Clarkson University

Addressing Student Success and Retention in STEM Majors Through Strategic Curriculum Pathways and Early Research Experiences

A Dissertation by

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The committee below have examined the thesis/dissertation entitled "**Addressing Student Success and Retention in STEM Majors Through Strategic Curriculum Pathways and Early Research Experiences**" presented by **Robert P. Jaspersohn**, a candidate for the degree of **Doctor of Philosophy, Physics**, and have certified that it is worthy of acceptance.

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Abstract

In this dissertation we discuss a common first-year STEM curriculum pathway for undergraduate students majoring in science, math, or engineering, and a modification to this curriculum pathway that has been implemented, based on students' needs prior to enrollment. The intent is increasing student retention and success in the university and in STEM. The effects of the modification on student success, progression, retention and persistence are assessed, specifically. Second year retention in the university for the students who went through the modification has increased by 5%. Alternate non-traditional pathways within the first year physics laboratory experience can be introduced to address student needs.

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Background

Chapter 1

Introduction

Retention of college students majoring in STEM (Science, Technology, Engineering and Mathematics) has historically been an issue of high priority for universities. Effectively implementing successful strategies to improve retention has been challenging and is further complicated with the traditionally rigorous demands of the curriculum. Students often change their major to a non-STEM major, or simply drop out of college altogether.[1] There is a call at the national level to take a serious look at current retention initiatives, as well as proposals to increase student retention in the STEM fields.[2] The President's Council of Advisors on Science and Technology (PCAST) report *Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics*[2] outlines recommendations that are aimed at transforming undergraduate education to help meet the demand for STEM retention in universities on a national level.

Based on national recommendations, and in an effort to strategically improve retention and persistence of students in STEM fields at Clarkson University, our innovations have focused on closing the "mathematical gap", diversifying pathways to enhance the completion rate of STEM degrees, and providing simulated research projects in early STEM courses. In this body of work, we outline an assessment plan to inform the implementation of these retention strategies. These initiatives include the use of predictive assessment models to strategically place first-year students into more carefully designed curriculum tracks, a diversified first-year curriculum for STEM majors, and opportunities for research within the first-year curriculum.[3–9]

To better implement retention strategies and understand the undergraduate STEM student experience, the First Year Council was created at Clarkson University. The members of the council, including deans, professors and administrators, were appointed by the provost in 2010, and tasked with exploring and implementing strategic initiatives to improve university retention and graduation rates, especially for students in STEM. Historically successful initiatives already in place were expanded upon, and were also used when crafting new strategies.[10–12] The strategic initiative that is the focus of this study is made possible because of a collaborative effort between the School of Engineering and the School of Arts and Sciences at Clarkson University.

The use of historical data as the foundation of a predictive model enables the strategic placement of students on a curriculum track that allows for a greater possible success in the critical first years in college. By using pre-college, or initial state, data, we identify the students who are most at-risk for being unsuccessful in the introductory STEM courses. Students will encounter these introductory STEM courses on different schedules based upon requirements of their chosen major, and preparedness.

The research opportunity leverages the concept of "early research" as a laboratory experience for students, and focuses on the mathematical modeling of a physical system, experimental investigation, and prediction of a future outcome. This method of instruction has been shown to increase student interest and retention in STEM courses.[3;10;11;13–15] The alternate first-year curriculum will focus on diversifying the path that students take through their first years in college.

Motivation

The proportion of STEM degrees being awarded to college graduates has been declining over the past decade.[1] If this trend should continue, the number of graduates entering the workforce in STEM fields will continue to drop. Recent studies suggest that the U.S. will need about 1 million more STEM professionals than we produce at the current rates in order to remain competitive in the fields of science.[16] Nationally, only about 40% of students who enter their undergraduate career intending to major in a STEM field actually complete the degree. Reasons for abandoning the degree differ depending on student demographics, ability and experience. High-performing students often find the first-year introductory classes to be uninspiring and boring. Low-performing students find that the mathematics required to be successful in these classes is frustratingly difficult.[2] These issues provide the impetus for developing new strategies to boost the number of college students continuing through to graduation in STEM fields.

For the purpose of this study, we focus our attention on assessing a suite of common STEM courses within the first two years of study, which include a four-course Mathematics sequence of Calculus I, II, III, and Differential Equations, a two-course Physics sequence with a laboratory component, and a two-course Chemistry sequence, also with a laboratory component.

Specific PCAST recommendations are to:

- **Address the math preparation gap.**
- **Diversify pathways to STEM careers.**
- **Replace standard laboratory courses with discovery-based research courses.**

Following in same vein as these recommendations, Clarkson University has implemented several efforts to address student retention and success. One such effort is a co-calculus or support level math course to coincide with the traditional first semester calculus course that has been in place since 2000.[17] It has been a practice within the institution to collect a pre-college mathematical skill assessment and provide recommendations for review over the pre-freshman summer.[12] For more than the past few years, the university has offered alternate curriculum paths within the first two years of study for STEM majors, and since 1997 has provided a simulated research lab experience in the first year physics sequence. The new pathway is based around the delaying of the first-year physics sequence for those students who have been identified as "high-risk" for being unsuccessful in their First-Year STEM courses. This alternate path will allow students to progress through to their STEM degree with a higher chance of success.

The modification to the first-year curriculum pathway is designed to allow students to learn the necessary mathematical skills before applying them in more rigorous subjects in science and engineering. This modification also gives a new pathway that students may take in order to progress through their STEM degrees more efficiently. Exposing students to relevant mathematical concepts prior to their direct application in physics, will help address the "math gap" that is outlined in the PCAST report.

It is an intent of this work to understand how this modification may result in a more efficient path to a STEM degree for "high-risk" students. These students are able to take a pathway that will result in a greater chance for success in their chosen STEM degree.

Goals

The goals of this study are to assess the impact of the pathway modification to the Early STEM curriculum on student retention, success and progression through their intended STEM degree. We intend to see if students who are identified in a "high-risk" category, who undergo the curriculum modification have a greater chance of success in their undergraduate career than students who were historically in the same category who did not have the modification.

Chapter 2

Relevant STEM Education Research

Much work has been done to address the issues of undergraduate retention and persistence, particularly in the STEM fields. Researchers have also sought to predict student behavior and success in their undergraduate careers. Much of the work done in this field builds upon the work and theories of Vincent Tinto[18–23], Alexander Astin[24–27], and John Bean[28–31]. Each of these researchers have proposed similar yet distinct models on student retention and persistence, which have been applied to all majors, not just those in the scientific fields. All of these education models rely on qualitative factors, such as student expectations and attitudes, student-faculty interaction, and student involvement.

Tinto's Interactionalist Theory of Student Departure seeks to understand and model a student going through the process of leaving their institution. By taking in pre-college characteristics such as family background, prior schooling and pre-college skills and abilities, the model seeks to predict success in college, and ultimately whether a student will continue or leave. Integration plays a large role in this model, as the student must integrate into the college environment, and transition away from the home environment. If a student does not "mesh" well with the institution, according to the model, they will most likely decide to depart[18;20]. Tinto's recommendation is for the academic institution to foster student involvement and create learning communities[21] to improve student integration.

Bean's Theory of Student Attrition is similar to Tinto's model, placing importance on much of the same characteristics and variables. Bean creates an analogy between student attrition and work organization turnover[28;29]. Using this model, Bean finds that students' interaction with faculty and student involvements on campus play key roles in a student persisting through their degree, in agreement with Tinto and Astin.

Astin's Theory of Involvement states that a student's persistence is related to their involvement in college[25], as the name implies. Astin places responsibility for involvement on the student, defining it as "the amount of physical and psychological energy that the student devotes to the academic experience"[24]. The "academic experience" not only refers to the scholarly activities, such as attending classes, completing assignments and studying, but also the social activities of joining extracurricular clubs and societies.

Researchers have used these theories, and have attempted to apply them specifically to STEM students. They have created models to attempt to explain STEM student behavior, and identify the factors that lead to a student leaving college. The factors that these later studies have looked at fall under both the qualitative, as described above, and quantitative categories. Quantitative factors are those that have a numerical value attributed to them, such as high school GPA, success in AP courses, and SAT scores.

One study that builds on all of these theories, and integrates them together with others, was performed by Davidson, Beck and Milligan[32]. Data were collected at four colleges (Angelo State University, Appalachian State University, Greenville Technical College, and Troy University-Montgomery), and used to create an early warning system in the form of a questionnaire. The questionnaire consisted of 53 questions, all on a five-point scale. A principle component analysis was performed on the results of the questionnaire, given at the four colleges for extra course credit. The result of this analysis led the researchers to categorize the questions using six factors: academic integration, social integration, supportive services satisfactions, degree commitment, institutional commitment, and academic conscientiousness. The new questionnaire, split into the six factors, was given to a new set of students at Angelo State University. This was combined with standardized test scores, high school rank, and whether the students returned to the university the following year. It was found that the institutional commitment (how confident and satisfied students are with their selection of school) was the most reliable predictor, with academic integration (as suggested by Tinto, Bean and Astin) and academic conscientiousness (the effort put into course work) also playing significant roles in the predictive model. Of note is the fact that the researchers do not agree with "a 'one size fits all' approach to retention," which is consistent with the approach taken by the First Year Council at Clarkson University, and the premise of this dissertation.

The model created by Veenstra, Dey and Herrin[33] builds upon Tinto's interactionalist theory, and applies it to engineering students at the University of Michigan. This model employs a multi-step process, starting with nine categories of pre-college characteristics, moving into the Freshman Year Process which included academic and social integration, and finishing with what they refer to as the Retention Decision. The pre-college characteristics range from qualitative (commitment, confidence, involvement, etc.) to demographic (family support, finances) to quantitative (high school academics, SAT Math, etc). The pre-college characteristics were used to generate nineteen independent variables to be used in the first year success model[34]. Applying the model to the 2004 and 2005 freshman classes as the University of Michigan showed that high school academics, quantitative knowledge, student commitment to goals, and student confidence in quantitative skills ranked as the most significant predictors of first year success. The high ranking of quantitative knowledge is consistent with the model being presented in this dissertation.

French, Immekus and Oakes[35] also look specifically at engineering student success. The researchers examined indicators based on empirical and theoretical evidence for two cohorts (2000 and 2001) of first year engineering students at Purdue University. The indicators (independent variables) include gender, high school rank, orientation class (participation in a first year orientation seminar), SAT scores, motivation[36], and institutional integration[37]. The measures for success were cumulative GPA, university and major persistence. Using a linear regression analysis, the researchers found that SAT scores, high school rank and gender were the most significant predictors for predicting GPA, with females having a higher GPA than males. Including GPA as a covariate in a logistic regression examining university persistence found that GPA was the only significant variable. Running a second logistic regression for engineering persistence found that GPA, SAT math score, high school rank, and motivation were the most significant variables.

Ackerman, Kanfer, and Beier[38] take a psychological approach at identifying predictors for academic success of STEM students. The study focuses on trait-complexes as predictors for academic success. Trait-complexes are groups of individual traits, that share commonalities, that can be used to describe or classify an individual[39]. The trait-complexes were comprised of a combination of cognitive (academics, SAT scores, etc.), affective (personality), and conative (motivations, interests, etc.) traits. By tracking 589 undergraduates through to their exit from the Georgia Institute of Technology, be it by attrition or graduation, the researchers were able to show that these trait-complexes represented significant predictors of academic achievement and STEM persistence.

Two studies in more recent years looked at students as being either *persisters* or a *switchers*. Shaw and Barbuti[40] examined the role of choosing an undergraduate major as having a role in the decision to be a persister or a switcher. In this context, the two titles referred to remaining in the STEM major that the students chose in high school. A high dimension model was created to determine what factors would determine whether a student became a persister or a switcher. The model incorporated many quantitative variables such as second and first year GPA, high school GPA (general, math and science), number of Advanced Placement (AP) exams taken, and demographic information. More qualitative factors were included as well, such as the declared major, highest degree goal, and a self estimate of science ability. The study showed that high school performance was significantly related to persistence, as were the goals and confidence the students showed in their ability. The researchers found slight variations in whether a student would switch out of their initial major between the individual majors, but did not report that any were significant.

A second study to examine students as persisters or switchers was performed by Pierrkos, Beam, Constantz, Johri, and Anderson[41]. The two titles are similar in context to the previous study, but the researchers are concerned solely with engineering students. The researchers used identity theory to examine the factors that contribute to creating an engineering student's identity, and observe how persister and switcher identities differ. It was found that both categories of students had high ability and interest in math and science, meaning that the difference between the two is not a matter of aptitude. Rather, the study showed, persisters had more exposure to, and knowledge of engineering as a profession than switchers. This study's findings were preliminary, but did give two recommendations. The first is to give students a pre-college engineering education, to give exposure to the profession. The second is that the first year of an engineer's undergraduate experience is critical to their success, aligning with the findings and recommendations of this dissertation.

The studies shown in this section align with the research being presented in that they look at identifying key factors that contribute to student success, retention, and persistence, and make specific recommendations for providing strategic student opportunities at any early point in a student's college experience. The research presented herein assesses the use of a *low dimension* predictive model based upon two quantitative pre-college factors allowing for ease of implementation in identifying a student's risk category and providing alternate pathways for success. The specific curriculum opportunities provided to students make use of the findings above by increasing student involvement, interaction with faculty, and knowledge of discipline, while taking into account a measure of the student's pre-enrollment conceptual understanding and math skills.

Chapter 3

Early STEM: The Undergraduate STEM Curriculum in the First Two Years

"The first two years of college are the most critical to the retention and recruitment of STEM majors." - President's Council of Advisors on Science and Technology (2012)

Over 60% of students who enter college intending to major in a STEM field in the United States will not complete their degree. Students that leave the STEM disciplines cite the courses encountered in their first two years as the main reason, describing them as dull and uninspiring, or that they experience difficulty with the mathematics. The current culture of these courses is one of "weeding out" students who may not be as well prepared as others. In this chapter, we will describe the current schedule of Early STEM courses at Clarkson University and present historical data to "set the stage" for the modification to the Early STEM curriculum and this project.

The majority of students majoring in STEM share a common first-year curriculum.

This is particularly true at Clarkson University, where the majority (83%) of students major in a STEM discipline. For the purpose of this study, we will label the suite of common STEM courses as the Early STEM courses. These Early STEM courses are often very challenging for students beginning their undergraduate careers, as they may present a significant departure (increased level and expectation) from the standard high school course load. These courses are typically prerequisites for many higher-level courses, and thus failure to pass one or more can not only negatively impact a student's GPA, but impede progress through their required curriculum, or even worse, terminate their undergraduate career. We identify the students that are most at-risk for not successfully passing a course, based on results of pre-college math and physics surveys, given to the students before they enter the university. Risk categories have been developed from historical data sets. Once a student's risk level is identified, a modification, if necessary, can be made to their first-year schedule to enhance their chance of success in their Early STEM courses. In this chapter, we describe the traditional Early STEM curriculum, provide a backdrop of majors at the institution of study, and describe the alternate pathway through the Early STEM suite of courses.

Traditional Early STEM Curriculum at Clarkson University

At Clarkson University, the majority of STEM majors share what is known as a "Common First-Year Curriculum" as shown in Table 3.1. For the purposes of our study, the majors or programs of study that we are including as STEM are:

- Aeronautical Engineering (AEROE-BS)
- Civil Engineering (CE-BS)
- Chemical Engineering (CHEME-BS)

- Computer Engineering (COMPE-BS)
- Electrical Engineering (EE-BS)
- Environmental Engineering (ENGVENG-BS)
- Mechanical Engineering (MECHE-BS)
- Software Engineering (SFTWE-BS)
- Biomolecular Science (BIOMO-BS)
- Chemistry (CHEM-BS)
- (Interdisciplinary) Engineering & Management ((I)EM-BS) [1]
- Mathematics (MATH-BS)
- Applied Mathematics and Statistics (MATSTAT-BS)
- Physics (PHY-BS)
- Biology (BIOLOGY-BS)
- Computer Science (CS-BS)
- Digital Arts (DIGART-BS)
- Environmental Health Science (EHS-BS)
- Environmental Science & Policy (ES&P-BS)

This differs from the definition of STEM given by the National Science Foundation (NSF), which includes the Social Sciences.[42] The Social Science majors at Clarkson University are not required to take the Common First-Year Curriculum, or any of the Early STEM courses, so we do not include them in our list. In addition, we also include three majors that are intended to be "stepping stones" for incoming students who are unsure of what major they intend to pursue. These majors share the Common First-Year Curriculum, and are as follows: Engineering Studies (ENGST), Science Studies (SCIST) and University Studies (UNIVST). Table 3.1 shows The Common First-Year Curriculum in engineering,[43] with the relevant STEM courses identified in red. The course titled "KA Elective" is a "Knowledge Area" course, the term that Clarkson University uses for a general education/elective course. These are courses with specific themes and selection rules that fulfill degree requirements for graduation. These themes are Contemporary & Global Issues, Cultures & Societies,

[1] E&M was an interdisciplinary program until 2009

Economics & Organizations, Imaginative Arts, Individual & Group Behavior, and Science, Technology & Society.

Table 3.1: The Common First-Year Curriculum in Engineering

The Common First-Year Curriculum in Engineering					
First Semester			**Second Semester**		
Course	*Title*	*Cr. Hrs.*	*Course*	*Title*	*Cr. Hrs.*
CM131	Chemistry I	4	CM132	Chemistry II	4
PH131	Physics I	4	PH132	Physics II	4
MA131	Calculus I	3	MA132	Calculus II	3
UNIV190	Clarkson Seminar	3		KA Elective	3
FY100	First-Year Seminar	1	ES100	Introduction to Engineering	2

This curriculum is relatively consistent with other schools that are part of the Association of Independent Technological Universities (AITU). While details of scheduling by semester/trimester may be different, most of the Early STEM courses remain in the first two years of students' academic careers, and have been identified as critical components in STEM education. The AITU is an organization of private techological universities and colleges[44] of which Clarkson University is a member. Only a handful of the 22 member institutions have a common first-year curriculum that is structured like the one found in Table 3.1. Students at the other universities may take equivalent Early STEM courses in different semesters than the students at Clarkson University.

Table 3.2 shows a comprehensive list of the majors at Clarkson University, and indicate the required STEM courses associated with each. The majors are broken up further, to give a sense of the discipline demographic at the institution of this study. The first list covers all engineering majors which share several courses within the second year as well as The Common First-Year Curriculum. The next group of majors includes others that require six or more Early STEM courses, but are not in the School of Engineering. The last two groups are majors that require two or more

Early STEM courses, and the remaining majors that do not require any Early STEM courses, respectively. Students may also be required to take other STEM courses that are not listed on this table, and for the purposes of this study, are not included as our Early STEM courses for quantitative reasoning purposes. These courses include Physics for Life Sciences (PH141/142), an algebra based physics course, and Introduction to College Math and Basic Calculus (MA180/181). The Chemistry Early STEM requirement is extended to those majors that require CM103 and CM104, which are requirements for the Chemistry major, and are included in the Early STEM courses.

Table 3.3 shows the same comprehensive list of the majors at Clarkson University, with the same breakdowns as Table 3.2, but with the populations of the majors grouped by year. Between 58% and 65% of students enrolled at Clarkson University since 2006 have been in an engineering major, and between 79% and 89% have been in a STEM major, defined by this study. By identifying the specific STEM students of this study that also represent such a large fraction of students within the institution of study, we intend to increase our understanding of the curriculum strategies that might better train and retain these students as well as potentially have a positive impact on retention at the university as a whole.

If a student fails either Physics I or Calculus I in their first semester (Fall), they are able to re-take the course in their second semester (Spring). Historically, Chemistry I was not offered in the Spring semesters. The same "off-semester" courses are also available for Physics II and Calculus II, but offered in the Fall semesters. The off-semester courses are also available for students entering Clarkson with credit in prior courses in the sequence.

Table 3.2: Course Requirements by Major

"X" signifies that the course is required

	Major \ Course	CM131	CM132	PH131	PH132	MA131	MA132	MA231	MA232	TOTAL
ENGINEERING	AEROE-BS	X	X	X	X	X	X	X	X	8
	CE-BS	X	X	X	X	X	X	X	X	8
	CHEME-BS	X	X	X	X	X	X	X	X	8
	COMPE-BS	X	X	X	X	X	X	X	X	8
	EE-BS	X	X	X	X	X	X	X	X	8
	ENGST	X	X	X	X	X	X			6
	ENVENG-BS	X	X	X	X	X	X	X	X	8
	MECHE-BS	X	X	X	X	X	X		X	7
	SFTWE-BS	X	X	X	X	X	X	X	X	8
6+ STEM Courses	BIOMO-BS	X	X	X	X	X	X			6
	CHEM-BS	X	X	X	X	X	X		X	7
	(I)EM-BS	X	X	X	X	X	X	X	X	8
	MATH-BS			X	X	X	X	X	X	6
	MATSTAT-BS			X	X	X	X	X	X	6
	PHY-BS	X	X	X	X	X	X	X	X	8
	SCIST	X	X	X	X	X	X			6
	UNIVST	X	X	X	X	X	X			6
2+ STEM	BIOLOGY-BS	X	X							2
	CS-BS					X	X			2
	DIGART-BS					X	X			2
	EHS-BS	X	X							2
	ES&P-BS	X	X							2
No STEM Courses (Not STEM)	AMERST-BS									0
	ARETE									0
	BTM-BS									0
	BUSST									0
	COMM-BS									0
	EBUS-BS									0
	ENTRE-BS									0
	FIA-BS									0
	HIST-BS									0
	HUM-BS									0
	IH-BS									0
	ISBP-BS									0
	LIBST-BS									0
	POLSCI-BS									0
	PSYC-BS									0
	SOCSCI-BS									0
	SUPPLY-BS									0

Table 3.3: Populations of Majors with Percentages by Year

	Major \ Year	2006-2010		2011		2012		2013		Combined % (All years)
		N	%	N	%	N	%	N	%	
ENGINEERING	AEROE-BS	241	7.30	55	6.96	58	7.97	42	6.10	59.99
	CE-BS	291	8.82	63	7.97	63	8.65	64	9.30	
	CHEME-BS	190	5.76	42	5.32	57	7.83	47	6.83	
	COMPE-BS	106	3.21	27	3.42	19	2.61	18	2.62	
	EE-BS	118	3.58	18	2.28	20	2.75	38	5.52	
	ENGST	346	10.48	80	10.13	84	11.54	82	11.92	
	ENVENG-BS	80	2.42	38	4.81	29	3.98	27	3.92	
	MECHE-BS	506	15.33	150	18.99	130	17.86	115	16.72	
	SFTWE-BS	37	1.12	12	1.52	6	0.82	4	0.58	
6+ STEM Courses	BIOMO-BS	72	2.18	10	1.27	16	2.20	10	1.45	17.38
	CHEM-BS	41	1.24	11	1.39	7	0.96	10	1.45	
	(I)EM-BS	230	6.97	52	6.58	41	5.63	48	6.98	
	MATH-BS	30	0.91	5	0.63	9	1.24	1	0.15	
	MATSTAT-BS	13	0.39	0	0.00	4	0.55	3	0.44	
	PHY-BS	46	1.39	9	1.14	9	1.24	12	1.74	
	SCIST	30	0.91	19	2.41	16	2.20	20	2.91	
	UNIVST	141	4.27	17	2.15	10	1.37	15	2.18	
2+ STEM	BIOLOGY-BS	134	4.06	44	5.57	47	6.46	36	5.23	8.72
	CS-BS	60	1.82	18	2.28	12	1.65	16	2.33	
	DIGART-BS	56	1.70	23	2.91	5	0.69	1	0.15	
	EHS-BS	3	0.09	2	0.25	0	0.00	0	0.00	
	ES&P-BS	14	0.42	4	0.51	4	0.55	1	0.15	
No STEM Courses (Not STEM)	AMERST-BS	2	0.06	0	0.00	0	0.00	0	0.00	13.91
	ARETE	34	1.03	4	0.51	5	0.69	5	0.73	
	BTM-BS	45	1.36	0	0.00	0	0.00	0	0.00	
	BUSST	278	8.42	54	6.84	52	7.14	52	7.56	
	COMM-BS	13	0.39	1	0.13	4	0.55	3	0.44	
	EBUS-BS	10	0.30	0	0.00	0	0.00	0	0.00	
	ENTRE-BS	5	0.15	0	0.00	1	0.14	3	0.44	
	FIA-BS	24	0.73	2	0.25	1	0.14	0	0.00	
	HIST-BS	7	0.21	3	0.38	2	0.27	2	0.29	
	HUM-BS	2	0.06	0	0.00	0	0.00	2	0.29	
	IH-BS	1	0.03	0	0.00	0	0.00	0	0.00	
	ISBP-BS	9	0.27	0	0.00	0	0.00	0	0.00	
	LIBST-BS	4	0.12	1	0.13	3	0.41	0	0.00	
	POLSCI-BS	13	0.39	4	0.51	4	0.55	2	0.29	
	PSYC-BS	59	1.79	22	2.78	9	1.24	4	0.58	
	SOCSCI-BS	2	0.06	0	0.00	1	0.14	4	0.58	
	SUPPLY-BS	7	0.21	0	0.00	0	0.00	1	0.15	

The six STEM courses highlighted in red in Table 3.1 account for 22 credit hours of a student's Early STEM curriculum. Anecdotally, the combination of introductory physics, introductory chemistry and calculus are dubbed by some at Clarkson University to be the "Triple Threat;" three conceptually challenging and mathematically rigorous courses per semester that the majority of students must complete towards their degrees. Students often cite these courses as the most challenging of their undergraduate career. Not only is the subject matter non-trivial, these are often the first technically rigorous college courses that the students take, often presenting a difficult adjustment from the course load faced in high school. Because of the numbers of students taking these courses, they are often taught in a large-lecture format, which some students may find uninspiring and disconnected, a common reason that is cited by students who leave STEM.[45;46] We also add Calculus III (MA231), and Differential Equations (MA232), to complete a suite of these eight courses that we call the "Early" STEM courses. This raises the Early STEM course credit total to 28, which is 23.3% of the credits required for an undergraduate degree.

Throughout this study, we will use certain terms that require definition. When we refer to **students**, we define them as full-time, first-time, bachelor degree seeking undergraduates enrolled at Clarkson University. **Second Year Retention** is defined as a student staying in their program, be it in STEM or more broadly in the university, from their first year to their second, defined as the student being enrolled before the 25th day of the first semester of their sophomore year. As a measure, it answers the question "Does the student come back for their third semester?" **Third Year Retention** is defined similarly to second year retention, but for a student's second to third year. **Progression** is defined as how the student navigates through their required courses to complete their degree. All majors have a traditional "road map" that outlines when certain courses are typically taken. An example of this navigational route is shown in table 3.1 for a first-year Engineering major. In Chapter 5, we will take a quantitative view of how quickly and efficiently a student progresses through the core STEM courses. **Persistence** is defined as a student staying in their program all the way through to graduation. Does the student stay in their initial program of study, or at the very least, stay enrolled at the university until graduation? The graduation rates for the years 2006 through 2010 are summarized in Table 3.4, with the US Average being based on 2010 graduation rates for 4-year private not-for-profit colleges.[47] The graduation rates are divided into 4- and 6-year rates, to reflect students graduating in 4 or 6 years. The 6-year rates reflect students that graduate later than 4 years due to a variety of reasons, such as health, failing classes, or taking on additional credits/courses. Universities must report these figures to the Integrated Postsecondary Education System (IPEDS), to be available to the public.[48] These rates are mostly above the national average for 4-year private not-for-profit colleges, however they are still quite low. When comparing to the AITU average for 2010, Clarkson is above the 4-year average rate, but below the 6-year average rate. We refer to the range of years, 2006 through 2010, as **historical**, as they define the set of years that we will compare more recent years to for analysis purposes.

Historically, before any treatment was applied to the Early STEM curriculum, the average overall retention in Clarkson University was approximately 85%. For students who were in STEM majors, the average retention rate was approximately 87%. At 78%, the retention rates in STEM are lower than those for the university. This is alarming, as it means that students in STEM majors are abandoning them for other, non-STEM majors, or are leaving the university.

The grades of the students in the Early STEM courses are also a concern. Historically, the mean GPA for the Early STEM courses is approximately 2.42 on a 4 point scale. According to the university's letter grade scale, this corresponds to below a C+. Table 3.7 shows the non-weighted average of course GPAs for the first six Early

[2]Data unavailable for Keck Graduate Institute and Webb Institute

Table 3.4: Graduation Rates for Clarkson University and US

	4-Year Rate	6-Year Rate	4-Year Men	4-Year Women	6-Year Men	6-Year Women
Clarkson University 2006	50.9%	70.1%	49.5%	69.3%	55.7%	72.5%
Clarkson University 2007	52.9%	70.1%	52.0%	70.8%	56.1%	67.7%
Clarkson University 2008	54.1%	69.6%	53.0%	68.5%	57.9%	73.2%
Clarkson University 2009	51.7%	69.6%	48.8%	68.9%	59.6%	71.5%
Clarkson University 2010	55.3%	69.5%	53.3%	69.2%	62.7%	70.4%
Clarkson University Historical Average	53.0%	69.7%	51.3%	58.4%	69.3%	71.1%
US Average (2010)	52.5%	65.5%	47.8%	56.2%	63.1%	67.4%
AITU Average (2010)[2]	48.8%	72.2%	45.6%	58.0%	70.3%	78.4%

STEM courses, as well as across the board, to be used as a simple success metric and indicator for comparison. These first six are the STEM courses that students will typically encounter in their first year of study. A measure of an effectively implemented academic success and retention strategy would see both an improvement of these grades as well as the retention rates.

Another concern is how the students are progressing through the Early STEM courses, on the way to earning their degrees. We have chosen a metric for "success" in a course, based on their final grade in that course. Table 3.6 shows Clarkson University's letter grades and the corresponding GPA for the historical years. In more

Table 3.5: Historical Second Year Retention Rates

Cohort	Second Year Overall Retention in University	Second Year STEM Retention in University	Second Year Retention in STEM
2006	82.82%	84.34%	72.48%
2007	82.99%	84.99%	74.84%
2008	85.31%	87.48%	80.83%
2009	86.76%	88.41%	80.32%
2010	85.39%	87.37%	81.75%
Average	84.74%	86.69%	78.04%

Table 3.6: Letter Grade/GPA Assignments for Clarkson University

Letter Grade	GPA
A	4
B+	3.5
B	3
C+	2.5
C	2
D+	1.5
D	1
F,W,LW	0

recent years, Clarkson University has changed the letter grade system, adding the letter grades A+, A-, B-, and C-. This has changed the GPA that corresponds to each letter grade, but the metric for success that we use is the same for all years of this study. If a student receives a GPA of 2.0 (corresponding to a letter grade of C) or better, they are considered to have been successful in that course. If they received a 1.5 (D+) or below, they are considered to have been unsuccessful in that course, even though a D+ or D are technically considered to be passing. The Clarkson University academic regulations states that a student is considered to be in good standing if their GPA is above a 2.0, corresponding to a letter grade of C.[49] Table 3.8 shows the progression of students in the historical cohorts through the typical first semester curriculum, consisting of Chemistry I (CM131), Calculus I (MA131), and Physics I (PH131), by displaying the number of students in that course, and the percentage of either successful (S) or unsuccessful (U) students.

Table 3.7: Historical Mean GPAs in First Six Early STEM Classes

Cohort	CM131	CM132	MA131	MA132	PH131	PH132	All STEM
2006	2.25	2.44	1.88	2.56	2.38	2.46	2.33
2007	2.42	2.58	2.3	2.52	2.47	2.72	2.50
2008	2.45	2.46	2.35	2.66	2.43	2.54	2.48
2009	2.27	2.49	2.01	2.45	2.36	2.55	2.39
2010	2.28	2.69	2.27	2.15	2.46	2.66	2.42
Average	2.33	2.53	2.16	2.46	2.42	2.59	2.42

Table 3.8: Historical Success Rates for the First Semester Classes by Semester

	CM131				**MA131**				**PH131**			
	U		**S**		**U**		**S**		**U**		**S**	
Semester	N	%	N	%	N	%	N	%	N	%	N	%
1	585	27.7	1529	72.3	765	33.1	1549	66.9	578	24.8	1755	75.2
2	0	0	0	0	179	54.7	148	45.3	51	19.6	209	80.4
3	44	45.8	52	54.2	23	65.7	12	34.3	9	45.0	11	55.0
4	0	0	2	100	6	37.5	10	62.5	6	100	0	0
5	8	53.3	7	46.7	3	33.3	6	66.7	0	0	5	100
6	0	0	1	100	3	60.0	2	40	0	0	0	0.0

In Chemistry, 5.7% of the students that took the course in the first semester repeated the course. In Calculus and Physics, 17.1% and 12.6% of the students repeated respectively. Even going out as far as the sixth semester, there are students repeating their Early STEM courses. This can cause problems for the students, as these courses are often prerequisites for other courses that students need in order to complete their degree. By having to repeat the courses, students delay their progression. There is also the negative impact associated with the feeling of failure when students are unsuccessful in a course. While the impact is difficult to measure, this experience may negatively affect their coursework and overall academic progress.

Chapter 4

Curriculum Intervention: Identification and Description

Identification of At-Risk Population

In this chapter, we describe how we identify students who are most at-risk for failing a course and having to repeat it. Once students are identified, we can provide opportunities for alternate curriculum pathways to make the undergraduate experience better for students. In order for this intervention to be effective, it must be implemented early. Since the Early STEM courses start in their first semester, a pre-enrollment measure capable of identifying a student's risk level, allows for them to be strategically placed in an appropriate curriculum path based on individual needs.

Creation of Predictive Model

We performed a Principle Component Analysis (PCA) of data that was collected prior to students attending Clarkson University, or immediately after the start of their first semester. The goal was to develop a low-dimensional predictive model that would identify or classify students into one of three general risk categories (low, medium and high).[50] PCA is a statistical analysis method used in model reduction and data classification. By looking at the variances in the data, a new set of basis vectors are chosen, to maximize the variance in the data.

A toy example demonstrating the utility of PCA is to think of an oscillating mass-spring system contained in a closed box with its direction of oscillation concealed or unknown.[51] You have some cameras that you can point into the box by poking a hole. However, you want to reduce the number of cameras that you use, yet observe the greatest variation in the motion of the system, to determine the direction of oscillation. PCA runs an analysis of the data that is given, then selects new Principle Components (PCs) based on the variances of the data and constructed from linear combinations of the variables. These PCs are arbitrary, they are created with the goal of maximizing the variances, resulting in the most information to be gleaned from the data. In our example, the results of the PCA would suggest placing the cameras to point perpendicular to the motion of the mass, as the camera would capture the greatest variance in the displacement of the mass.

One way to visualize PCA is to use what is known as a biplot. A biplot shows all of the data points, represented by the black numbers, plotted on the two most "important" PCs determined by the PCA. These components explain most of the variability of the data, which is useful in reducing the model. The important thing to remember is that the two PCs are arbitrary, they are two "viewpoints" for the data, to maximize the variance. This is important, because the red vectors representing the factors can also give us useful information for reducing the data to ultimately create a low-dimension predictive model. Figure 4.1 shows a biplot that was made in 2009, when the model was first being developed.[50] The data that were used for this analysis is summarized in Table 4.1.

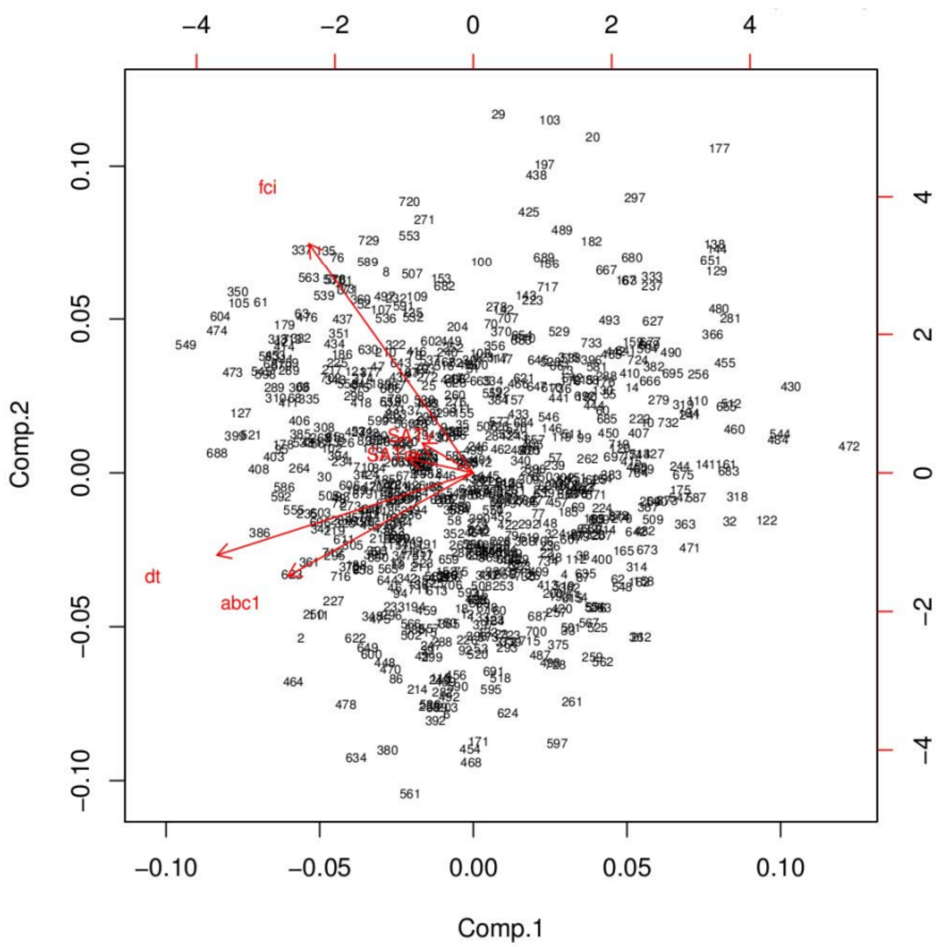


Figure 4.1: Biplot of Historical Inital State Data

The biplot in Figure 4.1 shows that three of the factors used in the PCA have the most variance along the two PCs: the Force Concepts Inventory, the Diagnostic Test and the Absolute Basic Competency test. The red vectors representing those three variables have the greatest magnitude, showing high variance. The two math tests are also oriented nearly perpendicular to the FCI, which shows a low correlation between them. Remembering the goal of the analysis, to identify risk factors for students to apply an intervention prior to the students arriving at Clarkson, the FCI and the Diagnostic Test were chosen to create a low-dimension predictive model by themselves, without relying on other factors.

By plotting these two factors, a distribution of the students was created, as seen

Table 4.1: Data Used in the Historical Principle Component Analysis. Examples of the FCI, Diagnostic Readiness Test and ABC Test can be found in the Appendices.

Variable	Description
FCI[52]	Force Concepts Inventory, a conceptual survey in Newtonian Mechanics
SATv	Scholastic Assessment Test – Verbal Score
SATm	Scholastic Assessment Test – Mathematical Score
dt[12]	Diagnostic Test, a test designed and given by the Clarkson University Math Department, used to place students in the appropriate math course
abc1[53,17]	Absolute Basic Competency (ABC) Test, a test of mathematical standards (designed by the Clarkson Math Department) that students in Calculus I take early in the semester

in Figure 4.2. The cutoffs for the Diagnostic Test, now called the Math Diagnostic Survey, was placed at 65%, which is the Math Department's passing cutoff for the original diagnostic test, prior to the creation of the curriculum intervention. The FCI, now termed the Physics Diagnostic Survey, for the purposes of this analysis, had an arbitrarily chosen cutoff of 50%. With these cutoffs initially defined, students could be placed into groups, based on their normalized scores. Each group carries with it a risk category for failing (or being Unsuccessful in) an Early STEM course. The groups are summarized in Table 4.2, where a "+" or "-" denotes a relative strength or weakness, respectively for Math (M) and Physics (P).

Table 4.2: MP Groups, Cutoffs, and Risk Categories

Group	Math Score	Physics Score	Risk Category
M-,P-	< 0.65	< 0.50	High
M-,P+	< 0.65	≥ 0.50	Medium
M+,P-	≥ 0.65	< 0.50	Medium
M+,P+	≥ 0.65	≥ 0.50	Low

For the Fall 2012 cohort and beyond, a fifth group was created, entitled M-,P-+. This group consists of students who were in the M-,P+ group, but were close to the

Physics Diagnostic cutoff. The cutoff line for this new group created a “wedge” in the plot, which can be seen in later figures. This group was created to fill the enrollment in a course that is part of the curriculum modification, and is re-assigned as a “high” risk category. This, and the original four groups are shown graphically, in Figure 4.2. The figure depicts a sunflower plot, which is used to display multiple data points at the same coordinates, which is useful for data sets with discrete data points. If there is one data point, it is represented by a black dot. Every time a new point occurs at the same coordinates as a previous point, a “petal” is added to that point. The more petals a set of coordinates has, the more data points are located there. We refer to this plot of Physics Diagnostic Score vs Math Diagnostic Score as an MP (Math-Physics) plot.

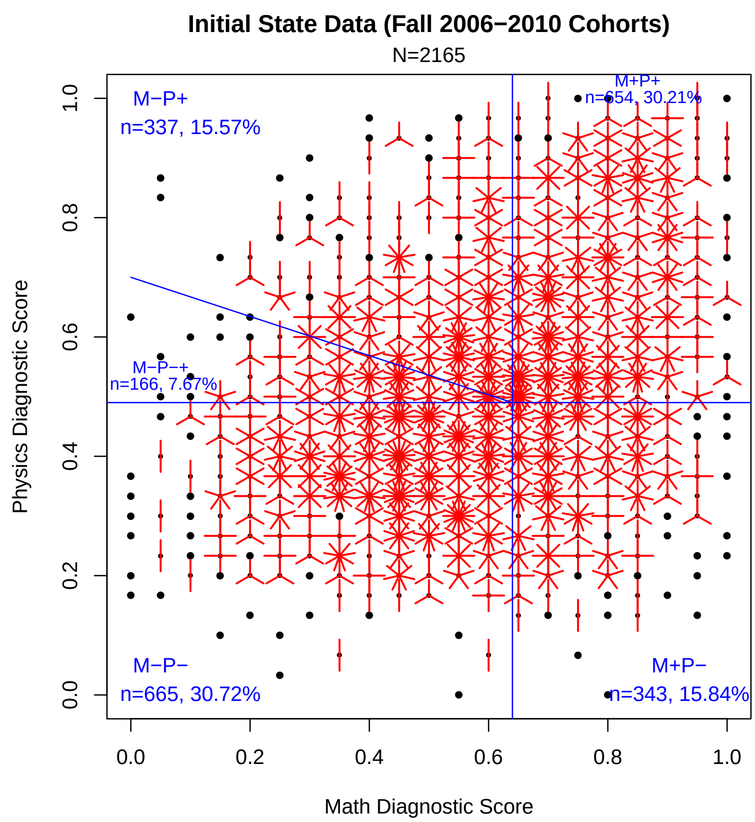


Figure 4.2: Sunflower Plot of Historical Initial State Data, with Group Labels, Sizes and Percent of the Total Population

The blue lines represent the cutoffs for each of the groups, and the blue labels identify each. Also included are the group sizes, in terms of number and percent of the historical cohort. This gives a picture of the initial state of students that entered Clarkson during the historical cohort years. Note the broad variance in this singular plot.

Validation of Predictive Model

In order to test the validity of the predictive model, we can look at the final grades of students in the historical cohorts, and see where they reside in the MP plot. Looking at the final grades of students in the different groups lets us see which groups contain the most at-risk students. Figures 4.3 to 4.5 are sunflower plots showing historically where the students with various grade ranges are located in the corresponding MP plot. The figures are accompanied by tables, Tables 4.3 to 4.5, showing the number and percentage of Successful (S) or Unsuccessful (U) students that are in each of the risk categories.

These figures and tables show that the majority of the students that receive a D+ or lower, referred to as Unsuccessful (U) and corresponding to a GPA below 2.0, are located in the M-,P- and M-,P-+ groups, located in the lower left corner of the plot. This tells us that the students most at risk for failing a course and having to repeat it are located in those groups. Once we identify those students, our goal is to apply a strategic curriculum modification as an intervention to improve their undergraduate experience and hopefully increase their success in STEM. This must balance "capturing" as many high-risk students as possible, while keeping the number of false positives down. While roughly one third of the successful students are in the high-risk groups, the figures show that the majority earned a C or C+ in their courses. While technically a successful grade, it is not ideal and has room for improvement.

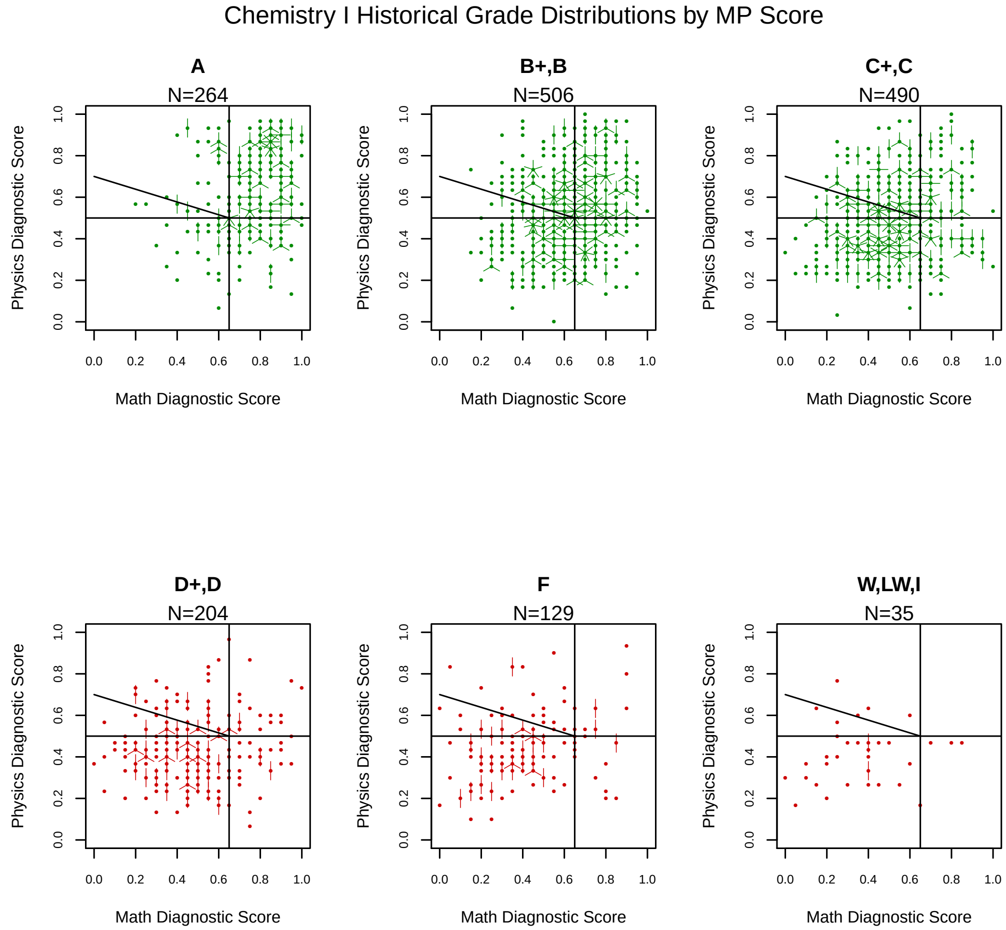


Figure 4.3: Sunflower Plots of Chemistry I Historical First Semester Grades

Table 4.3: Percentages of Successful (S) and Unsuccessful (U) students in Each Risk Category for CM131. Percentages are out of total students with similar success.

CM131	S		U	
	N	%	N	%
HR	418	33.17	244	66.30
MR	414	32.86	90	24.46
LR	428	33.97	34	9.24

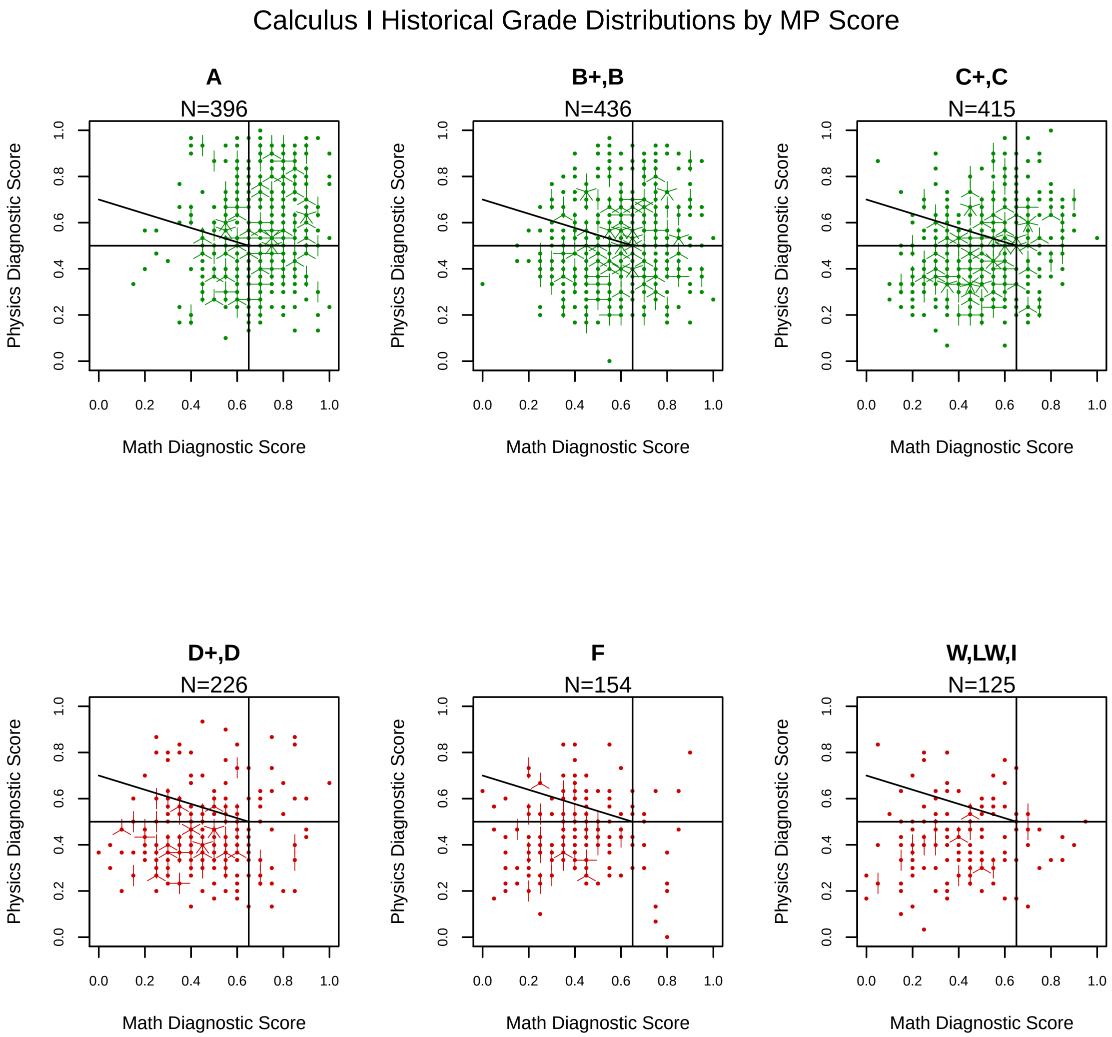


Figure 4.4: Sunflower Plots of Calculus I Historical First Semester Grades

Table 4.4: Percentages of Successful (S) and Unsuccessful (U) students in Each Risk Category for MA131. Percentages are out of total students with similar success.

MA131	S		U	
	N	%	N	%
HR	442	35.45	340	67.33
MR	438	35.12	134	26.53
LR	367	29.43	31	6.14

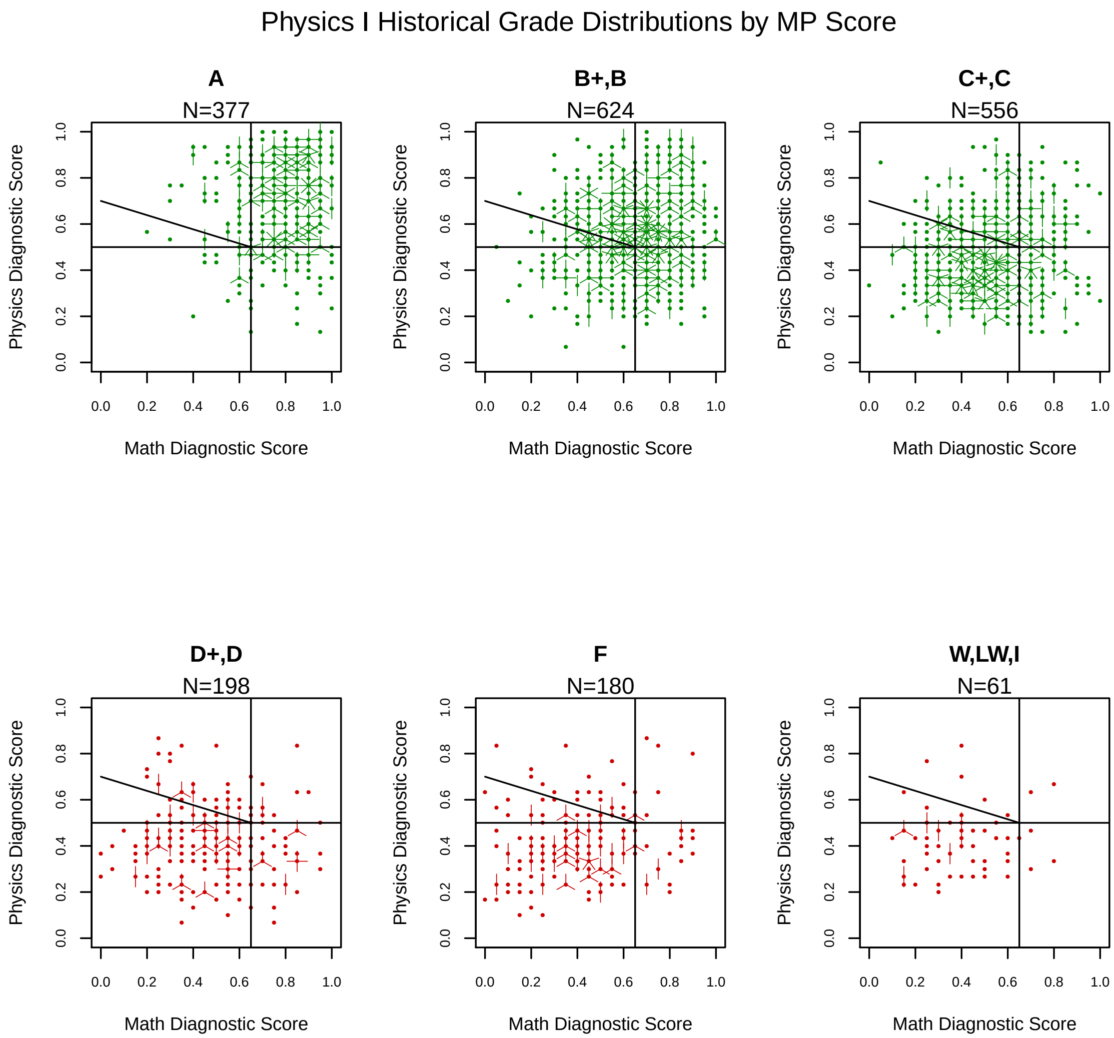


Figure 4.5: Sunflower Plots of Physics I Historical First Semester Grades

Table 4.5: Percentages of Successful (S) and Unsuccessful (U) students in Each Risk Category for PH131. Percentages are out of total students with similar success.

PH131	S		U	
	N	%	N	%
HR	445	28.58	300	68.34
MR	512	32.88	112	25.51
LR	600	38.54	27	6.15

Description of Curriculum Intervention

In order to make the first-year experience better for the students that are less well-prepared, and therefore at a higher risk of failing, a modification to the traditional first-year curriculum was made. If the students are in the School of Engineering, they are placed into an alternate STEM course, Engineering and Society (ES110), in place of Physics I. The description of this course can be found in the Clarkson University course catalog:

> Engineers apply scientific knowledge and principles, and use the engineering design process to develop technology. While engineers frequently develop solutions to problems in controlled environments, the products that are developed are used by 'real people' in the 'real world.' Thus, it is essential that engineers have an understanding of the interactions between engineering, technology development, and society. This course will highlight the diverse applications of engineering and technological skills in addition to ethical and other concerns about the societal consequences of technological developments. Students will gain an understanding of ways that conceptual models can be used to frame how both science and technology shape society and how society can shape science and technology. Students will be introduced to the engineering design process and use it to solve a simple engineering problem. Then, through case study, they will apply the societal models and gain an understanding of how the design process can be used to solve complex, open-ended, 'real-world' problems in the context of social, economic, and environmental considerations.

In short, the course introduces the social aspects of engineering to the students, which has been positively received.[54] Students found the discussion of social and ethical topics to be valuable for their engineering education. At Clarkson University, this course is referred to as a Knowledge Area course, and fulfills one of the requirements for an Engineering degree. Students identified as "high risk" take ES110 in place of PH131 in the first semester, and in the second semester they take PH131. When they return for their third semester, they take PH132. Table 4.6 shows the new first-year schedule for Engineering for those students who undergo the curriculum modification.

Figure 4.6 visually shows the process and different tracks that are suggested by the results of the Pre-College Surveys.

Table 4.6: The Modified First-Year Curriculum in Engineering for High-Risk Students

The Modified First-Year Curriculum in Engineering					
First Semester			**Second Semester**		
Course	*Title*	*Cr. Hrs.*	*Course*	*Title*	*Cr. Hrs.*
CM131	Chemistry I	4	CM132	Chemistry II	4
ES110	**Engineering and Society**	**3**	**PH131**	**Physics I**	**4**
MA131	Calculus I	3	MA132	Calculus II	3
UNIV190	Clarkson Seminar	3		KA Elective	3
FY100	First-Year Seminar	1	ES100	Introduction to Engineering	2

The rationale behind delaying Physics is to enable students who are less well-prepared in math to use the first semester to strengthen their mathematical skills, and be comfortable with mathematics, before applying it in Physics.

Table 4.7 shows the engineering majors at schools in the AITU, as well as the top 10 engineering state schools, and the semester in which the physics sequence starts for those majors. The majority of the schools/majors require or suggest that the engineering students begin taking physics in their second semester. This appears to be a "catch-all" method of addressing the issue of math preparedness. The intervention in place at Clarkson University is much more targeted and intentional than seems to be the norm at most engineering schools.

Table 4.7: Engineering Schools and the Semester That the Physics Sequence Starts for Each Major. 1.5 Refers to a Winter Session. Blank Spaces Refer to No Information.

	AEROE-BS	CE-BS	CHEME-BS	COMPE-BS	EE-BS	ENVENG-BS	MECHE-BS	SFTWE-BS
California Institute of Technology*								
Carnegie Mellon University (CMU)*		1	2			1		
Case Western Reserve University*	1	2	1	2	2		1	2
The Cooper Union for the Advancement*		2	2		2		2	
Embry-Riddle Aeronautical University*	1	1		1	1		1	1
Franklin W. Olin College of Engineering*								
Harvey Mudd College*								
Illinois Institute of Technology*	2	2		2	2		2	
Kettering University*			2	2	2		2	
Lawrence Technological University*		3		3	3		3	
Massachusetts Institute of Technology*								
Milwaukee School of Engineering*								
Polytechnic Institute of NYU*	2	2	3	2	2		2	
Rensselaer Polytechnic Institute (RPI)*								
Rochester Institute of Technology (RIT)*			2	2	2			
Rose-Hulman Institute of Technology*		1	1.5	1	1		1	1
Stevens Institute of Technology*								
Webb Institute*								
Worcester Polytechnic Institute (WPI)								
UC Berkley		2				2		
U Illinois Urbana-Champaign	2		2	2	2		2	
U michigan ann arbor	1	1	1	1	1	1	1	
U texas austin	2	2	2	2	2	2	2	
UC San Diego	1.5			2			1.5	
UCLA	1.5	1.5	1.5		1.5	1.5	1.5	
U Wisconsin Madison		5	2	2	2		4	
U Maryland College Park	2		2				2	
Penn State	1	2	2	1	1		2	
UC Santa Barbara			1.5		1.5		1.5	

*Member School of the AITU

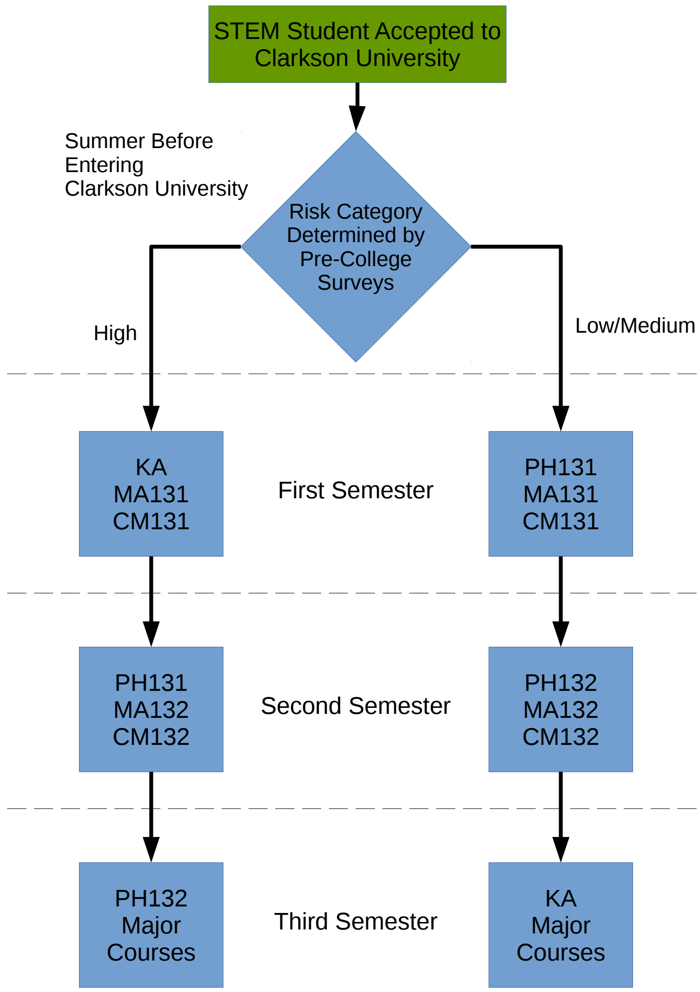


Figure 4.6: Flowchart Describing Different Suggested Early STEM Tracks Based on Risk Categories

Process and Implementation

In order to identify and group incoming students, an online course was created, entitled "Pre-College Surveys" through an online course management system that is used by Clarkson University. This course was designed to be open to the incoming students, to allow for easy enrollment. The students, once enrolled, are prompted to find their intended major on a list of all of the majors that Clarkson University offers. The list tells students if their major requires them to take the Phsyics Diagnostic and

Math Diagnostic Surveys. If they are not required to take the surveys, no further action is required from them. If they are required to take the surveys, they are then able to access them online. Instructions are given as to how to take the surveys. The results of the surveys are stored in the online grade book, allowing for quick analysis for group placement. This analysis is conducted by the First Year Council as a collaborative effort between the School of Arts and Sciences, specifically the Physics and Math Departments, and the School of Engineering at Clarkson University.

Other Curriculum Modifications

Other curriculum modifications in place, aside from delaying physics are not the focus of this particular study, and so any anticipated impact solely from them will not be analyzed. They are, however, mentioned for the sake of completeness in describing curriculum modification at Clarkson University.

The math department at Clarkson University has had a curriculum intervention in place since 2000. In the first weeks of their first semester, students take the Absolute Basic Competency (ABC) test for placement into the appropriate Calculus course.[53] [17] Traditionally, students that scored below a certain percentage were placed into MA41, a Co-Calculus course. This form of enrollment in the course has been dubbed "Fail In" enrollment, as the students who "fail" the ABC get enrolled. This method was met with criticism, as the sudden addition of a course can be disruptive to an already full schedule combined with the negative message associated with its implementation. Beginning in 2011, the enrollment method was modified. Currently, all students in Calculus I are placed into MA41. When the students "pass" the ABC, they are then permitted to drop the course from their schedule, in a method more positively termed "Pass Out" enrollment.

In the summer of 2012, a new survey was introduced to the Pre-College Surveys course. The Purdue Spatial Visualization Test: Rotation[55;56] tests the spatial thinking of students, by asking them to visualize how a shape would be rotated in three dimensions. These skills have been shown to be predictors of student success in engineering, as well as having an impact on retention in STEM.[57–59] If the students are in the School of Engineering, and they score below a certain threshold on the survey, they are recommended to enroll in ES41, a class specially developed to help strengthen spatial visualization skills. Similar courses have been implemented at engineering schools across the country, including a number of AITU schools.[60]

In the spring of 2012 the Chemistry Department decided to open a section of Chemistry I (CM131) in the spring. This off-semester course follows the same format as its analog in the Physics Department. This allows those students who are unsuccessful in CM131 in the Fall semester to be able to repeat the course the very next semester, and not have to wait an entire year. A section of Chemistry II (CM132) was opened in the Fall of 2013, for the same reasons.

It should be noted, that when the effects of the Delayed Physics program are discussed, it may be more prudent to think of it as a Delayed Physics "package" instead of just the one intervention. This is because the other curriculum modifications are so intertwined into student academics, that separating out the effects of just one is difficult, if not impossible. The Delayed Physics program is part of the "package" of the multitude of curriculum interventions, some of which are mentioned here.

Targeted Math-Physics Curriculum

In the Fall of 2015, a new program was put into place in an effort to coordinate the Calculus and Physics curricula, based on the ability to assign pre-enrollment risk categories to incoming STEM students. The Co-Ordinated Math-Physics Assessment for Student Success (COMPASS) program is a STEM curriculum pathway for medium risk students, and is funded by a National Science Foundation (NSF) grant.[61] Students who have been identified as having a Math Diagnostic score below the cutoff, but have a Physics Diagnostic score above the cutoff, places them in the "M-,P+" category, which is a "medium-risk" category, according to Table 4.2. A description of the program, as well as an initial analysis of the performance of the students will be discussed in Chapter 8.

Part II

Analysis

Chapter 5

Analysis of Intervention

In this study we assess the pathway modification in place at Clarkson University. This assessment will focus on quantifying the effects that delaying physics has on student academics, such as:

- student success in the Early STEM courses
- student progression through the Early STEM courses
- student retention
- student persistence

Retention and persistence will be measured at the university, as well as within a chosen student STEM discipline, and disaggregated by gender and race/ethnicity. We will measure the effect that providing alternative pathways through the Early STEM curriculum has on how students navigate through the first two years of college.

The data presented is organized according to the student's *cohort*. A student's cohort is defined by when they entered the university. To get a baseline for our analysis, we define a *historical* data set including cohorts that had no modification to the traditional curriculum path. We use the years 2006 to 2010 as our historical data set. For the years where there is curriculum modification, the cohorts are defined by their year. That is to say, 2011 is the first year that the pathway modification was introduced, so the students that entered the university during fall of the 2011-2012 academic year are defined as being in the Fall 2011 cohort. We refer to these cohorts collectively as the *treatment* cohorts. For the historical cohort, when we refer to the Targeted High-Risk (THR) students, we are referring to the engineering students who reside in the "High-Risk" MP groups (M-,P- and M-,P-+), who would have been delayed.

Student Success in Early STEM Courses

Success in an Early STEM course can be determined by the metric that was chosen and discussed in Chapter 3, using the grade points (GP) of a student to determine if they were successful (S) or unsuccessful (U) in a course. A student is considered to have "successfully" passed a course if their GP in the course is a 2.0 or above on a 4.0 scale.

Tables 5.1 and 5.2 numerically show the rates of unsuccessful grades in first and second semester Early STEM courses respectively, with Figures 5.1 and 5.2 showing the same information graphically. In the first semester, every course saw a decrease in the percent of students receiving an unsuccessful grade. Of particular interest is the Targeted High-Risk group in PH131. Only 60% of the students that were historically in the THR group (that would have been treated) were successfully passing. There remains a significant portion (40%)of these students who did not receive a successful grade. Now, after initiating the delayed physics program, the percent of unsuccessful grades has been reduced to approximately a third of the historical rate.

The second semester rates show a trend that fluctuates more than the first semester rates. In the most recent year for CM132 and MA132, the unsuccessful rate for the THR students has dropped by a significant amount. More data are needed to see the trend for PH132, as the THR students in the most recent cohort (2015) have not, as of the date of this writing, had a chance to take the course.

Table 5.1: Unsatisfactory (U) Rates for First Semester (First Attempt) Early STEM Courses. Rates for Targeted High-Risk students in PH131 are for the second semester.

	CM131		MA131		PH131	
Cohort	% U THR	% U Non-THR	% U THR	% U Non-THR	% U THR	% U Non-THR
Historical	39.07*	23.35	44.70*	28.91	38.94*	19.60
2011	29.08	21.11	47.55	32.12	26.32	18.72
2012	32.48	18.34	31.71	17.78	28.26	10.43
2013	21.54	20.15	25.71	20.06	10.22	8.46
2014	33.15	19.53	37.64	21.73	18.93	9.46
2015	27.93	24.24	23.53	20.18	13.25	13.17

*Would have been identified as high-risk

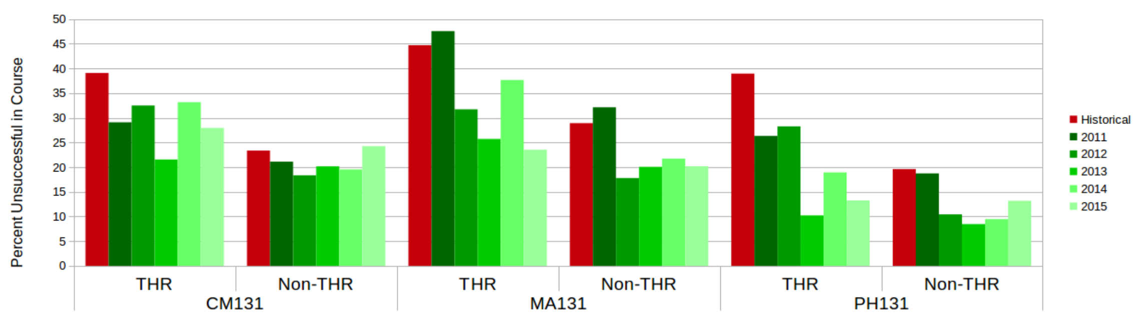


Figure 5.1: Unsatisfactory (U) Rates for First Semester (First Attempt) Early STEM Courses. Rates for Targeted High-Risk students in PH131 are for the second semester.

Unsurprisingly, the mean GPs in the Early STEM courses follow similar trends as the unsuccessful rates. This can be seen numerically in Tables 5.3 and 5.4, and graphically in Figures 5.3 and 5.4. However, in the most recent cohorts, the Targeted High-Risk students in the first semester Early STEM courses have moved from an average GP that would be considered unsuccessful, to one that would be considered successful, by the definition of this study.

Interestingly, in MA131 and PH131, the GP for the THR students has risen to be comparable to, or in some cases surpassing, the *Non-THR* historical GP. This puts

Table 5.2: Unsatisfactory (U) Rates for Second Semester (First Attempt) Early STEM Courses. Rates for Targeted High-Risk students in PH132 are for the third semester.

	CM132		MA132		PH132	
Cohort	% U THR	% U Non-THR	% U THR	% U Non-THR	% U THR	% U Non-THR
Historical	28.79*	17.68	33.18*	24.88	20.35*	11.69
2011	32.73	14.08	35.29	23.17	10.39	8.28
2012	29.37	15.79	39.68	23.15	24.47	12.29
2013	36.94	18.85	24.39	21.63	13.16	10.63
2014	35.29	21.59	28.78	21.35	28.24	10.32
2015	18.12	16.95	25.79	19.51	-	11.60

*Would have been identified as high-risk

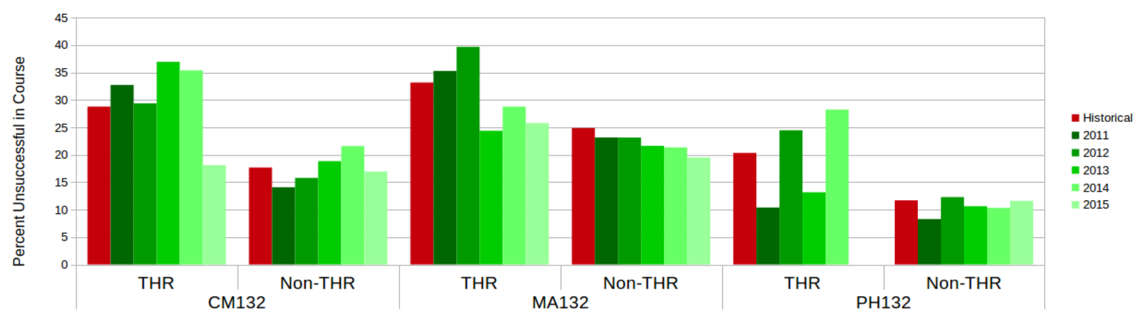


Figure 5.2: Unsatisfactory (U) Rates for Second Semester (First Attempt) Early STEM Courses. Rates for Targeted High-Risk students in PH132 are for the third semester.

the THR students' success rates at the same level as the students who were at lower risks of being unsuccessful.

To see if the differences in the GPs for each of the Early STEM courses described above are significant, a Wilcoxan Rank Sum test[62;63] is performed. The Student's t-test would have been used, but the distribution of the GPs for each of the courses does not follow the normal distribution. A student's GP can only be a certain number of discrete possibilities, instead of a continuous scale. For that reason, coupled with the fact that a GP of 0.0 does not necessarily correspond to a course score of zero and therefore does not give a "true" zero, the Student's t-test is not the correct test to apply in this situation.

Table 5.3: Mean GPs in First Semester (First Attempt) Early STEM Courses. GPs for Targeted High-Risk students in PH131 are for the second semester.

	CM131		MA131		PH131	
Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
Historical	1.90*	2.52	1.85*	2.43	1.79*	2.66
2011	2.18	2.59	1.84	2.38	2.26	2.58
2012	2.14	2.71	2.36	2.96	2.22	3.03
2013	2.41	2.70	2.61	2.87	2.86	3.13
2014	2.16	2.73	2.13	2.65	2.80	3.21
2015	2.25	2.53	2.40	2.76	2.83	3.05

*Would have been identified as high-risk

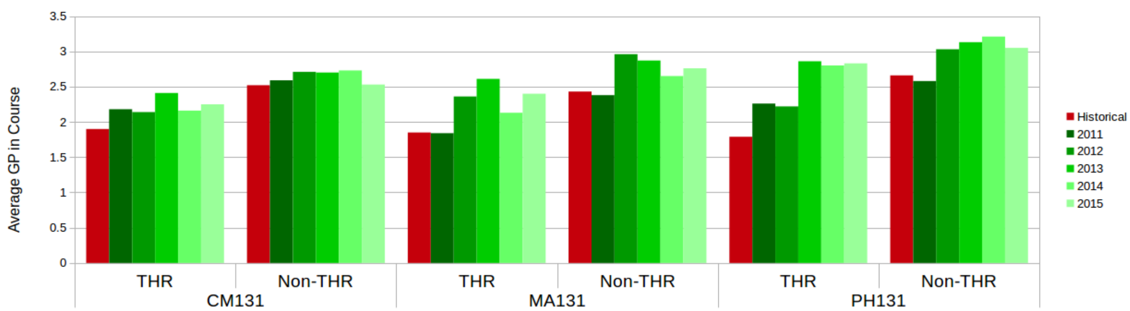


Figure 5.3: Mean GPs in First Semester (First Attempt) Early STEM Courses. GPs for Targeted High-Risk students in PH131 are for the second semester.

Table 5.5 shows the results of the Wilcoxan Rank Sum test applied to the GPs of the THR students in the treatment cohorts and the GPAs of both THR and Non-THR students in the historical cohort. The GPs in CM131 are significantly different from both the THR and Non-THR historical GPs. It appears that the treatment, though it was intended to affect the math and physics courses, did have an effect on the first semester chemistry course. The GPs of THR students was raised enough to be significantly higher than those of similar historical students, but not enough to be considered similar to those of the Non-THR historical students. A similar effect was seen in the 2012 and 2015 cohorts of CM132. The GPs for those cohorts were raised enough to be significantly different from the historical treated GPs. The other cohorts (2011, 2013 and 2014) were not significantly affected by the treatment, as

Table 5.4: Mean GPs in Second Semester (First Attempt) Early STEM Courses. GPs for Targeted High-Risk students in PH132 are for the third semester.

	CM132		MA132		PH132	
Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
Historical	2.19*	2.71	2.18*	2.61	2.26*	2.81
2011	2.19	2.78	2.00	2.56	2.79	2.97
2012	2.35	2.87	2.15	2.63	2.27	2.93
2013	2.13	2.77	2.53	2.77	2.76	3.00
2014	2.13	2.67	2.32	2.67	2.41	3.11
2015	2.44	2.72	2.30	2.76	-	3.04

*Would have been identified as high-risk

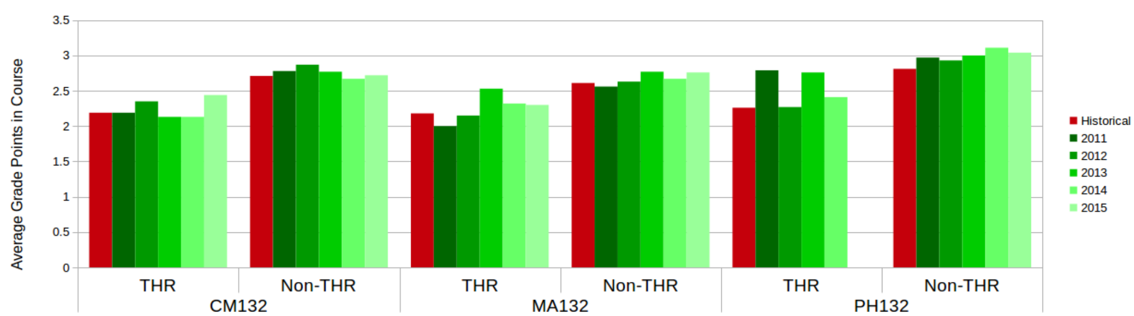


Figure 5.4: Mean GPs in Second Semester (First Attempt) Early STEM Courses. GPs for Targeted High-Risk students in PH132 are for the third semester.

seen in the p-values of the differences in the GPs.

The GPs in MA131 were initially not affected by the treatment. The GPs for the THR students in the 2011 cohort was not significantly different from the GP of the THR students in the historical cohort. The GPs for the subsequent cohorts were raised enough to be significantly higher than those of the THR historical students, *and* be similar to the GPs of the *Non-THR* historical students, with the exception of the 2014 cohort. The GPs for that cohort were still significantly higher than those for the historical THR students, but not enough to be similar to the GPs for the Non-THR historical students. In MA132, almost no effect was seen on the GPs for the THR students in the treatment cohorts. The treatment GPs were all similar to the historical THR GPs, and significantly different than the Non-THR historical

Table 5.5: P-values Comparing Treated Student GPs in Treatment Cohorts to Historical Student GPs in First and Second Semester Early STEM Courses. Values showing a significant difference (α=0.1) are highlighted.

First Semester (Second Semester for PH131 Treated Students)						
	CM131		MA131		PH131	
Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
2011	0.005621	0.0002179	0.8882	<0.0001	<0.0001	<0.0001
2012	0.01686	<0.0001	<0.0001	0.4903	<0.0001	<0.0001
2013	<0.0001	0.05114	<0.0001	0.2184	<0.0001	0.2593
2014	0.003272	<0.0001	0.008836	0.0007674	<0.0001	0.1492
2015	0.0001914	0.0005806	<0.0001	0.1397	<0.0001	0.4276
Second Semester (Third Semester for PH132 Treated Students)						
	CM132		MA132		PH132	
Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
2011	0.9555	<0.0001	0.3063	<0.0001	<0.0001	0.2704
2012	0.07092	0.0005257	0.948	0.0003249	0.4739	<0.0001
2013	0.4413	<0.0001	0.006499	0.1407	<0.0001	0.3337
2014	0.6816	<0.0001	0.1218	0.003117	0.02074	0.0002593
2015	0.01779	0.0003101	0.2891	0.0001363	-	-

GPs. The exception to this are the GPs for the 2013 cohort, which did see an effect, becoming similar to the historical Non-THR GPs.

In PH131, the GPs of the THR students were all positively affected by the treatment. The GPs for the THR students in the treatment cohorts were sufficiently affected so as to be significantly higher than the GPs for the historical THR students. Even more telling of the effect of the treatment on these students, is the fact that the GPs for the most recent cohorts (2013, 2014 and 2015) were similar to the historical *Non-THR* cohort. The THR students in those cohorts were receiving grades on par with the historical lower risk students. The effect of the treatment is less pronounced with the PH132 GPs. The majority of the treatment cohorts had GPs that were significantly different than those of the historical treated cohort, the exception being the 2012 cohort. The GPs for that cohort were back at the level of the historical THR cohort. The other THR cohorts were all positively affected, with the 2011 and 2013 cohorts becoming similar to the historical Non-THR cohort.

Student Progression Through Early STEM Courses

The effects of the pathway modification may also be modeled in a longitudinal study. Students that are unsuccessful in an Early STEM course see a disruption to their intended schedule, as they attempt to "catch up" to where they should be in their progression through their degrees. In addition, the Early STEM classes are prerequisites for many of the upper level classes, and having to repeat them can cause students to be enrolled in courses they are unprepared for, delay further courses, or have students consider drop a major or withdrawing from the university. The aim of the strategic placements in Early STEM (physics) program is to create alternate pathways for the students who are most at risk for being unsuccessful in Early STEM, so that they may progress at an individually tailored pace. These pathways strike a balance between the eager STEM students who want to solve technical problems and the challenges and demands of a mathematically rigorous course load.

Figure 5.5 shows a graphical representation of how quickly students progress through the chemistry and physics sequences. Each bar represents when students successfully pass through the Early STEM course in question. The population is based on all students in that cohort that took the course. The students that are in the "Not Satisfied" category are those that were unsuccessful in the course, and did not take the course again to raise their grade.

In Chemistry I, there is a positive trend of a greater percentage of the cohort passing the course in their first and second semesters respectively. This could be due to the less mathematically rigorous semester for the Targeted High-Risk students. The THR students are able to focus more on chemistry in their first semester, which can be seen later in the chapter, in Table 5.3. The Chemistry I GPs have risen for the treated students, by approximately 0.3 points. Chemistry II shows a decline, but this may be due to a greater percentage of students taking a biology course instead. For some engineering students, an alternate pathway is available, allowing them to

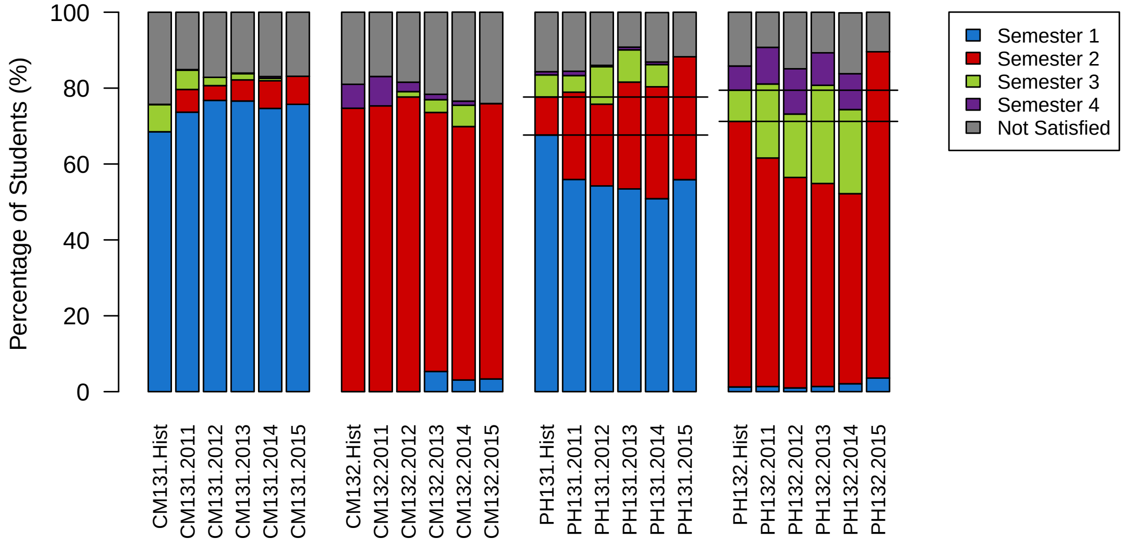


Figure 5.5: Bar Plots of Student Progress Through Early STEM Courses: Chemistry and Physics

take a biology course in place of Chemistry II. In the physics sequence, the delayed physics program is the cause of the initial drop in students passing Physics I in their first semester; more students are first attempting to pass Physics I in their second semester, instead of their first. Similar reasoning is used for Physics II, but for the second and third semester respectively. Because the sequence is delayed for some students, we compare the first semester rates in the historical cohort to the second (plus first) semester rates for the treatment cohorts. Physics II gets a similar comparison, but with the historical second semester to the third semester of the treatment cohorts. Physics I shows a large improvement over the historical first semester rate, and is even increased over the historical second semester rate. This means that by the end of the second semester, a greater percentage of students who were enrolled in Physics I have passed successfully than in previous years. By their third semester, more people have passed Physics II than have passed in their second semester historically.

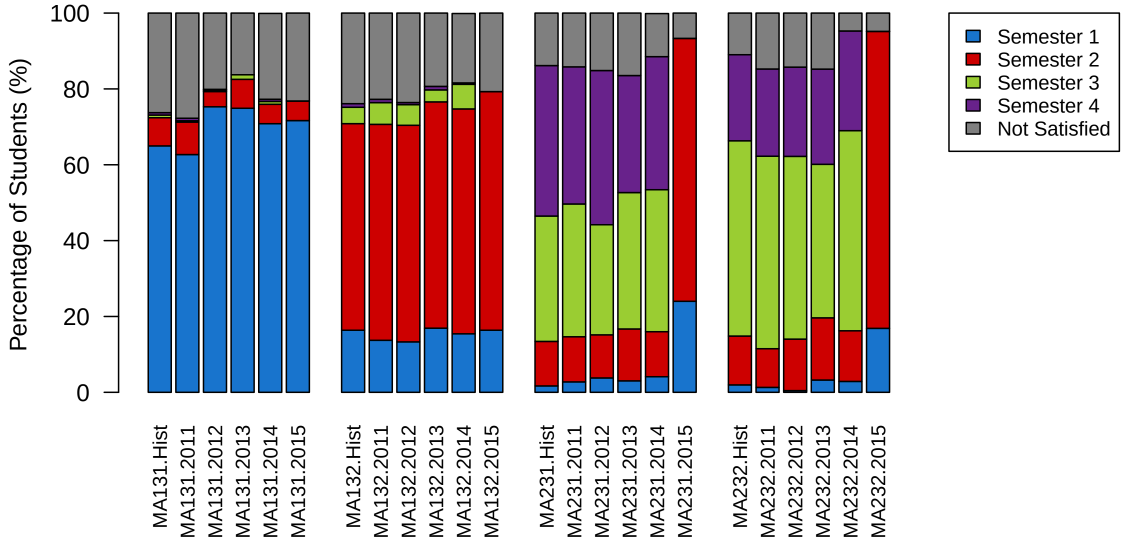


Figure 5.6: Bar Plots of Student Progress Through Early STEM Courses: Math

Figure 5.6 shows an analysis similar to Figure 5.5, but for the math sequence of courses. Calculus I shows a positive trend of students passing in their first semester, while in Calculus II, the percentage that passes by their second semester is increased from the historical cohort. Calculus III and Differential Equations are fluctuating a bit, but are up from the historical success rates for the most recent cohort (2014). Overall, the results look steady, with the first two Calculus courses showing improvement.

When looking at the progression plots for only the Targeted High-Risk students, the trends are similar to those that were seen when looking at all of the students that attempted the courses. Figures 5.7 and 5.8 show the results of looking at just the THR students. The only differences that can be observed are slight increases of the students passing Calculus III (MA231) and Differential Equations (MA232) by the end of their fourth semester.

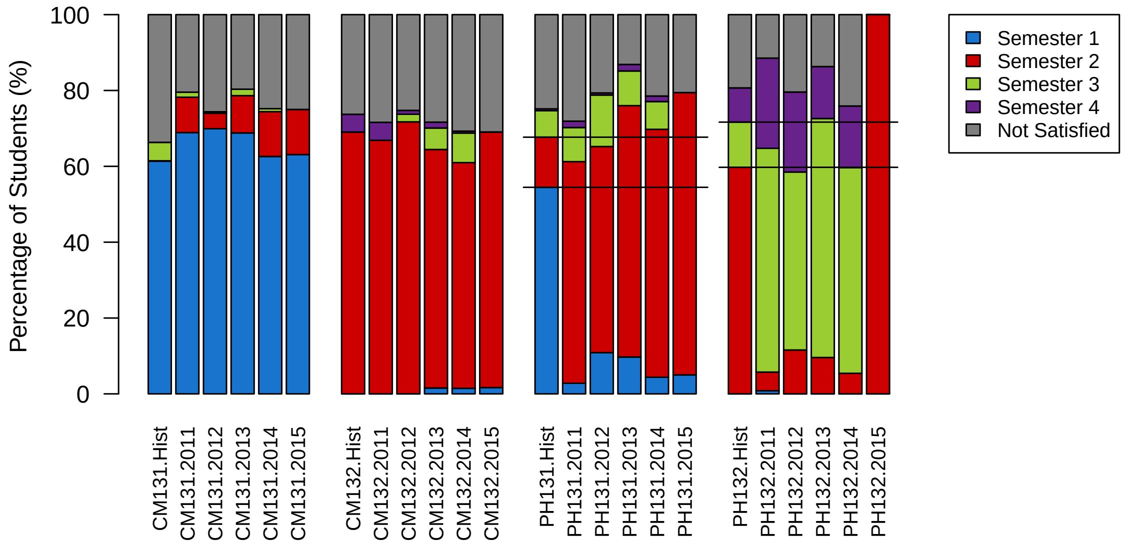


Figure 5.7: Bar Plots of Targeted High-Risk Student Progress Through Early STEM Courses: Chemistry and Physics

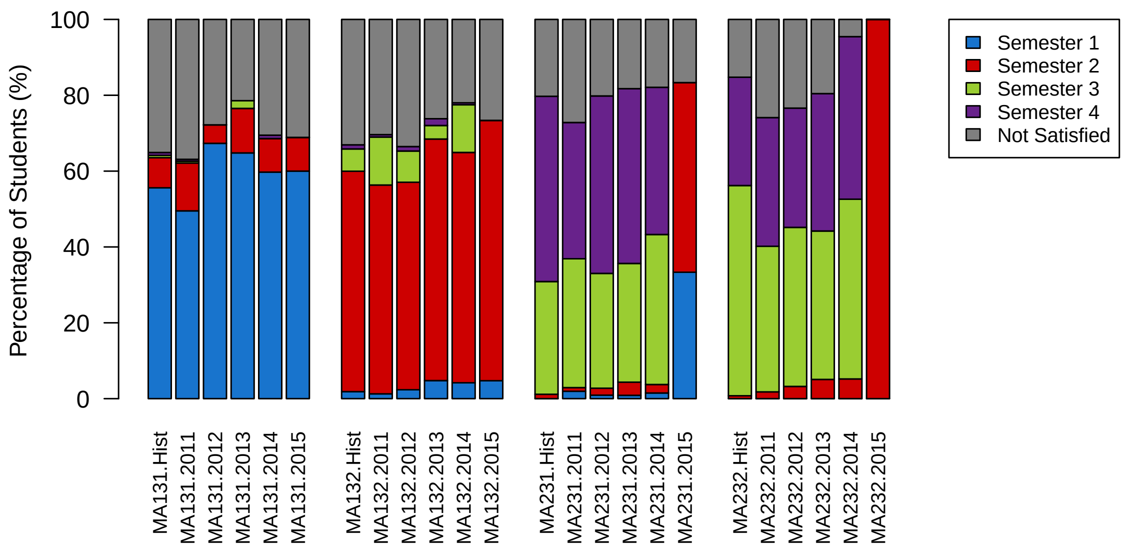


Figure 5.8: Bar Plots of Targeted High-Risk Student Progress Through Early STEM Courses: Math

Quantitative View of Student Progression Through Early STEM Courses

In this study, we developed a quantitative view of the efficiency of student progression through the Early STEM courses. This view allows for a measure of student success, and also allows students to have a measure of how they are progressing, when compared to the engineering majors of their cohort, and to the rest of their major.

The view shows the pathway that a student takes through the Early STEM courses, and compares it to the "ideal" pathway. This comparison comes in the form of both a visual and numerical measurement. The "ideal" pathway is based on the Common First-Year Curriculum in Engineering,[43] previously shown in Table 3.1, prior to the delay of physics. Extending this curriculum to further semesters, an ideal pathway through all of our identified seven Early STEM courses can be seen, as shown in Table 5.6. Because of the greater choice of alternate courses for Chemistry II, including a Biology course, it is not included in this view.

The average Early STEM courses passed for the engineering students and the

Table 5.6: "Ideal" Pathway for Engineering Majors

	Early STEM Courses	Cumulative Number of Early STEM Courses
Semester 1	CM131 MA131 PH131	3
Semester 2	MA132 PH132	5
Semester 3	MA231 or MA232	6
Semester 4	MA231 or MA232	7

specific major are calculated in such a way so as to remove those students that have stopped progressing through the courses. Figure 5.9 summarizes the steps to calculate the mean Early STEM courses successfully passed. To better illustrate the process, the steps taken are presented as pseudocode:

(comments are presented in parentheses)

- Load Table (Start with a table of cumulative Early STEM courses passed for all student in view, j rows by 8 columns)
- FOR each student, j (Start a loop that will go through each student, with an index of j, to run until j goes over the total number of students, N)
  - Set $i = 1$ (Start with the first semester)
  - FOR each semester, i (Start a loop that will look at each semester in turn, ending when semester i goes over 8)
    - IF $S_i = S_8$ (Check to see if the cumulative number of courses passed equals cumulative number at semester 8)
      - IF YES move to next step
      - IF NO $S_i = S_i$ (Keep current value of attempts, the student has stopped progressing.)
    - IF Attempts ≥ 7 (Check to see if student attempted to pass all seven courses)
      - IF YES $S_i = S_i$ (Keep current value of attempts, the student has stopped progressing.)
      - IF NO move to next step
    - IF $S_i = S_{i-1}$ (Check to see if attempts in current semester are the same as the previous one. This is to record the furthest attempt.)
      - IF YES move to next step
      - IF NO $S_i = S_i$ (Keep current value of attempts, the student has stopped progressing.)
    - IF Attempted S_i (Check to see if student attempted to pass in the current semester)
      - IF YES $S_i = S_i$ (Keep current value of attempts, the student has stopped progressing.)
      - IF NO $S_i = NA$ (Takes current and future semesters out of the calculation for that student.)
    - $i = i + 1$ (Advance the semester number by one)
  - $i > 8 \Rightarrow j = j + 1$ (When all 8 semesters are looped through, advance to the next student)
- $j > N$ students $\Rightarrow$ END (When all students have been looped through, end the calculation)

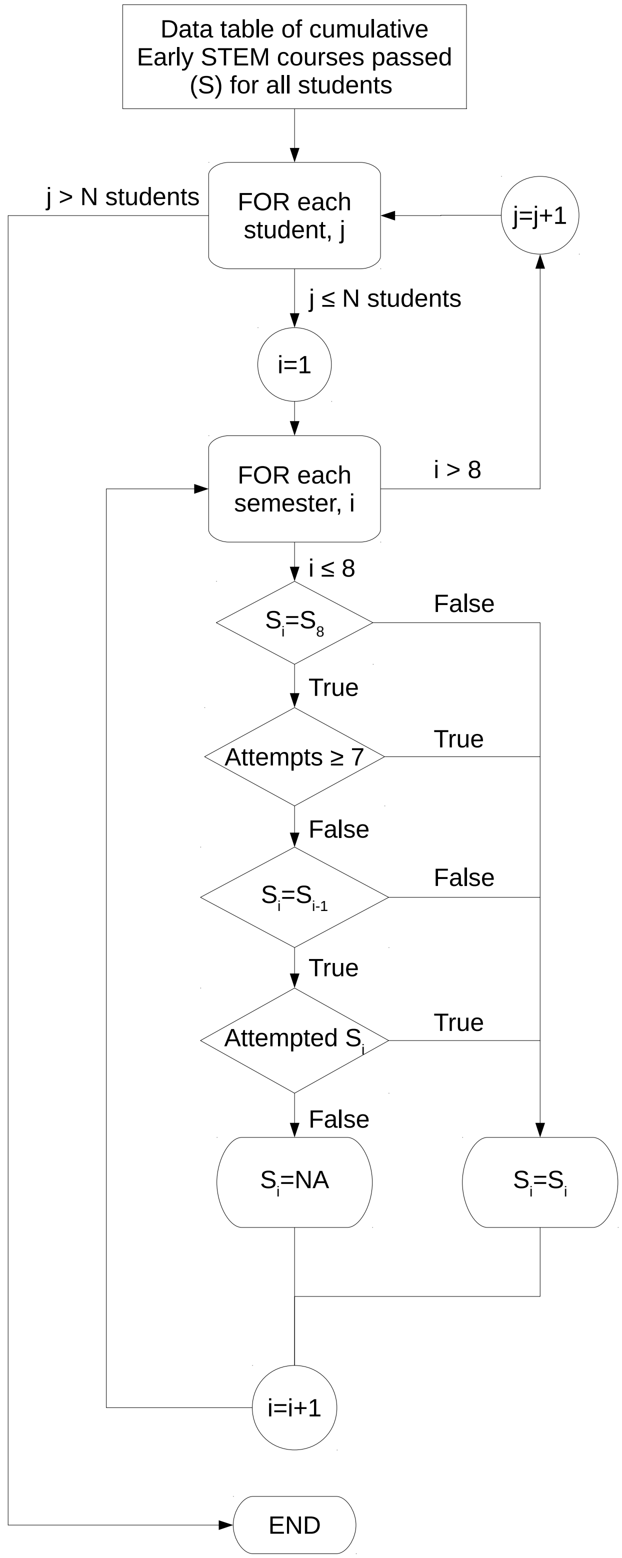


Figure 5.9: Flowchart of the Calculation of the Cumulative Average Number of Early STEM Courses Passed for Various Groups of Students

The view consists of two pieces: a numerical piece, and a graphical. The numerical portion of the view is given by how close to the "ideal" pathway the measured entity (student, ENG cohort, major, etc.) gets for each semester, i.e. what fraction of the "ideal" number of STEM courses passed has a student reached in a semester? The efficiency of the measured entity is based on the equation for mechanical efficiency, seen in Equation (5.1).

$$Efficiency = \frac{Measured\ Performance}{Ideal\ Performance} \tag{5.1}$$

The efficiency is calculated at each semester according to Equation (5.1), and included in a table attached to the plot. A student does not need to reach 100% efficiency to graduate with their chosen degree. The graphical piece of the view consists of the pathways that students take when progressing through the Early STEM courses. The average number of Early STEM Courses passed ($\bar{S}_i$ from the flowchart and description above) are plotted against the semester number (i from the flowchart and description above). A thick gold line represents the "ideal" pathway for an engineering student, described in Table 5.6, while the different colored pathways represent the progression of the students or majors that are being studied. The efficiency of the progression of the students is represented by how close to the "ideal" line the students get. Together, the two pieces compliment each other when performing an analysis.

This view can be used to evaluate the effects of the delayed physics program on student progression through the Early STEM courses. Figure 5.10 shows the view applied to the Targeted High-Risk engineering students in each cohort, with the fractional efficiencies shown in Table 5.7. The historical baseline is represented in red, while the treatment cohorts are shown in "cooler" colors, for contrast.

With the historical cohort establishing a baseline, the effects of the delayed physics

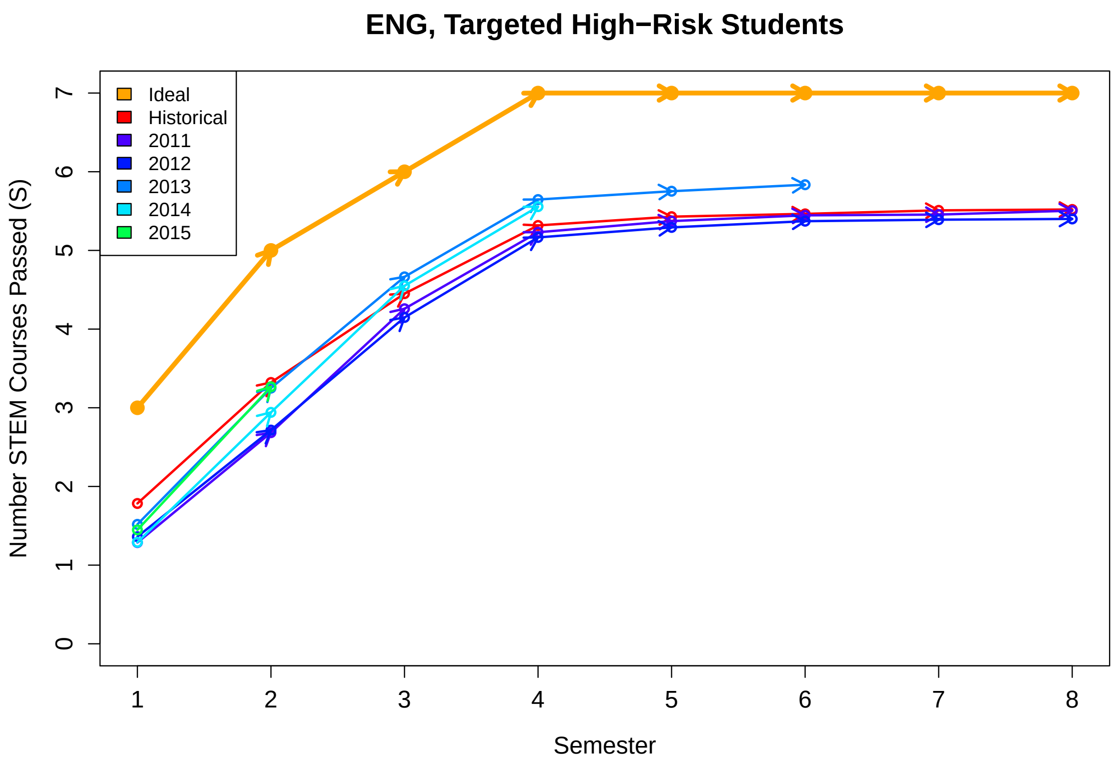


Figure 5.10: View Applied to Targeted High-Risk Engineering Students in Each Cohort. Note that the students in the treatment cohorts have caught up to or surpassed their historical counterparts by the 3rd or 4th semester.

program become apparent. Each of the treatment cohorts start below the historical baseline, since those cohorts only took two Early STEM courses in their first semester, as opposed to three in the historical cohort. The 2011 and 2012 cohorts most resemble the historical cohort after four semesters, almost reaching the same efficiency. As has been stated before, these two years can be thought of as "transition" years, with outside effects overshadowing the positive effects of the treatment. In the most recent cohorts, these positive effects can more readily be seen. The 2013 and 2014 cohorts have *surpassed* the historical baseline by the end of the third semester, and the 2015 cohort seems to be on track to do so as well. While more data are needed to see if this trend continues to hold true, the current results are promising. The engineering students in the treatment program are progressing through the Early STEM course

Table 5.7: Fractional Efficiencies of Targeted High-Risk Engineering Students by Cohort for each Semester: see Figure 5.10

Cohort	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Semester 6	Semester 7	Semester 8
Historical	0.595	0.664	0.742	0.76	0.776	0.781	0.787	0.789
2011	0.429	0.537	0.71	0.747	0.768	0.778	0.779	0.786
2012	0.454	0.543	0.691	0.738	0.756	0.767	0.77	0.771
2013	0.506	0.65	0.777	0.807	0.822	0.834	-	-
2014	0.43	0.588	0.758	0.794	-	-	-	-
2015	0.483	0.653	-	-	-	-	-	-

sequence at a higher rate, and therefore with more efficiency, than similar students have historically.

The progression of the cohorts reaches eight semesters at approximately five STEM courses passed. This is mainly due to the fact that some students will continue on, even if they received below 2.0 GPs. This can be seen by changing the "passing" GP to 1.0, and running the view again. Figure 5.11 shows the result of the change in the passing GP. The progression of each cohort is much closer to the ideal level of seven STEM courses passed. Similar effects to those seen in Figure 5.10 can be observed in this setup as well. The first two years of the delayed physics program are close to the historical baseline, while subsequent years "catch up" or surpass by the fourth semester.

The view can also be applied to individual students to show their progression when compared to their classmates. Two examples of the view applied in this manner can be seen in Figures 5.12 and 5.13. For anonymity, these two students in the historical cohort will be referred to as "Student A" and "Student B" in the course of this study. Both are engineering students, in the M-,P- group, and were unsuccessful in PH131 in their first semester. They would be counted in the THR group, if they were in a treatment cohort. The blue line represents the cumulative number of Early STEM

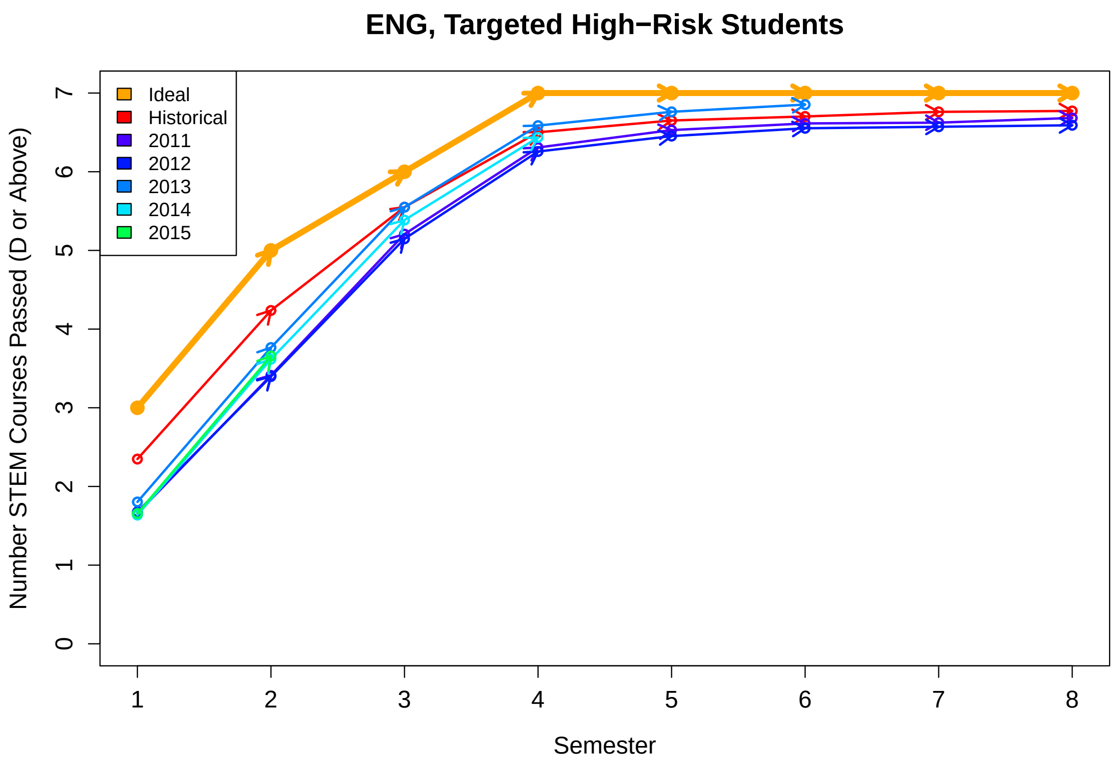
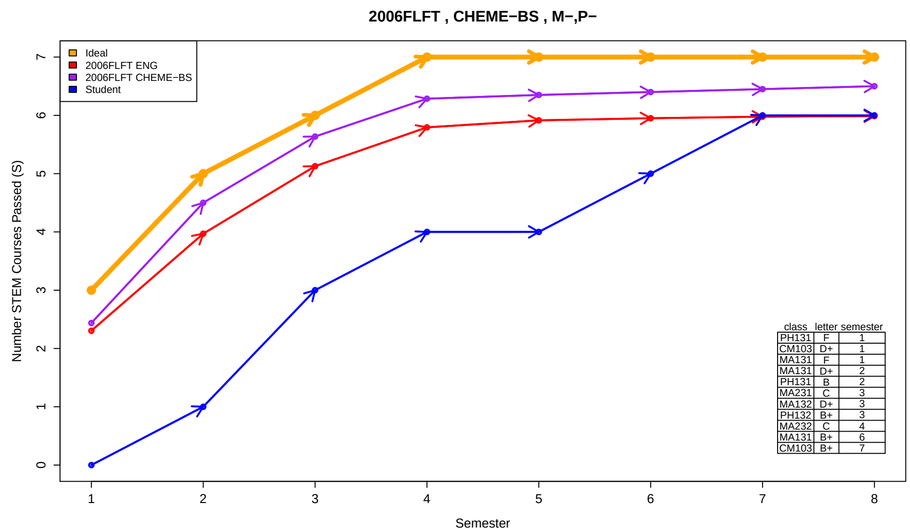


Figure 5.11: View applied to Targeted High-Risk engineering students in each cohort with the "passing" GPA changed to a 1.0. Note how the gap between the actual student performance and the "ideal" performance has shrunk.

courses that the student passed in each semester. The red line represents the average number of Early STEM courses passed by the engineering students in that cohort, while the purple line represents the same, but for the specific major that the student is in. The efficiencies of the individual student, the engineering program, and the student's major are calculated as well. If a student finishes below a 100% efficiency, that does not mean that they do not graduate. In the example of Student A, this student did graduate with their intended degree of Chemical Engineering, and having been successful (by the definition of this study) in only six of the seven Early STEM courses examined in this view.

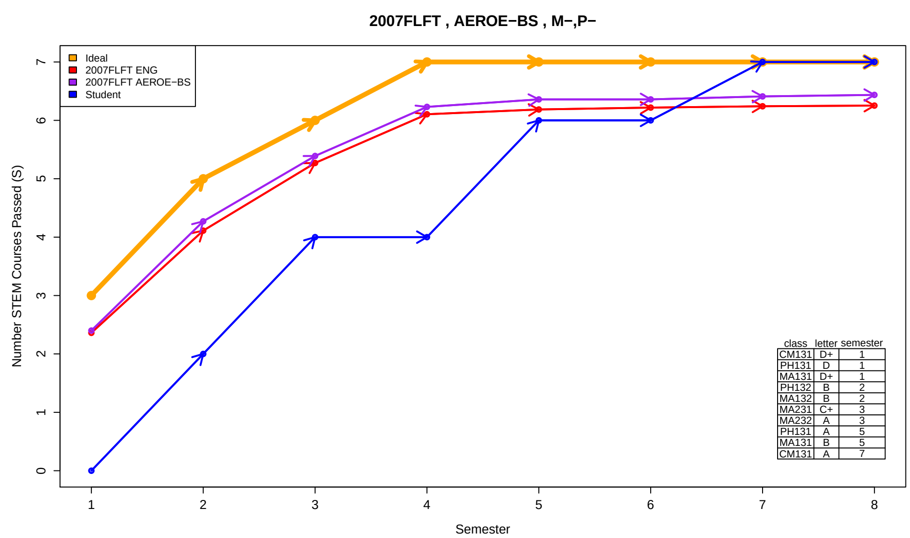
This view, while still in the preliminary stages, can prove useful to students and



Fractional Efficiencies

	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Semester 6	Semester 7	Semester 8
Student	0	0.2	0.5	0.571	0.571	0.714	0.857	0.857
2006FLFT ENG	0.768	0.794	0.855	0.828	0.845	0.85	0.854	0.855
2006FLFT CHEME−BS	0.812	0.9	0.939	0.898	0.907	0.914	0.921	0.929

Figure 5.12: View applied to "Student A", showing the individual pathway that the student took.



Fractional Efficiencies

	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Semester 6	Semester 7	Semester 8
Student	0	0.4	0.667	0.571	0.857	0.857	1	1
2007FLFT ENG	0.787	0.822	0.878	0.872	0.884	0.888	0.892	0.893
2007FLFT AEROE−BS	0.8	0.854	0.898	0.89	0.908	0.908	0.916	0.919

Figure 5.13: View applied to "Student B", showing the individual pathway that the student took.

educators. Using the individual view gives a student and their advisor a more readily available look at how the student in progressing when compared to others. The view can be tailored to include students in certain programs, even non-academic ones, such as sports teams and clubs.

The next stage for this view would be to turn it into a model that can predict the likelihood of a student taking a certain pathway, based upon their pre-college scores and even grades from first-year courses. This would allow for advisors and administrators to more strategically intervene, if it appears that the current pathway will not work for the student. This would open new alternate pathways for students to navigate, and would be based upon historical data.

Student Retention

We are able to compare historical retention rates with those of the subsequent cohorts. Table 5.8 and Figure 5.14 summarize the second year retention data that we have collected so far, for the entire university and for the engineering students (ENG).

Table 5.8: Second Year Retention in the University Data

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
University	Historical	629	538	85.53	2671	2317	86.75
	'11-'14	682	607	89.00	2238	1991	88.96
ENG	Historical	629	538	85.53	1286	1125	87.48
	'11-'14	682	607	89.00	1198	1104	92.15

Comparing the rates of the historical cohort to the treatment cohorts, the strategic placement of incoming STEM students appears to affect student retention in the university. The Targeted High-Risk students experienced an increase in their reten-

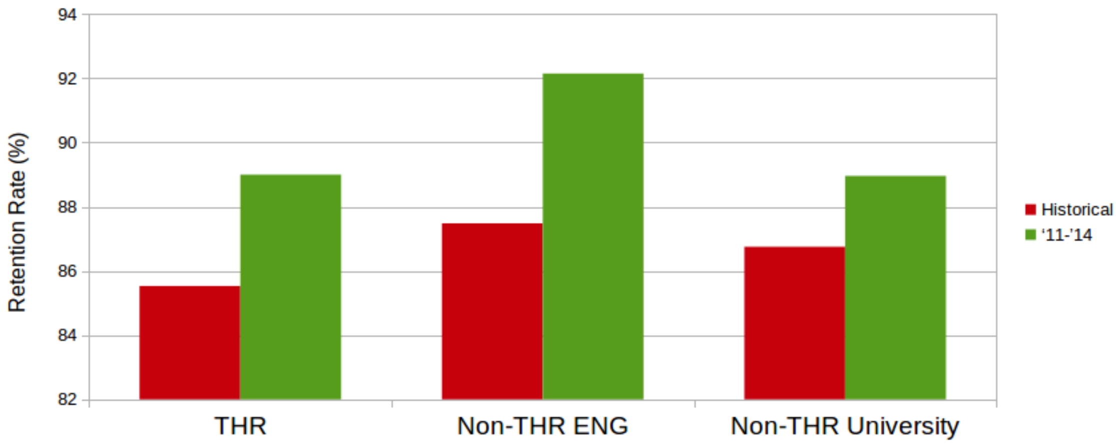


Figure 5.14: Second Year Retention in the University Data

tion rates, by approximately 4%. The delayed physics program may not be the only factor in the retention increase, as the Non-THR students also experienced a significant increase.

Along with measuring the retention of students at the university we measure retention in STEM. A student may remain enrolled in the university, but may have changed their major to a non-STEM degree. Table 5.9 and Figure 5.15 show the second year retention in STEM data for the engineering majors (ENG), and for the entire university. Here, the effects of the delayed physics program can more readily be seen where the THR students experienced an increase in retention rates of approximately 7%. This means that of the approximately 86% of THR students that were retained in the university, approximately 94% of them stayed in a STEM major, as opposed to the historical rate of 89%. The strategic placement of incoming STEM students has had significantly more students stay in STEM through their first, critical, year when compared to the historical first year curriculum for all.

Retention into the third year is less of a concern as second year retention, where the pre-entry academic preparedness student attributes affecting retention give way to a students institutional experience.[64] This is seen locally in Table 5.10 and Fig-

Table 5.9: Second Year Retention in STEM Data

	Cohort Group	Targeted High-Risk N	Targeted High-Risk N Retained	Targeted High-Risk % Retained	Non-THR N	Non-THR N Retained	Non-THR % Retained
University	Historical	629	480	76.31	2671	1627	60.91
	'11-'14	682	568	83.28	2238	1626	72.65
ENG	Historical	629	480	76.31	1286	1076	83.67
	'11-'14	682	568	83.28	1198	1084	90.48

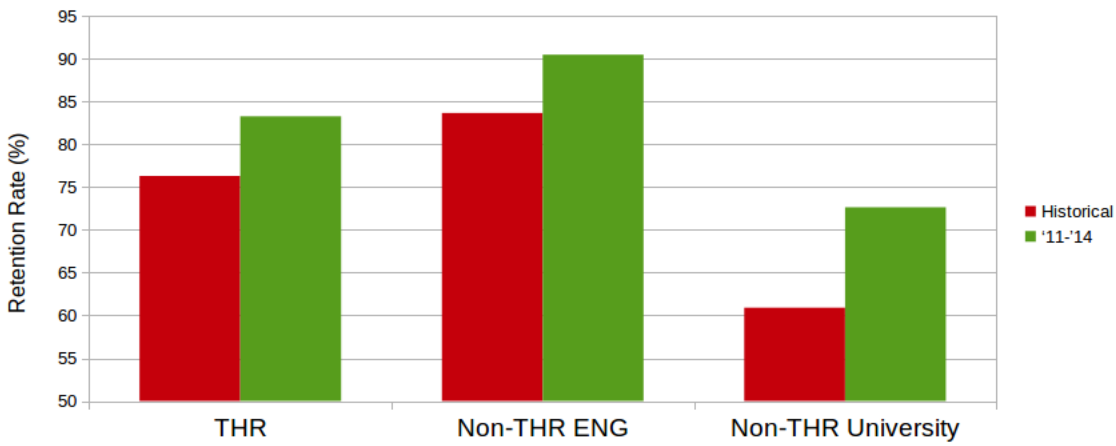


Figure 5.15: Second Year Retention in STEM Data

ure 5.16, once a student has stayed in both the university and STEM through to their second year, they are highly likely to continue through to their third year. The students that are included in the third year retention in the university data are those students who have already been retained through their second year. The university was historically retaining students into their third year at a rate above 90%. That rate rose approximately 2% in the subsequent cohorts. A similar trend is seen in the engineering students. The THR students did see an increase of approximately 4% in their third year retention rates, compared to the Non-THR university rate increase of 1%.

To ensure that the differences in the retention rates are statistically significant, a Wilcoxan Rank Sum test was run to compare the historical cohort to the treat-

Table 5.10: Third Year Retention in the University. Only students retained through to their second year are included.

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
University	Historical	538	472	87.73	2317	2117	91.37
	'11-'13	418	382	91.39	1527	1414	92.60
ENG	Historical	538	472	87.73	1125	1043	92.71
	'11-'13	418	382	91.39	841	787	93.58

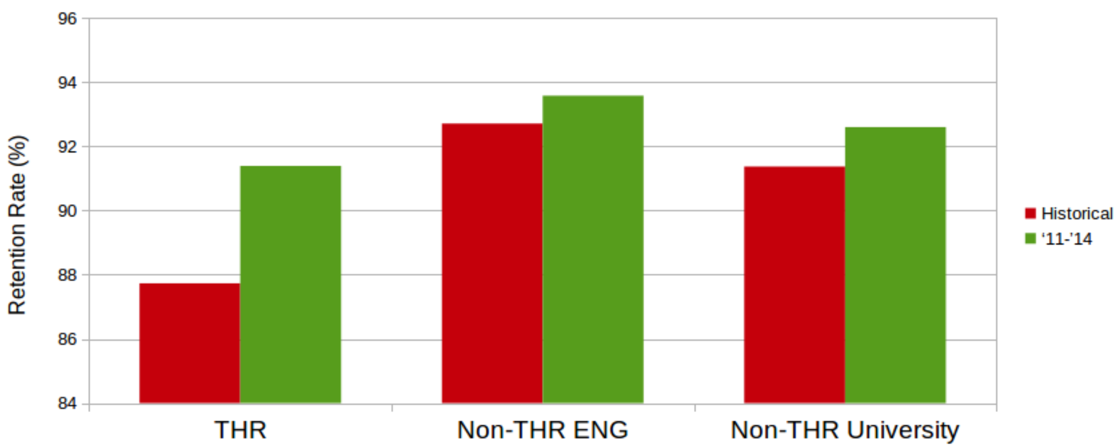


Figure 5.16: Third Year Retention in the University. Only students retained through to their second year are included.

ment cohorts. The Wilcoxan Rank Sum test is similar to the Student's t-test, in that it can be used to determine if two sets of data are significantly different from each other. However, the Wilcoxan Rank Sum test is nonparametric, and therefore does not assume that the data sets follow a normal distribution. This is important, as the retention data for each individual student is binary (retained=1, not retained=0). The results are still given as a p-value, which gives a numerical value to the significance of the differences in the data sets. The p-values are summarized in Table 5.11.

The increase in retention in the university rates for the THR students, both for second and third year retention, are significant. This means that the increases cannot be explained by random variations in the data. The increase in the second year retention rates for the Non-THR students were also significant, both for the university as

Table 5.11: P-values for Retention Rates Between the Historical Cohort and Treatment Cohorts. Values showing a significant difference (α=0.1) are highlighted.

2nd Year Retention in the University		
	Targeted High-Risk	Non-THR
University	0.03858	0.01829
ENG	0.03858	0.0001263
2nd Year Retention in STEM		
	Targeted High-Risk	Non-THR
University	<0.0001	<0.0001
ENG	<0.0001	<0.0001
3rd Year Retention in the University		
	Targeted High-Risk	Non-THR
University	0.06957	0.1719
ENG	0.06957	0.4532

well as the engineering students. This is strong evidence that the strategic placement of incoming STEM students, as well as other curriculum modifications mentioned in an earlier chapter, are helping students stay in the university, and stay in STEM.

The rates for retention in STEM have shown significant increases for all students. This means that more students are staying in a STEM degree through to their second year, and that the increases are not due to random variations. The curriculum modifications are helping to keep students in a STEM degree.

The increases in the third year retention in the university rates are significant for the THR students, but not for the Non-THR students. This is strong evidence that the strategic placement of incoming STEM students affects this increase. The rates for the non-treated students did increase, but they were not statistically significant.

Student Persistence

The goal is to persist through undergraduate courses to the completion of an undergraduate degree. Table 5.12 shows completion data for *any* undergraduate degree. We examine only the historical cohort as well as the first two treatment cohorts, as they are the only cohorts, to date, to reach the standard completion time of eight semesters.

Table 5.12: Completion Data for 8 Semesters, from the University

	Cohort	N THR	N Non-THR	N THR 8 Semesters	% THR 8 Semesters	N Non-THR 8 Semesters	% Non-THR 8 Semesters
ENG	Historical	805	1827	440	54.66	1235	67.60
	2011	198	518	97	48.99	369	71.24
	2012	215	407	126	58.60	296	72.73
Non-ENG	Historical	0	1107	0	-	746	67.39
	2011	0	306	0	-	189	61.76
	2012	0	259	0	-	193	74.52
All STEM	Historical	805	2934	440	54.66	1981	67.52
	2011	198	824	97	48.99	558	67.72
	2012	215	666	126	58.60	489	73.42

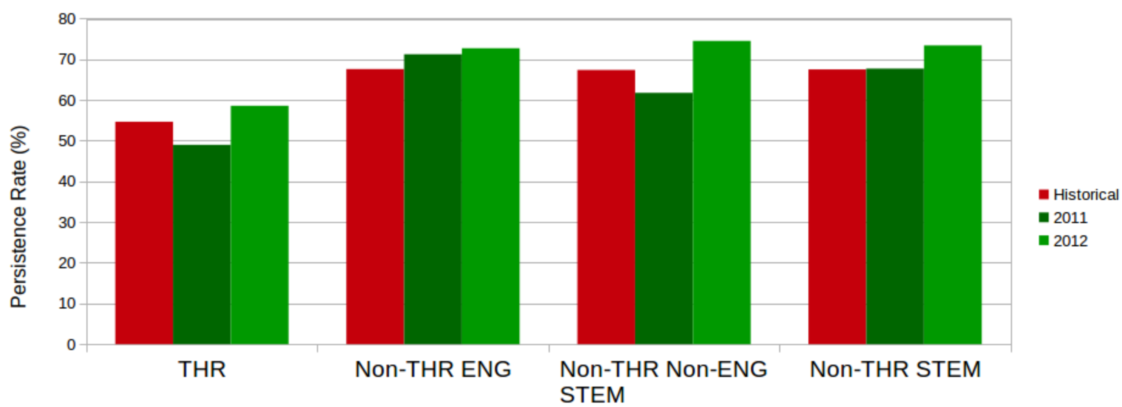


Figure 5.17: Completion Data for 8 Semesters, from the University

With only two treatment cohorts to examine, more data are needed to make full conclusions. Examining the data that we do have, the results do look positive. While the treated engineering students did experience an approximately 5% decrease in 2011, there was an approximately 4% *increase* over the historical cohort in 2012. Data for the next cohort (2013) to reach eight semesters may reveal a more meaningful trend. For the untreated engineering students, a trend is already starting to emerge.

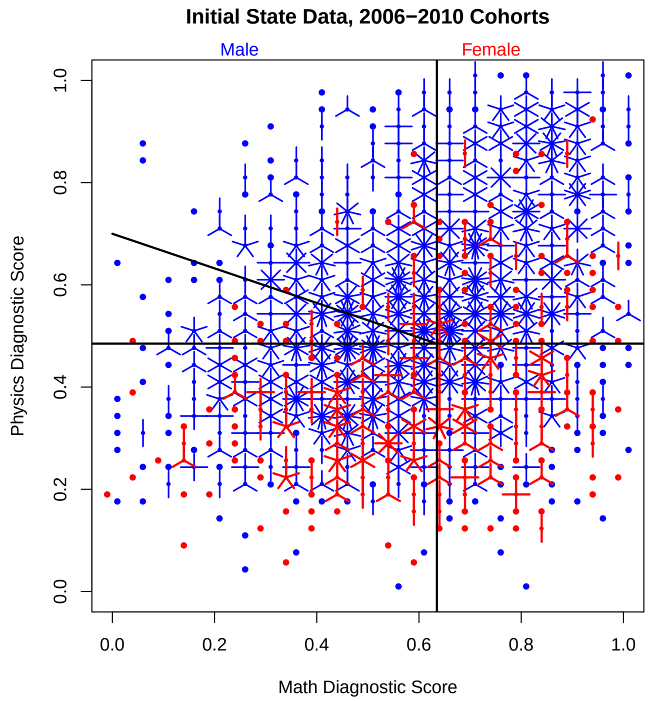
There has been a relatively sharp increase between the historical and 2011 cohorts of approximately 4%, with an approximately 1.5% increase over the already increased completion rate.

Chapter 6

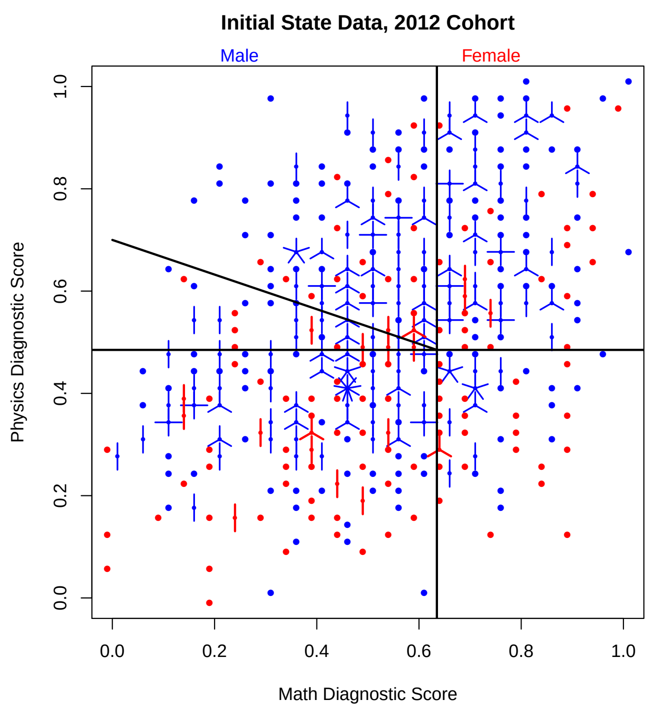
Analysis of Intervention Disaggregated by Gender and Race/Ethnicity

Disaggregation by Gender

The analysis that was performed was disaggregated by the gender that students indicated upon arrival at Clarkson. The gender data gathered from incoming students by the Admissions office is binary, either male or female. We acknowledge that some students may be non-binary gender, however we do not have a way to identify them based upon the data that we have. Table 6.1 shows the population of undergraduate students at Clarkson by cohort. The population of Clarkson University seems to be trending towards an increase of female students, however slightly, in recent years. Both genders have seen an increase in the percent of students being treated by the strategic placement of incoming STEM students. This follows the general trend seen by the program.



(a) MP Plot of the Historical Cohort, Divided by Gender



(b) MP Plot of the 2012 Cohort, Divided by Gender

Figure 6.1: MP Plots Divided by Gender

Table 6.1: Gender Demographics at Clarkson University by Cohort

Cohort	N Male	N Male THR	% Male	% Male THR	N Female	N Female THR	% Female	% Female THR
Historical	2549	500	72.62	19.62	961	125	27.38	13.01
2011	597	113	71.07	18.93	243	34	28.93	13.99
2012	540	138	71.71	25.56	213	30	28.29	14.08
2013	506	122	68.94	24.11	228	30	31.06	13.16
2014	517	146	68.12	28.24	242	49	31.88	20.25
2015	544	152	70.47	27.94	228	50	29.53	21.93

Figures 6.1a and 6.1b show the distribution of the math and physics diagnostic scores divided by gender, for the historical cohort and an example treatment cohort respectively. The points representing the students of either gender have been shifted slightly to prevent over-plotting. The female students appear to be distributed lower on the physics scale in the historical plot, meaning on average a lower score. Figure 6.2 show boxplots of the distribution of the survey scores by gender. There is almost no difference in the math diagnostic scores between the genders, however there is a noticeable difference of approximately 16% in the physics diagnostic scores. This is consistent with what the literature and research has shown in regards to a gender bias in the Force Concepts Inventory.[65]

Analysis of Student Success by Gender

The data on success in Early STEM courses has been disaggregated by gender. Table 6.2 shows the unsatisfactory (U) rates for the first semester Early STEM courses. In CM131, Non-THR students of male or female gender did not experience much of a change. However, the male Targeted High-Risk students experienced a %U average of 28.5%, compared to the historical average of 40.2%. The female students did experience a decrease as well, from 33% historically to 28.3%. In MA131, the THR students of a gender experienced a large decrease, approximately 20% for the most

Figure 6.2: Distributions of Scores on the Diagnostic Surveys by Gender

recent cohort (2015). The Non-THR students of a gender saw improvement as well, but not as pronounced as the THR students. A similar effect was seen in PH131 for a gender; the THR students experienced a greater improvement than the Non-THR students.

The pattern that was seen in the first semester chemistry course, was reflected in the second semester, for CM132. The THR students of both genders experienced a greater improvement over the historical unsatisfactory rates. The Non-THR students seem to be maintaining the historical rates. In MA132, differences in the unsatisfactory rates between the genders start to show. The male students, in the most recent cohorts, have seen an improvement, though not as much as for the first semester math course. This holds true for both the THR an Non-THR students. The THR female students at first seemed to be in a decline, with unsatisfactory rates rising above the historical baseline, but have returned to a similar rate in the most recent cohort. The Non-THR female students also experienced a fluctuation before returning to a similar rate. THR students of both genders experienced a fluctuating trend of rates for the

Table 6.2: Unsatisfactory (U) Rates for First Semester (First Attempt) Early STEM Courses, by Gender. Rates for Targeted High-Risk students in PH131 are for the second semester.

		CM131		MA131		PH131	
Sex	Cohort	%U(N) THR	%U(N) Non-THR	%U(N) THR	%U(N) Non-THR	%U(N) THR	%U(N) Non-THR
M	Historical	40.2(188)	23.3(194)	46.2(224)	29.1(182)	39.1(194)	18.4(139)
	2011	26.2(28)	20.3(42)	48.6(52)	31.9(75)	24.2(24)	17.4(41)
	2012	33.1(41)	19.9(39)	33.9(43)	20.0(33)	30.0(33)	10.9(23)
	2013	20.8(21)	22.1(42)	26.4(29)	21.5(37)	7.6(8)	8.9(17)
	2014	32.8(43)	18.6(33)	38.9(51)	25.3(45)	18.2(22)	8.6(19)
	2015	29.9(40)	23.4(48)	25.9(35)	22.0(37)	11.9(14)	12.6(22)
F	Historical	33.0(36)	23.6(13)	38.8(45)	28.1(32)	37.6(47)	23.9(44)
	2011	37.5(12)	22.9(14)	47.1(16)	29.9(15)	34.4(11)	25.0(12)
	2012	20.0(5)	15.0(7)	17.2(5)	12.1(5)	10.0(2)	8.8(4)
	2013	26.1(6)	14.9(12)	20.8(5)	14.0(4)	19.2(5)	3.0(1)
	2014	33.3(15)	20.0(15)	31.8(14)	12.8(9)	19.6(9)	9.0(6)
	2015	24.4(10)	26.0(18)	18.4(9)	16.2(5)	17.8(8)	16.7(7)

treatment cohorts in PH132. This, along with the less extreme fluctuations for the Non-THR students, follows the same trend seen earlier in this chapter, in Table 5.2.

Additional data on GPs for each Early STEM course have been disaggregated by gender. The disaggregated data can be seen in Tables 6.4 and 6.5. In all three of the first semester Early STEM courses, treated male students have increased the mean GP over the historical baseline. The female treated students saw less of an increase in chemistry. In math and physics, the two courses thought to be affected most by the delayed physics program, the female treated students experienced a large increase in the mean GP of those courses. In physics, the mean GP rose by approximately one GP point in the most recent cohort for a gender. This corresponds to a whole letter grade increase for those students that were at higher risk for being unsuccessful in the course.

Table 6.3: Unsatisfactory (U) Rates for Second Semester (First Attempt) Early STEM Courses, by Gender. Rates for Targeted High-Risk students in PH132 are for the third semester.

		CM132		MA132		PH132	
Sex	Cohort	%U(N) THR	%U(N) Non-THR	%U(N) THR	%U(N) Non-THR	%U(N) THR	%U(N) Non-THR
M	Historical	29.1(104)	18.3(121)	35.6(123)	27.1(187)	21.1(67)	13.0(107)
	2011	33.3(28)	13.0(30)	32.5(25)	21.6(49)	8.06(5)	7.9(21)
	2012	28.9(28)	17.7(33)	41.1(39)	26.3(46)	22.67(17)	12.0(24)
	2013	36.1(31)	20.6(38)	24.5(24)	25.0(40)	13.33(12)	11.6(20)
	2014	35.3(36)	24.0(46)	29.8(31)	23.2(43)	27.00(27)	11.9(25)
	2015	17.5(17)	16.2(27)	28.2(31)	18.7(36)	-	12.3(22)
F	Historical	27.8(25)	16.2(16)	22.5(20)	17.1(25)	16.5(14)	6.4(12)
	2011	29.2(7)	15.5(11)	43.5(10)	28.0(16)	14.3(2)	7.1(4)
	2012	30.4(7)	9.1(6)	36.0(9)	11.0(5)	23.1(3)	10.2(6)
	2013	40.0(8)	13.0(8)	25.0(5)	9.1(5)	15.0(3)	4.5(3)
	2014	33.3(11)	15.4(9)	25.7(9)	16.0(10)	30.0(9)	5.0(3)
	2015	21.6(8)	15.5(9)	22.2(10)	19.1(7)	-	4.0(1)

In second semester chemistry, treated students of a gender experienced an increase in the mean GP. The increase was not as pronounced as the first semester. In math and physics, the male treated students did fluctuate, but mostly were above the historical baseline. The fluctuations of the female treated students were greater than the males, and oscillated between above and below the historical baseline.

Table 6.4: Mean GP in First Semester (First Attempt) Early STEM Courses, by Gender. GPs for treated students in PH131 are for the second semester.

		CM131		MA131		PH131	
	Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
M	Historical	1.87	2.53	1.81	2.42	1.79	2.70
	2011	2.20	2.61	1.79	2.40	2.32	2.60
	2012	2.11	2.66	2.28	2.85	2.19	3.00
	2013	2.45	2.67	2.63	2.82	2.93	3.14
	2014	2.20	2.75	2.12	2.54	2.83	3.22
	2015	2.17	2.57	2.30	2.75	2.82	3.11
F	Historical	2.09	2.51	2.02	2.48	1.84	2.52
	2011	2.11	2.52	1.90	2.38	2.05	2.5
	2012	2.44	2.82	2.90	3.30	2.65	3.10
	2013	2.26	2.79	2.58	3.09	2.62	3.22
	2014	2.10	2.72	2.26	2.92	2.76	3.25
	2015	2.41	2.45	2.61	2.80	2.82	2.84

Table 6.5: Mean GP in Second Semester (First Attempt) Early STEM Courses, by Gender. GPs for treated students in PH132 are for the third semester.

		CM132		MA132		PH132	
	Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
M	Historical	2.17	2.69	2.11	2.53	2.25	2.79
	2011	2.15	2.77	2.07	2.58	2.85	2.94
	2012	2.34	2.78	2.12	2.51	2.34	2.91
	2013	2.13	2.74	2.55	2.66	2.74	2.97
	2014	2.06	2.56	2.25	2.60	2.49	3.05
	2015	2.41	2.69	2.25	2.81	-	3.07
F	Historical	2.28	2.81	2.47	2.86	2.36	2.92
	2011	2.29	2.89	1.80	2.56	2.61	3.17
	2012	2.46	3.12	2.32	3.05	2.12	3.15
	2013	1.98	2.87	2.43	3.18	2.78	3.19
	2014	2.35	2.98	2.50	2.84	2.24	3.33
	2015	2.49	2.78	2.35	2.80	-	3.20

Analysis of Student Progression by Gender

The progression of each gender through the Early STEM courses can be examined in the same fashion as was done previously in this chapter. The bar plots showing progression through the chemistry and physics sequences for male and female students can be seen in Figures 6.3 and 6.4 respectively. Both genders showed an increase in the rate of students passing CM131 in their first semester. CM132 shows a maintenance of the rate of students passing in their second semester for the male students, while the female students show an increase. Each gender showed an increase in the number of students passing PH131 by the end of their second semester, while PH132 shows a maintenance of the third semester passing rates.

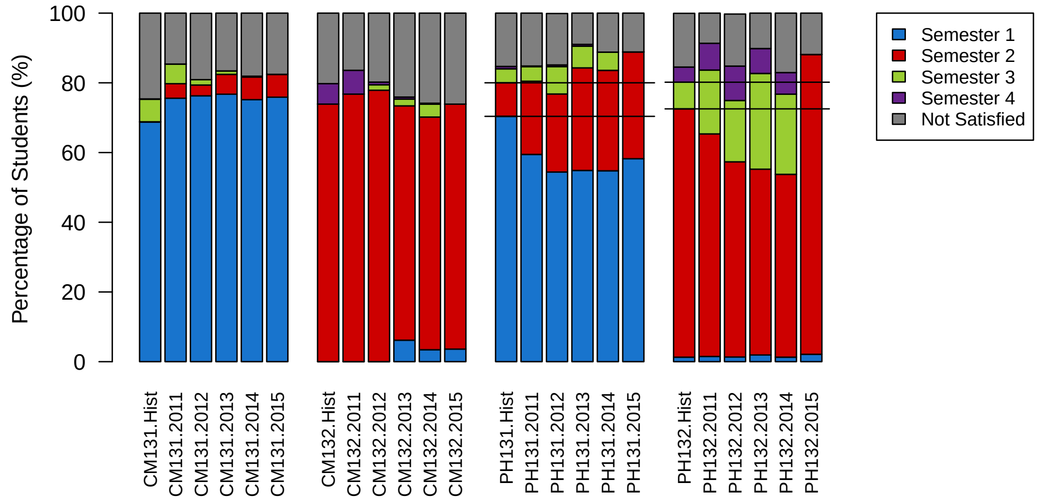


Figure 6.3: Bar Plots of Male Student Progress Through Early STEM Courses: Chemistry and Physics

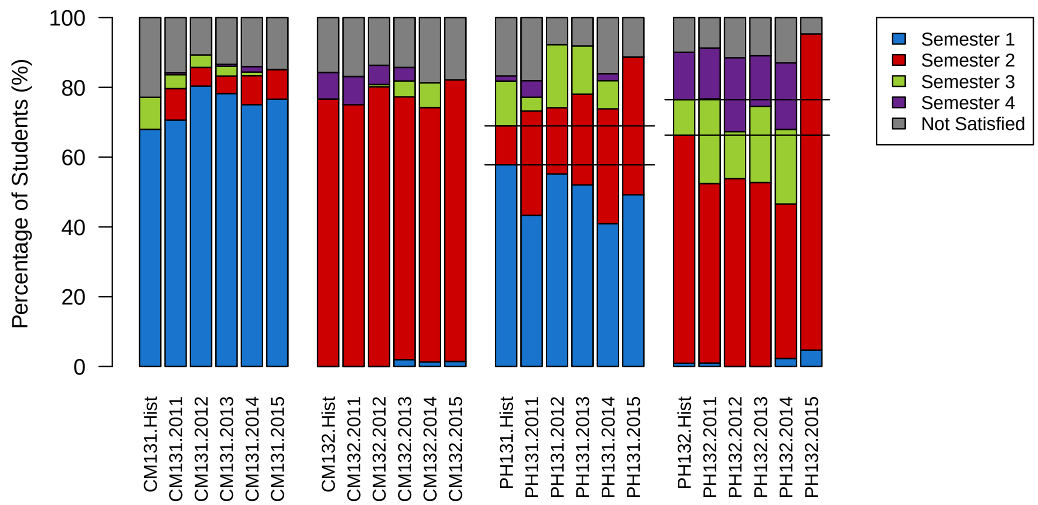


Figure 6.4: Bar Plots of Female Student Progress Through Early STEM Courses: Chemistry and Physics

The math sequence progression for male and female students can be seen in Figures 6.5 and 6.6, respectively. Each gender experienced increases in the number of students passing MA131 and MA132 in their first and second semesters respectively. Analysis of MA231 and MA232 is difficult on a semester by semester basis, since some students take MA231 in their third semester, while others take MA232. Thus, comparisons should be made of the fourth semester rates, for which each gender experienced either a maintenance or an increase.

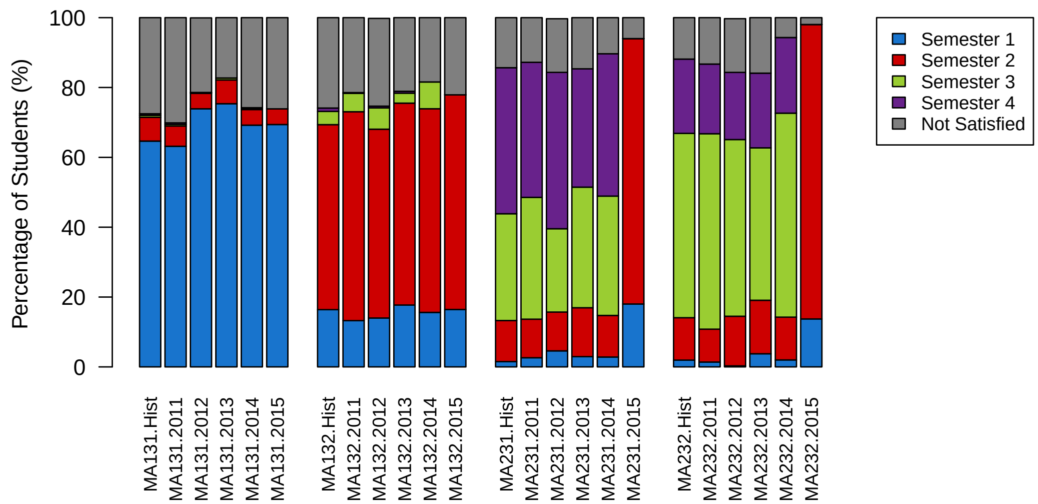


Figure 6.5: Bar Plots of Male Student Progress Through Early STEM Courses: Math

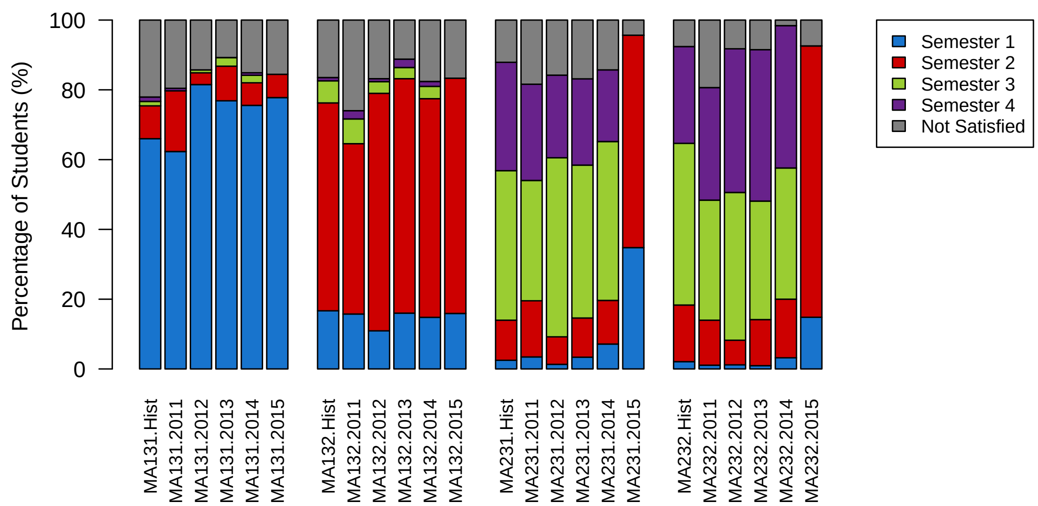


Figure 6.6: Bar Plots of Female Student Progress Through Early STEM Courses: Math

Quantitative View of Student Progression Through Early STEM Courses

The view of student progression presented earlier in the chapter was applied to each gender. Because of the nature of the view, only those students who were identified as High-Risk were included. Figures 6.7 and 6.8 show the visual "progression curves" of the treated engineering students of each gender, and Tables 6.6 and 6.7 show the corresponding fractional efficiencies. The male students in the more recent cohorts are surpassing the students in the historical cohort. They are passing more Early STEM courses by the end of their third semester than similar students did prior to the delayed physic program. The female students appear to be progressing through the Early STEM courses in a less efficient manner than the historical baseline. This may be due to small starting numbers. It also should be noted that this view does not reflect performance more precisely than a "pass" or "fail" designation.

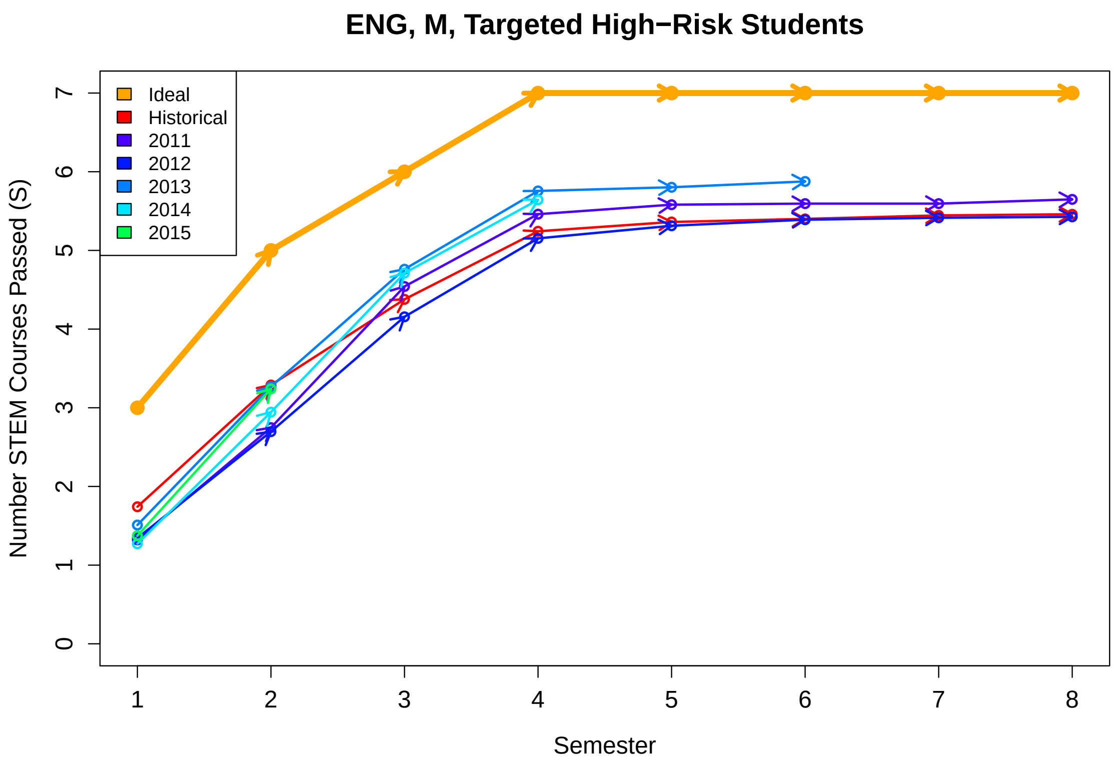


Figure 6.7: View Applied to Male Targeted High-Risk Engineering Students in Each Cohort

Table 6.6: Fractional Efficiencies of Male Targeted High-Risk Engineering Students by Cohort for each Semester: see Figure 6.7

Cohort(N)	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Semester 6	Semester 7	Semester 8
Hist.(500)	0.581	0.658	0.730	0.749	0.766	0.772	0.778	0.780
2011(109)	0.440	0.550	0.757	0.780	0.797	0.799	0.799	0.807
2012(122)	0.448	0.539	0.693	0.736	0.759	0.770	0.774	0.775
2013(104)	0.503	0.654	0.793	0.822	0.829	0.840	-	-
2014(118)	0.424	0.589	0.785	0.806	-	-	-	-
2015(115)	0.458	0.648	-	-	-	-	-	-

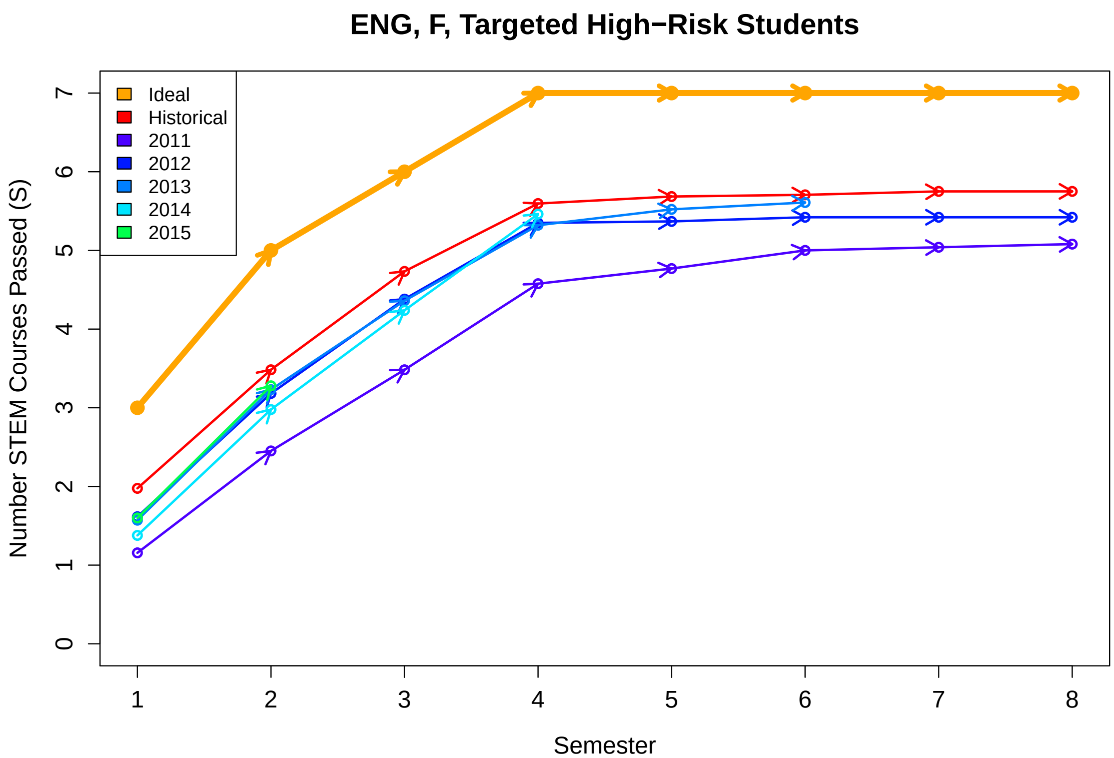


Figure 6.8: View Applied to Female Targeted High-Risk Engineering Students in Each Cohort

Table 6.7: Fractional Efficiencies of Female Targeted High-Risk Engineering Students by Cohort for each Semester: see Figure 6.8

Cohort(N)	Semester 1	Semester 2	Semester 3	Semester 4	Semester 5	Semester 6	Semester 7	Semester 8
Hist.(125)	0.659	0.697	0.789	0.799	0.812	0.815	0.821	0.821
2011(32)	0.385	0.490	0.580	0.654	0.681	0.714	0.720	0.726
2012(26)	0.538	0.636	0.730	0.764	0.767	0.774	0.774	0.774
2013(28)	0.524	0.646	0.727	0.760	0.789	0.801	-	-
2014(45)	0.459	0.595	0.706	0.780	-	-	-	-
2015(45)	0.533	0.656	-	-	-	-	-	-

Analysis of Student Retention by Gender

The second year retention data for the entire university were disaggregated by gender. Table 6.8 shows the disaggregation. Looking at the data, the rates for the THR female students has not changed by a significant amount. A small decrease did occur for the female THR students, but it is not a statistically significant decrease. Both the THR and Non-THR male students did experience increases in their retention rates, which were found to be statistically significant, as was the increase for the female Non-THR students.

Table 6.8: Second Year Retention in the University Data, Disaggregated by Gender. Only STEM majors were included in this table.

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
Male	Historical	500	421	84.20	1486	1206	81.16
	'11-'14	519	460	88.63	1351	1204	89.12
Female	Historical	125	114	91.20	333	271	81.38
	'11-'14	143	129	90.21	529	481	90.93

Table 6.9 shows the second year retention in STEM for all male and female students. Much like with the general population of the university, as well as the engineering students, greater, significant increases in the retention rates can be seen for each gender. The THR female students saw an increase of approximately 7%, while the THR male students saw an increase of approximately 8%. In the treatment cohorts, out of the 129 THR female students that were retained in the university, only one was not retained in STEM. Regardless of a student's gender, the strategic curriculum pathway improves their retention in STEM.

The third year retention in university rates that have been disaggregated by gender are shown in Table 6.10. The Non-THR female students experienced increases in their retention rates of approximately 3%. However, the female THR students

Table 6.9: Second Year Retention in STEM Data, Disaggregated by Gender. Only STEM majors were included in this table.

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
Male	Historical	500	375	75.00	1486	1065	71.67
	'11-'14	519	434	83.62	1351	1150	85.12
Female	Historical	125	103	82.4	333	257	77.18
	'11-'14	143	128	89.51	529	434	82.04

experienced a decrease in their retention rate, of approximately 3%. The THR male students saw an increase of approximately 4%, but the Non-THR male students experienced almost no change.

In order to see if the changes in retention rates were significant, or due to random

Table 6.10: Third Year Retention in the University Data, Disaggregated by Gender. Only students in STEM majors who were retained through to their second year are included.

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
Male	Historical	375	329	87.73	1190	1099	92.35
	'11-'13	311	286	91.96	890	827	92.92
Female	Historical	103	96	93.20	391	369	94.37
	'11-'13	82	74	90.24	320	311	97.19

variations, a Wilcoxan Rank Sum test was performed. Table 6.11 shows the p-values for the test performed between the historical cohort and the treatment cohorts, in the same fashion as Table 5.11. Like genders were compared to each other.

The effect of the delayed physics program on second year retention for male students shows that the changes in their retention rates are statistically significant. Looking at the significance of the changes in female student second year retention, the slight decrease in the rates are not significant.

Each gender shows the same pattern of significance in the second year retention in STEM data. The increases in the retention rates of the THR students are statistically

Table 6.11: P-values for Retention Rates Between the Historical Cohort and Treatment Cohorts, Disaggregated by Gender. Values showing a significant difference (α=0.1) are highlighted.

2nd Year Retention in the University		
	THR	Non-THR
Male	0.03773	0.03256
Female	0.7826	<0.0001
2nd Year Retention in STEM		
	THR	Non-THR
Male	0.0008579	<0.0001
Female	0.09317	<0.0001
3rd Year Retention in the University		
	THR	Non-THR
Male	0.02089	0.546
Female	<0.0001	0.08944

significant, and show strong evidence of the positive impact of the delayed physics program on retention in STEM. This also could suggest that the alternate STEM course (ES110) works well for any group, regardless of gender. The course could be increasing their interest in STEM.

For the male students, only those that were identified as High-Risk saw a significant increase in their third year retention in the university rates. The decrease in the rates for the female THR students was significant.

Analysis of Student Persistence by Gender

The disaggregation of the persistence data by gender is shown in Table 6.12. The rate at which male students have graduated from the university within eight semesters has maintained in the most recent cohort for which we have data. The Non-THR female student persistence rate has increased for the most recent cohort. For the THR students however, the rate has decreased, likely due to small numbers. It may be too early to give a meaningful conclusion about this effect, as it may be the result of a small population. Based upon the current data, it appears that delaying physics does not delay degree completion for a gender.

Table 6.12: Completion Data for 8 Semesters, from the University, by Gender

Sex	Cohort	N THR	N Non-THR	N THR 8 Semesters	% THR 8 Semesters	N Non-THR 8 Semesters	% Non-THR 8 Semesters
M	Historical	524	1652	253	48.28	983	59.50
	2011	120	449	56	46.67	274	61.02
	2012	141	353	70	49.65	212	60.06
F	Historical	132	580	82	62.12	421	72.59
	2011	36	149	15	41.67	104	69.80
	2012	31	138	16	51.61	106	76.81

Disaggregation by Race/Ethnicity

The analysis that was performed was disaggregated by race/ethnicity. The student population was divided into two groups, Underrepresented Minorities (URM), and Non-Under-Represented Minorities (NURM). Underrepresented minorities are defined[66] as:

- Black/African-American
- Hispanic/Latino
- American Indian, which includes:
  - Native American
  - Alaskan Native
  - Native Hawaiian

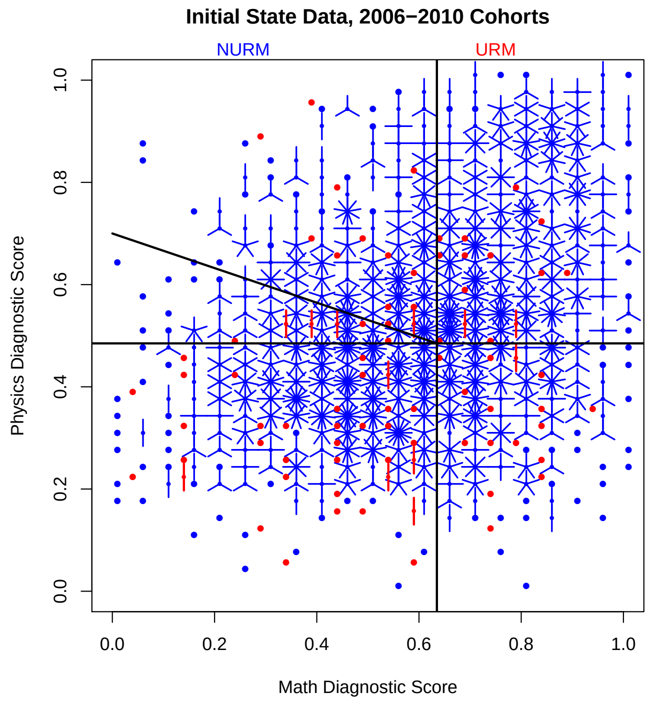
If a student did not indicate that they were part of any of these race/ethnicity groups, or if they did not specify their race/ethnicity, they were put into the NURM category. Table 6.13 shows the numbers and percentages of URM and NURM students at Clarkson University by cohort, as well as how many of each group was treated. The population of Clarkson University shows a decrease in the percentage of the population that identifies as an URM. The percent of students in the treatment program from each category is increasing, with the exception of the most recent cohort, 2015.

Figures 6.9a and 6.9b show the distribution of the math and physics diagnostic

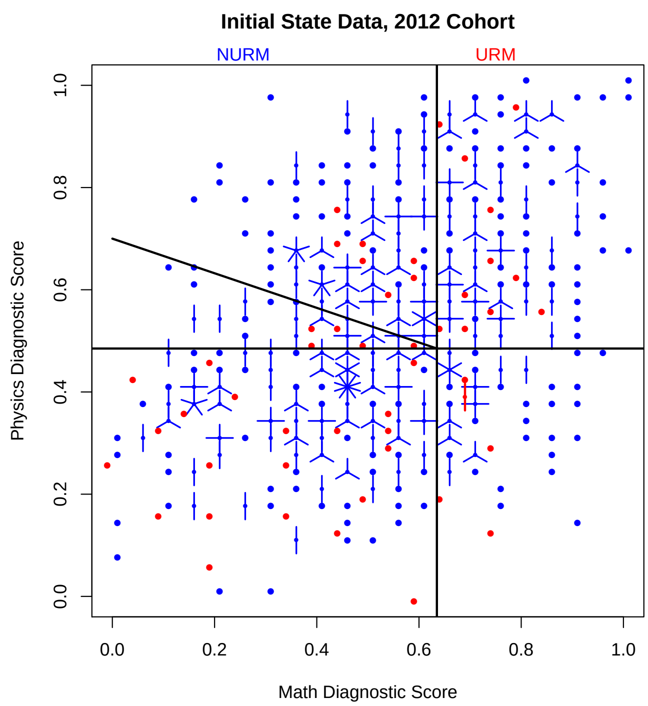
Table 6.13: Race/Ethnicity Demographics at Clarkson University by Cohort

Cohort	N URM	N URM THR	% URM	% URM THR	N NURM	N NURM THR	% NURM	% NURM THR
Historical	262	39	7.46	14.89	3248	586	92.54	18.04
2011	78	17	9.29	21.79	762	130	90.71	17.06
2012	69	15	9.16	21.74	684	153	90.84	22.37
2013	62	13	8.45	20.97	672	140	91.55	20.83
2014	67	21	8.83	31.34	692	174	91.17	25.14
2015	62	9	8.03	14.52	710	193	91.97	27.18

scores divided by race/ethnicity category, for the historical cohort and an example treatment cohort respectively. The points representing the students of either race/ethnicity have been shifted slightly to prevent over-plotting. Neither category seems to be concentrated in any particular MP group.



(a) MP Plot of the Historical Cohort, Divided by Race/Ethnicity



(b) MP Plot of the 2012 Cohort, Divided by Race/Ethnicity

Figure 6.9: MP Plots Divided by Race/Ethnicity

Analysis of Student Success by Race/Ethnicity

The Unsatisfactory rate data were disaggregated by race/ethnicity. These rates are summarized in Tables 6.14 and 6.15. In the first semester, all of the NURM students saw improvement over the historical baseline. The rates for the URM students fluctuated more than the NURM students. In chemistry and math, these fluctuations vary wildly, without a noticeable trend. In physics, the rates are almost consistently below the historical baseline, meaning more treated URM students are passing than historically.

Table 6.14: Unsatisfactory (U) Rates for First Semester (First Attempt) Early STEM Courses, by Race/Ethnicity. Rates for THR students in PH131 are for the second semester.

		CM131		MA131		PH131	
Race/Ethnicity	Cohort	%U THR(N)	%U Non-THR(N)	%U THR(N)	%U Non-THR(N)	%U THR(N)	%U Non-THR(N)
URM	Historical	33.3(12)	43.5(6)	43.2(16)	42.6(7)	50.0(19)	39.1(6)
	2011	41.2(7)	36.7(4)	62.5(10)	51.6(7)	52.9(2)	25.9(9)
	2012	40.0(6)	25.8(4)	60.0(9)	12.5(1)	27.3(4)	16.0(3)
	2013	37.5(3)	20.0(3)	23.1(3)	20.0(2)	23.1(2)	28.6(3)
	2014	61.9(13)	51.9(9)	38.9(7)	54.2(9)	31.3(4)	33.3(5)
	2015	37.5(3)	41.9(10)	62.5(5)	8.3(1)	33.3(4)	25.0(2)
NURM	Historical	39.2(212)	21.8(124)	44.9(253)	27.9(207)	38.1(222)	18.3(177)
	2011	27.1(33)	19.8(52)	46.4(58)	29.9(83)	22.8(51)	18.2(26)
	2012	29.9(40)	17.9(42)	27.7(39)	18.5(37)	26.9(23)	10.0(32)
	2013	20.7(24)	19.8(51)	25.6(31)	19.4(39)	8.4(16)	6.6(10)
	2014	29.0(45)	16.4(39)	36.9(58)	19.5(45)	17.2(21)	7.7(26)
	2015	28.1(47)	22.5(56)	22.2(39)	21.6(41)	12.7(25)	12.8(20)

For the second semester courses, the treated students in both race/ethnicity categories do not show clear trends in their Unsatisfactory rates. This is most likely due to the small number of treated URM students in each cohort. A similar pattern of fluctuations is seen in the untreated students of both race/ethnicity categories for CM132, and the untreated URM students for MA132. Untreated students of both race/ethnicity categories experienced an improvement in their rates for PH132, all falling below the historical baseline.

Table 6.15: Unsatisfactory (U) Rates for Second Semester (First Attempt) Early STEM Courses, by Race/Ethnicity. Rates for THR students in PH132 are for the third semester.

		CM132		MA132		PH132	
Race/Ethnicity	Cohort	%U THR(N)	%U Non-THR(N)	%U THR(N)	%U Non-THR(N)	%U THR(N)	%U Non-THR(N)
URM	Historical	46.4(13)	25.3(5)	41.4(12)	36.1(12)	33.3(8)	20.0(4)
	2011	54.6(6)	17.7(2)	37.5(3)	27.8(4)	10.0(1)	0.0(0)
	2012	81.8(9)	26.1(4)	50.0(5)	23.8(4)	50.0(4)	17.4(4)
	2013	0.0(0)	19.1(4)	0.0(0)	27.3(4)	11.1(1)	18.2(2)
	2014	50.0(6)	16.7(1)	27.2(3)	14.3(1)	60.0(6)	14.3(1)
	2015	33.3(1)	31.6(6)	25.0(1)	45.5(10)	-	13.3(2)
NURM	Historical	27.7(116)	17.4(132)	32.3(131)	24.2(200)	19.3(73)	11.4(115)
	2011	29.9(29)	13.4(39)	34.8(32)	22.6(61)	9.1(6)	8.2(25)
	2012	23.9(26)	14.5(35)	39.1(43)	22.3(47)	20.0(16)	11.1(26)
	2013	39.8(39)	18.1(42)	27.1(29)	19.8(41)	13.9(14)	9.6(21)
	2014	33.3(41)	22.0(54)	28.9(37)	21.6(52)	25.0(30)	10.3(27)
	2015	18.3(24)	14.8(30)	26.5(40)	16.4(33)	-	10.6(21)

As seen in Table 6.16, the GPAs of the THR NURM students in the first semester Early STEM courses were consistently above the historical baseline in all of the first semester Early STEM courses. The Non-THR students, for the most part, experienced the same effect. Neither the THR nor the Non-THR URM students were consistently above or below the historical baseline, likely due to small numbers. In the second semester Early STEM courses, as seen in Table 6.17, the THR NURM students were, for the most part, above the historical baseline. The same effect was also observed for the Non-THR students. Both the THR and Non-THR URM students showed the same inconsistencies relative to the historical baseline that was observed in the first semester courses.

Table 6.16: Mean GP in First Semester (First Attempt) Early STEM Courses, by Race/Ethnicity. GPs for THR students in PH131 are for the second semester.

		CM131		MA131		PH131	
Race/Ethnicity	Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
URM	Historical	1.82	1.93	1.89	1.94	1.68	1.97
	2011	1.73	2.03	1.13	1.85	1.76	2.15
	2012	1.70	2.13	1.87	2.88	1.73	2.56
	2013	2.31	2.60	2.69	2.84	2.62	2.54
	2014	1.54	1.58	1.61	1.74	2.21	2.19
	2015	1.79	1.98	1.38	2.92	1.83	2.79
NURM	Historical	1.91	2.57	1.85	2.47	1.81	2.71
	2011	2.24	2.63	1.90	2.44	2.32	2.61
	2012	2.22	2.75	2.45	2.97	2.31	3.06
	2013	2.42	2.72	2.61	2.90	2.89	3.18
	2014	2.84	2.42	2.21	2.71	2.88	3.27
	2015	2.25	2.58	2.42	2.75	2.85	3.07

Table 6.17: Mean GP in Second Semester (First Attempt) Early STEM Courses, by Race/Ethnicity. GPs for treated students in PH132 are for the third semester.

		CM132		MA132		PH132	
Race/Ethnicity	Cohort	THR	Non-THR	THR	Non-THR	THR	Non-THR
URM	Historical	1.98	2.41	2.1	2.33	2.13	2.45
	2011	1.82	2.65	1.69	2.53	2.3	3.03
	2012	1.5	2.39	1.65	2.57	1.75	2.65
	2013	2.5	2.59	2.86	2.75	2.85	2.64
	2014	1.94	2.26	2.09	2.64	1.87	2.62
	2015	2.33	2.26	2.17	2.39	-	2.71
NURM	Historical	2.2	2.73	2.19	2.62	2.28	2.82
	2011	2.23	2.81	2.04	2.58	2.88	2.98
	2012	2.45	2.91	2.2	2.65	2.36	2.98
	2013	2.07	2.8	2.49	2.81	2.74	3.04
	2014	2.15	2.68	2.34	2.67	2.48	3.12
	2015	2.43	2.73	2.28	2.84	-	3.11

Analysis of Student Progression by Race/Ethnicity

The data showing the progression of students through the Early STEM courses was disaggregated by race/ethnicity. The bar plots showing student progression through chemistry and physics, that have been disaggregated by ethnicity, can be seen in Figures 6.10 and 6.11. In the chemistry sequence, the NURM students show an increasing trend of students passing CM131 in their first semester, and a maintenance of students passing CM132 in their second semester. The same trends can be seen in the physics sequence as well, only with the semesters changed. In PH131, more NURM students are passing in their second semester than did in their first semester historically. In PH132, approximately the same amount of students are passing in their third semester as did in their second semester historically. The data for the URM students is not as consistent. Because of the small numbers, the passing rates for each course vary wildly, and a trend cannot be drawn.

Looking at the math sequence of courses, in Figures 6.12 and 6.13, the NURM students continue to follow the same pattern as seen earlier, with the full, aggregated, population. In MA131 and MA132, more students are passing in their first and second semesters respectively. A slight decline before a spike in 2014 is similar to what was seen with the full population. The rates for the URM students still wildly fluctuates, however some trends can be extracted. In MA132, there is a noticeable upward trend in the second semester passing rates, meaning that more URM students are passing in their second semester than were historically. In MA232, the rate of students passing by their fourth semester has risen back up to the historical baseline.

Because of the small numbers in the URM category that satisfy the requirements for the quantitative view of student progression, the view cannot be applied to the URM category. When applied to the NURM category, the view looks very similar to what was presented in Figure 5.10.

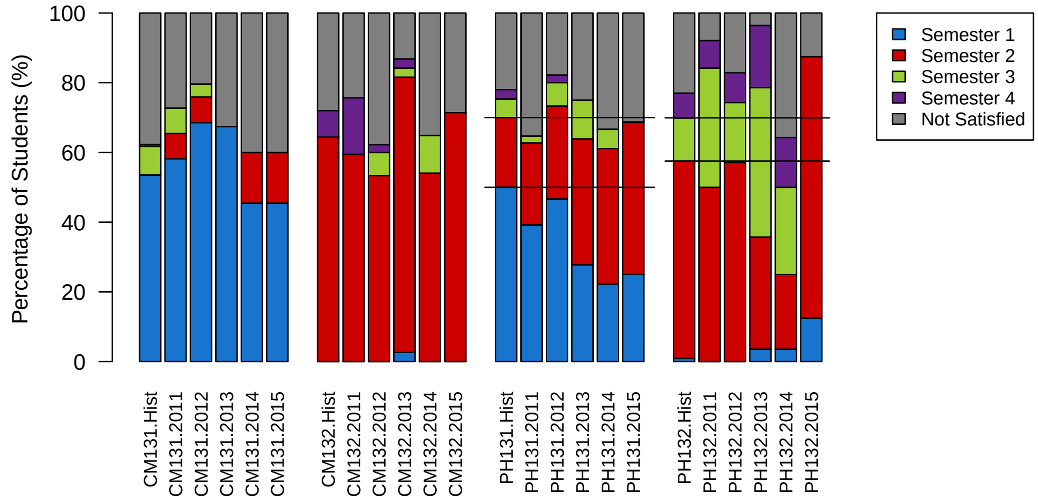


Figure 6.10: Bar Plots of URM Student Progress Through Early STEM Courses: Chemistry and Physics

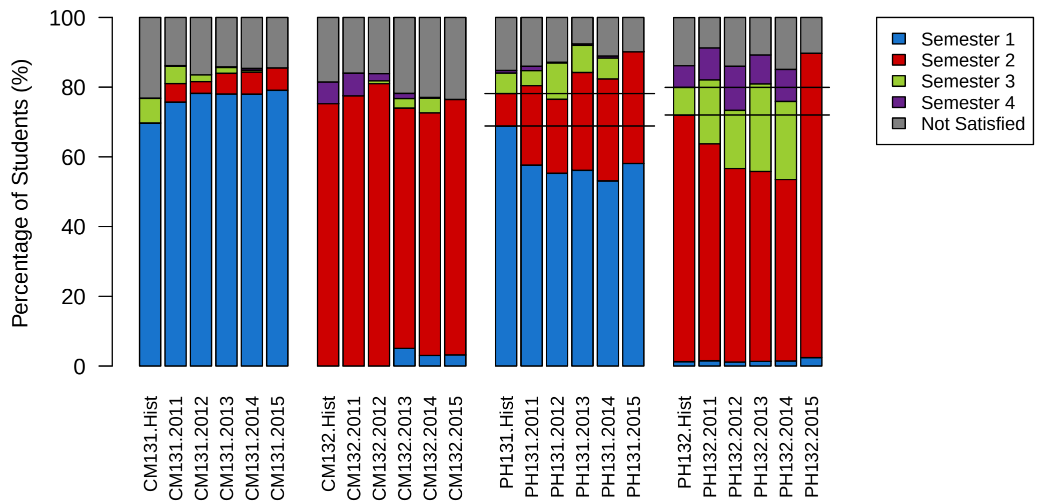


Figure 6.11: Bar Plots of NURM Student Progress Through Early STEM Courses: Chemistry and Physics

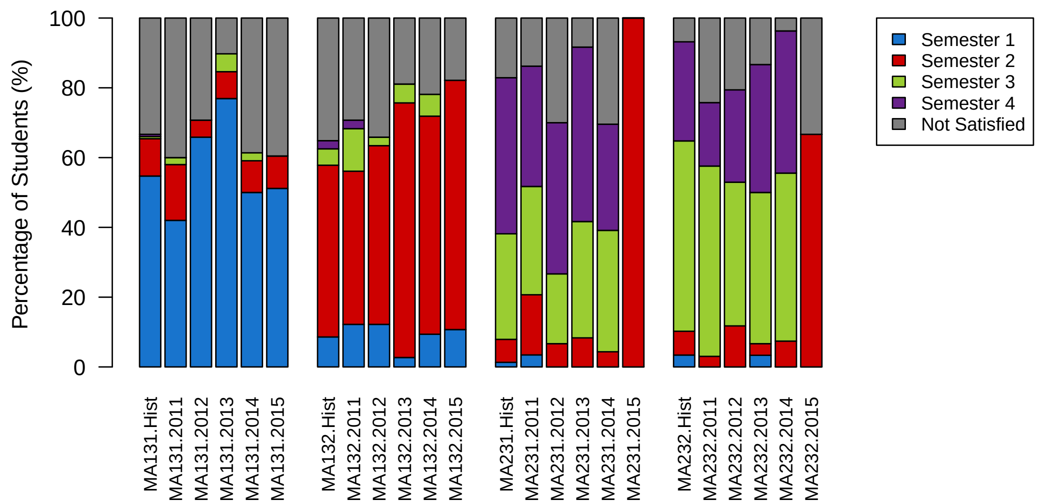


Figure 6.12: Bar Plots of URM Student Progress Through Early STEM Courses: Math

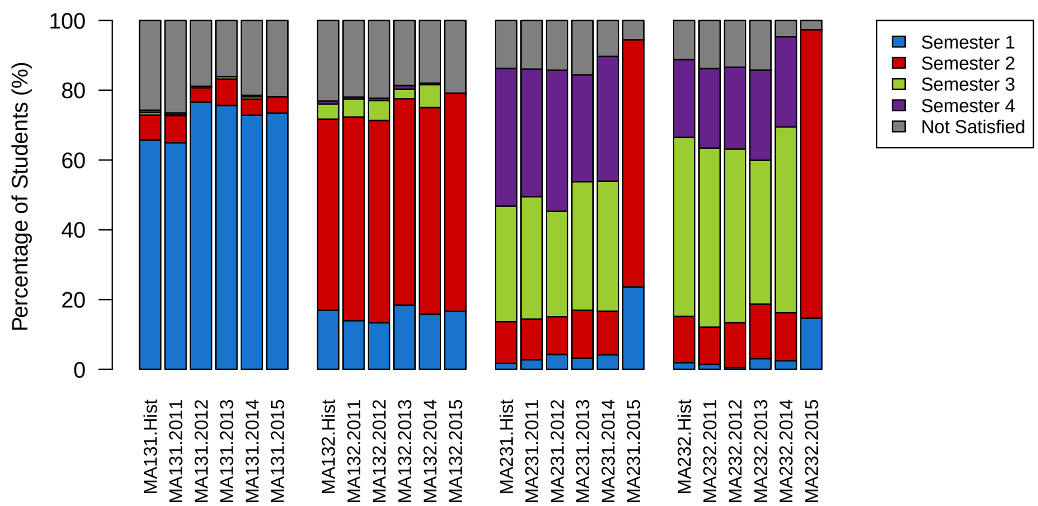


Figure 6.13: Bar Plots of NURM Student Progress Through Early STEM Courses: Math

Analysis of Student Retention by Race/Ethnicity

The retention data for the entire university that were presented earlier in the chapter were disaggregated by race/ethnicity, shown in Table 6.18. Both the THR and Non-THR URM students showed an increase in their retention rates. A similar pattern is seen when examining the NURM students, with both the THR and Non-THR students showing an increase in their retention rates.

Table 6.18: Second Year Retention in the University Data, Disaggregated by Race/Ethnicity

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
URM	Historical	39	33	84.62	130	106	81.54
	'11-'14	66	57	86.36	142	123	86.62
NURM	Historical	586	502	85.67	1866	1634	87.57
	'11-'14	596	532	89.26	1738	1562	89.87

Examining the second year retention in STEM data, both races/ethnicities have experienced increases in their respective retention rates, as seen in Table 6.19. The THR NURM students saw an average increase of approximately 9%. However, the THR and Non-THR URM students saw increases of approximately 12% and 10% respectively. These are very significant increases, but caution should be used here. Because of the (relatively) small number of students in this ethnicity category, any small change will be amplified. A significance test can determine the significance of these increases.

Third year retention, summarized in Table 6.20, has increased for students of both races/ethnicities. The THR URM students saw almost no change in their retention rate, while the THR NURM students saw an increase of approximately 3%. The Non-THR URM students saw an increase as well, of approximately 4%.

Table 6.19: Second Year Retention in STEM Data, Disaggregated by Race/Ethnicity

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
URM	Historical	39	27	69.23	130	91	70.00
	'11-'14	66	54	81.82	142	114	80.28
NURM	Historical	586	451	76.96	1866	1490	79.85
	'11-'14	597	508	85.09	1738	1470	84.58

Table 6.20: Third Year Retention in the University Data, Disaggregated by Race/Ethnicity. Only students retained through to their second year are included.

		Targeted High-Risk			Non-THR		
	Cohort Group	N	N Retained	% Retained	N	N Retained	% Retained
URM	Historical	27	23	85.19	91	80	87.91
	'11-'13	39	33	84.62	91	84	92.31
NURM	Historical	451	402	89.14	1490	1388	93.15
	'11-'13	354	327	92.37	1119	1054	94.19

To see if the treatment cohort retention data are significantly different from the historical baseline, a Wilcoxan Rank Sum test was applied. The results are shown in Table 6.21. The URM THR students did not seem to be affected by the delayed physics program. None of the increases in the treated URM retention rates were significant. This may be due to the (relatively) small number of treated URM students. The NURM students were affected more by the delayed physics program. The pattern of significance is similar to what was seen in Table 5.11. This makes sense, since students in the NURM category make up the majority of the students at Clarkson, and so would behave like the population as a whole.

Analysis of Student Persistence by Race/Ethnicity

Table 6.22 summarizes the persistence data, disaggregated by race/ethnicity. Because of the relatively small population size for the URM students, the treatment

Table 6.21: P-values for Retention Rates Between the Historical Cohort and Treatment Cohorts, Disaggregated by Race/Ethnicity. Values showing a significant difference (α=0.1) are highlighted.

2nd Year Retention in the University		
	THR	Non-THR
URM	0.8908	0.0003433
NURM	0.06042	0.01641
2nd Year Retention in STEM		
	THR	Non-THR
URM	0.1409	0.02318
NURM	0.0003615	<0.0001
3rd Year Retention in the University		
	THR	Non-THR
URM	0.9929	0.0001001
NURM	0.04336	0.2183

cohorts have been combined. Both the THR and Non-THR NURM students experienced a declining trend in the eight semester persistence rate. The URM students experienced either a maintenance or an increase in their eight semester persistence rate. The results are inconclusive right now, because of the small population of URM students, as well as the small number of treatment cohorts that have reached eight semesters.

Table 6.22: Completion Data for 8 Semesters, from the University, by Race/Ethnicity

Race/Ethnicity	Cohort	N THR	N Non-THR	N THR 8 Semesters	% THR 8 Semesters	N Non-THR 8 Semesters	% Non-THR 8 Semesters
URM	Historical	29	109	10	34.48	59	54.13
	2011-'12	27	78	9	33.33	47	60.26
NURM	Historical	499	1780	325	65.13	1345	75.56
	2011-'12	262	929	148	56.49	649	69.86

Chapter 7

Conclusions

This study explored the effects of strategically placing STEM students on a number of student academics:

- student success in the Early STEM courses
- student progression through the Early STEM courses
- student retention
- student persistence

These effects were disaggregated by gender and by ethnicity.

The students in the treatment program are passing their first semester Early STEM courses at a higher rate than students in similar risk categories were historically. In PH131, almost 40% of the high risk students were not successfully passing the course. That rate has dropped to 26% to 10% in the treatment cohorts. The Targeted High-Risk students that would most likely have had to retake the course again, now have a successful passing grade. Not only have the passing rates increased, the mean GP of the courses have increased as well. The PH131 GP has increased approximately one point, corresponding to a whole letter grade. Some of these increases in the mean GPA of the Early STEM courses have been shown to be significant; they are not due to random variations. The delayed physics program has positively affected student success in first semester STEM courses.

By examining the trends shown in Figures 5.5 and 5.6, more students are passing through the individual Early STEM courses than had been in the historical cohort. These figures, combined with Figure 5.10, show that students who are in the treatment program are not held back, but rather catch up to the rest of their classmates by the end of their third semester. Not only do they reach the level that similar students reached before the treatment, they are now *surpassing* the historical progression of those similar students. The delayed physics program has positively impacted these students, in their progression through the Early STEM courses.

The effects of the delayed physics program are evident when looking at student retention. The significance of the changes in the second and third year retention rates show that the program does have a positive effect on retention in the university. The program has a positive effect on whether a student will stay in STEM. The increases in retention in STEM, from 76% to 83%, are statistically significant. This shows that the strategic placement of High-Risk STEM students helps to create a better pathway for the high-risk students, giving them a more positive Early STEM experience, and leading to a greater chance for them to stay in a STEM field.

The effects of the delayed physics program are less evident when looking at student persistence. Only two of the treatment cohorts have completed eight semesters at the time of this writing. More data are needed to make meaningful conclusions about the effects of the delayed physics program on student persistence. From the data that have been collected, it appears that strategically delaying the physics sequence of Early STEM courses does not delay the eight semester completion rate when compared to the historical cohorts of students.

Though not directly affected by the curriculum intervention, the Non-THR students did seem to be affected, especially in PH131. This may be due to the fact that the THR students were removed from the course. This created a more homogeneous course for the students, as well as the instructor. With the less-prepared students no longer in the course, the instructor is able to teach more to the average level of the Non-THR students, instead of attempting to make sure everyone is comprehending the material at the same level.

When the data were disaggregated by both gender and ethnicity, it became evident that the two groups in each disaggregation were not of equal size. The disparity in the group sizes makes meaningful analysis difficult. This is especially true when looking at the disaggregation by ethnicity, as the URM group sizes were consistently too small to accurately perform the analysis. An interesting effect did become apparent during the analysis of the disaggregation by gender of the second year retention in the university data. While the male students were affected similarly to the general STEM population, the female students did not seem to be affected at all by the delayed physics program. There were some differences in the retention rates, but they were not found to be significant.

Once conclusion that can be drawn out of the disaggregation by gender is that the program may need to be changed for female students. There is evidence of a gender bias in the Force Concepts Inventory (Physics Diagnostic Survey).[65] This suggests that perhaps the cutoff for the Physics Diagnostic Survey should be lowered for female students to account for this bias. It does warrant further study.

Despite the gender bias in the Physics Diagnostic Survey, there does not appear to be a bias in student success. The same behavior that was seen when looking at all of the student in PH131 was seen when the data were disaggregated by gender. High-risk students were not successfully passing at a rate near 40% historically, and in the treatment cohorts, the unsuccessful rate was cut in half or better.

When looking at student retention data that were disaggregated by gender, the high-risk female students were staying from their first year to their second at approximately the same rate as they were historically. However, the high-risk female students that were being retained in the university were also being retained in STEM at a higher rate than the male students in their cohort.

Part III

Continuing and Future Work

Chapter 8

Continuing and Future Work

The success of the delayed physics program has led to future possible avenues of research, relating to the methods of identifying at-risk students, and providing multiple pathways for STEM students. One such "child" program of delayed physics has been implemented in the Fall of 2015. Other future research possibilities are still in the planning stages.

Targeted Math-Physics Curriculum

Motivated by the call to "produce one million" additional STEM graduates given in the PCAST report[2] a new program was put into place in the Fall of 2015, in an effort to coordinate the Calculus and Physics curricula in the first year of study. The Co-Ordinated Math-Physics Assessment for Student Success (COMPASS) program is funded by a National Science Foundation (NSF) grant[61] in the Division of Undergraduate Research (DUE),[67] specifically under the Improving Undergraduate STEM Education (IUSE) program.[68] It is a joint program between Clarkson University, and the University of Georgia. The Principle Investigator (PI) at Clarkson University is Dr. Michael Ramsdell in the Physics Department, and the PI at the University of Georgia is Dr. Kelly Black in the Mathematics Department. This discussion will focus on the students and curriculum at Clarkson University.

Description

The COMPASS program seeks to address the PCAST recommendations mentioned earlier in this work, specifically to:

- **Address the math preparation gap.**
- **Diversify pathways to STEM careers.**
- **Replace standard laboratory courses with discovery-based research courses.**

The pathways through the Early STEM courses have already been diversified for the high-risk (M-,P- and M-,P-+) students, through the delay of the Physics sequence of courses, discussed earlier in this work. The low-risk (M+,P+) students also have an alternative pathway in the Physics Team Design program.[69] This is an alternate laboratory experience based around the mathematical modeling of a physical system. It is an advanced lab that attracts students that are well-prepared and highly motivated, showing high interest in the STEM disciplines. The students in the medium-risk category do not yet have a program to meet their specific needs. That is what the COMPASS program hopes to provide.

This program specifically targets the students in the M-,P+ group, defined as those students that received a Math Diagnostic score below a 0.65, and a Physics Diagnostic Score above a 0.50. As a reminder, the groups are shown in Figure 8.1, with the M-,P+ group bounded in green. The students in the M-,P+ group are identified as having a relatively strong grasp on basic physics concepts, but are shown to have a relative weakness in their mathematical skills. It is this conceptual understanding of physics that the COMPASS program hopes to use to better teach the mathematical skills needed in the students' STEM careers.

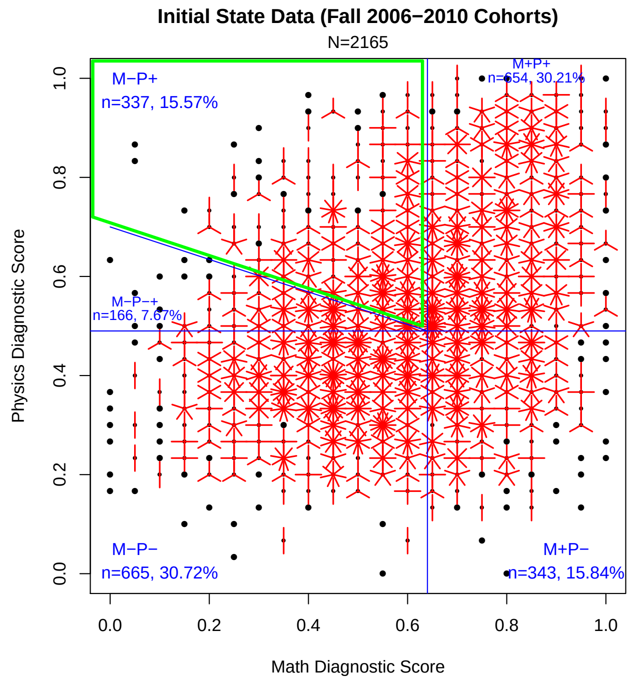


Figure 8.1: Sunflower Plot of Historical Initial State Data, with Group Labels, Sizes and Percent of the Total Population. The Targeted Group is Located in the Upper Left Corner of the Plot, Bounded in Green

In the Introductory Calculus course (MA131), the structure and schedule of the mathematical topics are changed to better reflect the topics being taught concurrently in the Introductory Physics course (PH131) A rough outline of the topics as they match up is shown in Table 8.1.

Table 8.1: Schedule of Physics I and Calculus I Topics for COMPASS Students

Physics I Topic	**Calculus I Topic**
1-Dimension Kinematics, relationship between position, velocity and acceleration	Rate of change, the derivative, relationship between position, velocity and acceleration
2 and 3-Dimension Kinematics, vectors	Further exploration of derivatives, vectors
Forces and causes of motion	Solving systems of equations, maximum and minimum values
Work, energy conservation	Anti-derivatives and integrals
Momentum, collisions, impulse	Continuity, limits
Rotational motion, oscillations	Trigonometric functions

These changes to the scheduling of the calculus topics affect the lecture and recitation portions of the course. The physics lecture and recitation remains the same. The laboratory portion of physics is also given a new curriculum.

Following in the same vein as the Physics Team Design program, students in the COMPASS laboratory sections will focus on mathematical modeling of a physical system. With a heavy focus on video analysis,[70][71] students undergo an early research experience, modeling the behavior of a foam arrow fired from a toy bow.[72] In separate laboratory sessions, student teams take various measurements on their bow, from the strength of the elastic material, to the exit velocity of the arrow, and use the data they collected in further experiments. Each experiment matches up with the current topic in the physics lecture. The ultimate goal of the lab is to use the data that was collected in previous experiments to predict the trajectory of the dart, in a challenge setting. The competition provides motivation for the students to take careful measurements and fully understand their model.

Initial Treatment Group

The Fall 2015 semester was the first implementation of the COMPASS program at both universities. Students were chosen and placed into the program prior to their arrival at Clarkson University, after the deadline for completing the Pre-College Surveys. In order to be chosen for the program, students had to satisfy the following conditions:

- **Must have completed all of the Pre-College Surveys**
- **Must be in the M-,P+ group**
- **Must be in the 2015FLFT cohort (the incoming cohort for that semester)**

Following these guidelines, the First Year Council selected 24 out of 60 eligible students. Each of these students signed a consent form, allowing them to be part of this experimental program. Figure 8.2 shows the distribution of all of the students enrolled in PH131 in the Fall 2015 semester for which we have complete MP data. This includes students taking the course in semesters beyond their first term. The points are "jittered" ("noise" added to randomly move a small distance from their position) to prevent overplotting, as well as color coded to represent the different "class groups" that the students can belong to. The pink points represent the students who are in the "traditional" course, and who follow the traditional laboratory experience. The red points represent the students that have been chosen to be in the COMPASS program. The blue points represent the comparison group, students who meet the above criteria, but were not chosen for the COMPASS program, who also follow the traditional laboratory experience. The final group, in green, is the Team Design group, who follow the alternate laboratory experience that is based around mathematical modeling of a single physical system.

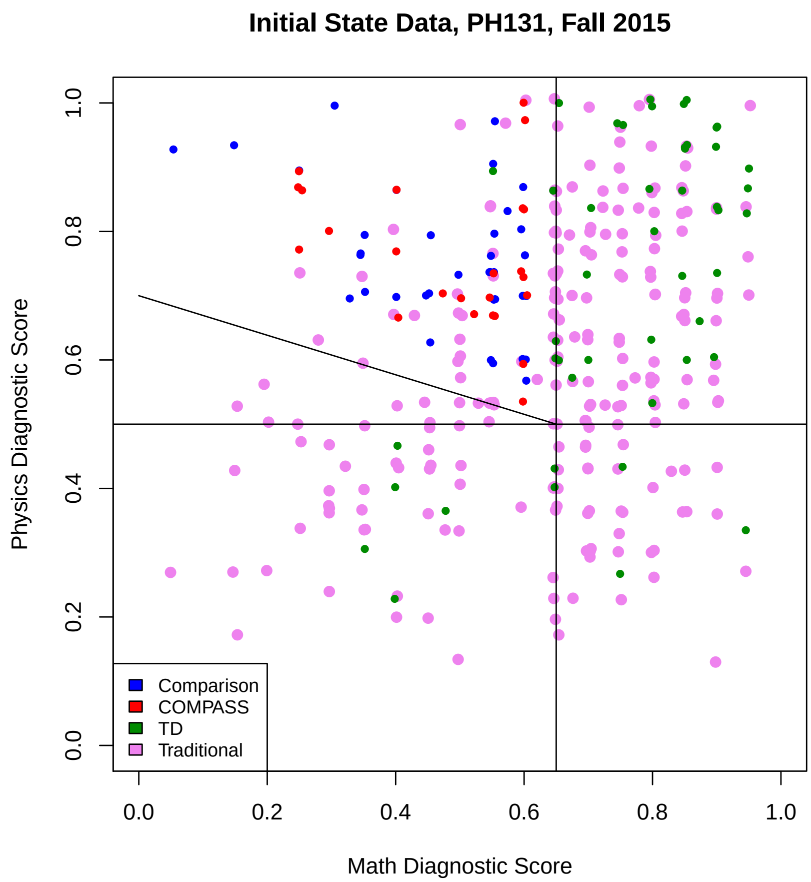


Figure 8.2: Scatter Plot of the Students Enrolled in PH131 in Fall 2015.

The COMPASS students are distributed throughout the M-,P+ group, as are the comparison students. The traditional students that are present in the M-,P+ group are those who are taking PH131 in a semester beyond their first.

Initial Results

The COMPASS students were compared to the other class groups in both PH131 and MA131. The comparison will focus on the performance of the students in each of their respective courses. As an additional measure, an extra group consisting of all students who were in the M-,P+ group in Fall 2014 will be used as another comparison group.

Table 8.2: Average exams scores for the class groups, after all retakes.

	Exam 1	Exam 2	Exam 3	Exam 4
COMPASS	82.03	80.87	86.05	68.84
F14 M-,P+	83.83	83.15	82.81	63.63
Comparison	84.55	87.86	86.71	70.69
Class	81.60	83.05	82.86	69.68
Team Design	89.28	89.97	90.47	79.45

Introductory Physics

In PH131, students are required to take four exams as part of their course grade. The first three exams are taken during the semester, and the fourth is given during the final exam period. Each exam is the same length, consisting of ten multiple choice questions, and two long answer problems, and are written such that students can complete them in the intended time of one hour. The final exam period is three hours long, and an opportunity is given for the students to retake any of the first three exams. The higher of the two grades for each exam is the one applied towards a student's final grade in the course. Figure 8.3 shows the average exam grade for each class group after the retake grades ave been applied. The COMPASS students average score was lower than that of the comparison group for all of the exams. However, comparing to the Fall 2014 students, on exams 3 and 4, the COMPASS students had higher scores. It is important to note that the Fall 2014 and the COMPASS students took different exams during their respective semesters. The exams are similar in scope and material though. Table 8.2 shows the average exam scores for each class group.

Approximately halfway through the semester, students are evaluated on their performance in the courses that they are taking. The grade that they receive is given as a Satisfactory (S) or Unsatisfactory (U). Figure 8.4 shows a bar plot of the percentages of each class group that received an S and U grade in PH131. The COMPASS

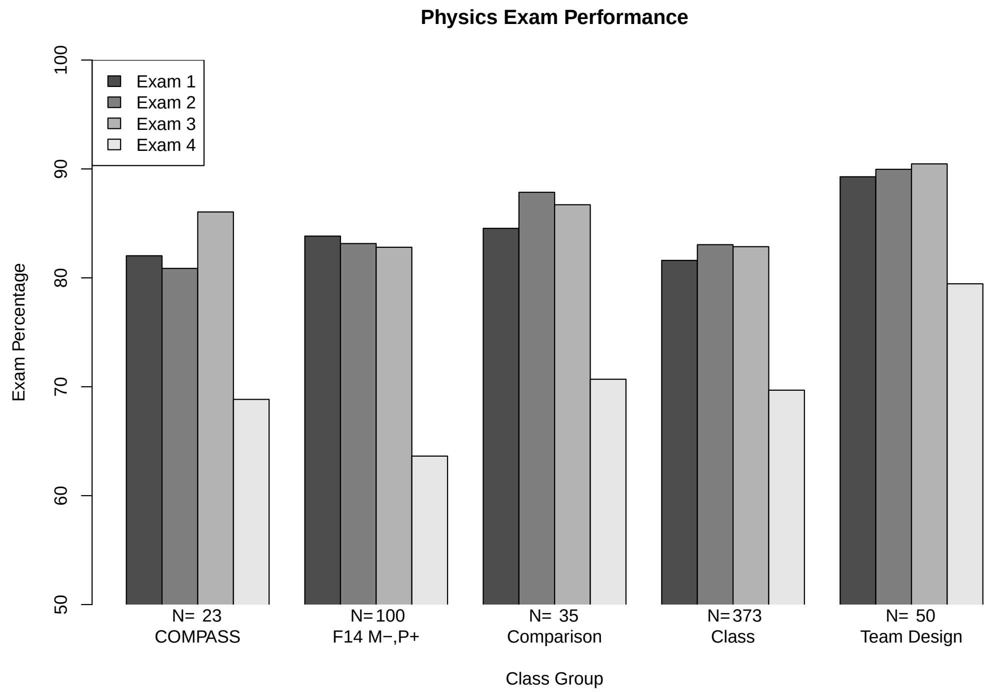


Figure 8.3: Bar plot showing the average exam grades after the retakes for each class group and the total class. Notice the scale on the y-axis.

students were below the comparison group, and comparable to the whole class, while every group was below the Fall 2014 M-,P+ students.

The final grade in PH131 is given by the student's "score" in the course, a number out of 1000 that takes into account every assignment that the students are required to complete. We are using the physics score instead of GPA, because we want to compare the groups without any effects from binning that the GPA would have. Figure 8.5 is a box plot of the average final physics score for each class group. A box plot (or box and whiskers diagram) shows the distribution of the data that is being plotted, with the "box" spanning the first to the third quartile, and the "whiskers" showing the maximum and minimum. Outliers are shown as single points outside of the whiskers. The notches on the boxes show the 95% confidence interval of the median (the thick black line at the center of the notch), and give a visual indication of the comparability of the data sets. If the two notches do not overlap, this is

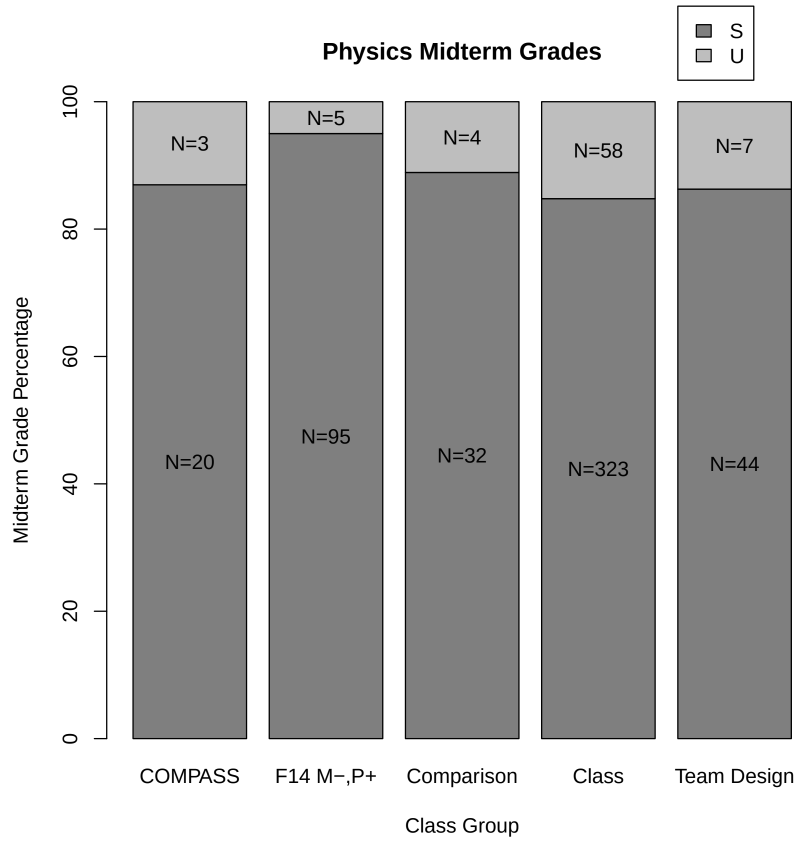


Figure 8.4: Stacked bar plot showing the percent of each class group receiving a Satisfactory (S) or Unsatisfactory (U) grade in PH131.

strong evidence that the medians do differ.[73] The notches for all of the class groups, with the exception of Team Design, overlap, so the medians for the course scores for those groups are relatively similar. The statistical means of the course scores for each group are shown in Table 8.3. The COMPASS students scored approximately seven points higher than the Fall 2014 students, and approximately 5 points lower than the comparison group.

To see if the differences in the statistical means of the physics exam scores and

Table 8.3: Average course scores for the class groups in PH131.

COMPASS	F14 M-,P+	Comparison	Class	TD
818.1	810.8	822.8	824.0	894.3

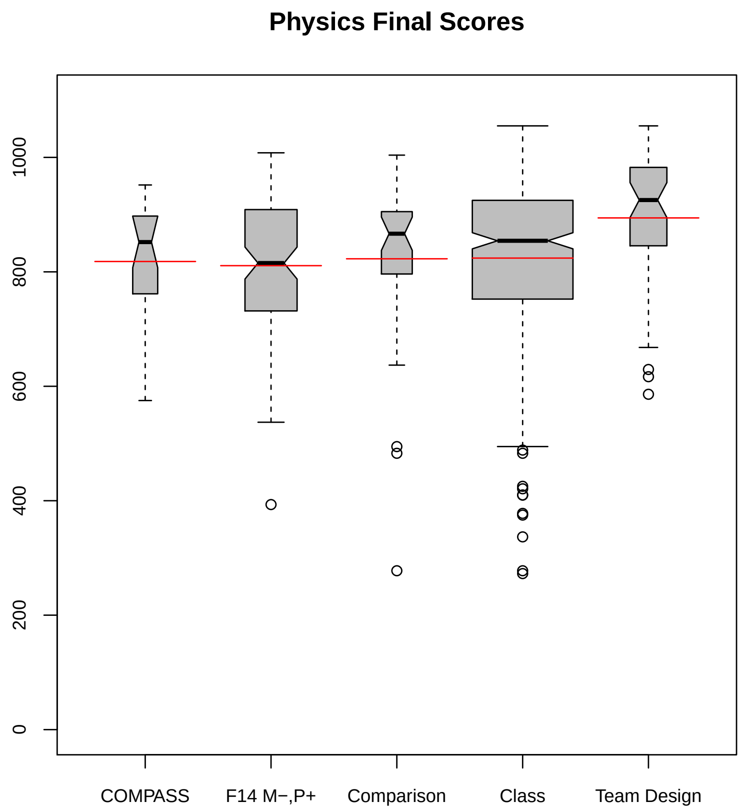


Figure 8.5: Box plot of the final course scores in PH131. The red lines represent the mean score.

final course score are due to random variations or if they are significantly different, a t-test was used. This test produces a p-value which gives a probability that any differences in the two statistical means of the groups are explained by random variations in the data. A p-value less than 0.10 shows that the statistical means of the two groups are significantly different. Table 8.4 shows the p-values for comparing the exam scores of the COMPASS students to those of the other class groups. Looking at the p-values, the differences in the statistical means between the COMPASS and comparison groups can be explained by random variations, except for exam 2. For that exam, there is a true statistical difference between the scores. The exam scores for the Fall 2014 group are all similar to the COMPASS scores, keeping in mind that the two groups took different exams. The p-values for the final physics scores are shown in Table 8.5. These p-values show that the mean final scores in physics are all similar, except for the Team Design group.

At the end of the semester, the students in PH131 take the Physics Diagnostic

Table 8.4: P-values for comparing the COMPASS exam scores, after retakes, to the other class groups.

	Exam 1	Exam 2	Exam 3	Exam 4
F14 M-,P+	0.5383	0.445	0.4703	0.3344
Comparison	0.4481	0.0344	0.8983	0.7576
Class	0.8725	0.4266	0.4534	0.8658
Team Design	0.0423	0.0105	0.392	0.0741

Table 8.5: P-values for comparing the COMPASS final physics scores to the other class groups.

	F14 M-,P+	Comparison	Class	Team Design
COMPASS	0.7766	0.889	0.8022	0.0092

survey again as a post test. The *fractional gain* of a student's score on the Physics Diagnostic survey gives a numerical value to show how much the student has learned. The fractional gain is calculated by the following equation:

$$\frac{< post - pre >}{< 1 - pre >} \tag{8.1}$$

The fractional gain of a student compares how much the student has improved with how much they are able to improve. COMPASS students showed a smaller fractional gain than any other class group. However, a further examination of the survey scores shows that the COMPASS students had the least to gain, because the pre-test scores for that group were higher than all of the others, as shown in Table 8.6.

Table 8.6: Average Pre-Test and Post-Test scores and average gains for each class group

	Average Pre	Average Post	Average Gain
COMPASS	0.774	0.802	0.123
Comparison	0.751	0.783	0.130
Class	0.641	0.698	0.158
Team Design	0.763	0.823	0.253

Introductory Calculus

In the introductory calculus course, students are co-enrolled in MA41, a Co-Calculus course. They remain in the course until they score a 90% or better on the Absolute Basic Competency (ABC) test, described earlier in this work. Students have a total of four chances to pass the ABC test throughout the semester. Figure 8.6 shows the cumulative progression of students in the class groups, as they pass the ABC. The COMPASS students started comparably with the comparison group, but then had a smaller percentage of the group pass the ABC than any of the other class groups. By formatting the ABC data to reflect whether a student has passed (1) or not passed (0) the ABC test, a t-test can be used to see if the percentages of each group that passed are statistically significantly different or not. Table 8.7 shows the p-values for each class group being compared to the COMPASS group. Each row represents the numbered attempt at passing the ABC test, and is cumulative with the previous attempts. The p-values show that the percentages of students in each of the class groups are not significantly different from the COMPASS group.

Looking at the mean maximum ABC score in each class group, the COMPASS students had the highest average. Comparing these averages with a t-test, each of the other class groups had mean ABC scores that are not significantly different from the COMPASS mean ABC score. The p-values are shown in Table 8.9. The mean maximum ABC scores for all the groups were not statistically significantly different from the COMPASS scores.

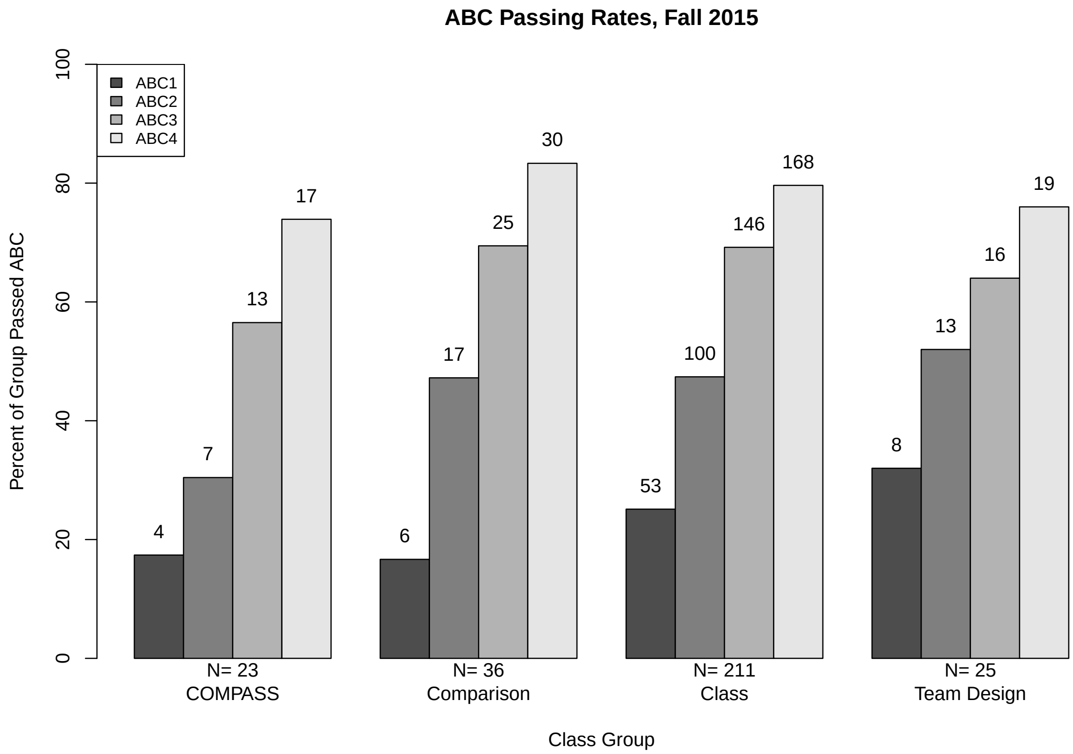


Figure 8.6: Bar plot showing the cumulative progression of students passing the ABC test for each class group.

Table 8.7: P-values for comparing the cumulative percentages of the class groups that passed the ABC test. Each row represents the attempt number at passing the ABC test.

	Comparison	Class	Team Design
ABC 1	0.9439	0.3774	0.2482
ABC 2	0.2205	0.1148	0.1344
ABC 3	0.3509	0.2621	0.6064
ABC 4	0.4351	0.5648	0.8711

Looking at the final exam scores for the class groups, the COMPASS students scored higher than any of the other groups, except for Team Design. Table 8.10 shows the mean scores for each group. Looking at the p-values for the final exam scores, shown in Table 8.11, the comparison and Team Design groups were not statistically significantly different than the COMPASS group. The full class, however,

Table 8.8: Mean maximum ABC scores for each class group.

COMPASS	Comparison	Class	Team Design
18.09	17.33	17.88	17.88

Table 8.9: P-values for comparing the COMPASS max ABC scores to the other class groups.

	Comparison	Class	Team Design
COMPASS	0.337	0.5111	0.6988

was significantly different than the COMPASS group. This means there is a high probability that the difference in the final exam scores between the class and the COMPASS group are a result of the different curriculum.

The COMPASS students had a higher mean score than the comparison group and

Table 8.10: Average final exam scores in MA131 for the class groups.

COMPASS	Comparison	Class	Team Design
77.17	76.82	72.68	79.80

the class, but lower than the Team Design group by approximately six points, as shown in Table 8.12. The course scores for the groups are represented by a box plot in Figure 8.7. The notches on each of the boxes seem to overlap somewhat, giving evidence that the medians do not significantly differ. A further examination of the course scores using a t-test reveals that the statistical means of each of the groups are not significantly different. The p-values for comparing the COMPASS students to the other class groups are listed in Table 8.13. The Team Design group is close to the “cutoff” of 0.1, meaning there could be some argument about the statistical difference in the means.

Table 8.11: P-values for comparing the COMPASS final exam scores in MA131 to the other class groups.

	Comparison	Class	Team Design
COMPASS	0.9293	0.07519	0.4601

Table 8.12: Average course scores in MA131 for the class groups.

COMPASS	Comparison	Class	Team Design
80.79	79.44	74.83	86.29

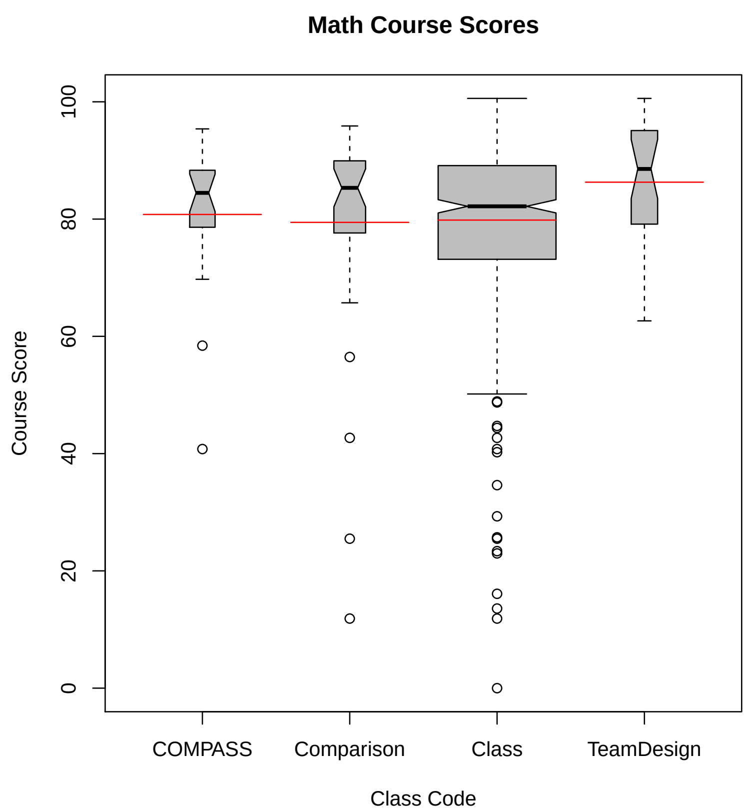


Figure 8.7: Box plot of the final course scores in MA131. The red lines represent the mean score.

Table 8.13: P-values for comparing the COMPASS course scores in MA131 to the other class groups.

	Comparison	Class	Team Design
COMPASS	0.7396	0.7203	0.1025

Future Work in COMPASS

The COMPASS program is funded through the NSF grant for three years. During that time, the program plans to accommodate twice as many students than the initial year. As the program moves through its second and third year, data will be collected on the students' retention, GPA, and progression through their chosen STEM degree. Further impacts upon the students will also be studied. The performance of the students at UGA and Clarkson will be compared as well.

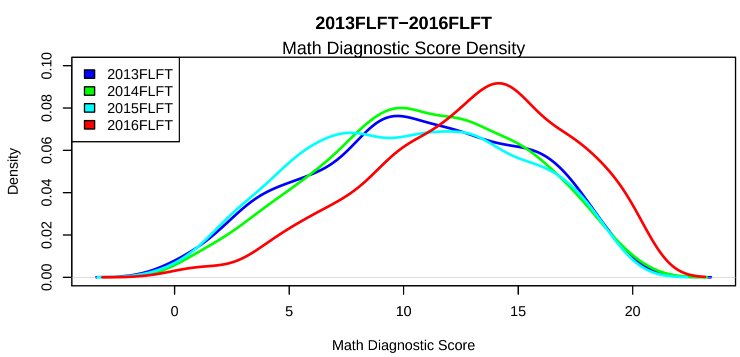
The curriculum for both the physics and the calculus courses will be further developed and refined. Observations taken during the initial year will be used to strengthen the educational impact of the modified physics laboratory curriculum.

Diagnostic Tool Reexamination

Periodically, as the delayed physics program continues, the methods that are used to identify the high-risk students should be reexamined. The students that enter Clarkson University may have different educational backgrounds, and therefore different educational needs, than the students presented in this study. One example of this will be presented.

Math Diagnostic Survey

The incoming Fall 2016 cohort, upon taking the Pre-College surveys, was found to have a much higher average score on the Math Diagnostic survey than previous cohorts. Figure 8.8 shows the density distributions of the math diagnostic scores for the past four incoming cohorts, along with accompanying statistics. The distribution for the 2016FLFT cohort is shifted higher than those of the previous cohorts, which is reflected in the means of the scores. Using a Student's t-test to compare the 2016FLFT cohort to the previous ones, the difference in the means is statistically significant.



	Mean	SD	p−value*
2013FLFT	10.6	4.65	0
2014FLFT	10.8	4.44	0
2015FLFT	10.29	4.65	0
2016FLFT	12.93	4.33	1

*When compared to 2016FLFT

Figure 8.8: Density distributions of the math diagnostic scores for the 2013FLFT through 2016FLFT cohorts, along with accompanying statistics.

To investigate the significant increase in math diagnostic scores, the same analysis was applied to the SAT-math test. The incoming students took the test prior to entering Clarkson, and it covers the same material as the math diagnostic. Figure 8.9 shows the density distributions for the same cohorts as the prior analysis. The distributions all seem to lay right on top of each other, with only a seven point difference in the means. The p-values from the corresponding t-tests show this as well, with there being no significant difference between the means of the SAT-Math scores.

The similarities of the means of the SAT-Math scores gives evidence to the theory

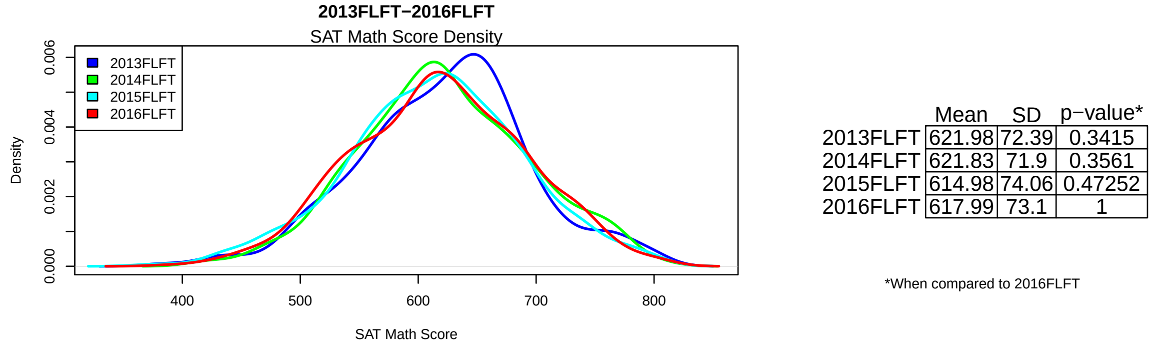


Figure 8.9: Density distributions of the SAT-Math scores for the 2013FLFT through 2016FLFT cohorts, along with accompanying statistics.

that the diagnostic test was different for the 2016FLFT cohort, while the incoming students were not. Further analysis can be applied as the semester continues, by looking at the ABC test. The results of the analysis on the first ABC test warrants further study. The distributions do seem to be shifted from each other, and the p-values confirm that the two cohorts are statistically different. Further analysis is needed to ascertain if the incoming students are truly different than those of previous years, or if the tests have changed.

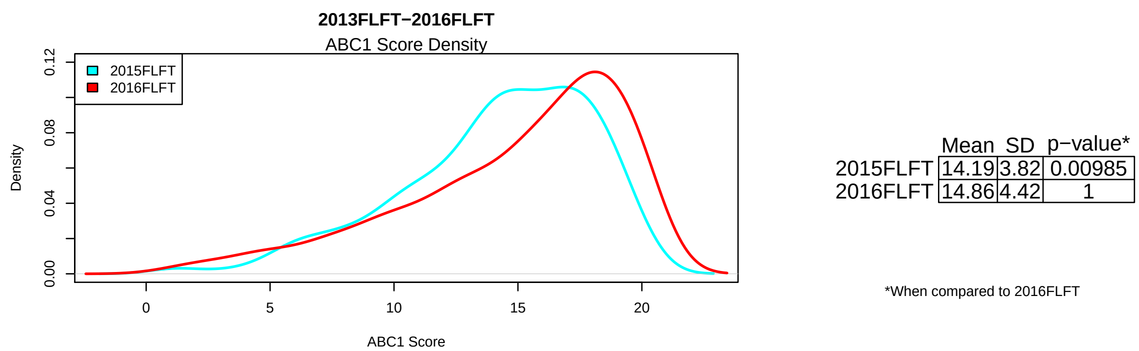


Figure 8.10: Density distributions of the SAT-Math scores for the 2013FLFT through 2016FLFT cohorts, along with accompanying statistics.

Spatial Visualization Survey

Beginning with the Fall 2012 cohort, the Purdue Spatial Visualization Test: Rotation[55] has been given as part of the Pre-College surveys. The inclusion of this test into the suite of Pre-College surveys presents an opportunity have a third measure in the predictive model. Analysis, such as PCA, needs to be done to determine the contribution of the SV test to the predictive model.

Preliminary results look promising for the addition of the SV into the predictive model. A cutoff was placed on the SV, at 50%, to determine if a student would fall into the S+ or S- category. By plotting these two SV categories on the MP plot, in much the same way seen earlier in this body of work, localization of the S- students can be seen in Figure 8.11. The S- students are primarily located in the high-risk groups, as defined earlier in this study. Further analysis can be done to assess how the SV score and post-course grades are correlated.

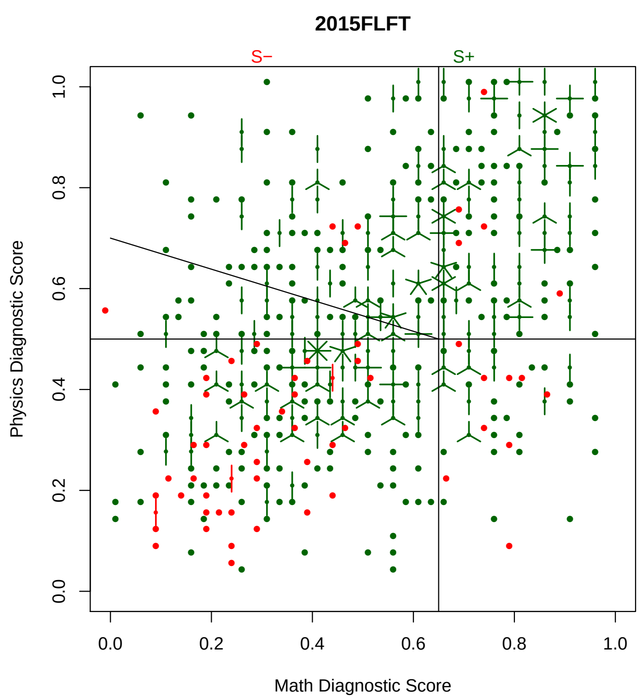


Figure 8.11: Sunflower Plot of the 2015FLFT Spatial-Visualization Scores Plotted on to the MP Plot.

Non-Cognitive Aspects

Much of the work that was referenced in Chapter 2 uses non-cognitive aspects to attempt to model undergraduate student retention and success. These aspects of the undergraduate student experience have been shown to be important to the retention of students. The analysis that is presented in this body of work focuses on the cognitive or academic aspects of students. A future endeavor that may benefit the undergraduate STEM students at Clarkson University would be to bring these non-cognitive aspects to our predictive model.

The research done by Tinto[18–23], Astin[24–27], and Bean[28–31] cite student-faculty interactions as being important for student retention. The COMPASS program, already in place, increases the interactions that students have with the physics faculty. The scope of the interactions and the extent to which it has affected the students in the program can be further explored as the program moves forward.

Further Assessment of Predictive Model

There is further work that can be done on the predictive model presented in this work. Along with the addition of other surveys and measures, the predictive capability of this model may be evaluated. Using the same methods as Schalk et al.[74], the ability to predict risk levels and possibly course grades may be assessed. The analysis using these methods may involve the other future work that have been addressed in this chapter.

Part IV

Bibliography and Appendices

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Appendices

Appendix A

Examples of Surveys and Tests Used in Analysis

A.1 Force Concepts Inventory

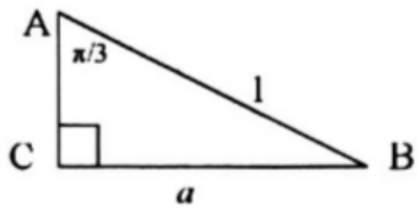
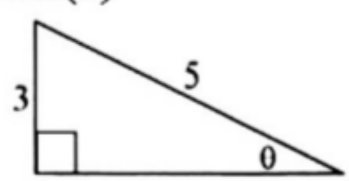
Due to the nature of the Force Concepts Inventory as a nationally used analysis tool, the pages cannot be duplicated here. A sample question can be seen at `https://www.physport.org/assessments/assessment.cfm?A=FCI`, as well as further information about the survey.

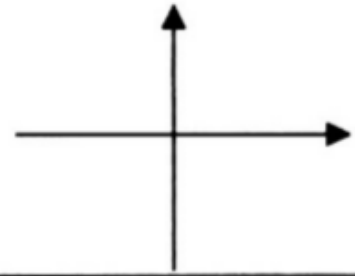
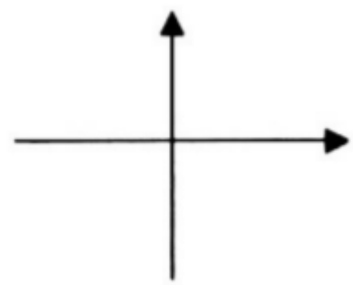
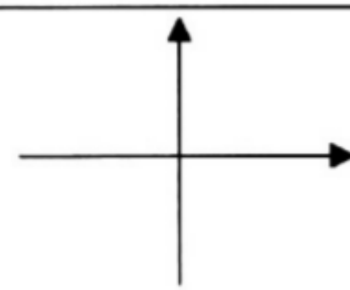
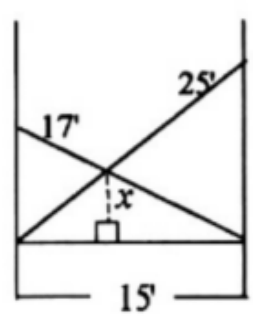
A.2 Example Math Diagnostic Test[1]

[1]Pages taken from[12]

Clarkson Calculus Readiness Test 25E

Name (PRINT!)____________________________ **Student ID # (if known)**_______________

	No books–no calculators	□ *Answers here* □
1.	Find the exact value of: $\sin\left(\frac{4\pi}{3}\right)$	
2.	Write the equation passing through the point (-2,4) with a slope of -2 in slope-intercept form.	
3.	As shown in the accompanying diagram in right triangle ABC: $\overline{AC} \perp \overline{BC}$ $AB = 1$ and $m\angle A = \frac{\pi}{3}$. Find the value of a: 	
4.	Solve for h in terms of V, r, and π. $V = \frac{1}{3}\pi r^2 h$	
5.	Find the exact value of: $\cos\left(\frac{\pi}{4}\right)$	
6.	Factor completely: $6x^2 + 5x - 4$	
7.	Solve for y: $\frac{6}{y-4} + 6 = \frac{1}{3}$	
8.	Solve for t: $\frac{6}{t-2} = \frac{t^2+t}{t-2}$	
9.	Express as a single fraction in simplest form. $\frac{1}{x-1} - \frac{1}{x^2-1}$	
10.	If $\lvert x-a \rvert > b$, then solve for x in terms of a and b.	
11.	Find the exact value of $\sec(\theta)$ 	
12	Find the product of $t^{1/4}$ and $t^{2/3}$.	

13.	Graph the function $y = \sin(x)$ for $-\pi \le x < \pi$. Label with the following values if appropriate each intercept location of each asymptote, and (x,y) coordinates of each minimum and maximum. Also show a scale	
14.	Simplify $\left(\frac{4}{9}\right)^{-\frac{1}{2}}$	
15.	Solve for x: (leave your answer as a fraction) $2^{7x+2} = \frac{1}{4}$	
16.	If $9^{x/2} = 8$ find values of a and b for which $x = \log_b a$	
17.	Sketch the graph of the equation $-2x + 3y = 6$. Label the $x-$ and $y-$ intercepts	
18.	Water is sitting in a pipe lying on the ground. If the inside diameter of the pipe is 34 inches, what is the width of the water's surface when the water is 9 inches deep?	
19.	Sketch the graph of $y = -x^2 + 4$; label all intercepts	
20.	The diagram at right represents two ladders crossing in an alleyway. If one of the ladders is 25 ft. long, the other 17 ft long, and the alleyway 15 ft wide, how high above the street (to the nearest tenth of a foot) do the ladders cross?	

A.3 Example Math ABC Test[2]

[2]Pages taken from[53]

Calculus ABC Test I—Version 1970 **Name:** ____________________

Lecture section: ________ **Student Number:** ____________

PUT ANSWERS IN BOXES. NO BOOKS/NOTES/CALCULATORS. DO YOUR OWN WORK. Simplify answers where possible. Include units where needed. All angles are in radians. $\log = \log_{10}$.

1. Simplify by combining using a common denominator:

$$\frac{17x}{8} - \frac{7x}{8}$$

2. Simplify as far as you can:

$$\frac{x-2}{x^2-4}$$

3. Solve for y:

$$\frac{y}{3} = \frac{y+6}{5}$$

4. Solve for t:

$$\frac{6}{t-2} = \frac{t^2+t}{t-2}$$

5. Solve for y:

$$3y + 11 < 5$$

6. Find the equation of the line through the point (-1,2) and parallel to the line $x - 2y = 6$ in *point-slope* form.

7. Factor: $6 + 5t - 6t^2$

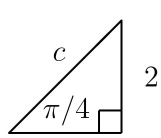
8. Find the value of:

$$\cos\left(\frac{11\pi}{6}\right)$$

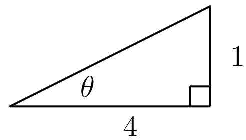
9. Find the value of:

$$\tan\left(\frac{\pi}{6}\right)$$

10. Find the value of c:



11. Find the value of $\csc(\theta)$:



12. Graph the function $y = \tan(x)$ for $-\pi \leq x \leq \pi$.
Label with the following values (if applicable): each intercept, location of each asymptote, and (x, y) coordinates of each min and max.

13. Simplify and eliminate any negative exponents:

$$\frac{y^{-3}z^4}{y^{-5}z^5}$$

14. Simplify:

$$\left(\frac{1}{2}\right)^4 4^{-2}$$

15. Solve for x (write answer as a rational number):

$$\left(\frac{1}{4}\right)^{1-2x} = 2$$

16. Solve for x:

$$3^{x+2} = 7$$

17. Graph the equation $-x + y = 3$.
Label with the following values (if applicable): each intercept, slope, and (x, y) coordinates of vertex.

18. Graph the function $y = (x - 1)^2$.
Label with the following values (if applicable): each intercept, slope, and (x, y) coordinates of vertex.

19. Find the perimeter of a triangle with sides of length 6 inches, 5 inches, and 3 inches.

20. Find the volume of a right circular cylinder (a can) with diameter 3 cm and height 2 cm.