2013) used a multinomial probit model to predict the probability of a student graduating in STEM, leaving STEM, and earning a degree in another field or leaving postsecondary education without a degree (Chen, 2013). Chen (2013) found that earning lower than 25% of all first-year units in STEM and earning 25–49% of all first-year units in STEM significantly predicted a student leaving STEM and eventually earning a degree in another field. While significant, the percentage of STEM units earned in the first year only increased students' chances of leaving STEM and earning a degree in another field by 0.175%. When looking specifically at STEM leavers who left postsecondary education without earning a degree in any field, the percentage of STEM units earned in the first year lost significance (Chen, 2013, 2015). So while STEM units earned in the first year may be important to persisting in STEM, they do not impact whether a student graduates. It is important to note that the percentage of first-year units in STEM does not consider actual academic performance, only whether or not a student earned units.

### **Enrollment in Math Courses**

Math coursework is, in fact, a strong and significant predictor of STEM achievement, but it also significantly predicts overall academic achievement (Bettinger, 2010; Herzog, 2005; Ost, 2010; Seymour & Hewitt, 1997). Given the importance of first-year math for all students, researchers have included type of math course taken during the first year of college as an independent variable when studying how first-year course enrollment impacts academic achievement for STEM leavers.

On average, those who leave STEM earn fewer math units in the first year than those who persist (ASU Freshman STEM Improvement Committee, 2007; Chen, 2013). Chen (2013)

found that 63% of STEM persisters took calculus or a more advanced math course during their first year of college. Contrarily, only 36% who left STEM and earned a degree in another field and 28% of those who left STEM and never earned a degree took calculus or a more advanced math course during the first year of college. STEM leavers who never graduated did not enroll in math during the first year at a higher rate (40%) than those who left STEM and eventually graduated in another field (30%; Chen, 2013). These findings mirror the results from studies that look at the impact of first-year math on the academic achievement of students from all disciplines. Drawing data from a large public institution in the United States, Herzog (2005) found that freshman who failed to complete or take math in the first year were 5 times less likely to be retained after the first year when compared to those who successfully completed a math course during their first year. Although math may not be as pertinent to the curriculum in non-STEM fields, research suggests enrollment in first-year math is positively associated with academic achievement, regardless of major.

### **Enrollment in Non-Math STEM Courses**

Compared to math courses, other first-year STEM courses, such as chemistry and other laboratory courses, receive far less attention from researchers. Chemistry and physics, like calculus, have been identified as “gatekeeping” courses that students often struggle to complete (Gainen & Willemsen, 1995; Zhang et al., 2004). Using national data from High School & Beyond (HS&B), Cabrera, Burkum, and La Nasa (2005) found that students in all majors who took one science course in their first year of enrollment were 20% more likely to complete a bachelor’s degree. Students who took three science courses in their first-year were 27% more likely to complete a bachelor’s degree when compared to those who took two or less (Cabrera et al., 2005). This study did not disaggregate between the type of science course taken. The



students in the study may have taken science courses that were different in rigor and in content. STEM persistence research has looked at the impact of enrolling in courses like chemistry, but these types of studies are only concerned with STEM persistence and not with overall academic achievement. Aside from the level of math completed, research should also examine how enrollment in first-year chemistry impacts overall academic achievement for STEM leavers.

Research examining how first-year STEM course enrollment impacts overall academic research fails to consider any outcome other than graduation. Specifically, how first-year course enrollment impacts time to degree warrants more attention from researchers, especially given that changing majors has been shown to increase time to degree (Karimi, Mateufel, & Peterson, 2015). Future studies should work to identify specific courses and their impacts on overall academic achievement, not just persistence in STEM.

### **Performance in STEM Courses**

Academic performance is by far the strongest predictor of retention/persistence and degree completion. Students with higher grades are more likely to be retained and graduate than those who struggle academically (DeBeard, Spielmans, & Julka, 2004). Research on STEM attrition confirms that the number one reason students leave STEM is poor academic performance (Adelman, 2006; Chen, 2013; Ost, 2010; Seymour & Hewitt, 1997; Watkins & Mazur, 2013). STEM leavers' chances of reaching high levels of academic achievement after leaving STEM are reduced by their performance in first-year STEM courses (Chen, 2013).

Descriptive data confirm that STEM leavers withdraw or fail in first year STEM courses at a higher rate than STEM persisters (Chen, 2013; Xie et al., 2005). Data from the BPS:04/09 show that STEM leavers who went on to earn a degree in another major failed/withdrew from 4% of first-year STEM courses, and STEM leavers who left college without earning a degree

failed/withdrew from 8% of first-year STEM courses (Chen, 2013). Xie et al.'s (2005) study of first-year STEM students in the University of Minnesota's General College revealed that 52.9% of STEM leavers failed at least two first-year STEM courses.

Due to poor performance in first-year STEM courses, STEM leavers also repeat first-year STEM courses more frequently than STEM persisters (Xie et al., 2005; ASU Freshman STEM Improvement Committee, 2007). STEM leavers are not only performing poorly in first-year STEM classes but also often duplicate their poor performance when attempting to repeat courses in order to continue in STEM. Xie et al. (2005) found that 22.1% of STEM leavers unsuccessfully repeated at least one first-year STEM course, while only 5.4% of STEM graduates unsuccessfully repeated at least one first-year STEM course (Xie et al., 2005). Main, Mumford, and Ohland (2015) argue that STEM leavers who choose to repeat courses may not factor their grades into their decision to continue to repeat STEM courses. Rather, the decision to repeat courses and continue to pursue a STEM degree may be a result of future employment prospects and/or beliefs based on social and cultural backgrounds.

The struggles of STEM leavers in first-year STEM courses are clearest when examining GPA in first-year STEM courses. Chen (2013) found that STEM leavers who dropped out of college earned a 2.3 GPA in first-year STEM courses, and those who left STEM and earned a degree in another field earned a 2.6 GPA in first-year STEM courses. Furthermore, both groups of STEM leavers earned higher grades in first-year non-STEM courses than in first-year STEM courses (Chen, 2013). Other studies on STEM attrition confirm that the majority of STEM leavers earn low grades in first-year STEM courses (Bettinger, 2010; Chen, 2015; Hartman & Hartman, 2006; Marra, Rodgers, Shen, & Bogue, 2012; Ohland, Zhang, Thorndyke, & Anderson, 2004).

Once a student decides to leave the STEM fields, they do so with an established academic history, and, on average, STEM leavers tend to have lower GPAs and earn less units (Chen, 2013). Low levels of academic achievement in the first year place STEM leavers at a disadvantage for achieving success in other fields as academic performance in the first year is a significant predictor of academic achievement in postsecondary education (Adelman, 2006; Kirby & Sharpe, 2001; Tinto, 1975, 1997).

Regardless of the field of study, research finds performance in first-year college level math to be the strongest predictor of postsecondary academic achievement (Cabrera, Burkum, & La Nasa, 2005; Adelman, 2006; Herzog, 2005). Drawing from a large public institution, Herzog (2005) found student performance in first-year math courses to be the second strongest predictor of retention behind first-year cumulative GPA. Students in the study that received a grade B or lower in remedial math were 50% more likely to leave after their first year than those who earned a B or higher (Herzog, 2005).

Other than math, research has yet to determine how performance in specific first-year STEM courses relate to overall academic achievement for those who leave STEM fields. STEM leavers are likely to take laboratory science courses (chemistry, biology, etc.), and research should examine how course performance in laboratory science courses relates to overall academic achievement.

### **Directions for Further Research**

Research on STEM attrition shows that the majority of students who leave STEM do so due to poor academic performance, which hinders students' chances of achieving academic success after departing from the STEM fields (Adelman, 2006; Chen, 2013; Ost, 2010; Seymour & Hewitt, 1997; Watkins & Mazur, 2013). Given the demanding and unit heavy STEM

curriculum, research must work to understand how the first-year STEM curriculum relates to STEM leavers' academic achievement levels in other fields. Researchers must conduct studies that focus on the STEM leaver population and how their enrollment, performance, and experiences in STEM courses relate to their levels of academic achievement in college. Additionally, aside from graduation, little is known about how the first-year STEM curriculum relates to other measures of academic achievement. Research should examine how enrollment and performance in first-year STEM courses relate to other metrics of academic achievement, such as GPA, time to degree, and yearly retention.

Previous studies suggest that enrollment and performance in first-year STEM courses can explain variance in academic achievement, both in STEM fields and overall. Aside from math, other first-year STEM courses, such as chemistry, receive little attention from researchers. An examination of how enrollment and performance in certain first-year STEM courses, specifically those that have been identified as “gatekeeping” courses, will provide some valuable insights and suggestions for curriculum reform and advisements of students who are at risk of leaving STEM fields.

### **Conclusion**

Although producing graduates and skilled workers in the STEM fields continues to be a pertinent issue for the United States and institutions, researchers and institutions cannot ignore the large population of students who end up leaving STEM fields due to the challenging nature of the first-year STEM curriculum. Research on enrollment and performance in first-year STEM courses can provide justification for curriculum reform so students do not face additional barriers to graduation after deciding to leave the STEM fields.

## CHAPTER III

### METHODS

#### **Introduction**

The purpose of this study is to investigate the relationship between enrollment and performance in first-year STEM courses and academic achievement for students who leave the STEM fields. Existing research confirms that a high percentage of students who plan to study in STEM fields ultimately leave, but there is a lack of existing research on whether students' enrollment and performance in STEM coursework are associated with future academic achievement in non-STEM fields. Coursework data from the PETS:09 allowed this study to control for STEM course enrollment and performance, which provided a new perspective on understanding how changes in academic major, specifically from a STEM to a non-STEM major, relate to academic achievement. The results of this study will potentially help administrators create major change policies and curriculum that allow students to successfully transition from major to major. The results will also potentially be useful for academic advisors when counseling students on major change.

This chapter will begin by introducing the research questions. I will then discuss the theoretical framework, data source, sample, and major variables that will be used in the study. Finally, this chapter will outline the data analysis methods and will discuss any limitations of this study.

This study will be guided by the following research questions:

1. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does the number of STEM credits attempted relate to:

- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
2. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in college level math relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
3. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in introductory laboratory science relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
4. After controlling for ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in STEM courses relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?

- Time to degree for STEM leavers?
- Cumulative GPA for STEM leavers?

### **Theoretical Framework**

This study will be guided by Tinto's (1975, 1997) theory of student departure. As previously discussed in Chapter II, Tinto argues that the level at which a student is academically and socially integrated on campus determines whether students are retained and ultimately achieve academic success.

Compared to other theories used to study student attrition, Tinto's model places emphasis on classroom experiences as the basis of social and academic integration (Tinto, 1993). By examining students' experiences in specific courses, research has found that such experiences either confirm or alter students' future coursework and major choices (Attewell, Heil, & Reisel, 2011; Chen, 2013; Crisp, Nora, & Taggart, 2009; Huang, Taddese, & Walter, 2000; Stinebrickner & Stinebrickner, 2011). After controlling for background variables, researchers use classroom experiences to measure academic and social integration to test Tinto's model of attrition for specific academic programs. Tinto's model does not differentiate among academic disciplines, and thus researchers commonly use Tinto's model as a basis for developing models that focus on a specific population and/or academic discipline.

Tinto's model is appropriate to guide this study given that this study's focus is on how students' classroom experiences (enrollment and performance) in first-year STEM courses relate to retention, graduation, and other measures of academic achievement. Tinto's model suggests the experiences of students in first-year STEM courses play an important part in determining how well a student integrates into the institution, which ultimately impacts the student's decision to persist at the institution.

## **Measures**

This section discusses the measures that were chosen based on the proposed theoretical framework of the study. I will first review the dependent variables used to assess academic achievement, followed by the academic integration independent variables (course enrollment, course performance), the social integration independent variables (study session attendance, institution type), and the background variables.

## **Source of Data**

Data used for this study will be drawn from the 2004/2009 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) and the associated 2009 Postsecondary Education Transcript Study (PETS:09). The BPS:04/09 and the PETS:09 were administered by the National Center for Education Statistics (NCES) and consist of a nationally representative sample of students first enrolling in postsecondary education in 2003. BPS:04/09 sample members were identified in the 2003–2004 National Postsecondary Student Aid Study (NPSAS:04). Given that the BPS:12/17 has yet to be released, the BPS:04/09 and the associated PETS:09 are the most recent national longitudinal dataset on postsecondary education outcomes that include data relating to student demographic characteristics, experiences, and course enrollment and performance.

Approximately 19,000 sample members were confirmed as first enrolling in postsecondary education in 2003. Interviews were conducted at the end of students' first year in postsecondary education, approximately three years and six years after initial enrollment. Researchers collected data on students' demographic characteristics, academic achievement, and more. The final BPS:04/09 sample contains approximately 16,700 students (Radford, Pearson, Ho, Chambers & Ferlazzo, 2012).



## Sample

This study will focus on a subsample of BPS:04/09 students who participated in the 2003–2004, 2006, and 2009 surveys. Additionally, the study sample was restricted to first-time, bachelor's degree-seeking students who enrolled at 4-year institutions in the fall of 2003 (approximately 7,800). Out of the approximately 7,800 bachelor's degree-seeking students, roughly 1,350 declared a STEM major during their first year of enrollment.

The BPS:04/09 used two-digit codes to categorize students' major. The two-digit codes that were recoded as a STEM major were: (03) Life Sciences; (04) Physical Sciences; (05) Math; (6) Computer/Information Science; (07) Engineering/Engineering Technologies. These fields are used by the NCES to define the STEM fields. Furthermore, this classification is consistent with Chen's (2013) NCES report on STEM attrition.

To answer the research questions, the sample was stratified to include students who meet the following criteria: (a) declared a major in the STEM fields upon enrollment in the fall of 2003 and (b) reported a non-STEM major in the final 2009 follow-up survey. To obtain this dataset, this study will use the BPS: 04/09 to identify variables related to students' reported major during their first year (MAJORS12) and students' reported major when last enrolled in 2009 or major for students' last reported degree through 2009 if the student was no longer enrolled in 2009 (LSFLD09). Additionally, students that transferred and stayed in STEM were counted as STEM leavers. The population of students in bachelor's degree programs who initially declared a STEM major and switched to a non-STEM major, transferred or did not graduate totaled 750.

The associated PETS:09 collected transcript data from 3,030 institutions that BPS students attended between July 1, 2003 and June 30, 2009. Approximately 87% of the eligible

institutions provided transcripts for students in the cohort, totaling 16,920 PETS samples. Additionally, 92% of the eligible students had at least one transcript accessible. Data obtained from the transcripts provide an in-depth representation of students' enrollment, course taking, and academic performance. In any longitudinal study, missing values issues are bound to occur. Researchers must address the issue of missing values or the validity of the study will be questioned. Specifically, when the internal validity of the study is inaccurate, the results cannot be generalized. Missing data can bias results, reduce generalizability and limit power.

After listwise deletion, the population totaled 540 students. The majority of the missing responses came from those variables taken from the PETS:09 sample. Introductory laboratory science GPA (10.24 nonresponse rate) and college level math GPA (10.68% nonresponse rate) had the highest number of missing cases. No variables were found to be strongly correlated with introductory laboratory science GPA and college level math GPA.

### **Methods**

Quantitative methodology will be used in the study because the study aims to answer questions about relationships among measured variables, with the purpose of explaining and predicting phenomena (Gay, Mills, & Airasian, 2009). The study seeks to explain the relationship between variables that predict academic achievement.

### **Design**

This study will utilize a non-experimental, exploratory, cross-sectional design (Johnson & Christensen, 2008) that uses linear and logistic regression to measure the relationship between predictor variables and the dependent variable of academic achievement as defined by graduation, first year retention, time to degree, and cumulative GPA. Multiple regression is most appropriate given that the study attempts to model the relationship between two or more

explanatory variables and a response variable. Additionally, the reasonably small set of predictor variables in this study makes multiple linear and logistic regression appropriate (Leech, Barrett, & Morgan, 2011).

Multiple regression allows the researcher to study the relationship between several predictor variables and the dependent variable by predicting the likelihood of achieving an outcome when considering multiple predictor variables (Field, 2009). Multiple linear regression will allow the researcher to utilize Tinto's theory of student departure to study the relationship between STEM attrition and academic achievement. This study will utilize four models: one for each research question. The dependent variables (first year retention, cumulative GPA, time to degree, and graduation) will remain constant in each model. The following independent variables will be included in all four models: ethnicity, gender, SAT/ACT math score, high school GPA, socioeconomic status, financial aid, and academic and social integration. To answer each research question, an additional independent variable will be included in each model. The first model will include the number of STEM courses taken; the second will include academic performance in college-level math; the third will include academic performance in introductory-level laboratory science; and the last will include STEM GPA.

Due to the threat that multicollinearity presents in multiple regression, I will first complete a descriptive correlation analysis to ensure that there is a linear relationship between each predictor variable and the dependent variable and that the error is uncorrelated with the predictor variables (Leech, Barrett, & Morgan, 2011, p. 107). Field (2009) suggests reviewing the Pearson Correlation Coefficient, the variance inflation factor (VIF), and the tolerance statistic between the predictor variables.

After running the descriptive correlation analysis, I will analyze the unstandardized coefficient beta weights and the standardized beta weights of each regression model. I will also note the R<sup>2</sup> change, F change, and Sig. F change to identify the relationship between the regression models and the dependent variable. The level of significance will be set to  $p < .05$ , which is the commonly used level of significance in statistical research (Leech, Barrett, & Morgan, 2011).

### **Multicollinearity**

To address possible issues of multicollinearity, a correlation matrix including all predictor variables in research question number one was run. According to Gray and Bristow (2014) a correlation between predictor variables of .6 and .7 or above infers a likelihood of multicollinearity. None of the variables were found to be highly correlated. The strongest correlation was between academic integration index and social integration index (.420); however, this does not reach the level of concern.

This study did not include all the focal predictors (STEM credits attempted, college-level math GPA, introductory laboratory science GPA and STEM GPA) into one model due to high levels of multicollinearity among these variables. Specifically, college-level math GPA and introductory laboratory science GPA are subsets of STEM GPA. Further, students who perform well in college-level math, introductory laboratory science and STEM courses are more likely to persist in STEM, which increases the number of STEM credits attempted. Therefore, the focal predictor variables were not included in one model.

### **Outcome Variables**

There are four outcome variables of interest in this study: first year retention, graduation, time to degree, and cumulative GPA.

## First Year Retention

First year retention will be measured by determining whether a student was still enrolled at their first institution attended after the 2003–2004 academic year (PROUTF1). Again, binary logistic regression will be used (Leech et al., 2011). Table 2 summarizes the descriptive statistics of the outcome variable: first year retention.

Table 1

*Descriptive Statistics of First-Year Retention (N=540)*

Variable	Number	Percentage
<b>Still Enrolled</b>	430	79.6%
<b>Not Enrolled</b>	110	20.4%

As noted in Table 2, of the 540 participants in the analytical sample (all having declared a STEM major upon initial enrollment), 430 were retained at the institution after the first year, and 110 were no longer enrolled at the institution after their first year of enrollment.

## Graduation

Graduation will be measured by whether a student attained a bachelor's degree at their initial institution by the end of the 2008–2009 academic year. Graduation at the initial institution will be measured using the variable ATBAF16Y. ATBAF16Y is a dichotomous variable, where GRAD=1 if a bachelor's degree was attained, and GRAD=0 if a bachelor's degree was not attained, regardless of whether the student was still enrolled. Binary logistic regression will be used given that graduation is a binary nominal variable (Leech et al., 2011). Table 1 summarizes the descriptive statistics of the outcome variable: graduation.

Table 2

*Descriptive Statistics for Graduation (N=540)*

Variable	Number	Percentage
<b>Bachelor's Degree Attained</b>	310	57.5%
<b>No Bachelor's Degree Attained</b>	230	42.5%

Table 1 demonstrates that 310 of the participants attained a bachelor's degree at their first institution by the end of the study in 2009, and 230 participants did not attain a bachelor's degree at their first institution.

**Time to Degree**

Time to degree will be measured by determining whether a student graduated within 4 years from their initial enrollment. The variable ATBAM6Y represented the number of months that elapsed from first month enrolled to the month the bachelor's degree was attained and will be recoded as a dichotomous variable, where 1=bachelor's degree earned in 48 months or less, and 0=no bachelor's degree earned or a bachelor's degree earned in 49 months or more. The typical curriculum is designed so that a student graduates in 4 years, and therefore the 48-month marker is appropriate to measure whether leaving STEM programs increases a student's chances of graduating in 4 years.

Table 3

*Descriptive Statistics for Time to Degree (N=540)*

Variable	Number	Percentage
----------	--------	------------

<b>Bachelor's Earned in 48 Months or Less</b>	110	20.4%
<b>Bachelor's Earned in 49 Months or More or No Degree Earned</b>	430	79.6%

Table 3 indicates that of the 540 participants, 110 earned a bachelor's degree within 48 months (4 years) of initial enrollment, and 430 either earned a bachelor's degree in 49 months or more or did not attain a bachelor's degree.

**Cumulative GPA**

Cumulative GPA will be measured using the variable MTGPA from the PETS:09. Cumulative GPA is a continuous variable, so linear regression will be utilized to answer this research question based on self-reported, estimated, cumulative GPA when last enrolled through 2009. Table 4 demonstrates that the mean cumulative GPA among participants was 2.66, with a standard deviation of .84.

Table 4

*Descriptive Statistics for Cumulative GPA*

Variable	Mean	SD	Min	Max
<b>Cumulative GPA</b>	2.667	.841	0.000	4.000

**Academic Integration and Social Integration Independent Variables**

This study includes the following four measures of academic integration variables: academic performance in introductory-level laboratory science courses (MTBPLB), number of

STEM courses taken (QESTMUN), academic performance in college-level math (MTGPMTH), and students' level on the BPS:04/09's academic integration index scale after the 2003–2004 academic year (ACAINX04). Social integration will be measured using students' level on the BPS:04/09's social integration index after the 2003–2004 academic year.

### **Academic Performance in Introductory Level Laboratory Science Courses and College-Level Math**

To determine how performance in STEM courses relates to academic achievement for STEM leavers, this study focuses on academic performance in introductory level laboratory science and math courses. These courses are a foundation of the first year STEM curriculum and using the academic performance in introductory-level laboratory science course variable (MTGPLB) of the BPS:04/09 will allow this study to focus on how performance in STEM courses relates to overall academic achievement for the STEM leaver population. The academic performance in college level math variable (MTGPMTH) of the BPS:04/09 will also be used. The BPS:04/09 calculated GPA using normalized credit values, which place course hours or units on a common scale to be compared across students and institutions.

In order to identify introductory laboratory science and college-level math courses, the BPS:04/09 used course classifications from the NCES's 2010 College Course Map (CCM:2010). The following courses were considered introductory laboratory science in the BPS 04/09: general biology, general biomedical sciences, botany/plant biology, zoology, general and analytic chemistry, and general physics. College level mathematics included general mathematics, algebra, geometry, calculus, and others. To answer the last research question, the model will include students' STEM GPA. The variable used will be MTGPSTM of the BPS:04/09.

### **Number of STEM Credits Attempted**



STEM credits attempted (QESTMATT) was included in the study in order to measure how enrollment in STEM courses relates to academic achievement. Using STEM credits attempted rather than STEM credits completed allowed the study to account for unsuccessful attempts (failures and withdraws).

### **Academic Integration Index and Social Integration Index**

To test Tinto's (1973, 1997) theory of institutional attrition, this study included students' score on the BPS:04/09 academic integration index after the 2003–2004 academic year (ACAINX04). All participants in the BPS:04/09 were asked to report various measures related to academic integration after the 2003–2004 academic year and during the follow-up survey in 2006. The BPS:04/09 academic integration index represents the mean score of the four measures used to determine students' academic engagement. The four measures that make up the academic integration index are: (a) meeting with faculty outside of class time; (b) meeting informally/socially with faculty; (c) meeting with advisors; and (d) participating in study groups. Students could respond with “never,” “sometimes,” or “often” (coded 0, 1, or 2, respectively). The index score was created by summing the responses, each multiplied by 100, and then dividing the total by 4 to yield a score between 0–200 on the index (Flynn, 2016). Therefore, the variable is scaled in 25-point increments.

Equally important to Tinto's (1973, 1997) theory is social integration, and this study will use students' score on the BPS:04/09 social integration index after the 2003–2004 academic year (SOCINX04). The social integration index is calculated using the same method as the academic integration index and is made up of the following items: (a) attends or participates in campus arts, drama, music, or fine arts activities; (b) attends or participates in campus clubs or organizations; and (c) participates in or attends campus varsity, intermural, or club sports

activities. Because there are only three components to the social integration index score, the variable is scaled in 33.333-point increments.

The BPS:04/09 metrics used in determining a students' academic and social integration index score are commonly used in research to measure academic and social integration. Additionally, by representing academic and social integration through different behaviors, the study considers different ways students engage on campus (Flynn, 2016).

It is important to note that the academic and social integration indices only provide approximations of student engagement. Although researchers have identified limitations of each index, Flynn (2012) found that the indices significantly predicted persistence and degree attainment and can be considered reliable measures of social and academic integration. Finally, French and Oakes (2004) found the scale scores had satisfactory internal consistency reliability and intercorrelations among the subscales and with the total scale.

### **Financial Aid Receipt**

The ability to afford tuition plays an important role in the ability of a student to socially integrate into their institution. Although financial need is negatively associated with persistence and graduation, research has found that financial aid receipt can offset the negative effects of financial need (Ganem & Manasse, 2011). Therefore, the amount of federal aid received will be included as an independent variable in all models. All models will include the BPS:04/09 variable TOTAID, which measures the cumulative amount of undergraduate federal loans and grants received during the 2003–2004 academic year. The distribution among responses for financial aid was highly skewed and therefore natural logarithmic transformation was used to make the responses for total aid more closely to the normal distribution.

### **Background Independent Variables**

According to Tinto (1973, 1997), students bring various background characteristics to college, which then interact with environmental conditions that determine the level of social and academic integration for a student. I will use five background characteristics that have been identified by research to influence academic integration variables and the outcome variables. Common background variables included in this study are students' gender, socioeconomic status (measured by respondents' income group for the 2003–2004 academic year), race/ethnicity, SAT/ACT math score, and high school GPA. SAT/ACT math score will be used, rather than the more commonly combined SAT/ACT score, due to its influence on academic achievement for STEM leavers (Bonous-Hammarth, 2000; Crisp, Nora, & Taggart, 2009; Whalen & Shelley II, 2010; Xie & Achen, 2009).

Table 5 summarizes the descriptive statistics of the categorical independent variables in the study sample. These variables include gender, race/ethnicity, and high school GPA. Male participants make up more than half (59.2%) of the sample, compared to female participants (40.8%). Although the BPS:2004/2009 dataset divides race/ethnicity into six classifications, the decision was made to reduce this number to two classifications: underrepresented minorities (URMs), made up of African Americans, Hispanics, Native Americans, and all other races/multiracial groups; and non-underrepresented minorities (non-URMs), comprising Whites and Asians. The rationale for this decision was based on the need for adequate numbers within the cells. Non-URMs make up the majority of the sample (96.3%), compared to URM participants (3.7%). Regarding high school GPA, again, the decision was made to reduce the number of categories from six to five. The cells C to C- and C- and below were combined to produce one cell: C and below. Again, this was based on the need for adequate numbers within the cells. A little less than half of the participants in the sample (44.4%) were high achieving

students in high school and reported a high school GPA in the range of 3.5–4.0. Of the participants, 33.3% reported a high school GPA of 3.0–3.4, and 9.3% reported a high school GPA in the B to B- range. Finally, 13.0% of the participants had a high school GPA of C or below.

Table 5

*Descriptive Statistics of the Independent Categorical Variables (N=540)*

<b>Variable</b>	<b>Number</b>	<b>Percentage</b>
<i>Individuals' Characteristics</i>		
<i>Gender</i>		
Male	320	59.2%
Female	220	40.8%
<i>Race/Ethnicity</i>		
Non-Underrepresented Minority (Non-URM)	520	96.3%
Underrepresented Minority (URM)	20	3.7%
<i>High School GPA</i>		
A to A- (3.5–4.0)	240	44.4%
A- to B (3.0–3.4)	180	33.3%
B to B- (2.5–2.9)	50	9.3%
C and below (0.0–2.0)	70	13.0%

Table 6 summarizes descriptive statistics for the independent continuous variables: academic integration index, social integration index, parental/independent income, SAT math score, total aid, college level math GPA, introductory laboratory science GPA, STEM GPA, and STEM credits attempted.

Table 6

*Descriptive Statistics of the Independent Continuous Variables (N=540)*

Variable	Mean	SD	Min	Max
<b>Academic Integration Index</b>	87.57	39.554	0	200
<b>Social Integration Index</b>	59.78	50.707	0	200
<b>Parental/Independent Income</b>	71262.45	54763.148	0	470000
<b>SAT Math Score</b>	516.76	154.826	0	800
<b>Total Aid</b>	8847.80	8556.032	0	40121
<b>College Math GPA</b>	2.4479	1.03480	.00	4.00
<b>Intro Lab Science GPA</b>	2.3677	1.02855	.00	4.00

<b>STEM GPA</b>	2.4824	.96717	.00	4.00
<b>STEM</b>	38.55	29.10839	00	225
<b>Credits</b>				
<b>Attempted</b>				

---

### **Weights**

All estimates in this study will be weighted to account for the unequal probability of being involved in the survey and for nonresponse. Applying weights prevents a biased estimate, which can cause inaccurate results. Weighting must be applied in all studies that utilize a complex sample prior to generalizing results to the entire population. Furthermore, utilizing sampling weights helps reduce the standard error, which then refines the accuracy of the significance of the estimate.

This study will use the sample weight panel (WTB000) and (WTC000), which are longitudinal weights that accommodate for students who participated in all three phases of the survey and the PETS:09 study. These weights will be attached to each unit and normalized to compensate for the sample size of this study.

### **Limitations**

It should be noted that using the BPS:04/09 creates some limitations for this study. First, the BPS:04/09 is a general-purpose study, and its questions and data collection instruments were not created to include variables that are specific to STEM education. Specifically, the BPS:04/09 does not provide any data related to classroom climate in STEM courses, which research suggests relates to STEM attrition (Seymour & Hewitt, 1997).

Secondly, prior research hints that differences exist between majors within the STEM fields. For example, Shaw & Barbuti (2010) suggest that engineering has more lower attrition rates than “softer” STEM fields. Furthermore, research suggests that the reason a student decides to leave a STEM major may also differ based on the specific STEM major (Ost, 2010; Rask, 2010). Due to the sample size, this study was unable to differentiate between different STEM fields.

Lastly, although the CCM:2010 was used to code participants’ transcripts, the PETS:09 is unable to account for differences in course content and rigor based on institution. For example, some institutions may define college-level math as calculus, whereas another considers algebra to be college-level math. Students’ academic performance is often related to institutional and course variables that this study is unable to account for.

### **Summary**

This chapter provided a description of the dataset used in this study (the BPS:04/09 and PETS:09) and the sample selected for the study. Next, the methodology to be used in analyzing the sample was reviewed, along with limitations of the study.

CHAPTER IV  
ANALYSIS OF THE DATA

**Introduction**

The purpose of this study was to examine the influence of STEM course enrollment and performance on various forms of academic achievement for students who originally enrolled in a STEM degree program and left the STEM fields. As described in Chapter Three, the analytic sample for this study was drawn from the Beginning Postsecondary Longitudinal Study (BPS:04/09) and the associated Postsecondary Transcript Study (PETS:09) data set. The final sample used for analyses represents the students who declared STEM majors upon enrollment in a bachelor's degree program and graduated in a non-STEM field or never graduated. Thus, the result will be reflective of this group, not all STEM students.

In this chapter, the statistical results of the analyses will be presented. I will first discuss the sample demographics and their distribution across the various outcome variables. Next, I will present inferential statistics to examine the relationship between the independent variables and the outcome variables of first year retention, graduation, time to degree and cumulative GPA. Sample sizes will be rounded to the nearest 10 given BPS:04/09 and PETS:09 are restricted NCES data.

In this study, I explored the following research questions:

1. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does the number of STEM credits attempted relate to:
  - First year retention rates for STEM leavers?



- Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
2. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in college level math relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
3. After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in introductory laboratory science relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?
  - Cumulative GPA for STEM leavers?
4. After controlling for ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in STEM courses relate to:
- First year retention rates for STEM leavers?
  - Graduation rates for STEM leavers?
  - Time to degree for STEM leavers?

- Cumulative GPA for STEM leavers?

### **Cross-Tabulation of Independent Categorical Variables**

Cross-tabulation analysis was carried out to compare background characteristics across the outcome variables. Table 7 shows the distribution of the independent categorical variables by *first year retention*. Among the male participants, 78.1% were retained after the first year. For the female participants, this figure was 91.9%. For the categorical variable *gender* (in Table 7), a single factor Pearson’s chi-square ( $\chi^2$ ) test was applied to the crosstabs procedure to determine whether the gender and the outcome variable of first year retention. The  $X^2$  ( $df = 2$ ) test statistic for gender was 1.317,  $p = .251$  and thus was not significant.

Of the 520 Non-URM participants, 78.8% were retained after the first year. In the URM participants, 50% were retained after the first-year. For the *race/ethnicity* variable, a single factor Pearson’s chi-square ( $X^2$ ) test was applied to the crosstabs procedure to determine whether there is a correlation between race/ethnicity and first-year retention. The  $X^2$  ( $df=1$ ) test statistic was 0.397,  $p = .528$  and thus was not significant. However, the *high school GPA* variable was significant at the .01 level ( $X^2(3) = 13.999$ ,  $p = .009$ ) so it can be concluded that high school GPA is related to first-year retention.

Table 7. *Descriptive Statistics of the Independent Categorical Variables by First Year Retention (N=540)*

<b>Variable</b>	<b><i>Retained</i></b>	<b><i>Not Retained</i></b>	<b><i>Chi-square test of significance</i></b>
<i>Individuals’ Characteristics</i>	Number (%)	Number (%)	$X^2$
<i>Gender</i>			1.317 <sup>+</sup>
Male	250 (78.1%)	70(21.9%)	
Female	180 (91.9%)	40 (8.1%)	
<i>Race/Ethnicity</i>			0.397 <sup>+</sup>
Non-URM	410 (78.8%)	110 (21.2%)	

URM	10 (50.0%)	10 (50.0%)	13.399**
<i>High School GPA</i>			
A to A- (3.5-4.0)	210 (87.5%)	30 (12.5%)	
A- to B (3.0-3.4)	140 (77.8%)	40 (22.2%)	
B to B- (2.5-2.9)	40 (80.0%)	10(20.0%)	
C and Below (2.0-0.0)	50 (71.4%)	20 (28.6%)	

Significant variables are presented with asterisks +<.10, \*p<.05, \*\*p<.01, \*\*\*p<.001

Table 8 shows the distribution of the independent categorical variables by *graduation*. Among the participants, 53.1% of males and 91.9% of females attained a bachelor’s degree. A single factor Pearson’s chi-square ( $\chi^2$ ) test was applied to the crosstabs procedure to determine whether there is a correlation exists between *gender* and the outcome variable of *graduation*. The  $\chi^2$  (df = 2) test statistic for *gender* was 5.639 p=.018 and thus it can be concluded gender is related to graduation. The *race/ethnicity* variable was not significant at the .05 level ( $\chi^2(2)=0.53$ , p=.819). The  $\chi^2$  (df=3) test statistic for *high school GPA* was 47.869, p=.000. Therefore, it can be concluded that high school GPA is related to graduation.

Table 8. *Descriptive Statistics of the Independent Categorical Variables by Graduation (N=540)*

<b>Variable</b>	<b><i>Bachelor’s Degree Attained</i></b>	<b><i>Bachelor’s Degree Not Attained</i></b>	<b><i>Chi-square test of significance</i></b>
<i>Individuals’ Characteristics</i>	Number (%)	Number (%)	X <sup>2</sup>
<i>Gender</i>			5.639*
Male	170 (53.1%)	150 (46.9%)	
Female	140 (91.9%)	80 (8.1%)	
<i>Race/Ethnicity</i>			0.53+
Non-URM	300 (60.0%)	200 (40.0%)	
URM	10 (50.0%)	10 (50.0%)	
<i>High School GPA</i>			47.869***
A to A- (3.5-4.0)	170 (87.5%)	70 (12.5%)	
A- to B (3.0-3.4)	90 (77.8%)	90 (22.2%)	
B to B- (2.5-2.9)	30 (80.0%)	20 (20.0%)	
C and Below (2.0-0.0)	20 (71.4%)	50 (28.6%)	

Significant variables are presented with asterisks +<.10, \*p<.05, \*\*p<.01, \*\*\*p<.001

Table 9 shows the distribution of the independent categorical variables by *time to degree*. Among the males, 84.4% either did not graduate or graduated in over 49 months, while 78.7% of the female participants either did not graduate or graduated in over 49 months. The  $X^2$  (df = 2) test statistic for *time to degree* was 10.403,  $p=.001$  and thus it can be concluded *gender* is related to *time to degree*. Females were more likely to graduate in 48 months or less. The *race/ethnicity* variable was not significant at the .05 level ( $\chi^2(2)=0.12$ ,  $p=.914$ ). The  $X^2$  (df=3) test statistic for *high school GPA* was 22.10,  $p=.000$ . Therefore, high school GPA is related to time to degree.

Table 9. *Descriptive Statistics of the Independent Categorical Variables by Time to Degree (N=540)*

<b>Variable</b>	<b>Graduated in 48 months or less</b>	<b>Graduated in 49 months or more/no graduation</b>	<b>Chi-square test of significance</b>
<i>Individuals' Characteristics</i>	Number (%)	Number (%)	$X^2$
<i>Gender</i>			10.403**
Male	50 (15.6%)	270 (84.4%)	
Female	60 (27.3%)	160 (78.7%)	
<i>Race/Ethnicity</i>			0.12 <sup>+</sup>
Non-URM	110 (21.2%)	410 (78.8%)	
URM	10 (50%)	10 (50%)	
<i>High School GPA</i>			22.102***
A to A- (3.5-4.0)	70 (29.1%)	170 (70.9%)	
A- to B (3.0-3.4)	30(16.7%)	150 (83.3%)	
B to B- (2.5-2.9)	10 (20.0%)	40 (80.0%)	
C and Below (2.0-0.0)	10(16.7%)	50 (83.3%)	

Significant variables are presented with asterisks +<.10, \*p<.05, \*\*p<.01, \*\*\*p<.001

## Analysis of Research Question 1

**Question 1:** After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does the number of STEM credits attempted relate to:

- First year retention rates for STEM leavers?
- Graduation rates for STEM leavers?
- Time to degree for STEM leavers?
- Cumulative GPA for STEM leavers?

### Binary Logistic Regression

Three separate binary logistic regression analyses were performed to assess the predictive impact of gender, race/ethnicity, total aid, academic integration index, social integration index, parental/independent income, SAT math score, high school GPA and number of STEM credits attempted on first year retention, graduation and time to degree.

### First Year Retention

The Tests of Model Coefficients table (Table 10) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 22.509, p = .007$ ), indicating that the fitted model was able to distinguish between participants who were retained or not retained past the first year. The chi-square statistic represents the difference in log-likelihood (-2LL) values between the null and fitted models. Goodness-of-fit tests are designed to determine the adequacy of the logistic regression model. A model that is poorly fitted can give invalid results on the statistical inferences based on the fitted model (Field, 2009).

Table 10 shows the -2LL for the fitted model (388.155) and two pseudo R<sup>2</sup> values, the Cox and Snell R<sup>2</sup> and the Nagelkerke R<sup>2</sup>. The -2LL statistic assesses the overall fit of the full model (Field, 2013). The -2LL of 388.155 is lower than the null model, which indicates the fitted model is predicting the outcome variable more accurately. The Cox and Snell (.052) and Nagelkerke (.081) are similar to the coefficient of determination used in OLS regression and are interpreted in the same way. Therefore, the fitted model explains between 5.2% and 8.1% of the variance in first year retention.

Table 10. *Goodness of Fit Statistics: First Year Retention (Research Question 1)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	22.509	9	.007
<b>Coefficients -2LL</b>	410.848		
<b>Cox &amp; Snell R<sup>2</sup></b>	.052		
<b>Nagelkerke R<sup>2</sup></b>	.081		

Table 11 presents the findings of the binary logistic regression analysis for first-year retention. *STEM credits attempted* was statistically significant ( $p < .001$ ) and had an EXP(B) of .978 (95% CI between .969 & .992). The odds ratio represents the constant effect of the predictor variable on the likelihood of the outcome. Thus, the EXP(B) of .978 indicates the odds of retention decrease .022 (1-.978) for each unit increase in STEM credits attempted. Additionally, *high school GPA* was found to be significant ( $p < .05$ ). No other variables were statistically significant.

These results are particularly important given the first year STEM curriculum requires students to enroll in a high number of math and science courses (Bettinger, 2010; Westrick, 2014; Zhang et al., 2004). The results indicate that enrolling in more STEM courses negatively

influenced first year retention. Bettinger (2010) found that STEM courses accounted for 52% of all first semester courses for first year STEM students. The results of this study suggest that first year STEM students are less likely to be retained after the first year due to the high percentage of STEM courses taken in the first year.

Table 11.

*Logistic Regression Results: First Year Retention (Research Question 1)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	-.109	.257	.671	.897	.541	1.485
Race/Ethnicity (non-URM)	-.232	.670	.729	.793	.214	2.946
High School GPA	-.063	.058	.278	.939	.838	1.052
Total Aid	.302	.313	.336	1.352	.732	2.498
SAT Math (10 point scale)	.000	.001	.886	1.000	.998	1.002
Social Integration (33.333 point scale)	.001	.003	.830	1.001	.995	1.006
Academic Integration (25 point scale)	-.001	.004	.674	.999	.992	1.005
Income	.140	.353	.692	1.000	.998	1.002
STEM Credits Attempted	-.022	.006	.000	.978	.966	.989
Constant	-1.612	2.270	.477	.199		

## Graduation

The Omnibus Tests of Model Coefficients table (Table 12) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 51.792, p < .001$ ), thus indicating the fitted model was able to distinguish between participants who were graduated or did not graduate. The Model Summary table shows the -2LL for the fitted model (518.940) and two pseudo R<sup>2</sup> values, the Cox and Snell R<sup>2</sup> and the Nagelkerke R<sup>2</sup>. The Cox and Snell (.116) and Nagelkerke (.156) demonstrate that the fitted model explains between 11.6% and 15.6% of the variance in graduation.

Table 12. *Goodness of Fit Statistics: Graduation (Research Question 1)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	51.792	9	.000
<b>Coefficients -2LL</b>	518.940		
<b>Cox &amp; Snell R<sup>2</sup></b>	.116		
<b>Nagelkerke R<sup>2</sup></b>	.156		

Table 13 presents the findings of the binary logistic regression analysis for graduation. The predictor variables of *high school GPA*, *SAT math* and *social integration index* were statistically significant ( $p < .05$ ). The odds ratio for *high school GPA* was 1.161 (95% CI between 1.035 and 1.302). This indicates that the odds of graduation increase 16.1 percentage points with each increase in high school GPA. The odds ratio for SAT math was 1.002 (95% CI between 1.001 and 1.004). This indicates that the odds of graduation increase .002 with each 10 point increase in SAT math score. Finally, the odds ratio for the social integration index was 1.005 (95% CI between 1.000 and 1.010), which indicates that the odds of graduation increase .005 with each 33.333 point increase in social integration index score. As noted in Chapter II, social integration score represents students' response to how often they participated in: (a) campus arts, drama, music, or fine arts activities; (b) campus clubs or organizations; and (c) campus varsity, intermural, or club sports activities. No other variables were found to be statistically significant.

Similar to the findings of Chen (2013), STEM credits attempted was not a significant predictor of graduation. This suggests that academic performance rather than enrollment in STEM courses influences graduation. While enrollment in STEM courses was not a significant predictor of graduation, this study did find that STEM course performance was a significant predictor of graduation.



Table 13. *Logistic Regression Results: Graduation (Research Question 1)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.405	.222	.068	1.499	.971	2.314
Race/Ethnicity (non-URM)	.141	.545	.796	1.151	.395	3.353
High School GPA	.149	.059	.011	1.161	1.035	1.302
Total Aid	-.154	.261	.556	.857	.514	1.431
SAT Math (10 point scale)	.002	.001	.005	1.002	1.001	1.004
Social Integration (33.333 point scale)	.005	.002	.031	1.005	1.000	1.010
Academic Integration (25 point scale)	.000	.003	.946	1.000	.994	1.006
Income	.362	.305	.236	1.437	.790	2.614
STEM Credits Attempted	.006	.004	.086	1.006	.999	1.013
Constant	-4.117	1.977	.037	.016		

### Time to Degree

The Omnibus Tests of Model Coefficients table (Table 14) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 43.363$ ,  $p < .001$ ), thus indicating that the fitted model was able to distinguish the participants who graduated in 48 months or less. The chi-square statistic represents the difference in log-likelihood (-2LL) values between the null and fitted models. The Model Summary table shows the -2LL for the fitted model (387.359), the Cox and Snell  $R^2$  (.098) and the Nagelkerke  $R^2$  (.153). Based on these figures, the fitted model explains between 9.8% and 15.3% of the variation in time to degree.

Table 14. *Goodness of Fit Statistics: Time to Degree (Research Question 1)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	43.363	9	.000
<b>Coefficients -2LL</b>	387.359		
<b>Cox &amp; Snell <math>R^2</math></b>	.098		
<b>Nagelkerke <math>R^2</math></b>	.153		

Table 15 presents the findings of the binary logistic regression analysis for time to degree. *Gender* and *SAT math score* were found to be statistically significant ( $p < .001$ ). *Gender* had an odds ratio of 2.633 (95% CI between 1.577 and 4.394), which indicates females are 1.633 times more likely to graduate in 48 months or less compared to males. *SAT math score* had an odds ratio of 1.003 (95% CI between 1.000 and 1.006), which indicates the odds of graduation in 48 months or less increases .3% for each 10 point increase in SAT math score. No other variables were found to be statically significant.

Similar to Ewert (2012) and Goldrick-Rab (2006), female participants in this study had higher levels of academic achievement than the male participants. Previous research has also identified that females are more likely to change out of the STEM fields due to strong grades in non-STEM courses (Mann & DiPrete, 2013; Ost, 2010). The findings of previous research and the results of this study suggest that females are more likely to successfully navigate the STEM to non-STEM major change due to higher levels of academic achievement.

Table 15. *Logistic Regression Results: Time to Degree*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender	.968	.261	.000	2.633	1.577	4.394
Race/Ethnicity	.255	.628	.684	1.291	.377	4.416
High School GPA	.113	.095	.234	1.119	.930	1.347
Total Aid	.192	.297	.516	1.212	.678	2.168
SAT Math	.003	.001	.020	1.002	1.000	1.006
Social Integration	.004	.003	.110	1.004	.999	1.010
Academic Integration	.003	.004	.357	.1003	.996	1.011
Income	.588	.409	.150	1.801	.809	4.011
STEM Credits Attempted	-.002	.005	.736	.998	.989	1.008
Constant	-9.440	2.520	.000	.000		

## Ordinary Least Squares Regression

### Cumulative GPA

A simultaneous multiple linear regression was run using the predictor variables with cumulative GPA as the dependent variable. The model summary below (Table 16) is shown with the adjusted  $R^2$  being .066.

Table 16. *Cumulative GPA – Model Summary (Research Question 1)*

Model	$R$	$R^2$	Adjusted $R^2$	Std. Error of the Estimate
1	.295	.087	.066	.816

The ANOVA data (Table 17) show that the model was statistically significant with  $F=4.124$ ,  $df=9$  and  $p<.001$ . Therefore, the combination of the predictor variables significantly predicted cumulative GPA.

Table 17. *Cumulative GPA ANOVA table (Research Question 1)*

Model	Sum of Squares	$Df$	Mean Square	$F$	$p$
1					
Regression	24.740	9	2.749	4.124	.000
Residual	259.307	510	.677		
Total	284.047	540			

The coefficients table demonstrates the beta values of the independent variables. Beta values represent the strength of influence of the independent variable on the dependent variable. Table 18 indicates *SAT math score*, *gender* and *STEM credits attempted* were the only significant variables, with  $p=.006$  and  $p<.001$ ,  $p=.026$ , respectively. Each 10-point increase in SAT math score increased cumulative GPA by .001 points. Further, being female increased cumulative

GPA by .356 points. Lastly, each increase in STEM credits attempted increased cumulative GPA by .003.

Again, as in previous research, the results indicate females have higher levels of academic achievement compared to males. Further, females are more likely to leave the STEM fields for reasons other than poor academic performance (Bettinger, 2010; Kulturel-Konak, D’Allegro and Dickinson 2011; Griffith, 2010). Therefore, the findings suggest females are less likely to be negatively affected by enrollment in STEM courses prior to changing to a non-STEM major.

It is also important to note that *STEM credits attempted* was positively associated with cumulative GPA. While *STEM credits attempted* is negatively associated with first year retention, attempting more STEM credits has the opposite effect on cumulative GPA. One explanation for this finding is that students who perform well in STEM courses may be more likely to continue to enroll in STEM courses, while students who perform poorly may drop out or transfer.

Table 18. *Coefficients Table: Cumulative GPA (Research Question 1)*

	Unstandardized Coefficients			
	B	Std. Error	t	Sig.
(Constant)	1.585	.740	2.142	.033
Gender (female)	.356	.085	4.181	.000
Race/Ethnicity (non-URM)	-.097	.209	-4.66	.642
High School GPA	.002	.020	.112	.911
Total Aid	-.099	.099	-1.000	.318
SAT Math (10 point scale)	.001	.000	2.241	.026
Social Integration (33.333 point scale)	0.00	.001	-.078	.937
Academic Integration (25 point scale)	.000	.001	.338	.735
Income	.098	.116	.841	.401

STEM Credits Attempted	.003	.001	2.241	.026
------------------------	------	------	-------	------

## Analysis of Research Question 2

**Question 2:** After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in college-level math relate to:

- First-year retention rates for STEM leavers?
- Graduation rates for STEM leavers?
- Time to degree for STEM leavers?
- Cumulative GPA for STEM leavers?

### Binary Logistic Regression

Three separate binary logistic regression analyses were performed to assess the predictive impact of gender, race/ethnicity, total aid, academic integration index, social integration index, parental/independent income, SAT math score, high school GPA and college level math GPA on first year retention, graduation and time to degree.

### First Year Retention

The fitted model chi-square was not statistically significant ( $\chi^2(9) = 11.927, p = .217$ ), thus indicating the fitted model was unable to distinguish between participants who were retained or not retained. Because the model did not reach significance, regression results are not included. The Model Summary table shows the -2LL for the fitted model, 246.987 and two pseudo  $R^2$  values, the Cox and Snell  $R^2$  and the Nagelkerke  $R^2$ . The Cox and Snell  $R^2$  (.042) and

Nagelkerke R<sup>2</sup> (.069) indicate the fitted model explains between 4.2 % and 6.9% of the variance in first-year retention.

Table 19. *Goodness of Fit Statistics: First Year Retention (Research Question 2)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	11.927	9	.217
<b>Coefficients -2LL</b>	246.987		
<b>Cox &amp; Snell R<sup>2</sup></b>	.042		
<b>Nagelkerke R<sup>2</sup></b>	.069		

Herzog (2005) found that freshman who failed to complete a math course in the first year were five times less likely to be retained compared to those who successfully completed a math course in the first year. As I will discuss later in this chapter, STEM GPA was a significant predictor of first year retention. This result suggests that for first year STEM students, academic performance in all STEM courses has greater influence on first year retention than just college level math.

## Graduation

The Omnibus Tests of Model Coefficients table (Table 20) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 54.830, p < .001$ ), indicating that it was able to distinguish between participants who graduated or did not graduate. The chi-square statistic represents the difference in log-likelihood (-2LL) values between the null and fitted models.

The Model Summary table shows the -2LL for the fitted model (314.740) and the Cox and Snell R<sup>2</sup> and the Nagelkerke R<sup>2</sup>. The Cox & Snell R<sup>2</sup> (.179) and Nagelkerke R<sup>2</sup> (.243) suggest that the fitted model explains between 17.9% and 24.3% of the variance in graduation.

Table 20. *Goodness of Fit Statistics: Graduation (Research Question 2)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	54.830	9	.000
<b>Coefficients -2LL</b>	314.740		
<b>Cox &amp; Snell R<sup>2</sup></b>	.179		
<b>Nagelkerke R<sup>2</sup></b>	.243		

Table 21 presents the findings of the binary logistic regression analysis for graduation. The predictor variables of *high school GPA* and *college level math GPA* were statistically significant ( $p < .05$ ). *High school GPA* had an odds ratio of 1.231 (95% CI between 1.051 and 1.440), which indicates for each high school GPA category, the odds of graduation increase by .231. The odds ratio for *college level math GPA* was 1.833 (95% CI between 1.382 and 2.431). This indicates that odds of graduation increases .833 with each unit increase in college level math GPA. These findings mirror the results of similar studies that found college level academic performance to be the most powerful predictor of academic achievement (Cabrera, Burkum, & La Nasa, 2005; Adelman, 2006). No other variables in the model were found to be statistically significant.

Table 21. *Logistic Regression Results: Graduation (Research Question 2)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.045	.297	.881	1.046	.584	1.872
Race/Ethnicity (non-URM)	-.130	.753	.863	.878	.201	3.845
High School GPA	.207	.080	.010	1.231	1.051	1.440
Total Aid	-.148	.359	.680	.863	.427	1.742
SAT Math (10 point scale)	.002	.001	.140	1.002	.999	1.004
Social Integration (33.333 point scale)	.003	.003	.412	1.003	.997	1.009
Academic Integration (25 point scale)	.004	.004	.301	1.004	.996	1.012
Income	.606	.437	.165	1.833	.779	4.312
College Level Math GPA	.606	.144	.000	1.833	1.382	2.431

Constant	-5.789	2.832	.031	.003
----------	--------	-------	------	------

### Time to Degree

The Omnibus Tests of Model Coefficients table (Table 22) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 30.679, p < .001$ ), indicating that it was able to distinguish the participants who graduated in 48 months or shorter. The Model Summary table shows the -2LL for the fitted model (259.317). The Cox and Snell  $R^2$  (.104) and Nagelkerke  $R^2$  (.161) suggest that the fitted model explains between 10.4% and 16.1% of the variation in time to degree.

Table 22. *Goodness of Fit Statistics: Time to Degree (Research Question 2)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	30.679	9	.000
<b>Coefficients -2LL</b>	259.317		
<b>Cox &amp; Snell <math>R^2</math></b>	.104		
<b>Nagelkerke <math>R^2</math></b>	.161		

Table 23 presents the findings of the binary logistic regression analysis for time to degree. *Gender* and *SAT math score* were found to be statistically significant ( $p < .001$ ). Gender had an odds ratio of 2.572 (95% CI between 1.331 and 4.971), which indicates that the odds of graduating in 48 months or less is 1.572 times more likely for females compared to males. SAT math had an odds ratio of 1.005 (95% CI between 1.002 and 1.008), which indicates the odds of graduating in 48 months or less increase .005 with each 10 point increase in SAT math score.

College level math performance was not a significant predictor in the model. Instead, pre-college academic achievement (*SAT math* and *high school GPA*) was significant and positively associated with graduation in 48 months or less. Although previous research (Green



& Zwick, 2007; Geiser & Sanelices, 2007; Tross, Harper, Osher, & Kneidiner, 2000) has found high school GPA and SAT math score to be significant predictors of academic achievement, pre-college academic achievement variables often lose significance when academic performance in college is considered (Adelman, 2006). Interestingly, the results of this study suggest pre-college academic achievement is a stronger predictor of graduation in four years than college level math performance. These findings suggest that college level math performance does not hinder academic progress once a student has transitioned into a non-STEM field.

Table 23. *Logistic Regression Results: Time to Degree (Research Question 2)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.954	.336	.006	2.572	1.331	4.971
Race/Ethnicity (non-URM)	.105	.846	.901	1.111	.211	5.832
High School GPA	.152	.127	.232	1.164	.907	1.493
Total Aid	.109	.376	.772	1.115	.534	2.328
SAT Math (10 point scale)	.005	.002	.005	1.005	1.002	1.008
Social Integration (33.333 point scale)	.003	.003	.426	1.003	.996	1.009
Academic Integration (25 point scale)	.002	.005	.736	1.002	.992	1.011
Income	.010	.512	.984	1.010	.370	2.756
College Level Math GPA	.116	.167	.489	1.122	.809	1.557
Constant	-7.531	3.253	.021	.001		

***Ordinary Least Squares Regression***

**Cumulative GPA**

A simultaneous multiple regression was run using the predictor variables with *cumulative GPA* as the dependent variable. The model summary (Table 24) is shown with the adjusted R<sup>2</sup> being .079.

Table 24. *Cumulative GPA – Model Summary (Research Question 2)*

Model	<i>R</i>	<i>R</i> <sup>2</sup>	Adjusted <i>R</i> <sup>2</sup>	Std. Error of the Estimate
1	.316	.100	.079	.81066

The ANOVA data (Table 25) shows that the model was statistically significant with  $F=4.803$ ,  $df=9$  and  $p<.001$ . The model significantly predicted cumulative GPA.

Table 25. *Cumulative GPA ANOVA table (Research Question 2)*

Model	Sum of Squares	<i>Df</i>	Mean Square	<i>F</i>	<i>p</i>
1					
Regression	28.408	9	3.156	4.803	.000
Residual	255.638	510	.657		
Total	284.047	540			

The coefficients table (Table 26) displays the beta values of the independent variables. Table 26 indicates *gender*, *SAT math score*, and *college level math* were the only significant variables with  $p<.001$ ,  $p=.006$ ,  $p=.001$ , respectively. For each 10 point increase in *SAT math score*, cumulative GPA increased .002. For each grade point increase in *college level math*, cumulative GPA increased .036. *Gender* had the strongest influence on cumulative GPA. This result aligns with previous research, which shows females tend to have higher levels of academic achievement outside of STEM fields (Ewert, 2012; Goldrick-Rab, 2006). Females may be better equipped to successfully transition from STEM to non-STEM fields.

*SAT math* and *college level math GPA* also reached significance and were positively associated with cumulative GPA. Previous research on STEM achievement has found SAT math and college level math GPA to be positively associated with STEM achievement and overall academic achievement in any field (Adelman, 2006; Cabrera, Burkum & La Nasa, 2005; Chen,

2013; Chen, 2015). The results of the regression model indicate college level math is a predictor of cumulative GPA regardless of whether in a STEM or non-STEM field.

Table 26. *Coefficients Table: Cumulative GPA (Research Question 2)*

	Unstandardized Coefficients			
	B	Std. Error	t	Sig.
(Constant)	1.583	.733	2.159	.031
Gender (female)	.352	.084	4.173	.000
Race/Ethnicity (non-URM)	-.081	.208	-.390	.696
High School GPA	.002	.020	.118	.906
Total Aid	-.113	.098	-1.147	.252
SAT Math (10 point scale)	.001	.000	2.775	.006
Social Integration (33.333 point scale)	0.00	.001	-.014	.989
Academic Integration (25 point scale)	.001	.001	.670	.503
Income	.098	.115	.848	.397
College Level Math GPA	.036	.011	3.267	.001

### Analysis of Research Question 3

**Question 3:** After controlling for race/ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in introductory level laboratory science relate to:

- First year retention rates for STEM leavers?
- Graduation rates for STEM leavers?
- Time to degree for STEM leavers?
- Cumulative GPA for STEM leavers?

### **Binary Logistic Regression**

Three separate binary logistic regression analyses were performed to assess the predictive impact of gender, race/ethnicity, total aid, academic integration index, social integration index,

parental/independent income, SAT math score, high school GPA and introductory laboratory science GPA on first year retention, graduation and time to degree.

### First Year Retention

The Omnibus Tests of Model Coefficients table (Table 27) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was not statistically significant ( $\chi^2(9) = 11.911$ ,  $p = .218$ ), indicating that the fitted model was unable to distinguish between participants who were retained or not retained. Thus, the results of the regression will not be reported. The chi-square statistic represents the difference in log-likelihood (-2LL) values between the null and fitted models. The Model Summary table shows the -2LL for the fitted model (273.281) and two pseudo R<sup>2</sup> values, the Cox and Snell R<sup>2</sup> (.038) and the Nagelkerke R<sup>2</sup> (.063). Therefore, the fitted model explains between 3.8% and 6.3% of the variance in first year retention.

Table 27. *Goodness of Fit Statistics: First Year Retention (Research Question 3)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	11.911	9	.211
<b>Coefficients -2LL</b>	273.281		
<b>Cox &amp; Snell R<sup>2</sup></b>	.038		
<b>Nagelkerke R<sup>2</sup></b>	.063		

### Graduation

The Omnibus Tests of Model Coefficients table (Table 28) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 52.463$ ,  $p < .001$ ), thus indicating that it was able to distinguish between participants who graduated and those who did not graduate. The chi-square statistic

represents the difference in log-likelihood (-2LL) values between the null and fitted models. The Model Summary table shows the -2LL for the fitted model (350.583) and two pseudo R<sup>2</sup> values, the Cox and Snell R<sup>2</sup> and the Nagelkerke R<sup>2</sup>. The Cox & Snell R<sup>2</sup> (.158) and Nagelkerke R<sup>2</sup> (.215) show that the fitted model explains between 15.8% and 21.5% of the variance in graduation.

Table 28. *Goodness of Fit Statistics: Graduation (Research Question 3)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	52.463	9	.000
<b>Coefficients -2LL</b>	350.583		
<b>Cox &amp; Snell R<sup>2</sup></b>	.158		
<b>Nagelkerke R<sup>2</sup></b>	.215		

Table 29 presents the findings of the binary logistic regression analysis for graduation. The predictor variables of *gender* and *introductory laboratory science GPA* were statistically significant ( $p < .05$ ). *Gender* had an odds ratio of 1.750 (95% CI between 1.019 and 3.005). Females were .750 more likely to graduate compares to males. The odds ratio for *introductory laboratory science GPA* was 1.962 (95% CI between 1.482 and 2.597). For each increase in *introductory laboratory science GPA*, the odds of graduation increased by .962. With regards to gender, these findings support previous research that found females achieve higher levels of academic achievement in non-STEM fields (Ewert, 2012).

Compared to the results of the logistic regression model examining the relationship between *college level math GPA* and graduation (see Table 21), *introductory laboratory science* had a greater effect on graduation. As noted in Chapter 2, there are few studies that address the relationship between courses other than math and English and academic achievement in the non-

STEM fields. This study found that introductory lab science was a stronger predictor of graduation than college level math.

Table 29. *Logistic Regression Results: Graduation (Research Question 3)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.560	.276	.042	1.750	1.019	3.005
Race/Ethnicity (non-URM)	.162	.698	.816	1.176	.299	4.618
High School GPA	.110	.067	.101	1.116	.979	1.272
Total Aid	.024	.334	.942	1.025	.532	1.974
SAT Math (10 point scale)	.002	.001	.088	1.002	.999	1.004
Social Integration (33.333 point scale)	.003	.003	.322	1.003	.997	1.008
Academic Integration (25 point scale)	.000	.004	.932	1.000	.997	1.007
Income	.383	.381	.942	1.025	.532	1.974
Intro Lab Science GPA	.674	.143	.000	1.962	1.483	2.597
Constant	-5.628	2.516	.025	.004		

### Time to Degree

The Omnibus Tests of Model Coefficients table (Table 30) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 40.149$ ,  $p < .001$ ), indicating that it was able to distinguish the participants who graduated in 48 months or shorter. The Model Summary table shows the -2LL for the fitted model (293.755). The Cox & Snell  $R^2$  (.123) and Nagelkerke  $R^2$  (.185) indicate that the fitted model explains between 12.3% and 18.5% of the variation in time to degree.

Table 30. *Goodness of Fit Statistics: Time to Degree (Research Question 3)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	40.149	9	.000
<b>Coefficients -2LL</b>	293.755		
<b>Cox &amp; Snell <math>R^2</math></b>	.123		
<b>Nagelkerke <math>R^2</math></b>	.185		

Table 31 presents the findings of the binary logistic regression analysis for time to degree. *Gender* and *introductory lab science GPA* were found to be statistically significant ( $p < .001$ ). *Gender* had an odds ratio of 2.730 (95% CI between 1.513 and 4.924), which means that the odds of graduating in 48 months or less is 1.730 times more likely for females compared to their male counterparts. *Introductory laboratory science GPA* had an odds ratio of 1.807 (95% CI between 1.382 and 2.546), indicating the odds of graduating in 48 months or less increase .807 for each grade point increase in *introductory lab science GPA*.

*Introductory laboratory science GPA* was also a significant predictor of graduation in 48 months or less. While introductory laboratory science is only one component of the STEM curriculum, the positive association between introductory laboratory science GPA and graduation in 48 months or less suggests that academic performance is an important factor in determining whether students can handle the major transition from STEM to non-STEM.

Table 31. *Logistic Regression Results: Time to Degree (Research Question 3)*

	B	SE	Sig	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	1.004	.301	.001	2.730	1.513	4.924
Race/Ethnicity (non-URM)	.471	.711	.507	1.603	.398	6.457
High School GPA	.043	.086	.616	1.044	.882	1.235
Total Aid	.343	.351	.328	1.410	.998	1.004
SAT Math (10 point scale)	.001	.001	.433	1.001	.998	1.004
Social Integration (33.333 point scale)	.002	.003	.441	1.002	.996	1.008
Academic Integration (25 point scale)	.005	.004	.264	1.005	.996	1.013
Income	.579	.454	.202	1.784	.733	4.341
Intro Lab Science GPA	.592	.175	.001	1.807	1.382	2.546
Constant	-10.204	2.831	.000	.000		

## Ordinary Least Squares Regression

### Cumulative GPA

A simultaneous multiple linear regression was run using the predictor variables with cumulative GPA as the dependent variable. The model summary is shown (Table 32) with the adjusted  $R^2$  being .102.

Table 32. *Cumulative GPA – Model Summary (Research Question 3)*

Model	$R$	$R^2$	Adjusted $R^2$	Std. Error of the Estimate
1	.350	.122	.102	.791

The ANOVA data (Table 33) show that the model was statistically significant with  $F=6.017$ ,  $df=9$  and  $p<.001$ . This indicates the model was able to significantly predict cumulative GPA.

Table 33. *Cumulative GPA ANOVA table (Research Question 3)*

Model	Sum of Squares	$Df$	Mean Square	$F$	$p$
1					
Regression	33.916	9	3.768	6.017	.000
Residual	242.989	510	.626		
Total	276.905	540			

The coefficients table (Table 34) demonstrates the beta values of the independent variables. Table 34 indicates *gender*, *SAT math score*, and *introductory laboratory science GPA* were the only significant variables with  $p=.001$ ,  $p=.011$  and  $p<.001$ , respectively. *Gender* had the strongest influence on cumulative GPA. Being female increases cumulative GPA by .271, which supports previous research on the academic achievement of females compared to males (Ewert, 2012). *Introductory laboratory science GPA* was positively associated with cumulative



GPA. This is not necessarily surprising given students' course performance is likely indicative of their overall GPA. However, it does indicate that students who do not do well in introductory lab science may struggle to raise their GPAs after switching out of the STEM fields.

Table 34. *Coefficients Table: Cumulative GPA (Research Question 3)*

	Unstandardized Coefficients			
	B	Std. Error	t	Sig.
(Constant)	1.646	.715	2.303	.022
Gender (female)	.271	.084	3.213	.001
Race/Ethnicity (non-URM)	-.077	.203	-.381	.703
High School GPA	.002	.020	..091	.928
Total Aid	-.077	.096	-.797	.426
SAT Math (10 point scale)	.001	.000	2.566	.011
Social Integration (33.333 point scale)	.000	.001	.005	.996
Academic Integration (25 point scale)	.000	.001	.098	.922
Income	.094	.112	.834	.405
Intro Lab Science GPA	.020	.005	4.291	.000

#### Analysis of Research Question 4

**Question 4:** After controlling for ethnicity, SAT/ACT math score, high school GPA, gender, socioeconomic status, receipt of financial aid, academic integration, and social integration, how does academic performance in STEM courses relate to:

- First year retention rates for STEM leavers?
- Time to degree for STEM leavers?
- Graduation rates for STEM leavers?
- Cumulative GPA for STEM leavers?

#### *Binary Logistic Regression*

Three separate binary logistic regression analyses were performed to assess the predictive impact of gender, race/ethnicity, total aid, academic integration index, social integration index, parental/independent income, SAT math score, and academic performance in STEM courses on first year retention, graduation and time to degree.

**First Year Retention**

The Omnibus Tests of Model Coefficients table (Table 35) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was not statistically significant ( $\chi^2(9) = 13.489, p=.142$ , indicating that it was unable to distinguish the participants who were retained or not retained after the first year. The Model Summary table shows the -2LL for the fitted model (402.783), and the Cox & Snell R<sup>2</sup> (.032) and Nagelkerke R<sup>2</sup> (.051). Therefore, the fitted model explains between 3.2% and 5.1% of the first year retention.

Table 35. *Goodness of Fit Statistics: First Year Retention (Research Question 4)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	13.489	9	.142
<b>Coefficients -2LL</b>	402.783		
<b>Cox &amp; Snell R<sup>2</sup></b>	.032		
<b>Nagelkerke R<sup>2</sup></b>	.051		

**Graduation**

The Omnibus Tests of Model Coefficients table (Table 36) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 105.133, p <.001$ ), indicating that the fitted model was able to distinguish between participants who graduated or did not graduate. The chi-square statistic represents the difference in log-likelihood (-2LL) values between the null and fitted models.

The Model Summary table shows the -2LL for the fitted model (453.663) and two pseudo R<sup>2</sup> values, the Cox and Snell R<sup>2</sup> and the Nagelkerke R<sup>2</sup>. The Cox & Snell R<sup>2</sup> (.226) and Nagelkerke R<sup>2</sup> (.304) indicate that the fitted model explains between 22.6% and 30.4% of the variance in graduation.

Table 36. *Goodness of Fit Statistics: Graduation (Research Question 4)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	105.133	9	.000
<b>Coefficients -2LL</b>	453.663		
<b>Cox &amp; Snell R<sup>2</sup></b>	.226		
<b>Nagelkerke R<sup>2</sup></b>	.304		

Table 37 presents the findings of the binary logistic regression analysis for graduation. The predictor variables of *STEM GPA*, *high school GPA*, and *social integration index* were statistically significant ( $p < .05$ ). *STEM GPA* had an odds ratio of 3.003 (95% CI between 2.210 and 4.164). Every grade point increase in *STEM GPA* increases odds of graduating by 2.003 times. No other variables were statistically significant.

Chen (2013) found that the most common reason students leave the STEM fields is due to poor academic performance. Considering these findings, the results of the regression are especially alarming with regards to the STEM to non-STEM major change and graduation. Course performance in STEM courses strongly influences chances of graduation in a non-STEM field. Because most students leave the STEM fields due to poor performance and STEM GPA is a significant predictor of graduation, the findings of the regression model suggest the STEM to non-STEM major change puts students at risk of never graduating.

High school GPA had an odds ratio of 1.209 (95% CI between 1.077 and 1.358), indicating the odds of graduating increase .209 times for each unit increase in high school GPA. Students with lower high school GPAs are less likely to reach high levels of academic achievement in the STEM fields (Chen, 2013; Crisp, Nora, & Taggart, 2009; Whalen & Shelley II, 2010). Students with stronger academic profiles in high school may be more equipped to successfully navigate the STEM to non-STEM major change due to their preparedness to successful complete college coursework.

Table 37. *Logistic Regression Results: Graduation (Research Question 4)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.174	.244	.475	1.190	.738	1.918
Race/Ethnicity (non-URM)	.330	.627	.599	1.391	.407	4.757
High School GPA	.190	.059	.001	1.209	1.077	1.358
Total Aid	.039	.287	.813	1.039	.592	1.823
SAT Math (10 point scale)	.001	.001	.278	1.001	.999	1.003
Social Integration (33.333 point scale)	.007	.003	.010	1.007	1.002	1.012
Academic Integration (25 point scale)	.001	.003	.859	1.001	.999	1.007
Income	.382	.330	.247	1.465	.767	2.798
STEM GPA	1.110	.162	.000	3.003	2.210	4.164
Constant	-6.947	2.222	9.779	.002	.001	

### Time to Degree

The Omnibus Tests of Model Coefficients table (Table 38) displays the model chi-square and tests for overall significance of the fitted model. The fitted model chi-square was statistically significant ( $\chi^2(9) = 64.166, p < .001$ ), thus indicating the fitted model was able to distinguish the participants who graduated in 48 months or shorter. The Model Summary table shows the -2LL for the fitted model, (360.128). The Cox & Snell  $R^2$  (.145) and Nagelkerke  $R^2$

(.225) suggest that the fitted model explains between 14.5% and 22.5% of the variance in *time to degree*.

Table 38. *Goodness of Fit Statistics: Time to Degree (Research Question 4)*

Test	$\chi^2$	df	Sig.
<b>Omnibus Tests of Model Coefficients</b>	64.166	9	.000
<b>Coefficients -2LL</b>	360.128		
<b>Cox &amp; Snell R<sup>2</sup></b>	.145		
<b>Nagelkerke R<sup>2</sup></b>	.225		

Table 39. *Logistic Regression Results: Time to Degree (Research Question 4)*

	B	SE	Sig.	Exp(B)	95% CI for EXP (B)	
					Lower	Upper
Gender (female)	.749	.273	.006	2.114	1.237	3.612
Race/Ethnicity (non-URM)	.215	.683	.753	1.240	.325	4.733
High School GPA	.101	.083	.227	1.106	.939	1.302
Total Aid	.338	.311	.277	1.402	.762	2.576
SAT Math (10 point scale)	.001	.001	.278	1.001	.999	1.004
Social Integration (33.333 point scale)	.005	.004	.057	1.005	.999	1.011
Academic Integration (25 point scale)	.004	.004	.318	1.004	.996	1.012
Income	.653	.419	.119	1.922	.845	4.372
STEM GPA	.891	.201	.000	2.438	1.642	3.618
Constant	-11.484	2.662	.000	.000		

The predictor variables of *STEM GPA* and *gender* were statistically significant ( $p < .05$ ). No other variables were found to be statistically significant. *STEM GPA* had an odds ratio of 2.438 (95% CI between 1.642 and 3.618). This indicates that for every grade point increase in *STEM GPA*, the odds of graduating in 48 months or less increases by 1.438. *Gender* had an odds ratio of 2.113 (95% CI between 1.237 and 3.612), which indicates females are 1.114 times more likely to graduate in 48 months or less than their male counterparts.

As previously noted, the most common reason students leave the STEM fields is due to poor academic performance (Chen, 2013). The findings indicate that academic performance in STEM courses plays an important role in whether time to degree is increased as a result of leaving a STEM major. In the regression model used to answer research question 1, *STEM credits attempted* was not a significant predictor of time to degree. The findings of this study show that academic performance is the strongest predictor of academic achievement after leaving the STEM field.

### ***Ordinary Least Squares Regression***

#### **Cumulative GPA**

A simultaneous multiple linear regression was run using the predictor variables with *cumulative GPA* as the dependent variable. A model summary (Table 40) is shown below with the adjusted  $R^2$  revealed as .601.

Table 40. *Cumulative GPA – Model Summary (Research Question 4)*

Model	<i>R</i>	$R^2$	Adjusted $R^2$	Std. Error of the Estimate
1	.781	.610	.601	.527

The ANOVA data (Table 38) shows that the model was statistically significant with  $F=66.749$ ,  $df=9$  and  $p<.001$ . This indicates that it was able to significantly predict cumulative GPA.

Table 41. *Cumulative GPA ANOVA table (Research Question 4)*

Model	Sum of Squares	<i>Df</i>	Mean Square	<i>F</i>	<i>p</i>
1					
Regression	167.116	9	18.568	66.749	.000

Residual	106.822	510	.78
Total	273.938	540	

Table 42 indicates *gender*, *high school GPA* and *STEM GPA* were significant predictors of cumulative GPA. *STEM GPA* had the strongest influence on cumulative GPA with a beta value of .758. *Gender* had a beta value of .149 and *high school GPA* had a beta value of .031. No other variables were found to be significant.

The results of the ordinary least squares regression used for research questions 2 and 3 found college level math GPA and introductory laboratory science GPA to be significant predictors; however, the beta values were significantly lower compared to the beta value of STEM GPA. This is not incredibly surprising as STEM GPA encompasses more coursework than just college level math or introductory laboratory science.

Table 42. *Coefficients Table: Cumulative GPA (Research Question 4)*

	Unstandardized Coefficients			
	B	Std. Error	t	Sig.
(Constant)	-.353	.490	-.719	.472
Gender (female)	.149	.056	2.648	.008
Race/Ethnicity (non-URM)	-.050	.135	-.369	.712
High School GPA	.031	.013	2.388	.017
Total Aid	.098	.076	1.182	.238
SAT Math (10 point scale)	.000	.000	-.633	.527
Social Integration (33.333 point scale)	.000	.001	-.276	.783
Academic Integration (25 point scale)	.001	.001	1.366	.173
Income	.089	.076	1.182	.238
STEM GPA	.758	.033	22.844	.000

Next, I will review the key findings and discuss implications.

## CHAPTER V

### CONCLUSION AND IMPLICATIONS

#### **Introduction**

The purpose of this study was to provide an understanding of how the STEM curriculum relates to the academic achievement of students who leave STEM degree programs. Rather than focusing on what causes students to leave the STEM fields, this study focused on how enrollment and performance in STEM courses contributed to first year retention, graduation, time to degree and cumulative GPA.

The analytical sample for this study was taken from the Beginning Postsecondary Educational Study 2004:2009 (BPS:04/09) and the associated Postsecondary Education Transcript Study (PETS:09). The sample included students that declared a STEM major upon their initial enrollment and changed their major to a non-STEM field or students that stayed in STEM and either transferred or did not graduate.

In this chapter, I will review discuss the key findings of the study. I will then draw conclusions and recommendations for policy and practice. Lastly, I will provide recommendations for future research.

#### **Key Findings & Conclusions**

##### **STEM Credits Attempted**

Along with academic performance in STEM courses, this study aimed to determine how enrollment in STEM courses related to academic achievement after leaving the STEM fields. With regards to first year retention, this study found that STEM credits attempted was a significant predictor of first year retention. Each increase in STEM credits attempted reduced



the chances of first year retention by 2.2%. The negative relationship between STEM credits attempted and first year retention suggests the STEM curriculum puts STEM leavers at risk of attrition. The STEM curriculum requires enrollment in multiple “gatekeeping” courses that are particularly challenging for students (Bettinger, 2010; Westrick, 2014; Zhang et al., 2004) and the results suggest enrolling in more STEM courses increases the chances of a student not being retained after the first year. This may be a result of the challenging nature of STEM courses and that STEM leavers perform poorly in these courses.

The final regression model run to answer research question number one focused on cumulative GPA. Surprisingly, STEM credits attempted was positively associated with cumulative GPA. Students that leave the STEM fields most often cite poor academic performance in STEM courses as the reason for changing majors (Bettinger, 2010; Chen, 2013; 2015). Students that leave the STEM fields most often cite poor academic performance in STEM courses as the reason for changing majors (Bettinger, 2010; Chen, 2013, 2015). Therefore, it is reasonable to believe that an increase in STEM credits attempted would decrease cumulative GPA. Conversely, this study found an increase in STEM units attempted increased cumulative GPA by .003. This finding suggests that students may leave the STEM fields due to reasons other than poor academic achievement. The results may also suggest that STEM leavers who perform poorly in STEM courses drop out or transfer rather than continue to take additional STEM credits. Especially, since students who perform poorly in the first year are less likely to persist at their first institution (Adelman, 2006; Bettinger, 2010; Chen, 2013, 2015).

### **College Level Math GPA**

The second research question aimed to determine how academic performance in college

level math related to academic achievement for STEM leavers. Each grade point increase in college level math GPA increased the chances of graduation by .833. These results are not necessarily surprising given previous research has found academic performance in college level math to be a significant predictor of academic achievement (Adelman, 2006; Cabrera, Burkum, & La Nasa, 2005; Herzog, 2005). Still, the results do suggest that college level math course predicts graduation after students leave the STEM fields.

The regression model examining first year retention failed to reach significance. This is somewhat surprising given previous research identifies college level mathematics as a strong predictor of retention. For example, Herzog (2005) found that failing to complete a math course was a significant predictor of attrition after the first year. One explanation the failure of the model to reach significance is that students that initially enroll in a STEM major are taking multiple STEM courses along with college level math. On the other hand, students in a non-STEM major are unlikely to take multiple STEM courses besides math. Further, college-level math may have not reached significance since the population included students who initially enrolled in a STEM major and therefore the students in the study are more likely to have taken college-level math. The differences in course enrollment between STEM and non-STEM students may explain why the model failed to reach significance.

### **Introductory Laboratory Science GPA**

Introductory laboratory science is unlikely to apply to non-STEM major requirements; however, student performance in these courses significantly predicted graduation. Introductory laboratory science GPA was significant and positively associated with graduation. Each grade point increase in introductory laboratory science GPA resulted in an .962 increase in the odds of graduation. Although research has yet to examine the influence of courses other than math and

English on graduation, the results of this study suggest for STEM leavers, performance in introductory laboratory science courses is a significant predictor of graduation.

## **STEM GPA**

Previous research and the high attrition rates in the STEM fields demonstrate that the majority of students fail to persist in STEM fields due to poor academic performance (Bettinger, 2010; Chen, 2013, 2015). STEM GPA had the largest effect in the regression model for the outcome variable of graduation. Each grade point increase in STEM GPA increased the odds of graduation by a factor of 2.003. Similarly, STEM GPA was significant and positively associated with time to degree and cumulative GPA. Even though the participants in this study all left the STEM fields, the results for research question number four demonstrate the importance of STEM course performance on academic achievement after leaving STEM. Students that fail to achieve in STEM courses are unlikely to see high levels of academic achievement after leaving STEM fields.

## **Gender**

Although the main focus of this study was to examine the relationship between STEM course enrollment and performance and academic performance, the findings related to gender are noteworthy. Specifically, in all the regression models examining time to degree, gender was the strongest predictor of graduation in 48 months or less. Females were more likely to graduate in 48 months or less compared to males. Also, three out of four of the regression models found being female to be positively associated with cumulative GPA.

Previous research on females in the STEM fields provides context to the findings of this study. Females are more likely to leave the STEM fields due to non-academic reasons (Seymour and Hewitt, 2007). Further, females have higher levels of academic achievement compared to

males (Ewert, 2012; Goldrick-Rab, 2006). Therefore, one explanation for the positive association between time to degree and cumulative GPA and being female is that females leave the STEM fields with strong academic profiles, which allows for a smooth transition from the STEM to non-STEM fields.

### **Recommendations for Policy, Practice and Future Research**

Based on this study's findings and review of the literature, the following recommendations are offered:

#### **Policy and Practice**

**Recommendation 1.** Institutions and faculty should consider reforming the STEM curriculum to provide students with the opportunity to gain exposure to courses from different disciplines, especially during the first year of enrollment.

The decision to pursue a STEM major upon initial enrollment is often does not give consideration to interests and/or academic strengths (Cueso, 2005). Compared to students who declare a non-STEM major or are undeclared upon initial enrollment, students who initially enroll in a STEM major have less freedom to enroll in courses from different disciplines. Allowing students to ease into the STEM curriculum will provide the opportunity to confirm their interests and strengths. The negative relationship between STEM credits attempted and first year retention found in this study demonstrates that many students are not prepared for the enrollment in STEM coursework and would benefit from taking courses in other disciplines. Although delaying enrollment in required STEM courses could increase time to degree for students that end up persisting in STEM, delaying STEM coursework in the would increase the

retention rates for the institution. Further, students could use summer school to prevent an increase in time to degree.

**Recommendation 2.** Academic advisors and faculty should target students who did not perform well in STEM fields and provide intervention that either provides additional resources to aid STEM course performance or steer students to non-STEM fields before poor academic performance causes students to drop out of college. For example, students that fail at least one STEM course should be required to meet with an advisor to discuss their academic program and also academic advisors could provide students with resources to explore options outside the STEM fields. This study confirmed the importance of academic performance in college level math, introductory level lab science and all STEM courses on academic achievement after leaving the STEM fields and intervention from academic advising may be able to prevent poor academic performance through intervention.

**Recommendation 3.** Institutions should offer remedial courses and extra academic support for introductory laboratory level science courses. One of the most interesting findings of this study was that introductory laboratory science was a significant predictor of graduation. Many institutions have targeted college level math as a course that is a strong predictor of graduation and, as a result, institutions offer remedial courses and provide extra academic support for math courses. The results of this study and previous research indicate institutions should provide remediation and extra support for first year STEM courses. For example, Hessler and Gregory (2016) studied the impact of instructional support sessions on academic performance in college level chemistry for underprepared students. The study found that after

receiving additional instruction, underprepared students achieved at the same level as college ready students.

**Recommendation 4.** Institutions should require students meet certain academic benchmarks early in their academic career before fully declaring a STEM major. As shown by the results in this study, academic performance in STEM courses is the key to successfully navigating the STEM to non-STEM major change. Although students may want to pursue a STEM major, their grades often indicate whether their choice is major in a STEM field is appropriate. By making students meet academic benchmarks prior to fully declaring a STEM major, students who do not meet the benchmarks would be forced to change their major, which could prevent poor performance from compounding. Pre-major requirements are becoming more common in the STEM fields; however, pre-major requirements still tend to be more prevalent in the engineering fields. Creating additional academic benchmarks and requirements for STEM students early in their academic careers could result in more students leaving the institution due to failing to these benchmarks. However, providing additional advisement to the students who fail to meet STEM benchmarks could prevent students from leaving higher education. While there could be some negative consequences of this recommendation, based on the results of this study, I recommend pre-major requirements should be applied to all STEM majors.

### **Recommendations for Future Research**

**Recommendation 1.** Control for specific first year STEM courses in order to identify which first year STEM courses are most strongly associated with academic achievement for STEM leavers. This study attempted to identify the relationship between certain STEM course types (college level math and introductory laboratory science) on academic achievement for

STEM leavers. By classifying STEM courses more specifically, future research can identify how specific college level math and introductory level lab science courses relate to academic achievement in non-STEM fields. For example, examining enrollment and academic performance in calculus, biology and chemistry will provide a deeper analysis into how the STEM curriculum relates to academic achievement for STEM leavers.

**Recommendation 2.** Qualitative analysis should be conducted to better understand the challenges students face when switching out of the STEM fields. Qualitative analysis on the STEM to non-STEM major challenge will provide the student, faculty and staff perspective on the challenges associated with leaving the STEM fields. The study of course enrollment and academic performance does not tell the entire story of why or why not a student is able to achieve academically after leaving the STEM fields. One potential explanation that qualitative analysis could explore is how students perceive the value of a non-STEM degree and whether these notions related to the decision to pursue a degree after leaving the STEM fields.

**Recommendation 3.** Replicate this study, but change the sample to students who change from a non-STEM to a different non-STEM major. This study focused on the STEM to non-STEM major change due to the uniqueness of the STEM curriculum, which can present challenges for students who leave the STEM fields. Studying the non-STEM to non-STEM major change and how course enrollment and performance in students' first course of study relates to overall academic achievement will provide context to the findings of this study and help determine if the STEM to non-STEM major change is in fact more challenging to navigate than a non-STEM to non-STEM major change.

## Summary

The need for a skilled STEM workforce in the United States and the struggle of colleges and universities to produce enough STEM graduates has led to a substantial body of empirical research examining why students leave STEM. This body of research has identified poor academic performance as the most common reason students fail to persist in STEM fields (Bettinger, 2010; Chen, 2013, 2015). Combined with poor academic performance, STEM leavers also face the challenge of failing behind due to the restrictive nature of the STEM curriculum, which limits students' ability to take courses from other disciplines (Bettinger, 2010).

Despite the findings of previous research, few studies exist that examine how the STEM to non-STEM major change relates to academic achievement after leaving the STEM fields. This study aimed to determine how the STEM to non-STEM major change relates to academic achievement by examining the relationship between STEM course enrollment and academic performance on academic achievement (first year retention, graduation, time to degree and cumulative GPA) for STEM leavers. The results of this study suggest academic performance in STEM courses and STEM course enrollment are significant predictors of academic achievement for STEM leavers. The results should be utilized by academic advisors and faculty to help students successfully navigate the STEM to non-STEM major change. Further, the results warrant further research on the STEM curriculum to determine if the traditional STEM curriculum should be revised.

In conclusion, this study provides an insight into an at-risk population that has been widely ignored by educational researchers. It is my hope that this study will lead to more



research on STEM leaver population and policies and practices that foster the academic achievement of STEM leavers.

## REFERENCES

- Adelman, C. (1999). Answers in the Tool Box. Academic Intensity, Attendance Patterns, and Bachelor's Degree Attainment.
- Adelman, C. (2006). The Toolbox Revisited: Paths to Degree Completion From High School Through College. *US Department of Education*.
- Adelman, C., Daniel, B., & Berkovits, I. (2003). Postsecondary Attainment, Attendance, Curriculum, and Performance: Selected Results from the NELS: 88/2000 Postsecondary Education Transcript Study (PETS), 2000. ED Tabs.
- Alexander, K. L., & Pallas, A. M. (1984). Curriculum reform and school performance: An evaluation of the "new basics". *American Journal of Education*, 391-420
- Aljohani, O. (2016). A comprehensive review of the major studies and theoretical models of student retention in higher education. *Higher Education Studies*, 6(2), 1.
- Altonji, J. G., & Dunn, T. A. (1996). Using siblings to estimate the effect of school quality on wages. *The Review of Economics and Statistics*, 665-671.
- Allen, D. (1999). Desire to finish college: An empirical link between motivation and persistence. *Research in higher education*, 40(4), 461-485.
- Allen, W. R., Bonous-Hammarth, M., and Suh, S. A. "Who goes to college? High school context, academic preparation, the college choice process, and college attendance." In E. P. St. John (ed.), *Readings on Equal Education*. Vol. 20: Improving Access and College Success for Diverse Students: Studies of the Gates Millennium Scholars Program. New York: AMS Press, 2004.
- Allen, J., Robbins, S. B., Casillas, A., & Oh, I. S. (2008). Third-year college retention and

- transfer: Effects of academic performance, motivation, and social connectedness. *Research in Higher Education*, 49(7), 647-664.
- Alon, S., & Tienda, M. (2005). Assessing the “mismatch” hypothesis: Differences in college graduation rates by institutional selectivity. *Sociology of Education*, 78(4), 294-315.
- Anaya, G., & Cole, D. G. (2001). Latina/o student achievement: Exploring the influence of student-faculty interactions on college grades. *Journal of college student development*, 42(1), 3-14.
- Anderson, D. M., Broton, K. M., Goldrick-Rab, S., & Kelchen, R. (2018). Experimental evidence on the impacts of need-based financial aid: Longitudinal assessment of the wisconsin scholars grant.
- Anderson, E. L., & Kim, D. (2006). *Increasing the success of minority students in science and technology* (No. 4). American Council on Education.
- Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics*, 121(1), 343-375.
- Arizona State University Freshman STEM Committee (2007). ASU freshman STEM improvement committee report.
- Attewell, P., Heil, S., & Reisel, L. (2011). Competing explanations of undergraduate noncompletion. *American Educational Research Journal*, 48(3), 536-559.
- Attewell, P., Heil, S., & Reisel, L. (2012). What is academic momentum? And does it matter?. *Educational Evaluation and Policy Analysis*, 34(1), 27-44.
- Alting, A., & Walser, A. (2007, June). Retention and persistence of undergraduate engineering students: What happens after the first year?. In *Proceedings of the American Society for Engineering Education Annual Conference and Exposition*.

- Astin, A. W. (1984). Student involvement: A developmental theory for higher education. *Journal of college student personnel*, 25(4), 297-308.
- Astin, A. W., & Oseguera, L. (2005). *Degree attainment rates at American colleges and universities*. Higher Education Research Institute.
- Astin, A. W., & Sax, L. J. (1998). How undergraduates are affected by service participation. *Service Participation*, 39(3), 251.
- Aud, S., Hussar, W., Planty, M., Snyder, T., Bianco, K., Fox, M. A., ... & Drake, L. (2010). The condition of education 2010. NCES 2010-028. *National Center for Education Statistics*.
- Bahr, P. R. (2008). Does mathematics remediation work?: A comparative analysis of academic attainment among community college students. *Research in Higher Education*, 49(5), 420-450.
- Barr, D. A., Matsui, J., Wanat, S. F., & Gonzalez, M. E. (2010). Chemistry courses as the turning point for premedical students. *Advances in health sciences education*, 15(1), 45-54.
- Barrow, L., & Rouse, C. E. (2006). The economic value of education by race and ethnicity. *Economic Perspectives*, Second Quarter.
- Barth, P., & Haycock, K. (2004). A core curriculum for all students. *Harvard Education Letter*, 20(3), 8.
- Baum, Sandy, Jennifer Ma, Matea Pender, and CJ Libassi (2018), Trends in Student Aid 2018, New York: The College Board.
- Bean, J. P. (1980). Dropouts and turnover: The synthesis and test of a causal model of student attrition. *Research in higher education*, 12(2), 155-187.
- Bean, J. P. (1982). Student attrition, intentions, and confidence: Interaction effects in a path model. *Research in higher education*, 17(4), 291-320.

- Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, 55(4), 485-540.
- Beecher, M., & Fischer, L. (1999). High school courses and scores as predictors of college success. *Journal of College Admission*, 163, 4-9.
- Berger, J. B., Milem, J. F., & Paulsen, M. B. (1998). The exploration of “habitus” as a multi dimensional construct. In *annual meeting of the Association for the Study of Higher Education, Miami, FL*.
- Bettinger, E. (2004). How financial aid affects persistence. In *College choices: The economics of where to go, when to go, and how to pay for it* (pp. 207-238). University of Chicago Press.
- Bettinger, E. (2010). To be or not to be: Major choices in budding scientists. In *American universities in a global market* (pp. 69-98). University of Chicago Press.
- Bonous-Hammarth, M. (2000). Pathways to success: Affirming opportunities for science, mathematics, and engineering majors. *Journal of Negro Education*, 92-111.
- Bozick, R., & DeLuca, S. (2005). Better late than never? Delayed enrollment in the high school to college transition. *Social Forces*, 84(1), 531-554.
- Bozick, R., & Ingels, S. J. (2008). Mathematics coursetaking and achievement at the end of high school: Evidence from the education longitudinal study of 2002 (ELS: 2002). Statistical Analysis Report. NCES 2008-319. *National Center for Education Statistics*.
- Budny, D., LeBold, W., & Bjedov, G. (1998). Assessment of the impact of the freshman engineering courses. *Journal of Engineering Education*, 87(4), 405-411.
- Burkam, D. T., & Lee, V. E. (2003). Mathematics, foreign language, and science coursetaking

- and the NELS: 88 transcript data. Working Paper No. 2003-01. *National Center for Education Statistics*.
- Cabrera, A. F., Nora, A., & Castaneda, M. B. (1992). The role of finances in the persistence process: A structural model. *Research in higher education, 33*(5), 571-593.
- Cabrera, A. F., Burkum, K. R., & La Nasa, S. M. (2005). Pathways to a four-year degree. *College student retention: Formula for student success*, 155-214.
- Callahan, J., & Belcheir, M. (2017). Testing our assumptions: The role of first course grade and course level in mathematics and english. *Journal of College Student Retention: Research, Theory & Practice, 19*(2), 161-175.
- Carter, D. F. (2006). Key issues in the persistence of underrepresented minority students. *New directions for institutional research, 130*, 33.
- Castleman, B. L., Long, B. T., & Mabel, Z. (2018). Can financial aid help to address the growing need for STEM Education? The effects of need-based grants on the completion of science, technology, engineering, and math courses and degrees. *Journal of Policy Analysis and Management, 37*(1), 136-166.
- Ceci, S. J., Williams, W. M., & Barnett, S. M. (2009). Women's underrepresentation in science: Sociocultural and biological considerations. *Psychological bulletin, 135*(2), 218.
- Center for Institutional Data Exchange and Analysis. (2000). 1999-2000 SMET retention report. Norman, OK: University of Oklahoma.
- Chang, M. J., Cerna, O., Han, J., & Saenz, V. (2008). The contradictory roles of institutional status in retaining underrepresented minorities in biomedical and behavioral science majors. *The Review of Higher Education, 31*(4), 433-464.
- Chen, X., & Carroll, C. D. (2005). First-generation students in postsecondary education: A

- look at their college transcripts. Postsecondary Education Descriptive Analysis Report. NCES 2005-171. *National Center for Education Statistics*.
- Chen, J., & Hossler, D. (2017). The effects of financial aid on college success of two-year beginning nontraditional students. *Research in Higher Education*, 58(1), 40-76.
- 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*.
- Chen, X. (2009). Students who study science, technology, engineering, and mathematics (STEM) in postsecondary education. Stats in Brief. NCES 2009-161. *National Center for Education Statistics*.
- Chen, X. (2015). STEM attrition among high-performing college students in the United States: scope and potential causes. *Journal of Technology and Science Education*, 5(1).
- Cho, D. (2007). The role of high school performance in explaining women's rising college enrollment. *Economics of Education Review*, 26(4), 450-462.
- Conger, D., & Long, M. C. (2010). Why are men falling behind? Explanations for the gender gap in college outcomes. *Annals of the American Academy of Political and Social Science*, 627(1), 184-214.
- Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal*, 46(4), 924-942.
- Cruce, T. M., Kuh, G. D., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The journal of higher education*, 79(5), 540-563.

- Cullinane, J., & Lincove, J. A. (2014). The effects of institutional inputs on time to degree for traditional and nontraditional college students. In *annual Association of Education Finance and Policy conference, San Antonio, TX*.
- Cuseo, J. (2005). Decided, undecided, and in transition: Implications for academic advisement, career counseling, and student retention. *Improving the first year of college: Research and practice*, 27-48.
- Dancy, M., & Henderson, C. (2008). Barriers and promises in STEM reform. In *National Academies of Science Promising Practices Workshop*.
- Davies, S., & Guppy, N. (1997). Fields of study, college selectivity, and student inequalities in higher education. *Social forces*, 75(4), 1417-1438.
- DeAngelo, L., Franke, R., Hurtado, S., Pryor, J. H., & Tran, S. (2011). Completing college: Assessing graduation rates at four-year institutions. *Los Angeles: Higher Education Research Institute, UCLA*.
- DeBerard, M. S., Spielmans, G. I., & Julka, D. L. (2004). Predictors of academic achievement and retention among college freshmen: A longitudinal study. *College Student Journal*, 38(1), 66-80.
- Demetriou, C., & Schmitz-Sciborski, A. (2011). Integration, motivation, strengths and optimism: Retention theories past, present and future. In *Proceedings of the 7th National Symposium on student retention* (pp. 300-312).
- DesJardins, S. L., Ahlburg, D. A., & McCall, B. P. (2002). A temporal investigation of factors related to timely degree completion. *Journal of Higher Education*, 555-581.
- Dienstag, J. L. (2008). Relevance and rigor in premedical education. *New England Journal of Medicine*, 359(3), 221-224.



- DiPrete, T. A., & Buchmann, C. (2006). Gender-specific trends in the value of education and the emerging gender gap in college completion. *Demography*, 43(1), 1-24.
- Durkheim, E. (1897). *Le suicide: étude de sociologie*. F. Alcan.
- Eagan, M. K., Garcia, G. A., Hurtado, S., & Gasiewski, J. A. (2012). Passing through the gates: Identifying and developing talent in introductory STEM courses. *Manuscript in preparation*.
- Eagan, K., Stolzenberg, E. B., Ramirez, J. J., Aragon, M. C., Suchard, M. R., & Hurtado, S. (2014). The American freshman: National norms fall 2014. *Los Angeles: Higher Education Research Institute, UCLA*.
- Elliott, R., Strenta, A. C., Adair, R., Matier, M., & Scott, J. (1996). The role of ethnicity in choosing and leaving science in highly selective institutions. *Research in Higher Education*, 37(6), 681-709.
- Ewert, S. (2012). Fewer diplomas for men: The influence of college experiences on the gender gap in college graduation. *The Journal of Higher Education*, 83(6), 824-850.
- Feagin, J. R., Vera, H., & Imani, N. (1996). *The agony of education: Black students at White colleges and universities*. Psychology Press.
- Ferrare, J. J., & Lee, Y. G. (2014). Should we still be talking about leaving? A comparative examination of social inequality in undergraduate patterns of switching majors. WCER Working Paper No. 2014-5. *Wisconsin Center for Education Research*.
- Field, A. (2009). *Discovering statistics using SPSS*. Sage publications.
- Flynn, D. (2014). Baccalaureate attainment of college students at 4-year institutions as a function of student engagement behaviors: Social and academic student engagement behaviors matter. *Research in Higher Education*, 55(5), 467-493.

- 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.
- Franke, R. (2014). Revisiting college degree completion: New evidence on the effects of financial aid, college experience, and institutional climate. Scholars' Press.
- French, B. F., & Oakes, W. (2004). Reliability and validity evidence for the institutional integration scale. *Educational and Psychological Measurement*, *64*(1), 88–98.
- Fries-Britt, S. L., Younger, T. K., & Hall, W. D. (2010). Lessons from high-achieving students of color in physics. *New Directions for Institutional Research*, *2010*(148), 75-83
- Fryer, R. G., & Levitt, S. D. (2010). An empirical analysis of the gender gap in mathematics. *American Economic Journal: Applied Economics*, *2*(2), 210-240.
- Gainen, J. (1995). Barriers to success in quantitative gatekeeper courses. *New directions for teaching and learning*, *1995*(61), 5-14.
- Gainen, J., & Willemsen, E. W. (1995). *Fostering student success in quantitative gateway courses* (No. 61). Jossey-Bass.
- Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in higher education*, *53*(2), 229-261.
- Ganem, N. M., & Manasse, M. (2011). The relationship between scholarships and student success: An art and design case study. *Education Research International*, *2011*.
- Gay, L. R., Mills, G. E., & Airasian, P. W. (2009). *Educational research: Competencies for*

*analysis and applications*. Merrill/Pearson.

Gayles, J. G., & Ampaw, F. (2014). The impact of college experiences on degree completion in STEM fields at four-year institutions: Does gender matter?. *The Journal of Higher Education, 85*(4), 439-468.

Geiser, S., & Santelices, V. (2004). The role of advanced placement and honors courses in college admissions. *Expanding opportunity in higher education: Leveraging promise*, 75-113.

Geiser, S., & Santelices, M. V. (2007). Validity of high-school grades in predicting student success beyond the freshman year: High-school record vs. standardized tests as indicators of four-year college outcomes (CSHE.6.07). Berkeley, CA: Center for Studies in Higher Education.

Gilmer, T. C. (2007). An understanding of the improved grades, retention and graduation rates of STEM majors at the Academic Investment in Math and Science (AIMS) Program of Bowling Green State University (BGSU). *Journal of STEM Education: Innovations and Research, 8*(1/2), 11.

Goldrick-Rab, S. (2006). Following their every move: An investigation of social-class differences in college pathways. *Sociology of Education, 79*(1), 67-79.

Gonzalez, H. B., & Kuenzi, J. J. (2012). Science, technology, engineering, and mathematics (STEM) education: A primer. Congressional Research Service, Library of Congress.

Gray, M., & Bristow, D. (2014, July 10). Wellcome Trust Centre for Neuroimaging. Retrieved from <http://www.fil.ion.ucl.ac.uk/~mgray/>

Greene, J. P., & Forster, G. (2003). Public high school graduation and college readiness rates in the United States. Education Working Paper No. 3. *Center for Civic Innovation*.

- Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters?. *Economics of Education Review*, 29(6), 911-922.
- Hartman, H., & Hartman, M. (2006). Leaving engineering: Lessons from Rowan University's college of engineering. *Journal of Engineering Education*, 95(1), 49.
- Heidel, J., Ali, H., Corbett, B., Liu, J., Morrison, B., O'Connor, M., & ... Ryan, C. (2011). Increasing the number of homegrown STEM majors: What works and what doesn't. *Science Educator*, 20(1), 49-54.
- Herzog, S. (2005). Measuring determinants of student return vs. dropout/stopout vs. transfer: A first-to-second year analysis of new freshmen. *Research in Higher Education*, 46(8), 883-928.
- Hoffman, K., Llagas, C., & Snyder, T. D. (2003). Status and Trends in the Education of Blacks.
- Hoover, N. (2007). Cultural disparities of SAT scores and the influence on higher education opportunities for African American and Latino students.
- Higher Education Research Institute at UCLA (2010). Degrees of success: Degree completion rates among initial STEM major.
- Himelhoch, C. R., Nichols, A., Ball, S. R., & Black, L. C. (1997). A comparative study of the factors which predict persistence for african american students at historically black institutions and predominantly white institutions. ASHE Annual Meeting Paper.
- Huang, G., Taddese, N., & Walter, E. (2000). Entry and persistence of women and minorities in college science and engineering education. *Education Statistics Quarterly*, 2(3), 59-60.
- Hunter, M. S. (2006). Fostering student learning and success through first-year programs. *Peer Review*, 8(3), 4.
- Hunter, M. S., & Linder, C. W. (2005). First-year seminars. *Challenging and supporting the*

- first-year student: A handbook for improving the first year of college*, 275-291.
- Hurtado, S., Carter, D. F., & Spuler, A. (1996). Latino student transition to college: Assessing difficulties and factors in successful college adjustment. *Research in higher education*, 37(2), 135-157.
- Hurtado, S., & Kamimura, M. (2003). Latina/o retention in four-year institutions. *The majority in the minority: Expanding the representation of Latina/o faculty, administrators, and students in higher education*, 139-150.
- Hurtado, S., Cabrera, N. L., Lin, M. H., Arellano, L., & Espinosa, L. L. (2009). Diversifying science: Underrepresented student experiences in structured research programs. *Research in Higher Education*, 50(2), 189-214.
- Hurtado, S., Newman, C. B., Tran, M. C., & Chang, M. J. (2010). Improving the rate of success for underrepresented racial minorities in STEM fields: Insights from a national project. *New Directions for Institutional Research*, 2010(148), 5-15.
- Ishiyama, J. (2002). Does early participation in undergraduate research benefit social science and humanities students?. *College Student Journal*, 36(3), 380.
- Jackson, M., Luijckx, R., Pollak, R., Vallet, L. A., & van de Werfhorst, H. G. (2008). Educational fields of study and the intergenerational mobility process in comparative perspective. *International Journal of Comparative Sociology*, 49(4-5), 369-388.
- Johnson, B., & Christensen, L. (2008). *Educational research: Quantitative, qualitative, and mixed approaches*. Sage.
- Karimi, A., Manteufel, R., & Peterson, L. (2015). Reasons for Taking Students Too Long to Complete Engineering Degrees.
- Kewal-Ramani, A., Laird, J., Ifill, N., & Chapman, C. (2010). Trends in high school dropout and

- completion rates in the United States: 1972–2009.
- Kirby, D., & Sharpe, D. (2001). Student attrition from Newfoundland and Labrador's public college. *Alberta Journal of Educational Research*, 47(4), 353.
- Klepfer, K., & Hull, J. (2012). High school rigor and good advice: Setting up students to succeed. *Center for Public Education for the National School Boards Association*.
- Klopfenstein, K., & Thomas, M. K. (2005). The advanced placement performance advantage: Fact or fiction. *Texas Christian University and Mississippi State University*.
- Kuenzi, J. J. (2008). Science, technology, engineering, and mathematics (STEM) education: Background, federal policy, and legislative action.
- Kulturel-Konak, S., D'Allegro, M. L., & Dickinson, S. (2011). Review of gender differences in learning styles: Suggestions for STEM education. *Contemporary Issues in Education Research*, 4(3), 9.
- Kuh, G. D., & Hu, S. (2001). The effects of student-faculty interaction in the 1990s. *The Review of Higher Education*, 24(3), 309-332.
- Kuh, G. D., Kinzie, J., Buckley, J. A., Bridges, B. K., & Hayek, J. C. (2006). What matters to student success: A review of the literature. In *Commissioned report for the national symposium on postsecondary student success: Spearheading a dialog on student success*.
- Lacey, T. A., & Wright, B. (2009). Employment outlook: 2008-18-occupational employment projections to 2018. *Monthly Lab. Rev.*, 132, 82.
- Larson, L. M., Pesch, K. M., Surapaneni, S., Bonitz, V. S., Wu, T. -S., & Werbel, J. D. (2014). Predicting graduation: The role of mathematics/science self-efficacy. *Journal of Career Assessment*, 1–11.
- Lau, L. K. (2003). Institutional factors affecting student retention. *Education*, 124(1), 126.

- Lauff, E., & Ingels, S. J. (2015). Education Longitudinal Study of 2002 (ELS: 2002): a first look at the postsecondary transcripts of 2002 high school sophomores (NCES 2015-034). *US Department of Education. Washington, DC: National Center for Education Statistics.*
- Le, H., Robbins, S. B., & Westrick, P. (2014). Predicting student enrollment and persistence in college STEM fields using an expanded PE fit framework: A large-scale multilevel study. *Journal of Applied Psychology, 99*(5), 915.
- Leech, N. L., Barrett, K. C., & Morgan, G. A. (2011). *IBM SPSS for Intermediate Statistics: Use and Interpretation.* New York, NY: Taylor and Francis.
- Liu, R., & Liu, E. (2000). Institutional Integration: An Analysis of Tinto's Theory.
- Longwell-Grice, R., & Longwell-Grice, H. (2008). Testing Tinto: how do retention theories work for first-generation, working-class students?. *Journal of College Student Retention: Research, Theory & Practice, 9*(4), 407-420.
- Lotkowski, V. A., Robbins, S. B., & Noeth, R. J. (2004). The role of academic and non academic factors in improving college retention. ACT Policy Report. *American College Testing ACT Inc.*
- Lubinski, D., & Benbow, C. P. (1992). Gender differences in abilities and preferences among the gifted: Implications for the math-science pipeline. *Current Directions in Psychological Science, 1*(2), 61-66.
- Main, J. B., Mumford, K. J., & Ohland, M. W. (2015). Examining the influence of engineering students' course grades on major choice and major switching behavior. *International Journal of Engineering Education, 31*(6), 1468-1475.
- 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.

- Marra, R. M., Rodgers, K. A., Shen, D., & Bogue, B. (2012). Leaving engineering: A multi-year single institution study. *Journal of Engineering Education*, 101(1), 6.
- Marx, B. M., & Turner, L. J. (2019). Student loan nudges: Experimental evidence on borrowing and educational attainment. *American Economic Journal: Economic Policy*, 11(2), 108-41.
- McCubbin, I. (2003). An examination of criticisms made of Tinto's 1975 student integration model of attrition. Retrieved July, 2, 2008.
- Mertler, C. A., & Rachel, A. Vannatta. 2001. Advanced and multivariate statistical methods.
- Mervis, J. (2010). Better intro courses seen as key to reducing attrition of STEM majors. *Science*, 330(6002), 306-306.
- Metz, G. W. (2002). Challenges and Changes to Tinto's Persistence Theory.
- Mitchell, D., Goldman, B., & Smith, M. (1999). Change factors affecting college matriculation: A re-analysis. *Journal of The First-Year Experience & Students in Transition*, 11(2), 75-91.
- Moore, C. D. (2014). *Socioeconomic stratification in the STEM pathway from college to the labor market* (Doctoral dissertation).
- Moreno, S. E., & Muller, C. (1999). Success and diversity: The transition through first-year calculus in the university. *American Journal of Education*, 108(1), 30-57.
- Morgan, G. A., Leech, N. L., Gloeckner, G. W., & Barrett, K. C. (2011). IBM SPSS for.
- Murtaugh, P. A., Burns, L. D., & Schuster, J. (1999). Predicting the retention of university students. *Research in higher education*, 40(3), 355-371.
- Musu-Gillette, L., de Brey, C., McFarland, J., Hussar, W., Sonnenberg, W., & Wilkinson



- Flicker, S. (2017). Status and trends in the education of racial and ethnic groups 2017. NCES 2017-051. *National Center for Education Statistics*.
- Myers, R. D. (2003). College success programs. *Washington, DC: Pathways to College Network Clearinghouse*.
- National Science Board (2014). Science and engineering indicators 2014. Arlington VA: National Science Foundation.
- Nguyen, T., Kramer, J., & Evans, B. (2018). The effects of grant aid on student persistence and degree attainment: a systematic review and meta-analysis of the causal evidence. *Work. Pap*, 18-04
- Noel-Levitz, Inc. (2006). Student success in developmental math: Strategies to overcome barriers to retention. Iowa City, Iowa: Author.
- Nora, A., Cabrera, A., Hagedorn, L. S., & Pascarella, E. (1996). Differential impacts of academic and social experiences on college-related behavioral outcomes across different ethnic and gender groups at four-year institutions. *Research in higher education*, 37(4), 427-451.
- Nora, A., & Cabrera, A. F. (1996). The role of perceptions of prejudice and discrimination on the adjustment of minority students to college. *The Journal of Higher Education*, 119-148.
- Ohland, M. W., Zhang, G., Thorndyke, B., & Anderson, T. J. (2004, October). Grade-point average, changes of major, and majors selected by students leaving engineering. In *Frontiers in Education, 2004. FIE 2004. 34th Annual*(pp. T1G-12). IEEE.
- Orr, M. K., Ramirez, N. M., & Ohland, M. W. (2011, June). Socioeconomic trends in engineering: Enrollment, persistence, and academic achievement. In *Proc. American Society for Engineering Education Annual Conference*.
- Ost, B. (2010). The role of peers and grades in determining major persistence in the

- sciences. *Economics of Education Review*, 29(6), 923-934.
- Pallas, A. M., & Alexander, K. L. (1983). Sex differences in quantitative SAT performance: New evidence on the differential coursework hypothesis. *American Educational Research Journal*, 20(2), 165-182.
- Palmer, R. T., Maramba, D. C., & Dancy, T. E. (2011). A qualitative investigation of factors promoting the retention and persistence of students of color in STEM. *The Journal of Negro Education*, 491-504.
- Panos, R. J., & Astin, A. W. (1968). Attrition among college students. *American Educational Research Journal*, 5(1), 57-72
- Pascarella, E. T., Duby, P. B., Miller, V. A., & Rasher, S. P. (1981). Preenrollment variables and academic performance as predictors of freshman year persistence, early withdrawal, and stopout behavior in an urban, nonresidential university. *Research in Higher Education*, 15(4), 329-349.
- Pascarella, E. T., Duby, P. B., & Iverson, B. K. (1983). A text and reconceptualization of a theoretical model of college withdrawal in a commuter institution setting. *Sociology of Education*, 88-100.
- Pascarella, E. T., & Terenzini, P. T. (2005). *How College Affects Students: A Third Decade of Research. Volume 2*. Jossey-Bass, An Imprint of Wiley. 10475 Crosspoint Blvd, Indianapolis, IN 46256.
- Pedhazur, E. J. (8). Schmelkin, LP (1991). Measurement, design, and analysis: An integrated approach. *Hillsdale, NJ: Erlbaum*.
- Pike, G. R., Kuh, G. D., & Massa-McKinley, R. C. (2008). First-year students' employment,

- engagement, and academic achievement: Untangling the relationship between work and grades. *Naspa Journal*, 45(4), 560-582.
- Pope, L. (1990). The true aims of education. *The College Board Review*, 157, 27-28.
- “President Trump Signs Memorandum for STEM Education Funding.” *The White House*, The United States Government, 13 Nov. 2017, [www.whitehouse.gov/articles/president-trump-signs-memorandum-stem-education-funding/](http://www.whitehouse.gov/articles/president-trump-signs-memorandum-stem-education-funding/).
- Price, J. (2010). The effect of instructor race and gender on student persistence in STEM fields. *Economics of Education Review*, 29(6), 901-910.
- Radford, A. W., Pearson, J., Ho, P., Chambers, E., & Ferlazzo, D. (2012). Remedial coursework in postsecondary education: The students, their outcomes, and strategies for improvement. *MPR Associates, Inc.*
- 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.
- Reason, R. D. (2009). Student variables that predict retention: Recent research and new developments. *NASPA journal*, 46(3), 482-501.
- Reeve, E. M. (2015). STEM thinking!. *Technology and Engineering Teacher*, 75(4), 8-16.
- Riegle-Crumb, C., King, B., Grodsky, E., & Muller, C. (2012). The more things change, the more they stay the same? Examining gender equality in prior achievement and entry into STEM college majors over time. *American educational research journal*, 49(6).
- Rockwell, C. (2011). “Factors Affecting parental involvement with children’s education: A qualitative study of parent’s socioeconomic status, level of education, and parent school relationship.” *Perspectives (University of New Hampshire)* 94-98.
- Roderick, M. (1995). Grade retention and school dropout: Policy debate and research questions.

- The Research Bulletin*, 15, 88-92.
- Rose, H., & Betts, J. R. (2001). *Math matters: The links between high school curriculum, college graduation, and earnings*. *Public Policy Instit. of CA*
- Ross, T., Kena, G., Rathbun, A., KewalRamani, A., Zhang, J., Kristapovich, P., & Manning, E. (2012). Higher education: Gaps in access and persistence study. Statistical Analysis Report. NCES 2012-046. *National Center for Education Statistics*.
- Russell, M. L., & Atwater, M. M. (2005). Traveling the road to success: A discourse on persistence throughout the science pipeline with African American students at a predominantly white institution. *Journal of Research in Science Teaching*, 42(6), 691-715.
- Sackett, P. R., Kuncel, N. R., Beatty, A. S., Rigdon, J. L., Shen, W., & Kiger, T. B. (2012). The role of socioeconomic status in SAT-grade relationships and in college admissions decisions. *Psychological science*, 0956797612438732.
- Sandiford, J. R., & Jackson, D. K. (2003). Predictors of first semester attrition and their relation to retention of generic associate degree nursing students.
- Scogin, J. M. (2007). *Predicting first year academic success of the student-athlete population at the University of Missouri* (Doctoral dissertation, University of Missouri--Columbia).
- Scott, T. P., Tolson, H., & Huang, T. Y. (2009). Predicting retention of mathematics and science majors at a research one institution and suggested advising tools. *Journal of College Admission*, 204, 20-24.
- Seymour, E. (1999). The role of socialization in shaping the career-related choices of undergraduate women in science, mathematics, and engineering majors. *Annals of the New York Academy of Sciences*, 869(1), 118-126.

- Seymour, E. (2000). *Talking about leaving: Why undergraduates leave the sciences*. Westview Press.
- Seymour, E. (2002). Tracking the processes of change in US undergraduate education in science, mathematics, engineering, and technology. *Science Education*, 86(1), 79-105.
- Seymour, E. H., & Hewett, N. M. N.(1997). *Talking about leaving: Why undergraduates leave the sciences*.
- Shapiro, D., Dundar, A., Wakhungu, P.K., Yuan, X., Nathan, A. & Hwang, Y. (2016). Completing college: A national view of student attainment rates – Fall 2010 cohort (Signature Report No. 12).
- 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.
- Shettle, C., Roey, S., Mordica, J., Perkins, R., Nord, C., Teodorovic, J., ... & Brown, J. (2007). The Nation's Report Card [TM]: America's High School Graduates. NCES 2007-467. *National Center for Education Statistics*.
- Sklar, J. (2015). The impact of change of major on time to Bachelor's degree completion with special emphasis on STEM disciplines: A multilevel discrete-time hazard modeling Xapproach final report.
- Smedley, B. D., Myers, H. F., & Harrell, S. P. (1993). Minority-status stresses and the college adjustment of ethnic minority freshmen. *Journal of Higher Education*, 434-45.
- Spady, W. G. (1970). Dropouts from higher education: An interdisciplinary review and synthesis. *Interchange*, 1(1), 64-85.
- Steele, T. (1994). Representing the people: university adult education and the origins of 'cultural studies'. *Studies in the Education of Adults*, 26(2), 180-200.
- Strauss, L. C., & Terenzini, P. T. (2007). The effects of students' in-and out-of-class experiences

- on their analytical and group skills: A study of engineering education. *Research in Higher Education*, 48(8), 967-992.
- Stinebrickner, T. R., & Stinebrickner, R. (2011). *Math or science? Using longitudinal expectations data to examine the process of choosing a college major* (No. w16869). National Bureau of Economic Research.
- Strommer, D. W. (1993). *Portals of entry: University colleges and undergraduate divisions* (No.12). National Resource Center for the Freshman Year Experience & Students in Transition.
- Tai, R. H., Sadler, P. M., & Loehr, J. F. (2005). Factors influencing success in introductory college chemistry. *Journal of Research in Science Teaching*, 42(9), 987-1012.
- Terenzini, P. T., & Pascarella, E. T. (1980). Toward the validation of Tinto's model of college student attrition: A review of recent studies. *Research in Higher Education*, 12(3), 271-282.
- Terenzini, P. T., Cabrera, A. F., & Bernal, E. M. (2001). Swimming against the tide: The poor in American higher education. Research Report No. 2001-1. *College Entrance Examination Board*.
- Thurmond, V. B., & Cregler, L. L. (1999). Why students drop out of the pipeline to health professions careers: a follow-up of gifted minority high school students. *Academic medicine*, 74(4), 448-51.
- Tienken, C. H. (2012). The influence of poverty on achievement. *Kappa Delta Pi Record*, 48(3), 105-107.
- Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of educational research*, 45(1), 89-125.

- Tinto, V. (1988). Stages of student departure: Reflections on the longitudinal character of student leaving. *The Journal of Higher Education*, 438-455.
- Tinto, V. (1993). Building community. *Liberal Education*, 79(4), 16-21.
- Tinto, V. (1997). Classrooms as communities: Exploring the educational character of student persistence. *Journal of higher education*, 599-623.
- Tinto, V. (2006). Research and practice of student retention: What next?. *Journal of College Student Retention: Research, Theory & Practice*, 8(1), 1-19.
- Tinto, V. (2007). *Taking student retention seriously*. Syracuse University.
- Titus, M. A. (2006). Understanding the influence of the financial context of institutions on student persistence at four-year colleges and universities. *The Journal of Higher Education*, 77(2), 353-375.
- Tobias, S. (1990). *They're not dumb, they're different* (Vol. 101). Tucson, AZ: Research Corporation.
- Tobias, S., & Lin, H. (1991). They're not dumb, they're different: Stalking the second tier.
- Torche, F. (2011). Is a college degree still the great equalizer? Intergenerational Mobility across levels of schooling in the United States<sup>1</sup>. *American Journal of Sociology*, 117(3), 763-807.
- Torres, J. B., & Solberg, V. S. (2001). Role of self-efficacy, stress, social integration, and family support in Latino college student persistence and health. *Journal of vocational behavior*, 59(1), 53-63.
- Tross, S. A., Harper, J. P., Osher, L. W., Kneidinger, L. M. (2000). Not just the usual cast of characteristics: Using personality to predict college performance and retention. *Journal of College Student Development*, 41, 323-334.

- Tyson, W., Lee, R., Borman, K. M., & Hanson, M. A. (2007). Science, technology, engineering, and mathematics (STEM) pathways: High school science and math coursework and postsecondary degree attainment. *Journal of Education for Students Placed at Risk, 12*(3), 243-270.
- Ulriksen, L., Madsen, L. M., & Holmegaard, H. T. (2017). The first-year experience of non traditional students in Danish science and engineering university programmes. *European Educational Research Journal, 16*(1), 45-61.
- Veenstra, C. P., Dey, E. L., & Herrin, G. D. (2009). A model for freshman engineering Retention. *Advances in Engineering Education, 1*(3), n3.
- Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The review of higher education, 27*(1), 45-73.
- Wang, X. (2013). Why students choose STEM majors motivation, high school learning, and postsecondary context of support. *American Educational Research Journal, 0002831213488622*.
- Watkins, J., & Mazur, E. (2013). Retaining students in science, technology, engineering, and mathematics (STEM) majors. *Journal of College Science Teaching, 42*(5), 36-41.
- Whalen, D. F., & Shelley II, M. C. (2010). Academic success for STEM and non-STEM majors. *Journal of STEM Education: Innovations and research, 11*(1/2), 45.
- Whittaker, J. A., & Montgomery, B. L. (2012). Cultivating diversity and competency in STEM: Challenges and remedies for removing virtual barriers to constructing diverse higher education communities of success. *Journal of Undergraduate Neuroscience Education, 11*(1), A44.
- Wilson, K. L., & Boldizar, J. P. (1990). Gender segregation in higher education: Effects of



- aspirations, mathematics achievement, and income. *Sociology of education*, 62-74.
- Wirt, J., Choy, S., Rooney, P., Provasnik, S., Sen, A., & Tobin, R. (2004). The condition of education 2004 (NCES 2004-077). Washington, DC: US Department of Education. *National Center for Education Statistics*.
- Wolfe, R. N., & Johnson, S. D. (1995). Personality as a predictor of college performance. *Educational and psychological measurement*, 55(2), 177-185.
- Xie, Y., & Achen, A. (2009). Science on the decline? Educational outcomes of three cohorts of young Americans. *Population Studies Center Research Report*, 9, 684.
- Xie, B., Franko, J., Wambach, C., Jansen, E., & Connor, J. (2005). What Advising Files Tell Us about Students Who Leave General College?.
- Xu, Y. J., & Webber, K. L. (2018). College student retention on a racially diverse campus: A theoretically guided reality check. *Journal of College Student Retention: Research, Theory & Practice*, 20(1), 2-28.
- Yoon, S. Y., Imbrie, P. K., & Reed, T. (2014). First year mathematics course credits and graduation status in engineering. In *Proceedings of the Sixth Annual First Year Engineering Experience (FYEE) Conference, College Station, TX, USA*, 5 pages.
- Zhang, G., Anderson, T. J., Ohland, M. W., & Thorndyke, B. R. (2004). Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study. *Journal of Engineering Education*, 93(4), 313-320.
- Zwick, R., & Greif Green, J. (2007). New perspectives on the correlation of SAT scores, high school grades, and socioeconomic factors. *Journal of Educational Measurement*, 44(1), 23-45.