2020

EXPLORING THE IMPACT OF A COREQUISITE MODEL ON ACADEMIC PERFORMANCE IN PRECALCULUS: WHO BENEFITS WHEN?

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By

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A Dissertation Submitted to the

Graduate School

In Partial Fulfillment of the

Requirements for the Degree of

DOCTOR OF EDUCATION

Benerd College
Educational Administration and Leadership

University of the Pacific
Stockton, California

2020

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DEDICATION

This dissertation is dedicated to my parents: my father, late Mr. M. N. Sharma, who has been the inspiration behind this project, and my mother, Mrs. Janak Dulari Sharma, whose love, motivation, and constant encouragement inspired me to work hard and accomplish my learning goals.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my research supervisor, Professor Rachelle Kisst Hackett, for her invaluable guidance, motivation, enthusiasm, immense knowledge, and continuous support throughout the course of my research. She taught me the methodology to carry out the research and to present it as clearly as possible. Even amidst an extremely busy schedule, Dr. Hackett always found time to edit my work, give her expert feedback, and suggest improvements in my writing. It was a great privilege and honor to work with her and receive her guidance. In all honesty, I could not have imagined a better advisor and mentor for my research studies.

I would also like to thank my committee members, Professor Delores McNair and Dr. Jacquelyn Ollison, whose suggestions, feedback, and ideas were very helpful in improving the quality of my work.

In addition, thank you to Dr. Jessie Garza Roderick, the dean at Delta College Mountain House Campus, who believed in me and encouraged me to start this research work. I was a little hesitant in the beginning, but her words, “You can do it; go for it,” gave me the confidence to embark on this project. Additionally, Laura Ochoa-Sanchez, the dean of the mathematics and science division at San Joaquin Delta College, has been very supportive of my work from the very beginning. I acknowledge and appreciate her support. I also appreciate the encouragement and motivation derived from discussions about the shared challenges in our research journeys with Pablo Ortega from the counseling and special services division at the Mountain House campus of Delta College, who happened to be pursuing his research studies at the same time as I was.

I also want to take opportunity to thank some of my colleagues and staff members at Delta College who contributed to my research work in their own ways. The names which require special mention are Jacquelynn Schwegel, professor of mathematics, Tina Akers, director of Institutional Research, Jacqueline Marcos, Mountain House campus manager, Malaykone Keokhiokham, IT support technician, and Arturo Espinoza, the student programs specialist from the Mountain House campus of San Joaquin Delta College.

My deep gratitude is due to Molly Rentscher, the graduate support coordinator at University of the Pacific's Student Writing Center. She offered great help by providing suggestions and answering all my formatting questions — even on a weekend. My thanks are also due to Melanie Hash, the manager of the writing center, who was very helpful in the initial stages of my dissertation proposal writing.

I would also like to express my gratitude to those serving in the Institutional Research departments at two California community colleges who provided me with the de-identified data used in this study. To protect the identity of the institutions and its students, the colleges are simply referred to as "College A" and "College B" here and throughout this manuscript. Nonetheless, the study would not have been possible without their cooperation for which I am very appreciative.

I am indebted to many of my dear friends and family members who showered their love and appreciation from time to time to keep me going with this project. Blessings from my mother, my dear brothers, sisters-in-law, nephews, and my in-laws helped me focus on my work. The constant support and encouragement from my sister-in-law, Shruti, deserves special accolades. Throughout this journey, she continuously instilled a positive attitude in me to accomplish this task, which looked so formidable in the beginning.

I acknowledge with gratitude the support and love from my husband, Sandeep, and my boys, Anshul and Utkarsh. Their cooperation and their best wishes kept me going and turned the completion of this dissertation into a reality.

Finally, I am grateful to the divine for bestowing on me good health, energy, and a desire to persevere and accomplish a long-time life goal of completing my research degree.

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Abstract

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With AB 705 being enforced in all California community colleges since Fall 2019, colleges have devised corequisite courses in almost all English and mathematics gateway courses. Some quantitative and qualitative studies have shown positive results of corequisite courses in English, and some math courses such as statistics, but there is limited quantitative research on the effects of the corequisite model on student academic performance in STEM math courses, like college algebra and precalculus. Many mathematics department faculty members believe that the corequisite model, especially in STEM math courses, may not work in community colleges due to the population consisting of a large number of non-traditional and under-prepared students at these institutions. This causal comparative study attempted to compare the academic performance of students from corequisite and prerequisite (traditional) types of precalculus courses after controlling for their gender, generational status, prior academic achievement (high school grade point average, HSGPA), and ethnicity. The study also investigated whether the effect of course type on precalculus course grades is moderated by students' generational status, prior academic achievement, and ethnicity. The moderating effects of variables were studied after controlling for the other background variables. Samples for this study were taken from two California community colleges that taught precalculus courses with both models (corequisite and prerequisite) prior to Fall 2019. The data for each of the colleges

were analyzed separately because of their different academic systems (semester versus quarter). Sequential multiple regression was used and variations were found in the results from the two colleges. In addition to tests of statistical significance, effect sizes (based on Cohen's *d*) were calculated to measure the magnitude of the difference between groups. Statistically significant findings from College A (a pseudonym) suggest that the corequisite model of courses in precalculus impacts overall student grades in a positive way. In contrast, there was insufficient evidence based upon data from College B to conclude that corequisite precalculus courses impact course grades. Furthermore, moderating effects were found. In College A, some subgroups (such as Filipinx, Latinx, and White students, those with higher prior academic achievement, or who were first-generation college students) were found to perform better in corequisite courses than prerequisite courses, while students with lower prior achievement (based on HSGPA) performed better with the prerequisite type of courses. The results from both Colleges A and B were consistent in finding that students with lower HSGPA performed worse on average in corequisite precalculus courses. Ethnicity was found to moderate the effect of course type on precalculus course grades when the data from College B was analyzed. The results showed a medium-large effect ($d = -0.65$) for Latinx students who, on average, performed worse in the corequisite precalculus course as compared to the prerequisite version. However, students at College A, regardless of ethnicity, performed better on average in the corequisite classes, and the effect sizes ranged from small to medium-large across the ethnic groups. Limitations of the study, suggestions for further research, and implications for practice and policy are discussed in the following chapters.

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CHAPTER 1: INTRODUCTION

Community colleges, or two-year colleges, are open access institutions and are known for providing higher education to students from a variety of backgrounds in United States (Cohen, Kisker & Brawer, 2013). The objective of these two-year colleges is to equip students with skills and talents to start a career or to transfer to a university for further higher education (Bailey, Jankins, & Jaggars, 2015). Earning a solid grade in a transfer-level math and English course is a major milestone for community college students (Hayward & Willett, 2014). Success in these courses demonstrates that a student has the ability to succeed in challenging college courses, transfer to a four-year college, and earn a bachelor's degree (Adelman, 2006; Hayward, 2011, Moore & Shulock, 2009). Community colleges serve students from a variety of backgrounds. These open access institutions accept students who may not have resources to be successful in a four-year college (Cohen, Kisker & Brawer, 2013). A good community college system embraces the diversity of its students and helps all students achieve their educational goals — irrespective of their social and economic backgrounds. Even though two -year colleges are providing easy and economical access to higher education, the majority of students enrolled in these colleges do not achieve their educational objectives in a timely manner (Bailey, Jaggars, & Jenkins, 2015). It has been found that a large number of students entering community colleges start their college education with remedial courses, and the drop-out rate in these courses is very high (Bailey, Jaggars, and Jenkins, 2015). This results in very few students actually earning an associate degree. In their book, *Redesigning America's Community Colleges,* Bailey, Jaggars, and Jenkins (2015) write: "Yet most students who enter these two-year colleges never finish: fewer than four of every ten complete any type of degree or certificate within six years" (p. 1). The success rate of students from marginalized communities is even lower. It is evident that the colleges, which were started with an objective of easy access to higher education, are struggling to meet the actualization of student success.

Developmental Education

Developmental (remedial or below college-level) education has been the focus of much attention in postsecondary education (Bailey, 2009; Bettinger & Long, 2005; Grubb, 2001; Levin & Colcagno, 2008; Melguizo et al., 2008). Several studies over the last few years have attempted to understand the complex process of remedial education in community colleges. National statistics indicate that 68% of students begin their community college math and English education with below college-level courses (Jaggars & Stacey, 2014). It is found that the majority of first-time community college students (about two-thirds) require remedial math assistance (Bailey, Jeong, & Cho, 2010). Based on an assessment process, Park et al. (2018) also reported that roughly 60% of community college students are referred to developmental math courses upon entry. However, nearly three-fourths of the students who begin the remedial math sequence do not complete college-level math courses successfully (Bahr, 2012; Bailey, 2009). Compared to other post-secondary courses, the highest failure and withdrawal rates are in developmental math courses. One research study estimated the failure rate in developmental math as 14.2% with a withdrawal rate of 20.8% (Adelman, 2004). Developmental courses are supposed to provide support to underprepared students, but a growing body of research suggests that students placed in developmental education, especially in math, are highly unlikely to obtain an associate degree or transfer to a four-year college (Bailey et al., 2010; Colcagno, Crosta, Bailey, & Jenkins, 2007; Fong, Melguizo, & Prather, 2015).

To achieve student competency in math has long been a matter of national concern. In 2012, the then president, Barack Obama, called for math and science education to be made a national priority in order meet the demands of the overall economy (Cortes, Nomi, & Goodman, 2013).

For these reasons, postsecondary institutions nationwide are rethinking their approach to improve students' math preparation (Burdman et al., 2018).

Accelerating Developmental Education

States and colleges all over the U. S. are adopting newer approaches to developmental education to improve graduation rates for struggling students. Organizations like Complete College America (CCA), California Acceleration Project (CAP), Dana Center of University of Texas at Austin, and Carnegie Foundation for the Advancement of Teaching are advocating for acceleration of the remediation process in math and English courses. Several different models of acceleration, like paired courses, compressed courses, and modularized instruction, are being used by different institutions all over the nation to accelerate the math and English developmental education. One of the models of acceleration which has gained rapid acceptance is the corequisite model.

Corequisite Model

The corequisite model is one strategy to provide accelerated developmental education in math and English. In this model, underprepared students are placed directly into a college-level math or English course with additional support in the form of labs, tutoring, supplemental instruction, and just-in-time remediation (Edgecomb, 2011; Venezia & Hughes, 2013; Kosiewicz, Ngo & Fonk, 2016; Complete College America, 2016). An online overview by California Acceleration Project (CAP) (n.d.) on the corequisite model states:

> Corequisite models are the most powerful strategy for increasing completion of transfer-level math and English for students designated "not college ready." In states that have replaced traditional remediation with corequisite models, such as Tennessee, Colorado, Indiana, and West Virginia, students are completing transfer requirements in math and English at nearly three times the national average, and in half the time. (para. 2)

Colleges are replacing the traditional approach to remediation with the accelerated corequisite approach in the first college level English and math courses, like statistics, quantitative reasoning, and precalculus. Although there is evidence suggesting good results with a corequisite model in statistics, there is not much research available on the results of a corequisite model in math courses like college algebra or precalculus.

Colleges are experimenting with different versions of a corequisite model. A research report by Rand Corporation found at least five different types of corequisite models being implemented by the participating community colleges in the state of Texas (Daugherty, Gomez, Carew, Mendoza-Graf, & Miller, 2018). Some of these types include pairing a transfer-level course with a support course, extending instructional time through additional lecture or lab hours, or requiring students to participate in academic support services or supplemental instruction (Daugherty et al., 2018).

The process of concurrent enrollment in a first college-level (gateway) course and a support course, though relatively new, has been adopted by several community colleges nationwide. The Accelerated Learning Program (ALP) of the Community College of Baltimore County (CCBC) is one of the first corequisite models and became very popular. It was designed for an English classroom at CCBC in 2009. The model was studied by the Community College Research Center (CCRC) in 2010 (Jenkins et al., 2010) and 2012 (Cho et al., 2012). The ALP model reported improved outcomes in college-level English. This improvement was very prominent for remedial students just beneath the highest placement cut-off. Another noteworthy study on a corequisite math model was conducted by the City University of New York (CUNY) at three of their participating community colleges (Logue, Watanabe-Rose, & Douglas, 2016). The CUNY study conducted as a randomized controlled trial (RCT) compared the outcomes of students from similar remedial backgrounds who were randomly placed into three math course designs: a traditional version of remedial elementary algebra (EA), a corequisite version of remedial elementary algebra with an added workshop (EA-WS), and a corequisite version of college-level statistics which also had a workshop added (Stat-WS). The study reported higher pass rates in the corequisite college-level statistics course (Logue, Watanabe-Rose, and Douglas, 2016). The CUNY study is important, as it is the only randomized controlled trial (RCT) on corequisite models thus far. However, there have been other qualitative and non-RCT quantitative studies reporting positive outcomes of corequisite models in a statistics course (Atkins, 2016; Kashyap & Mathew, 2017).

Corequisite model in California. In California, at least 20 community colleges implemented corequisite models in English and math (mostly statistics) courses in the years 2016 and 2017. Despite the advocacy of the corequisite model by California Acceleration Project (CAP), many community colleges were reluctant to adopt it in algebra intensive STEM math courses, like college algebra and precalculus. CAP colleges like Cuyamaca and Los Medanos have been some early implementers of corequisite models in math courses. Recently, looking at the promising results of the corequisite model from some other states, the state of California passed a law which mandates the use of a corequisite model to replace the sequence of developmental courses in math and English.

AB 705 Law

In October 2017, California Governor, Jerry Brown, passed state law AB 705, which guides colleges towards adopting the corequisite model. The new legislation aims at helping more students succeed in completing a degree, certificate, or transfer by ensuring that they have access to college-level courses when they first enter a community college. In order to maximize the likelihood that students will complete college-level coursework in English and math within a one-year timeframe, AB 705:

- requires colleges to use high school transcript data, and sets a standard for how community colleges use this data, to place students into math and English courses
- allows more students to enroll directly into college-level courses in which they can be successful. (The Campaign for College Opportunity, 2017, para. 1).

AB 705 mandates that colleges may not put a student into a remedial course unless they can demonstrate that the student is "highly unlikely" to succeed in a college-level course without it (Seymour-Campbell Student Success Act of 2012, 2017). All colleges were mandated to adopt the law starting Fall 2019.

The corequisite model supported by the AB 705 law claims student success by direct enrollment into a college-level English or math course. However, not many colleges offered the corequisite model in a precalculus class prior to Fall 2019, and majority of the results showed success of the model in English and math courses, like statistics and quantitative reasoning. The research on success of a corequisite model in a STEM (Science, Technology, Engineering and Mathematics) math course, like precalculus, is lacking.

To be complaint with AB 705, all community colleges in California have adopted different designs of corequisite models in all first college-level (gateway) math courses, including statistics, college algebra, and precalculus. Cuyamaca College in San Diego was the first community college in California to adopt a corequisite model in all math courses. Positive results have been reported with corequisite models in non-STEM math courses, but more research is needed to study the effect of corequisite models on a STEM gateway course. The focus of this study is on a corequisite model in precalculus, which is a gateway math course in the STEM field. The study will also explore the effect of the corequisite model on student populations like first-generation students and historically marginalized students, such as Latinx and African Americans students. It will also investigate how placing students directly into a college -level course with the corequisite model affects students with low levels of prior academic achievement. High school grade point average (HSGPA) will be used to determine the prior skill level of a student.

Problem Statement

Research suggests that absence of college readiness in math can be the greatest obstacle to students' success (Park, et al., 2018). Often students abandon their goals of higher education due to frustration caused by the long sequence of remedial courses like basic arithmetic, prealgebra, elementary algebra, and intermediate algebra. The national and state directives are trying to improve the situation by promoting alternative teaching models to developmental education. The AB 705 law of California recommends replacing the long sequence of prerequisite remedial courses with corequisite courses in math and English (Seymour-Campbell Student Success Act of 2012, 2017). Though a number of developmental education reforms have been successful in improving student outcomes (Cho et al., 2012; Edgecomb, 2011), research suggests that in some cases the results have not been very encouraging. There are some studies of learning communities and modularized math reforms which are found to have few positive impacts (Bickerstaff, Fay, and Trimble, 2016; Gardenhire et al., 2016). In a report on

“The Corequisite Reform Movement” on the CAP website by Goudas (2017), the author writes that the benefits of corequisites are best for those remedial students who are just beneath the college-level cutoff. Besides, most of the corequisite models in math have focused on student achievement in non-STEM math courses, like statistics and quantitative reasoning. These courses are known to be not very algebra intensive. Currently, there are fewer corequisite models in the courses leading to science, technology, and engineering careers. These courses require a strong background in algebra, and whether a corequisite model in a STEM gateway course of college algebra or precalculus improves students’ academic performance in such courses must be understood. Additionally, college success rates for first generation students, African American/Hispanic students, or students with low prior academic achievement have been a cause of concern. More research is needed to study the effect of a corequisite model in a STEM math course for students in general, as well as for marginalized student subgroups.

Purpose of the Study

The purpose of the study is to investigate a possible cause and effect relationship between the type of developmental education model (traditional vs corequisite) a student completed and the academic performance by the student in a STEM gateway course of precalculus. In addition, the study explores whether the impact of a corequisite model on academic performance varies across student subgroups based on their generational status, ethnicity, and prior academic achievement.

Research Questions

The study is designed to address the following questions.

1. Are average course grades in a STEM gateway math course better for those who completed the corequisite model than those who completed it with the traditional

model after controlling for prior academic achievement, gender, generational status, and ethnicity?

2. Does the impact of a developmental education model (traditional vs corequisite) on course grades in a STEM math course vary by the generational status (first generation versus non-first generation) of a student after controlling for their gender, ethnicity and prior academic achievement?

3. Does the impact of the type of model on course grades in a STEM math course vary by the prior academic achievement level of a student after controlling for their gender, ethnicity and generational status?

4. Does the impact of the type of model on course grades in a STEM math course vary by the ethnicity of a student after controlling for their gender, generational status and prior academic achievement?

Significance of the Study

The study is significant in the field of higher education as it relates to student success in a community college gateway course, which further paves the way for degree completion or transfer to a four-year college by students of all groups and subgroups. In 1947, the Truman Administration's Commission on Higher Education called for an expanded community college network by placing a two-year college education within reach of all American citizens. The Obama administration also called for modernizing community colleges and expanding course offerings to raise Americans' skill and education levels (The White House, 2009). Community colleges teach courses to help local industries get more educated workers (Gilbert & Heller, 2013). Success in college helps students meet their long-term personal and career goals and provides them with a range of monetary, psychosocial, and physical benefits (Baum & Ma, 2007). Based on the abovementioned facts, there is a widespread awareness of the need to improve the outcomes of community college students. The AB 705 law for community college education aims at accelerating the process of gateway course completion by restricting enrollment into developmental courses and thus increasing college degree completion and transfer rates. Such legislatures and professional regulations have immediate and long-term effects on students, teachers, parents, and — ultimately — our communities and nation.

Research also suggests that completion of mathematics remediation may be the single largest barrier to increase graduation rates (Attewell et al., 2006; Complete College America, 2012). Low college completion rates reflect widespread failure, disappointment, and reduced potential among a large number of community college students. According to Bahr (2013), “It is unquestionably true that assisting every community college student to achieve college-level math competency is a highly desirable goal, benefitting both the students themselves and society as a whole” (p. 172).

Studies also show less positive effects of remediation on students from historically underserved and marginalized populations. According to a report by Complete College America, 85.6% of African American students and 76.2% of Hispanic students could not finish their remediation and associated college-level courses in two years (Complete College America, 2012). A research brief from California Community Colleges (CCC) reported that first-generation students were more likely to enroll in a developmental course and were slightly less likely to complete courses successfully (California Community Colleges, Sept. 2014).

The current study, using the principles of scientific and evidence-based inquiry, investigates the effectiveness of corequisite math courses, especially in the STEM field, on students in general as well as students from some underserved backgrounds. Results from the study will help to ascertain the effects of a corequisite model in gateway courses of precalculus. This will be significant to all the educators, administrators, and policy makers who are trying to bring about a positive change in the academic outcomes of community colleges nationwide.

Definition of Key Terms

The following key terms are used in this study. A short definition of these terms is provided below.

Developmental Courses

The courses below college-level are called remedial or developmental courses (Hagedorn & Kuznetsova, 2015). Underprepared students coming to community colleges have traditionally been placed into developmental courses based upon their score from an assessment process. This process of placement is under revision, and new measures are being suggested to place students into a college-level class.

Acceleration

The process of shortening the sequence of developmental courses is termed acceleration (Jaggars, Hodara, Cho, & Xu, 2015). There are several forms of accelerated pathways.

Corequisite Model

A corequisite model is a popular form of academic acceleration. In this model, students complete the developmental course content within or concurrent with the gateway course (Edgecombe, 2011). Students are directly placed into an introductory college-level course with remedial support through mandatory companion classes, labs, or other learning support (Edgecombe, 2011). Students in a corequisite model do not need to complete the long sequence of developmental courses.

Prerequisite Model

In this study, the prerequisite model refers to the traditional approach to developmental course sequence, where students finish a maximum of four levels of developmental math courses before starting a college-level math course.

Cohort Corequisite Model

In a cohort model of corequisites, students form a cohort of a support class and a mainstream class, which are generally taught by the same teacher.

Comingling Corequisite Model

Comingling is a kind of corequisite teaching where students in a support class may be from different mainstream classes taught mostly by different teachers.

STEM Versus Non-STEM Math Courses

Math courses can be categorized into two broad fields: STEM (Science, Technology, Engineering, and Mathematics), and non-STEM. Students interested in statistics/liberal arts mathematics generally enroll in non-STEM math courses, while students preparing for careers in STEM opt for math courses like college algebra or precalculus, leading to a series of calculus courses. As per Burdman et al., (2018), “Leading math associations note that college algebra is not an effective course for most students in the humanities and social sciences” (p. 33). Traditionally, most colleges require completion of intermediate algebra for all math students as a default general education requirement. This practice has been questioned, since not much of algebra is relevant for students not interested in STEM majors.

Gateway Course

A gateway course is the first college-level course in any discipline. College algebra and pre-calculus are gateway STEM courses, as these are the first courses in a series of transferable college-level math courses for students in STEM majors (Henson et al., 2017). Statistics and quantitative reasoning are the gateway math courses for non-STEM students.

AB 705 Law

AB 705 (Seymour-Campbell Student Success Act of 2012, 2017) was passed in October 2017 with a mission to increase college graduates in California. Under this law, community colleges are expected to maximize the chances that students who seek to transfer can enter and complete a transfer-level math course within a one-year time frame. The law mandates the use of multiple measures, including students' high school records, to determine whether students need remedial coursework.

Multiple Measures Assessment

Traditionally, assessment exams like COMPASS and ACCUPLACER have been used to assess a student's skill level, but under the new AB 705 law, colleges are required to base placement decisions on more than one factor, which includes students' high school experience and academic records. Under a multiple measures approach, standardized testing is no longer the primary means of assessing if a student is prepared for college-level coursework (California Community Colleges, n.d.).

Multiple Measures Assessment Project (MMAP)

The MMAP project led by the RP Group was originally designed to develop, pilot, and assess implementation of a statewide placement tool using a multiple measure approach. The MMAP project, now engaged with over 90 pilot colleges statewide, is working with the Community College Chancellor's Office to provide support, research, and recommendations on maximizing students' likelihood of completing a transfer level math or English course in one year, or an ESL course in three years. (The RP Group, n.d.).

Statway

Statway is an accelerated course in statistics that combines college-level statistics with developmental math support (Carnegie Math Pathways, n.d.-a).

Quantway

Quantway is a set of quantitative reasoning course options designed to promote success in community college mathematics and to develop quantitatively literate students (Carnegie Math Pathways, n.d.-b).

Delimitations

The AB 705 law and the corequisite model is applicable in math, English, and ESL courses. Corequisite models have been found to be successful in English (ALP model of Baltimore) and statistics (Logue, Watanabe-Rose, & Douglas, 2016), but the current study will focus on the STEM branch of math courses. College algebra and precalculus are two popular STEM gateway courses. This study will focus on the effects of a corequisite model on the academic performance of students in a precalculus course.

Summary

The research on developmental/remedial education in the field of higher education is plentiful. A large number of students who are underprepared for college-level work enroll in community colleges due to their open access policies. Many of these students are put through a long sequence of remedial courses, which sometimes takes two to three years to complete and, finally, get to a gateway course. Research shows that a longer sequence of remedial courses results in many exit points. Many students drop out in frustration without completing the remedial course sequence. Because of this, a very small number of students reach a college-level/gateway course, and an even smaller number of students reach their goal of college degree completion or transferring to a four-year university. Corequisite models allow students to be placed directly into a college-level course along with remedial support. This may give students a better chance of finishing their academic goals faster because they are not wasting time in what could be a number of unnecessary courses. The research shows that the accelerated models in English and some non-STEM math gateway courses lead to student success in a shorter time frame (Logue, Watanabe-Rose, & Douglas, 2016). In terms of math courses, available research is mostly on corequisite models in statistics courses. Unlike statistics, the STEM math course of precalculus is an algebra intensive course. More research is needed to know the effect of the recently introduced corequisite model on student success in a STEM math course. This study will investigate a corequisite model in a precalculus, STEM math class. It will also explore the effect of the model on underserved and marginalized populations, such as first-generation students, Hispanic or African-American students, and at-risk (low-performing) students.

CHAPTER 2: LITERATURE REVIEW

This chapter reviews the literature on developmental education in math at community colleges. Focus is on issues with developmental education, and recent attempts to fix these issues. Many accelerated pathways to developmental education are recommended in the literature, and one of the more popular accelerated models is called the corequisite model. In this chapter, studies of different corequisite model forms are discussed in detail as an attempt to identify the gap in research by critically reviewing these models. Later in the chapter, there is a discussion on some of the historically underserved student populations at community colleges, like first-generation students, racial minority students, and students with lower academic skills, followed by the chapter summary.

Community colleges provide higher education to a wide variety of students. Their open access policies provide advanced educational opportunities for millions of students who might not otherwise be able to pursue them. Unfortunately, about 60% of college freshmen students are unprepared for college-level work (Grubb et al., 2011), and these deficiencies are most often found in mathematics courses (Attwell, Lavin, Domina, & Levey, 2006). Usually, college policies require these students to complete a sequence of remedial courses in math prior to taking college-level courses. However, the percentage of successful completion of the remedial courses is low (Bailey, Jeong, & Cho, 2010).

Furthermore, some students that are assigned to remedial courses wait to take them or never take them, which delays or prevents their graduation (Bailey et al., 2010). Each year in California, more than 170,000 students start community college in a remedial math course (Henson, Huntsman, Hern & Snell, 2017). It is alarming but important to note that more than

110,000 students never complete the math course(s) required for a degree (Student Success Scorecard, CA, 2017). According to a report from the Public Policy Institute of California (PPIC), "In its current form, developmental education may be one of the largest impediments to success in California's community colleges" (Mejia, Rodriguez, & Johnson, 2016). Students are designated as "unprepared" and placed into remedial courses based upon standardized tests, which do not always accurately reflect their academic capabilities (Belfield & Crosta, 2012). A growing body of research shows that these students are far more capable of academic success than previously recognized (Complete College America, 2016). Faced with this evidence, policymakers and administrators are calling for change in developmental education policies (Bettinger, Boatman, & Long, 2013). Community colleges across the United States are developing new or alternative models of course delivery that accelerate the process of gateway course completion by reducing the potential exit points in developmental education (Carnegie Foundation for the Advancement of Teaching, n. d.). Some colleges are experimenting with accelerated developmental pathways, which allow students to complete remediation and enroll in college-level courses in a shorter time frame (Jaggars, Hodara, Cho, & Xu (2015). The need for acceleration is realized due to several identified issues with traditional developmental education.

Problems with Developmental Education

Community colleges serve the largest proportion of nontraditional students (Hagedorn & Kuznetsova, 2016). Students entering the developmental pipeline are advised to enroll in one or more developmental courses (Hagedorn & Kuznetsova, 2016). Placement into these courses is based upon performance on placement exams, such as the ACCUPLACER or COMPASS (Bailey, Jeong & Cho, 2010; Hughes & Scott-Clayton, 2011). Generally, these courses are offered as a sequence of remedial courses in math and English, which could be up to three or four levels below the first college-level (gateway) course. The developmental courses are intended to give less-prepared students a chance to catch up and meet the challenges of college-level course work (Hern, 2012).

A growing body of research suggests that students placed in developmental education are not likely to obtain an associate degree or transfer to a four-year college (Bailey, Jeong, & Cho, 2010; Fong, Melguizo, & Prather, 2015, Hagedorn & Kuznetsova, 2016). Issues surrounding developmental education, student engagement, and low retention rates have been of major concern in community colleges all over the nation (Center for Community College Student Engagement, 2015; Bettinger, Boatman, & Long, 2013). Below are four of the most salient issues with developmental education discussed in detail.

Lengthy Sequence

In the past, community colleges have offered many different levels of remedial courses for developmental education. Some community colleges in California offered up to four levels of math remediation below the first college-level course. Table 1 below, adopted from Hagedorn and Kuznetsova (2016), shows these courses.

Table 1
An Example of Hierarchical Levels in Developmental Math Education

Level	**Math Course(s)**
0 - Fundamental	Arithmetic
1 - Remedial	Pre-algebra
2 – Basic	Elementary Algebra
3 – Intermediate	Intermediate Algebra
4- First College-Level Course (Gateway)	College Algebra, Precalculus, or Statistics

Source: Hagedorn, L. S., & Kuznetsova, I. (2016). Developmental, remedial, and basic skills: Diverse programs and approaches at community colleges. *New Directions for Institutional Research*

The lengthy remedial course sequence provides too many opportunities for students to drop out (Hern, 2010; Bailey et al., 2010). Research shows that students drop out even if they pass courses within a sequence. According to a report by the Community College Research Center (CCRC), out of the students placed three or more levels below college-level math, fewer than 10% ever go on to complete a college-level math course. In other words, 90% of these students are lost before they even start their college-level education (Hayward & Willett, 2014). A study of 57 colleges from an initiative called "Achieving the Dream" found that only one in five students beginning the remedial math sequence at three or more levels below college-level math completed the highest level of the remedial sequence successfully, and only one in ten completed the gateway transfer-level math course. (Hayward & Willett, 2014). Myra Snell, the cofounder of the California Acceleration Project (CAP), developed a framework called the "multiplication principle" to explain the attrition of students in developmental course sequences (Hern, 2010). According to this principle, students drop out at each level of the developmental sequence, thus diminishing the number of students that ultimately progress to a gateway course (Edgecombe, 2011). Figure 2 below, as given by Hayward & Willett (2014), describes the statewide progression of students from three levels below transfer to a gateway math course within Fall 2010 to Spring 2013. It explains that at each level, students are lost not only because some of them do not pass the course, but also because some of the successful students fail to enroll in the subsequent course. The pass percentage at each level is high, but the number of students who successfully complete the gateway course is just 7% (3,383 out of 31,959) of the students who enrolled at the lowest level of the developmental sequence.

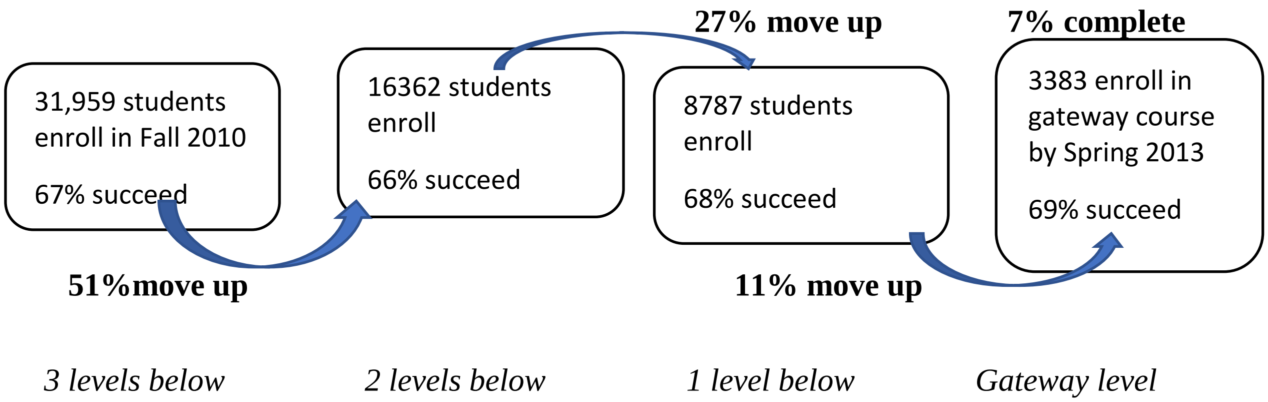

Figure 1. Attrition rate in various levels of developmental math courses. Source: Curricular redesign and gatekeeper completion: A multi-college evaluation of the CAP (2014) by Hayward, & Willett

Placement into Remediation

According to Fields and Prasad (2012), over 90% of all community colleges in the country used a placement test to determine students' readiness for college-level work. Another article by Bailey, Jeong, and Cho, (2010) reported that nearly 60% of all incoming community college students enrolled in a remedial course. According to one research article, nearly 25% of students were misplaced into their math courses by commonly used placement tests (Scott-Clayton, Crosta, & Belfield, 2014). Placement errors pose serious consequences for educational attainments. Students must pay tuition for remedial courses, but the credits they earn do not count toward graduation requirements (Scott-Clayton, 2012). A research study by the CCRC found that many of the students placed into remedial courses did not need remediation (Scott-Clayton, 2012). The study predicted that 50 percent of incoming students would succeed in college-level math courses, while just 25% were eligible to take them based upon their placement scores. Katie Hern, the cofounder of CAP, feels that placement tests are weak predictors of students' ability. According to her, by relying on these tests, community colleges underestimate the abilities of many students (Hern, 2012). Researchers found that using additional information, such as high school GPA, could improve placement accuracy. Another study by CCRC observed, “High school GPA is an extremely good and consistent predictor of college performance, and it appears to encapsulate all the predictive power of a full high school transcript in explaining college outcomes” (Belfield & Crosta, 2012, p. 39). The Multiple Measures Assessment Project (MMAP) analyzed a dataset from California high schools and community colleges and found that a large percentage of incoming community college students could be placed directly into college-level courses by using high school transcript data instead of their scores on placement tests. The MMAP study conducted by Research and Planning Group (RP Group) for California community colleges states that “…students placed via placement tests did not differ in their rate of success from students placed via high school achievement, on average, but more students qualified to take college-level coursework based on high school achievement (Bahr et al.,2017, p. 29).

Cost of Remediation

Remediation in higher education comes at a great cost. The national cost is estimated to be well more than a billion dollars a year at public colleges alone (Strong American Schools, 2008). Based upon a study in 2011, the total cost of delivering remediation nationwide for college students enrolled during the 2007-2008 academic year was $5.6 billion (Alliance for Excellent Education, 2011). This cost included direct costs both to students and institutions in the form of tuition and instructional costs, and indirect cost in the form of lost lifetime wages due to the likelihood of remedial students dropping out of college before earning a degree (Pretlow & Wathington, 2012; Boatman & Long, 2018). A recent report from the Center for American Progress estimated that, nationally, students pay approximately $1.3 billion for remediation each year (Jimenez, Sargrad, Morales, & Thompson, 2016).

No Credit Courses

Developmental courses do not typically count toward a degree or certificate, which delays students' progress toward a college degree and/or certificate (Crisp & Delgado, 2014). This results in additional educational costs and opportunity costs of foregone earnings (Bailey, Jeong & Cho, 2010); Hughes & Scott-Clayton, 2011; Levin & Colcagno, 2008). Bahr et al. (2017) also noted that a student in developmental education might spend considerable time and money without making progress toward a degree.

Discussing the issues with developmental education, Boylan and Trawick (2015) wrote, "Standalone remedial courses are generally not very effective, our assessment and placement processes are often poorly designed and poorly implemented, and too few participants in remedial courses graduate" (p. 33). Many states in the US have started adopting policies to accelerate students through the developmental course sequence by redesigning the course structure. Some states have revised their placement policies to allow greater flexibility in terms of developmental course requirements, or they have changed the way these courses are being taught (Bailey & Jaggars, 2016; Park, Woods, Hu, Jones, & Tandberg, 2018). Colleges are experimenting with the programs designed to shorten the developmental sequence, decrease the number of exit points, and increase completion of transfer-level English and math courses. The emerging pathways of developmental education are termed accelerated pathways. Colleges are using different types of accelerated pathways, which are explained in the section below.

Accelerated Pathways

Acceleration in community colleges is a reorganization of structure and curriculum in a way that facilitates completion of educational requirements in an expedited manner (Edgecombe, 2011). The case for accelerating developmental education was first made by Boylan (2004) when the author described a model of improved student placement and integrated support intervention to move students to college-level courses more quickly (Saxon & Martirosyan, 2017). More recently there has been a substantial push to accelerate the instruction and delivery of developmental mathematics courses. Accelerated course structures differ across institutions. Following are some of the common models adopted by some community colleges.

Modularization

In modularized courses, content is broken into smaller learning units intended to strengthen a particular skill (Venezia & Hughes, 2013) and is presented in standalone modules. Students participate only in those modules which cover materials they need to learn, thus accelerating students' journeys through the developmental sequence (Hagedorn & Kuznetsova, 2016).

Compression

Compressed courses combine multiple developmental courses and shorten the length of time for skills development (Venezia & Hughes, 2013). In some cases, the content of a single course is compressed into the first half of a semester, followed by the next course in the sequence in the latter half (Edgecomb, 2011).

Combination or Pairing

This course structure combines two sequential developmental courses into a single course with the same overall number of contact hours (Bailey et al. 2015).

Curricular Redesign

Curriculum may be redesigned by eliminating the redundant content and modifying it to meet the learning objectives of a particular academic pathway (Edgecomb, 2011).

Corequisite Remediation

Corequisite remediation allows students of all skill levels to be placed directly into a college-level course while receiving support designed to help them succeed in that course (Bailey et al. 2015).

The *FastStart* program of the Community College of Denver is an example of the combination model, where students placed at the lowest level of math and required to complete three developmental math courses have the option of taking two of these courses together in one semester (Edgecombe, 2011). The Carnegie Foundation for the Advancement of Teaching adopted curricular redesign by designing two accelerated math pathways: Statway and Quantway. These programs shorten the long sequence of remedial math courses to one pre-transfer level course which students can take regardless of their placement scores. All community colleges in the state of Virginia have accelerated their developmental math education by modularizing the course content. Colleges and organizations using accelerated models are very optimistic about the results. Jaggars, Hodara, Cho, and Xu (2015) studied acceleration models in math and English in three different community colleges and analyzed the results in a one- and three-year-time frames. Students from the accelerated class model were more likely to succeed in a college-level math class. The progress report at Virginia community colleges (2015) shows that this redesign of mathematics courses led to an increase in the number of students completing the math sequence in one year from 5% to 18% (Hagedorn & Kuznetsova, 2016). Similarly, Statway and Quantway models found a substantial increase in the proportion of students who completed a college-level math course in one year (Mullin, 2012). Even though accelerated course structures differ across institutions, one of the most popular accelerated models is the *corequisite* model.

Corequisite Model

The corequisite model "comes closer than any other acceleration strategies to blurring the distinction between college-ready and developmental students and to integrating remedial supports into college-level coursework" (Bailey et al., 2015, pp. 133-134). In this model, students take college-level classes rather than remedial courses. These students get simultaneous remedial support through mandatory companion classes, labs, or other learning support (Edgecombe, 2011). One of the earliest and best-known examples of acceleration using a corequisite model is the Accelerated Learning Program (ALP) at the Community College of Baltimore County (Edgecombe, 2011). In 2009, the Community College of Baltimore County (CCBC) enrolled upper-level developmental English students in a regular college composition class along with a simultaneous small-group support class taught by the same instructor (Edgecombe, 2011; Hern 2012). A study found that 73% of ALP students completed college-level English with a grade of C or higher within three years, compared to 45% of similar non-ALP students (Bailey et al., 2015).

One randomized research study investigated the effectiveness of a corequisite model in a mathematics (statistics) course. Three community colleges at the City University of New York (CUNY) performed a randomized controlled study (Logue, Watanabe-Rose, & Douglas, 2016). Students needing remedial elementary algebra were assigned to one of three different Fall 2013 courses: 1) traditional elementary algebra (Group EA); 2) same course with weekly workshops (Group EA-WS); 3) college-level statistics with weekly workshops (Group Stat-WS). The third group involved the co-requisite instruction model. The results showed that the "Stat-WS students passed statistics at not the hypothesized same rate as the elementary algebra students but at a significantly higher rate than did the EA and EA-WS students" (Logue, Watanabe-Rose, &

Douglas, 2016, p. 592). These results indicate that the corequisite remediation approach has the potential to affect the academic progress of many college students positively. Tennessee's Austin Pea State University has also seen impressive results from replacing remedial courses with corequisite models (Belfield, Jenkins, & Lahr, 2016). These results determined that corequisite models enhance student motivation by placing them directly into a college-level course (Belfield et al.,2016).

In 2012, the Louisiana Board of Regents did a statewide pilot study of the corequisite delivery model at two-year colleges and regional universities (Campbell & Cintron, 2018). Students within two points of the statewide cut score for placement into college-level math and English were put into the co-requisite pilot courses. Findings showed that students in the pilot group were able to complete both their remedial requirement and college-level math within one semester without a significant difference in their passing rate from students in other groups who spent multiple semesters completing their remedial requirement and college-level math (Campbell & Cintron, 2018).

Kashyap and Mathews (2017) studied a corequisite model for a college-level math course called Quantitative Reasoning (QR) in a private liberal arts institution. In this study, the QR course was offered under three different course sequence models. 1) prerequisite model, 2) corequisite model with remediation support 3) Quantitative Reasoning course alone. Results showed that grades of students in the corequisite model were higher than that of the prerequisite model.

Park et al. (2018) investigated the course enrollment patterns and success rates for underprepared first-time-in-college (FTIC) students in Florida, who elected to take intermediate algebra, a gateway math course in Florida. Though developmental education is optional in

Florida, a small percentage of students enrolling in intermediate algebra also enrolled in developmental math in the same semester through a compressed or corequisite course. FTIC students who received same semester developmental support were more likely to pass intermediate algebra compared with similar underprepared students who took the course in the traditional way without any developmental support. Among the successful students were those who were slightly underprepared and took the same semester developmental coursework along with gateway course (Park, Woods, Hu, Jones, and Tandberg, 2018).

Corequisite models have been adopted in many different designs. Institutions have considerable freedom to design and implement corequisite courses in different ways. For example, Daugherty and Gomez et al. (2018) found five different types of corequisite models being implemented in the state of Texas. The reported models from the state of Texas are presented in Table 2.

Table 2
Different Designs of Corequisite Model

Paired Course model	Students are enrolled in the developmental course and the college-level course simultaneously in one semester rather than staggering the courses over two semesters.
Extended instructional time model	Developmental support is designed as an extension of the college-level course. Most of the support is designed as one credit hour, and in most cases is taught by the same instructor teaching the college-level course.
ALP model	This model is based upon the ALP-prescribed design. In this design, developmental support is structured as classroom instruction with the college-level course offered as a mix of college-ready students and developmental students. The support course could be offered as one, two, or three credit hours of developmental support with a reduced student-to-instructor ratio in the support class.
Academic support service model	This model requires mandatory, regular participation in academic support services offered by the institution. Mandatory participation in support services, like attending tutoring services, writing centers, and instructor office hours is needed alongside the college-level course.
Technology-mediated support model	Here, developmental support primarily relies on technology-mediated instruction through work on computer-adaptive modules in lab settings. This model often has one-credit hour support, and in most cases managed by a different instructor facilitating the lab sessions.

Source: Adapted from Daugherty, L., Gomez, C. J., Carew, D. G., Mendoza-Graf, A. & Miller, T. (2018). Designing and implementing corequisite models of developmental education: Findings from Texas community colleges. Santa Monica, CA: RAND Corporation. Retrieved from: https://www. rand. org/pubs/research_reports/RR2337. html.

Accelerating Developmental Education and Corequisite Models in California

California Acceleration Project (CAP), a faculty-led professional development network was founded in 2010 to promote the acceleration of developmental education in California (Hern, 2012; Hayward & Willett, 2014). It supports the state’s 114 community colleges to transform remediation and increase student completion of transfer-level math and English courses. Two CAP colleges, Cuyamaca college and Los Medanos College, were early implementers of accelerated education in mathematics. Los Medanos College designed an accelerated pathway for students interested in taking statistics as their college-level mathematics requirement (Hayward & Willett, 2014). The college designed a new course called the "Path2Stats" course, a one-semester developmental course leading to college statistics with no pre-requisites or minimum placement score (Hern, 2012). A quasi-experimental study by the Research and Planning Group for California Community Colleges (RP Group) examined student outcomes at the first 16 CAP colleges. The report on the project supported the hypothesis that accelerated pathways can improve student completion of college-level gateway courses (Hayward & Willett, 2014). The study found that in accelerated math pathways, students' odds of completing college-level math (statistics) were four-and-a-half times higher than in traditional remediation. The accelerated pathways were also found to benefit students from all racial/ethnic groups and placement levels.

In 2017, California state government passed AB 705, mandating all its community colleges to move towards adopting corequisite models of acceleration starting fall of 2019. Some colleges have already followed suit with other colleges of the nation, and at least 20 California community colleges were implementing corequisite models in English or some math courses in 2016 or 2017. Cuyamaca college was the first community college in California to completely transform math remediation by adopting corequisite model for all math courses.

AB 705 Law

AB 705 of California was passed in October of 2017 as a major overhaul for remedial education. "This new law requires colleges to maximize students' chances of enrolling in and completing a math course appropriate to their education goals within one year of first attempting a math course" (Burdman et al.,2018, p. 2). The law recommends that all students should be directly enrolled into a college-level course unless it can be demonstrated that a student is "highly unlikely" to succeed in that course.

With AB 705, there is a change in the student placement policies as well. The new placement directives are called Multiple Measures and Placement (MMAP). Under a multiple measures approach, standardized testing is no longer the primary means of assessing if a student is prepared for college-level coursework (California Community Colleges, n. d.). Colleges are required to base placement decisions on more than one factor, including students' high school experience and academic records. The law leaves room for colleges to exercise local control over placement in response to research on their own student body. "AB 705 does not dictate specific placement rules or criteria; rather, it sets standards that colleges must use in their local decision-making. These standards are designed to ensure that placement decisions maximize a student's likelihood of completing math and English milestones" (The Campaign for College Opportunity, 2017, para. 1)

With the new AB 705 guidelines, students of all skill levels can choose to enroll in a college-level math course. The following tables (Table 3 & Table 4) are from a recent memorandum by California Community Colleges on AB 705 implementation. These tables present a high school performance metric for placement into college-level math courses from statistics/liberal arts mathematics and BSTEM mathematics. BSTEM here refers to Business, Science, Technology, Engineering, & Mathematics courses. The skill level of students is based on their high school GPA (HSGPA).

Table 3
High School Performance Metric for Statistics/Liberal Arts Mathematics

High School Performance Metric for Statistics/Liberal Arts Mathematics	**Recommended AB 705 Placement for Statistics/Liberal Arts Mathematics**
HSGPA ≥ 3.0	**Transfer-Level Statistics/Liberal Arts Mathematics** No additional academic or concurrent support required for students
HSGPA from 2.3 to 2.9	**Transfer-Level Statistics/Liberal Arts Mathematics** Additional academic and concurrent support recommended for students
HSGPA < 2.3	**Transfer-Level Statistics/Liberal Arts Mathematics** Additional academic and concurrent support strongly recommended for students

Source: California Community Colleges Memorandum (July 11, 2018). *Assembly Bill AB 705 Implementation.*

Table 4
High School Performance Metric for BSTEM Mathematics

High School Performance Metric BSTEM Mathematics	**Recommended AB 705 Placement for BSTEM Mathematics**
HSGPA ≥ 3.4 **OR** **HSGPA ≥ 2.6 AND enrolled in a HS Calculus course**	**Transfer-Level BSTEM Mathematics** No additional academic or concurrent support required for students
HSGPA ≥2.6 or Enrolled in HS Precalculus	**Transfer-Level BSTEM Mathematics** Additional academic and concurrent support recommended for students
HSGPA < 2. 6 and no Precalculus	**Transfer-Level BSTEM Mathematics** Additional academic and concurrent support strongly recommended for students

Source: California Community Colleges Memorandum (July 11, 2018). *Assembly Bill AB 705 Implementation.*

A Critical Review of Corequisite Model

The corequisite model, though showing promising results, is not without criticism.

Many academicians and math professors express serious concerns about removing remedial courses. They argue that the new model fails to give students a firm grounding in the basic mathematical concepts required for students to handle the rigor of college-level math courses.

Some research also suggests that this kind of acceleration works only for those students who are close to the cut-off score for remedial placement. Boatman and Long (2018) found less positive results of acceleration on students with very low math skills. They write, “[R]emedial courses can help or hinder students differently depending on their incoming levels of academic preparedness” (p. 29). CCRC’s studies of the ALP program’s corequisite model provide evidence that many students of the lowest skill levels benefit from acceleration strategies (Cho et al. 2012), but programs like the ALP provide a high level of intensive in-class support, consistent with the learning facilitation approach (Bailey et al.,2015). It seems unlikely that very poorly scoring students would benefit from a corequisite approach without such strong support (Kezar & Lester, 2009). Kashyap and Mathew (2017) feel that the “corequisite model may not serve the needs of all students, especially those students in high need of remediation” (p. 28).

Similarly, Kosiewicz, Ngo, and Fong (2016) found that “despite the push for alternative approaches, the traditional prerequisite model prevailed in the delivery of developmental math over time” (p. 205). Park et al. (2018) noted that even though underprepared students can be successful in a corequisite gateway course, future research is needed on how to ensure their success. Jaggars, Hodara, Cho, and Xu (2015) felt that the research on the topic is sparse.

Gap in the Literature

CAP colleges like Cuyamaca and Las Medanos report positive results of corequisite models in math courses, but the studies so far have focused on corequisite models in a non-STEM gateway course of statistics. There is a gap in the research regarding a corequisite model in STEM math gateway courses of college algebra or precalculus. This literature review did not find any study on a corequisite model in courses such as precalculus or college algebra. The current study is an attempt to fill this gap by exploring the effect of a corequisite model in a precalculus class. It will also explore whether a corequisite model in a precalculus class may affect differentially on some subsets of community college students. The section below describes some historically underserved student populations in community colleges.

Historically Underserved Student Populations

Community colleges serve a large number of underserved students who may be low-income, immigrant, first-generation, or minority students. Many students are employed, older than traditional students, and/or have families to support (Hagedorn & Kuznetsova, 2016). In fact, as per the American Association of Community Colleges (2015), nontraditional students far outnumber traditional college students. The accessibility and relatively low-cost of community colleges make them especially important for low-income students, students of color, and first-generation college students. Approximately one-fourth of community college students come from families earning at least 125 % below the federal poverty level (Horn & Nevill, 2006). Fifty-six percent of community college students are female and are between the age of 22 and 39 years (American Association of Community Colleges, 2017). The following sections will discuss these non-traditional student populations in greater detail.

First-Generation Students

First-generation students are the students who are the first members of their families to attend college. These students are more likely to be female (Nomi, 2005), older (Engel et al.,2006) and dependent on financial aid (Nunez & Cuccaro-Alamin, 1998) as compared to other students. First-generation students are at a distinct disadvantage in gaining access to postsecondary education (Berkner & Chavez, 1997). This disadvantage can be seen in basic knowledge about college education (e.g. costs, application process), level of family income and support, degree expectations and plans, secondary school academic preparation, and persistence into second year (Berkner & Chavez, 1997; Chen & Carroll, 2005; War-burton, Bugarin, & Nunez, 2001). Moreover, these students are less likely to complete coursework successfully (Davis, 2010).

Most first-generation research findings are based upon students from four-year colleges rather than community colleges. Pascarella, Wolniak, Pierson, and Terenzini (2003) performed one study on experiences and outcomes of first-generation students in community colleges and found that first-generation students completed fewer credit hours, took fewer humanities and fine arts courses, studied fewer hours, and were less likely to participate in an honors program when compared to other students. A National Center for Education Statistics (NCES) 2005 report provides a comprehensive analysis of the course-taking patterns of first-generation students based upon the data from the Postsecondary Education Transcript Study (PETS) of the National Educational Longitudinal Study of 1988. The analysis focused on a subset of the NELS 1992 12th graders who had enrolled in postsecondary education between 1992 and 2000. The first-generation students were less likely than other students to attend college within eight years after high school. Roughly 43% first-generation students who entered postsecondary education during this period left without a degree by 2000, while only 24% had graduated with a bachelor's degree.

First generation students in the California Community College (CCC) system. An analysis of data collected by the California Community Colleges Chancellor's Office (CCCCO) from the summer of 2012 to the spring of 2014 found that in a sample of 789,708 California Community College (CCC) students, 40% were first-generation. Moreover, first-generation students were slightly more likely to be female (Table 5), and recipients of a Pell Grant, a financial aid option based upon economic need (Table 6). The CCCO data analysis also found that first generation students were more likely to enroll in below college-level courses and they were slightly less likely to complete courses successfully.

Table 5
Gender of First-generation Status

Gender	First-generation	Non-first-generation	Total
Female	56%	52%	54%
Male	44%	48%	46%

Table 6
Pell Grant Award of First-generation Status

Pell Grant	First-generation	Non-first-generation	Total
No	79%	88%	84%
Yes	21%	12%	16%

Source: Reprinted from California Community Colleges (Research Brief, Sept. 2014). *First-Generation Students in The California Community College System.* Retrieved from https://extranet. cccco. edu/Portals/1/TRIS/Research/Analysis/First-Generation%20Students%20in%20the%20California%20Community%20College%20System. pdf

Racial Minority Students

Community colleges have an increasing population of African-American and Hispanic students. According to Mullin (2012), community colleges serve more students of color than any other sector of higher education. For example, nearly 30% of community college students are African American or Hispanic, as compared to 20% of students enrolled in four-year colleges (Horn & Nevill, 2006). However, research shows that very few of these students succeed in college. According to Berkner and Choy (2008), only 14% of African American students and 15% of Hispanic and Native American students earn a certificate or degree within three years. Such disparity of results signifies an achievement gap and equity issues in community colleges. This study will address this issue by investigating whether a corequisite model in STEM math classes affects the performance of some minority student populations in community college.

Students with Lower Academic Skills

Before AB 705 became operational, the majority of students registering into community colleges took a placement test, such as ACCUPLACER or COMPASS. These tests were given to identify students' level of college readiness, and the results were used to place students into different levels of remediation. Analysis of Achieving the Dream — an initiative started in 2004 to focus on closing the achievement gaps in community colleges — data by the CCRC found that only 31% of students referred to developmental math could complete the recommended sequence of courses within three years (Bailey et al., 2010). Results for students who were placed at the lowest levels of the developmental sequence were even worse. Only 16% of students who enrolled in math courses three or more levels below college-level could successfully complete the sequence (Edgecomb, 2011). With the passing of AB 705 in the state, colleges are required to use multiple measures for student placement into various courses. The new measures investigate HSGPA, as is evident from Table 4 on page 49. In Table 4, the high school performance metric for BSTEM mathematics considers HSGPA of 2.6 as a cut point for the students who need additional support.

Summary

Community colleges, with their open access policies, attract many students who may be underprepared for college-level work. A large majority of these underprepared students are placed into developmental courses. Research shows that a longer sequence of remedial courses gives many exit points to students, and therefore, more students are likely to quit than to continue with the track as is. This results in a small number of students reaching a college-level/gateway course, and an even smaller number who reach their goal of college transfer or an associate degree completion. A recent model of remediation called the corequisite model allows students to be placed into a college-level course along with remedial support. Some pilot studies across the nation have shown encouraging results of the new model. Research shows that the accelerated models lead to student success in statistics, a non-STEM gateway course, in a shorter time frame than what a traditional, non-accelerated model would have taken. There are comparatively fewer research studies on corequisite models in the STEM field. Some findings suggest that corequisite models may not help all student populations equally. More research is needed to understand whether these models help diverse community-college student populations, including first-generation students, students of color, and students who are underprepared for college-level work. This study contributes to the body of research on the efficacy of corequisite models by investigating how a corequisite model in a STEM gateway course, precalculus, may affect academic performance of students in general and from underserved and marginalized populations. Chapter 3 discusses the methodology that will be used to complete this study.

CHAPTER 3: METHODOLOGY

This chapter discusses the research design and methodology of the study. The study attempts to investigate the academic performance in a STEM math gateway course during the current, ongoing efforts of community colleges to increase their student degree completion and transfer rates. The AB 705 law of California stresses replacing the traditional developmental courses in math and English with new courses, which will enable community college students at a developmental level to enroll directly into college-level (gateway) courses with concurrent support. The new proposed model of course delivery is called the corequisite model. The traditional approach to developmental course sequence is called a prerequisite model in this study. As we have seen in Chapter 2, research suggests that developmental education is a stumbling block to student academic achievement. We also learned that there are studies which showed positive results of a corequisite model in English and math (statistics) education. The randomized study by CUNY established how the corequisite approach in a statistics course increased the student success rate in the non-STEM math gateway course (Logue, Watanabe-Rose, & Douglas, 2016). This study is an attempt to explore the effectiveness of the corequisite approach in a STEM math course of precalculus in community colleges. Using a quantitative approach, the study will compare the impact of two models of course delivery: Corequisite versus Prerequisite. This study will also test how a corequisite model in precalculus affects some historically underserved student populations, like first-generation students, African American and Hispanic students, and students who have a low level of prior academic achievement.

In this study, students with high school GPAs (HSGPA) less than 2.7 are considered to have a low level of prior academic achievement. (students with HSGPA < 2.7 are at the level B- or lower.) The rationale behind choosing this cut-off is explained in Chapter 4.

Research Questions

The following research questions will focus the study.

> Research Question One (RQ1): Are average course grades in a STEM gateway math course better for those who completed the corequisite model than those who completed it with the traditional model after controlling for prior academic achievement, gender, generational status, and ethnicity?
>
> Research Question Two (RQ2): Does the impact of the type of model on course grades in a precalculus course vary by the generational status of a student after controlling for their gender, ethnicity and prior academic achievement?
>
> Research Question Three (RQ3): Does the impact of the type of model on course grades in a precalculus course vary by the prior academic achievement level of a student after controlling for their gender, ethnicity and generational status?
>
> Research Question Four (RQ4): Does the impact of the type of model on course grades in a precalculus course vary by the ethnicity of a student after controlling for their gender, generational status and prior academic achievement?

Research Design and Methodology

A crucial element in research design is deciding the best approach for the purpose of the study (Creswell, 2012). A quantitative approach will be used for this study. The existing data on student performance in precalculus classes using two different course delivery models will be analyzed statistically. An ex-post facto design will investigate a hypothesized causal relationship between the course delivery model and student performance. According to McMillan & Schumacher (2006), ex-post facto research focuses on what has happened differently for comparable groups of subjects. It compares two or more samples and studies possible causes after they have occurred (McMillan & Schumacher, 2006). The ex post facto design is suitable for this study because data from samples of students who were enrolled in two different course delivery models will be collected by contacting the institutions in California who offered precalculus courses using the corequisite model prior to fall of 2019. The use of ex-post facto data offers several benefits. Using existing data saves researchers time and money while providing access to quality data (Bryman, 2012). Additionally, collecting existing data provides researchers the opportunity to spend more time analyzing the data, which allows for essential features of research, like validating and developing new theories, to take place (Bryman, 2012).

Participants

The target population in this study consists of all community college students nationwide who are aspiring to succeed in the gateway course of precalculus. The accessible population includes those California community colleges who have adopted the corequisite model in a precalculus class. AB 705 mandated all California community colleges to adopt the corequisite model starting fall of 2019. Prior to fall of 2019, not many California community colleges used the corequisite teaching approach in STEM and non-STEM math classes. Although corequisite models in Statistics were more common, only a handful of community colleges taught precalculus with a corequisite approach. Participants for this study were chosen from two colleges, one each from northern California and southern California. For the sake of anonymity, these colleges will be called College A and College B. The sample consists of all students from College A and B taking a precalculus class, either with a corequisite or a traditional model. The sample will be divided into two groups: corequisite or prerequisite. As the name suggests, the corequisite group will include all precalculus students in a class that used the corequisite approach of teaching, while the prerequisite group will consist of students in a precalculus class that used the traditional method of teaching. The timeline for data selection is between Fall 2016 and Spring 2019. The data considered for this study is from academic terms where both corequisite and prerequisite type of classes are offered during the same term. In this way, students had a choice to choose a precalculus class either with a corequisite approach or a prerequisite approach. Selecting students from adjacent academic terms ensures that the demographics of the students served are similar and that there is not much variability in the subjects from the two groups within each of the colleges.

It is important to note that AB 705 provides freedom to colleges to adopt the corequisite style of teaching in a way which suits their college the best. Some colleges use the corequisite course delivery model in a *comingling* style, where students choose one support class and have a freedom to choose any mainstream precalculus class. In this corequisite approach, a mainstream class may have a mix of students from different support classes. The other style of the corequisite model is called the *cohort* style, where students go to a combination of support classes and one mainstream class as a part of one cohort group. Both of the sample colleges in this study use the cohort style of corequisite teaching in precalculus. Students can either choose just to take a precalculus class in the traditional style, or they can participate in a cohort of a support class alongside the mainstream precalculus class.

The demographic characteristics of participants in terms of the independent variable and control variables are displayed in Table 7 below.

Table 7

Demographic Characteristics of Participants

Demographic Characteristics		Corequisite		Prerequisite	
		n	%	n	%
Gender	M				
	F				
Generation Status	First-Gen				
	Other				
Prior Achievement	Low				
	Not Low				
Ethnicity	Caucasian				
	African American				
	Hispanic/Latino				
	Asian				

Sample Size

G* Power analysis (Faul, Erdfelder, Buchner, & Lang, 2009) was used to determine the sample size requirements. The minimum sample size depends upon the number of tested predictors, total predictors, and the effect size f^2. A summary of the inputs and results for RQ4 (testing the moderating effect of ethnicity), which has ten predictors in total and three tested predictors, is shown in Table 8 below.

As per this analysis, if we assume that the effect size is in the small-medium range (as indicated by an f^2 value of .08 and a corresponding *partial* R^2 value of .075) then a sample of 141 participants is needed. If the effect is less pronounced (as indicated by an f^2 value of .05 and a corresponding *partial* R^2 value of .048) then a sample of 221 participants is needed to be reasonably sure (at a probability of .80) that the test of significance will be able to detect the effect (e. g. , of ethnicity moderating the impact of type of course delivery on academic performance) if, in fact, there is a true effect to detect (that is, the null hypothesis really is false).

Based on this power analysis, the goal for this study will be to obtain a database which contains a minimum of 221 student records of those students who meet the selection criteria.

Table 8
*Summary of G*Power Inputs and Results for Determining Minimum Sample Size to Address Research Question 4 (the moderating effect of ethnicity).*

Set Parameters:		
Test family		F tests
Statistical test		Linear multiple regression: Fixed model, R^2 increase
Type of power analysis		A priori: Compute required sample size-given α, power, and effect size
α error probability		.05
Power (1-β error probability)		.80
Number of tested predictors		3
Total number of predictors		10
Varying Inputs (Effect size f^2):		Results (total sample size)
Small	.02	550
Small-Medium	.05	221
Small-Medium	.08	141
Medium	.15	78
Large	.35	37

Data Collection and Procedures

Data is collected from two community colleges in California: one from southern California and the other from northern California. As a cluster sample, the sample consists of all students taking a precalculus class, either with a traditional or a corequisite approach. The College Institutional Research (IR) Department was instrumental in providing the records for all student participants in the sample. It is customary for all California community college students to apply through a common web-application, CCCApply. On this application, students provide information about their demographics, e.g. parental education, socioeconomic status, information related to their prior education — like high school GPA (HSGPA) — and course taking patterns in high school. These records are later transferred to college databases and are handled by the college IR department. This data is provided to a researcher or other interested groups after deleting the students' names. Thus, all the relevant student information for this study, like their first-generation status, prior academic achievement, and current grades, was obtained anonymously from the college IR department.

Data for this study is reliable as it comes directly from the colleges' databases and the demographics are provided by the students themselves**.** Choosing students from adjacent semesters will ensure that there is not much difference in the students' demographics or other variables relevant for this study.

One thing to be noted here is that the course grades in this study are an indication of performance in the precalculus class, which may be measured differently by different professors. It might be useful to watch for any kind of standardization across professors in terms of what they test and their weighting policy for different course components, like attendance, homework, tests, final exam, projects, etc.

IRB Requirement

The required procedures were followed for IRB approval for data collection. Given the archival nature of the data (with no identifiers), IRB considered this study as exempt.

Data Analysis and Presentation

The statistical analysis of the data will include several techniques, like descriptive statistics, correlational analysis, sequential multiple regression, ANOVA, and Chi-squared tests. The statistical software SPSS will be used for data analysis.

Variables

The study uses one dependent and several independent variables, including control variables.

Dependent variable. The dependent variable is Course Grades for students from the gateway course of precalculus.

Independent variable. The key independent variable is Course Type. It has two categories: Prerequisite or Corequisite (depending upon the type of course a student chose).

Control variables. The study uses several control variables. These control variables are Prior Academic Achievement, Generation Status, Ethnicity, and Gender.

Dummy Coding

Dummy coding is used for each of the control variables. Variables like Prior Academic Achievement (HSGPA ≥ 2.7 or HSGPA < 2.7), Generation Status (first-generation or non-first-generation), and Gender (male or female) will have two categories each and therefore will use only one dummy variable.

The control variable ethnicity has more than two categories, and hence will be dummy coded separately. Depending upon the number of ethnic groups in each college, three to four dummy variables will be used. Table 10 explains a possible situation for dummy coding the ethnic categories. In the table, dummy variables Asian, Hispanic, and Filipinx with the reference group as White are shown as column headings and actual student ethnicity categories are shown as rows.

Table 9
Dummy Coding for Ethnicity with Dummy Variables as Column Headings and Actual Student Race/Ethnicity Categories as Rows.

	Asian	Filipinx	Hispanic
Asian	1	0	0
Filipinx	0	1	0
Hispanic	0	0	1
White	0	0	0

Preliminary Analyses

Descriptive statistics will be used to calculate percentages, means, and standard deviations. Correlational analysis will investigate the relationships between the dependent variable and the independent variables used in this study. Table 10 presents this analysis between all variables except ethnicity.

Table 10
Correlations and Descriptive Statistics between All Variables Except Ethnicity

	Students in the Sample	1	2	3	4	5	% coded 1	M	SD
1	Course Grades								
2	Prior Academic Achievement (1 = HSGPA $\geq$ 2.7; 0 = HSGPA $<$ 2.7)								
3	Generation Status (1 = First-generation, 0 = Non-first-generation)								
4	Gender (1= Female, 0 = Male)								
5	Course Type (1 = Corequisite, 0 = Prerequisite)								

*p < 0.05

The independent variables Prior Academic Achievement, Generational Status, Gender, and Course Type (Prerequisite or Corequisite) are dichotomous variables, and the correlation between such variables is called a *Phi-correlation.* The table also presents correlations between the dependent variable of Course Grades and each of the four dichotomous variables. These are *point-biserial correlations.* Correlation between ethnicity and the rest of the variables will be established using Chi-squared analysis and ANOVA as shown in Table 11 and Table 12. Such a correlation is called a *Cramer's V estimate correlation*.

Table 11
Grades by Ethnicity: ANOVA

	Mean	SD
White		
Asian		
Hispanic		
Filipinx		
Note: *F* (-- , --) = ---- , *p* = . - -		

Table 12
Type of Model × Ethnicity: Chi-Squared Test of Association

	Corequisite		Prerequisite	
	n	%	n	%
White				
Asian				
Hispanic				
Filipinx				
Note: $\aleph^2$(3, N = --) = ----, p = 0. ---				

Multiple & Sequential Regression

Techniques of multiple regression will be used to establish the regression equations, which could predict student academic performance in a precalculus class with a prerequisite or a corequisite model. As a causal comparative study, the effect of the independent variables for gender, first-generation status, ethnicity, and level of prior academic achievement will be controlled in this prediction model. This will be attempted by applying a sequential regression model in a sequence of two or three blocks.

For research question RQ1, sequential regression will be applied in two blocks. Variables for demographics and other student characteristics will enter in the first block, allowing estimation of the percentage of variation in the course performance that this set accounts for. Then, in the second block, the indicator for type of course enters the model and the change in R^2 quantifies the percentage of additional variance in course performance that is explained, an indicator of effect size attributed to the difference between prerequisite vs corequisite course models. Research questions RQ2, RQ3, and RQ4 will explore the moderating effects of students' generational status, prior academic achievement, and ethnicity on the effect of the type of course delivery model on the STEM math gateway course grades. The moderation analysis (Baron & Kenny, 1986) will be used to study these effects. The moderating effect will be studied in each of the research questions, RQ2, RQ3 and RQ4, by entering an interaction term of the control variable with the type of model in Block 3 of the sequential regression. Moderating effects will be established in case all the assumptions for multiple regression are met; otherwise, alternative approaches will be established to answer these research questions.

Data analysis for RQ 1. Table 13 below gives the data analysis for RQ 1.

Table 13

Sequential Multiple Regression of Course Grades on Course Type Controlling for Prior Achievement, Generational Status, Ethnicity, and Gender

	b	SE_b	β	t	R^2	ΔR^2
Block 1						
Prior Academic Achievement (1 = HSGPA ≥ 2.7)				**		
Generation Status (1 = first-generation, 0 = non-first generation)						
Ethnicity (0 = White) Asian						
Hispanic						
Filipinx						
Gender (1 = Female, 0 = Male)						
Block 2						*
Course Type (1 = Corequisite, 0 = Prerequisite)	+			*		
$^*p < 0.05$, ** $p < 0.01$						

Here the sequential multiple regression is done in two blocks. Block 1 is used to control the effects of variables like prior achievement, generational status, ethnicity, and gender. After controlling for these variables, multiple regression in Block 2 gives the regression equation to predict the course grades based upon the type of course delivery model and the control variables. In this table, for example, we see that t-value for prior achievement is statistically significant ($p < 0.01$) in Block 1, and in Block 2 the t-value is significant ($p < 0.05$) for the variable Type of Model. This means that both would account for unique variation in course grades. The ΔR^2 from Block 1 to Block 2 indicates how much variation in the data is explained by the additional variable (type of course) added in the second block. If the t-value for the type of course is significant, and the regression coefficient is positive, the answer to RQ 1 is yes.

Data analysis for RQ 2. Table 14 provides descriptive statistics for course grades broken down by both generational status and type of course.

Table 14

Course Grades by Generational Status and Type of Course

	Corequisite			Prerequisite		
	n	M	SD	n	M	SD
First- gen						
Non-first-gen						

Table 15 presents the regression results for RQ 2. This question attempts to ascertain if the generational status of a student moderates the effect of type of course delivery model on course grades. In other words, we can see if the amount of difference in course performance due to type of course depends (or varies) on the generational status (first-gen or not) of the student. There is an additional block in this case which will check for the interaction effect, Generational Status × Course Type, between the two variables. If the model satisfies all the assumptions and the t-value for the interaction term (Block 3) comes out to be significant, then the answer to RQ 2 is yes.

Table 15

Testing for Generational Status as a Moderator of the Effect of Course Type on Course Grades.

	b	SE_b	β	t	R^2	ΔR^2
Block 1						
Prior Academic Achievement (1 = HSGPA ≥ 2.7)				**		
Ethnicity (0 = Caucasian) Asian						
Hispanic						
Filipinx						
Gender (1 = Female)						
Block 2						*
Course Type (1 = Corequisite)				*		
Generation Status (1 = 1st gen)						
Block 3						*
Generation Status × Course Type				*		
p < 0.05, ** p < 0.01						

A characterization of the possible positive impact of type of course varying by generational status can be explained by Figure 2 below.

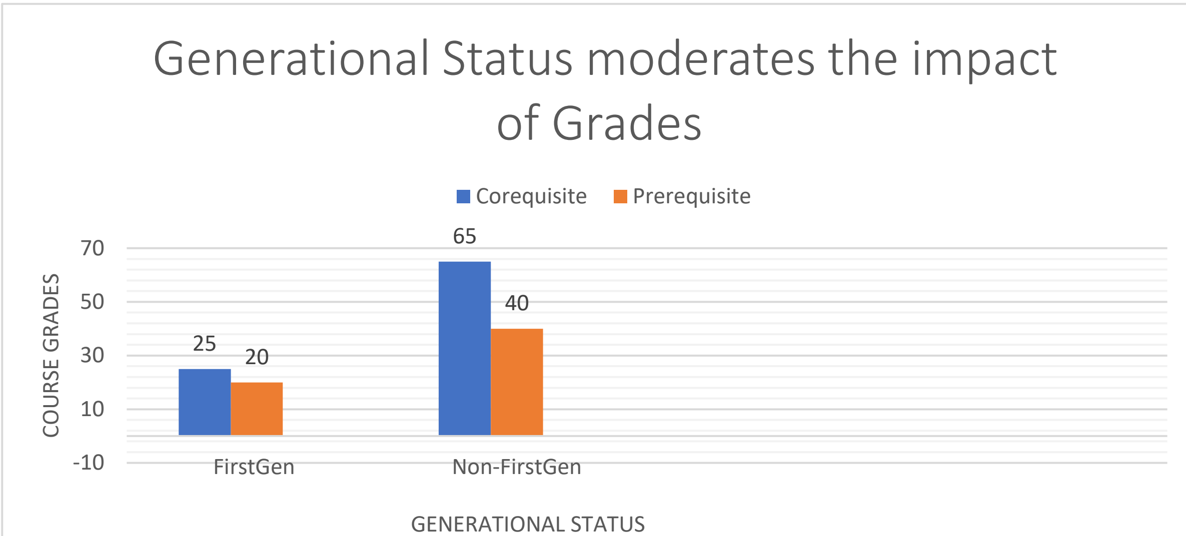

Figure 2. Generational status moderates the impact of grades (self-made based upon hypothetical data).

Data analysis for RQ 3. Table 16 provides descriptive statistics for course grades broken down by both prior academic achievement and type of model. Similar to the analysis in RQ2, prior academic achievement will be tested for moderating the effect of type of course on course grades. This will be done by checking for the interaction between students' prior achievement and type of course by adding the cross product variable Prior Academic Achievement × Course Type in Block 3 of the regression model. A significant t-value for the interaction term would mean that the answer to RQ 3 is yes. Table 17 presents the regression model for RQ3.

Table 16

Course Grades by Prior Academic Achievement and the Course Type

	Corequisite			Prerequisite		
	n	Mean	SD	n	Mean	SD
Low Prior Achievement						
Not Low Prior Achievement						

Table 17

Testing for Prior Academic Achievement as a Moderator of the Effect of Type of Model on Course Grades.

	b	SE_b	β	t	R^2	ΔR^2
Block 1						
Generational Status (1 = 1st gen)						
Ethnicity (0 = Caucasian) Asian						
Hispanic						
Filipinx						
Gender (1 = Female)						
Block 2						*
Course Type (1 = Corequisite)				*		
Prior Academic Achievement (1 = HSGPA $\geq$ 2.7)				**		
Block 3						*
Prior Achievement $\times$ Course Type				*		
$p < 0.05$, ** $p < 0.01$						

Data analysis for RQ 4. Research Question 4 tests for ethnicity as a moderator for Course grades based upon the type of course. The descriptive statistics for course grades broken down by both ethnicity and type of course is provided in Table 18. Similar to RQ2 and RQ3, ethnicity will be tested as a moderator of the effect of course type on course grades (Table 19). Provided all the assumptions for multiple regression are met, the answer to RQ 4 will depend upon the t-value of the interaction term added in Block 3. A significant t-value will imply that the answer is affirmative. In case the assumptions of multiple regression are not met, alternative approach of separate regression analysis for each ethnic subgroup will be used.

Table 18

Course Grades by Ethnicity and Type of Course

	Corequisite			Prerequisite		
	n	Mean	SD	n	Mean	SD
Asian						
Hispanic						
African American						
White						

Table 19

Testing for Ethnicity as a Moderator of the Effect of Type of Course on Course Grades

	b	SE_b	β	t	R^2	ΔR^2
<u>Block 1</u>						
Prior Academic Achievement				**		
Generational Status (1 = 1st gen)						
Gender (1 = Female)						
<u>Block 2</u>						*
Type of Model (1 = Corequisite)				*		
Ethnicity (0 = Caucasian) Asian						
Hispanic						
Filipinx						
<u>Block 3</u>						*
Asian × Course Type				*		
Hispanic × Course Type						
Filipinx × Course Type				*		
$p < 0.05$, ** $p < 0.01$						

Assumptions and Limitations of the Study

Limitations

The study has following limitations.

1. The process of accelerating developmental education, the corequisite model of math education, and AB 705 is a recent phenomenon. There are only a handful of colleges in California and other states who have fully adopted the co-requisite model in math. So, generalization of results is limited to the specific type of student population used for this study, and the results may not be generalizable for the community college population as a whole.

2. Another limitation could be non-availability of the high school data, as some students applying to community colleges may not have their HSGPA. In general, such limitations are handled by the process of imputation or different coding techniques. In the case of a substantial number of students missing a high school GPA, alternate strategies will be used to overcome the effect of unknown GPA cases.

3. One limitation of this study concerns the validity of performance measurement tools. The course grades in any class depend upon the class performance, but the performance measurement tools may be different across different class rooms taught by different professors. Lack of standardization across professors in terms of testing and weighting of different course components (attendance, homework, tests, final exam, projects, etc.) may be a threat to validity of the measurement tools.

4. As per the law, colleges have some flexibility in choosing the form of a corequisite model. Variability in the way colleges choose to operationalize their corequisite model, e.g. with a lab, with a support course, or with emporium model, could be another potential limitation of this study.

5. Another limitation of this study is lack of clarity in the repeat status of some students. Students may have repeated a course one, two, or more times. Besides, the repeat pattern of students may be different. For example, a student may repeat a corequisite style of class, while another student may be repeating a corequisite class from a prior prerequisite style of class. This limitation of the study is resolved by ignoring the course repeaters completely and performing the analysis only for those students who took the course just one time.

6. The repeat status of students from the very first academic term of the collected data set is ambiguous. Since the study involves only those students who are non-repeaters, the students from the first academic term are excluded from the analysis.

7. Another limitation of the study is that the status of 'W' students is not clear in the data set. Sometimes students withdraw from the course much later in the semester/quarter to earn a W grade. These students may re-register in to a future

course without getting a repeaters label. A study including only non-repeater students may include those students who got a W grade in a prior semester but are not actually taking the course for the first time.

Assumptions

The study is based upon some statistical, methodological, and substantive assumptions.

Methodological assumptions. The data provided by the IR offices is taken from student self-reported data on the web application and it is based upon the assumption that students report the data accurately.

Statistical assumptions. All quantitative techniques are based upon certain statistical assumptions. The multiple regressions design is based upon the assumptions of linearity, normality of residuals, homoscedasticity, and no multicollinearity (McMillan & Schumacher, 2006). The following assumptions need to be met to apply multiple regression which may be challenging:

1. Linearity --There must be a linear relationship between the outcome variable and the independent variables.

2. Multivariate Normality – Multiple regression assumes that the residuals are normally distributed.

3. No Multicollinearity -- Multiple regression assumes that the independent variables are not highly correlated with each other.

4. Homoscedasticity–This assumption states that the variance of error terms is similar across the values of the independent variables.

Substantive assumptions. The study also assumes that the delivery of corequisite classes, or even the prerequisite classes, in all participating colleges are meeting the basic minimal requirements of the model**.**

Summary

With the recent state policy changes toward developmental education, it is important to study the impact of the new law on community college math students. AB 705 recommends direct entry of all students into a gateway course with concurrent additional support. This chapter describes the methodology and data analysis procedures to compare the course grades in the precalculus course offered with the traditional or newly proposed corequisite model of course delivery. By using multiple regression, the methodology used for the study looks for a causal relationship between the types of course delivery model and course grades. Sequential regression studies the moderating effect of certain student populations on course grades. The effects are studied on students from different ethnic groups like African American, Hispanic, and Asian. The data analysis also attempts to learn how the new model affects students of first generational status and students of lower prior academic achievement. To be specific, besides studying the effect of the corequisite type of course in general on precalculus students, the current study uses the techniques of moderation analysis to measure the equitableness of the new required mandate, AB 705.

CHAPTER 4: RESULTS

Introduction

The purpose of this study is to explore the effects of a corequisite model of education on a STEM math course. It further examines the effect of the corequisite model on students from different ethnicities, generational status, and levels of prior academic achievement. The techniques of multiple regression are used to analyze the sample data, which was obtained from two different community colleges in California. The sample colleges adopted the corequisite style of course delivery in a STEM math course prior to the formal implementation of the AB 705 law by California community colleges in Fall 2019. To preserve anonymity, the colleges are referred to as College A and College B. Sequential regression is used to examine the effect of the corequisite model on course grades in a precalculus class. The study also explores whether prior academic achievement (HSGPA), generational status, and ethnicity of students moderate the effect of corequisite or prerequisite (traditional) styles of course delivery on course grades in a STEM math gateway (precalculus) class. The results are analyzed for the following research questions.

> Research Question One (RQ1): Are average course grades in a STEM gateway math course better for those who completed the corequisite model than those who completed it with the traditional model after controlling for prior academic achievement, gender, generational status, and ethnicity?
>
> Research Question Two (RQ2): Does the impact of the type of model on course grades in a precalculus course vary by the generational status of a student after controlling for their gender, ethnicity and prior academic achievement?
>
> Research Question Three (RQ3): Does the impact of the type of model on course grades in a precalculus course vary by the prior academic achievement level of a student after controlling for their gender, ethnicity and generational status?

> Research Question Four (RQ4): Does the impact of the type of model on course grades in a precalculus course vary by the ethnicity of a student after controlling for their gender, generational status and prior academic achievement?

The above research questions will be answered by analyzing data for each college separately using the records for non-repeater students. The rationale behind choosing the appropriate dataset for this study is explained in the following sections.

Defining Prior Academic Achievement Level

As per the state guidelines for AB 705, colleges may not restrict a student from registering into a transfer level class, irrespective of their prior achievement. Table 4 in chapter 2 provides a cut-off of 2.6 for HSGPA as a guideline for students to choose between a corequisite or a traditional math class in the STEM field. This study uses the HSGPA cut-off of 2.7 to differentiate between high and low prior academic achievement because it was used as a HSGPA cut-off in the data provided by one of the sample colleges.

Rationale for Separating Analyses by Colleges

The academic terms chosen for this study are based upon the availability of both corequisite and traditional types of precalculus classes in the same term. The sample colleges, one each from northern and southern California, differ in their academic term lengths: semester versus quarter. Therefore, data for these colleges are analyzed separately.

Rationale for Focusing on Non-Repeaters

Another point of consideration for selecting the final data was the repeat status of students. The data included many students who repeated the class one or more times. The repeat status for students in College A was explicitly stated on the database obtained from its institutional research department, unlike for College B, where repeat status needed to be constructed by matching the masked student IDs and the academic terms for which students were registered in a precalculus class.

The course repeating patterns for College A were not distinguishable, as their database only stated whether a student was a repeater or not. But for College B, after the repeaters were identified, it was noted that there were different repeat patterns. Some students repeated a corequisite class, while others repeated a traditional class, and there were some who repeated the class with a mix of these two models of course delivery. Some students went for a traditional class after taking a corequisite or vice versa. It is assumed that some differences in the motivation level of students may exist between those who are repeaters versus those who are non-repeaters. Therefore, in an effort to help control for student motivation levels, it was decided to base this study only on the non-repeater students' data.

The institutional research department for College B provided data from fall of 2016 and after. With no prior data to compare, it was not possible to determine the repeat status of students from Fall 2016, who might be repeating the course. Given our inability to make this determination, the Fall 2016 data from College B was not used. The database for College B also included a small number of students from the Summer 2017 and Summer 2018. As summer terms are not a regular semester length, this data was also ignored in this data analysis. The final timeline for the data to be used for the study is shown in the following table.

Table 20
Overview of the Academic Terms from which Data are Used from Each of Two Colleges

College	Spring 2017	Fall 2017	Winter 2018	Spring 2018	Fall 2018	Winter 2019	Spring 2019
A					X	X	X
B	X	X		X	X		X

Note. College A uses the quarter system; College B uses the semester system.
Note. X's denote the academic terms for which the data are used from each college.

For College A and B, the data is analyzed separately. The data for College B will be analyzed with two different approaches, as explained later. The preliminary analyses for each college focus on the sample demographics and the relationships between the dependent, independent and all control variables. A section on verification of assumptions of multiple regression is presented next. A detailed analysis of verifying assumptions results for College A and two approaches for College B is available in Appendices A, B, & C respectively. Finally, in the main analysis section for each college, the results of sequential regression tests are presented to inform each of the research questions separately. Cohen's effect sizes were also calculated in each case. The following section explains the rationale behind using both p-values and effect sizes.

Justification for Presenting Both p-Values and Effect Sizes

Both effect sizes and p-values were used in this study to answer the research questions. This is because, sometimes, a small sample size may not reach statistical significance (due to low power) but the sample statistics suggest there could be a real — even if small — effect. Some of the samples used in this study are very small. The results obtained by using effect sizes are independent of the sample size. According to Sullivan and Feinn (2012), using both p-value and effect sizes help in understanding the full impact of the results in any quantitative research. The following reasons justify the use of p-values and effect sizes in this study.

- P-value can inform whether an effect exists, but cannot reveal the size of the effect, while effect size gives the magnitude of the difference between groups.
- In case of large samples, statistically significant results using p-value sometimes are not practically significant. The results found using effect sizes are independent of the sample size and have practical significance.

Coding Design for Course Grades

The course grades were coded from 0 = F to 12 = A+. Table 21 explains the complete coding design.

Table 21
Coding Design for Course Grades

Codes		**Letter Grades**	**Codes**		**Letter Grades**
12	=	A+	5	=	C
11	=	A	4	=	C-
10	=	A-	3	=	D+
9	=	B+	2	=	D
8	=	B	1	=	D-
7	=	B-	0	=	F
6	=	C+			

Data Analysis for College A

This section presents the data analysis of the non-repeaters' data from Fall 2018, Winter 2019, and Spring 2019 from College A, which uses the quarter system.

Preliminary Analysis

Descriptive statistics for College A data is explained in this section.

Table 22

Demographic Characteristics of All Participants from College A

Demographic Characteristics		n	%
Gender	Male	219	33.8%
	Female	114	65.0%
	Unknown	4	1.2%
Generation Status	First	116	34.4%
	Non-First	197	58.5%
	Unknown	24	7.1%
Prior Achievement	Low (HSGPA<2. 7)	113	33.5%
	High (HSGPA >=2. 7)	224	66.5%
Ethnicity	African American	10	3.0%
	Asian	43	12.8%
	Filipino	20	5.9%
	Hispanic/Latinx	168	49.9%
	White	84	24.9%
	Pacific Islander	7	2.1%
	Declined to state	5	1.5%
Course Type	Corequisite	251	74.5%
	Prerequisite (Traditional)	86	25.5%

Sample demographics. Table 22, above, presents the sample demographics for College A. As is seen in the table, there are some unknown cases for gender, generational status, and ethnicity. Since these background characteristics are to be controlled, the unknown cases will not be used for the main analysis. It is also noted that too few African American and Pacific Islanders are present in the dataset to provide stable estimates and sufficient statistical power. Thus, these ethnic subgroups also were excluded from the main analysis.

The student demographics in corequisite and traditional types of courses for the main analyses are displayed in Table 23.

Table 23

College A: Demographic Characteristics of Chosen Participants in Each Model

Demographic Characteristics		Corequisite		Prerequisite	
		n	%	n	%
Gender	Male	131	67.5%	39	61.9%
	Female	63	32.5%	24	38.1%
Generation Status	First- gen	81	41.8%	19	30.2%
	Non-first-gen	113	58.2%	44	61.1%
Prior Achievement	Low (HSGPA<2.7)	67	34.5%	8	12.7%
	Not Low (HSGPA >=2.7)	127	65.5%	55	87.3%
Ethnicity	Asian	22	11.3%	15	23.8%
	Filipinx	11	5.7%	5	7.9%
	Hispanic/Latinx	107	55.2%	26	41.3%
	White	54	27.8%	17	27.0%

Associations and relationships between variables. This section explains the differences between and associations with all different type of variables. The Chi-squared test of association and Pearson's correlation coefficients are used to study these associations and relationships.

Differences between and associations with the independent variable (type of course model). Chi-squared tests of association with each of the row variables in the table above (gender, first generation status, prior academic achievement, and ethnicity) separately cross-tabulated with the type of course model (corequisite versus prerequisite) were performed to see the associations between all the control variables and the independent variable (type of course model) . Prior academic achievement was found to have a significant association with the type of course model $\chi^2(1, N = 257) = 10.\ 97; p = 0.00)$. Specifically, a higher proportion of students with low prior achievement (67/75) enrolled in a corequisite course than the proportion of students with high prior achievement (127/182) did. Relatedly, among those in the corequisite course, 35% had low prior achievement, whereas among those in the prerequisite course, just

13% had low prior achievement. These results are consistent with the result of correlation between HSGPA and course type (1 = corequisite, 0 = prerequisite) in Table 24. The negative correlation (r = -.207, p < .01) between HSGPA and course type indicates that those enrolled in a corequisite model had lower prior achievement on average than those enrolled in the prerequisite model.

Ethnicity approached but was not significantly associated with the type of course model, $\chi^2(3, N = 257) = 7.31; p = 0.06$. The other two control variables of gender and first-generation status also did not show a significant association with the choice of course delivery model, $\chi^2(1, n = 257) = .67; p = .41, and\ \ \chi^2(1, n = 257) = 2.69; p = 0.10$, respectively.

Differences between and associations with the dependent variable (precalculus course grades). Pearson's correlation coefficients were calculated to explore the relationships with the course grades (see Table 24). Generational status (1= first generation, 0=not a first generation) was statistically significantly correlated (r = -.21, p < .01) with final course grades. The moderately small and negative correlation indicates that first-generation students, on average, had lower course grades than non-first-generation students. Neither of the correlations between gender and course grades (r = -.07), and between course type and course grades *(r* = .08*)* were statistically significant.

Table 24
Correlation Between All Variables Other Than Ethnicity

	Course Grade	Gender	Generational Status	Prior Achievement	Course Type
Course Grade	1				
Gender	-.07	1			
Generational Status	$-.21^{**}$	-.03	1		
Prior Academic Achievement	.07	$.15^{*}$	$-.24^{**}$	1	
Course Type	.08	-.05	.10	$-.21^{**}$	1

Note. $^{*}p<.05$, $^{**}\ p<.01$ $N = 257$. Dummy coding assigned the higher code of 1 to the corequisite, female, and first-generation subgroups and lower code of 0 to the prerequisite, male, and non-first-generation subgroups.

The control variable ethnicity has more than two subgroups; therefore, the relationship between ethnicity and course grades was checked by using ANOVA. Table 25 displays the results of ANOVA and provides the mean and standard deviation of the grades for each ethnic group. The significant association *($p < .01$)* between grades and ethnicity indicates that the average grades vary between at least two different ethnic subgroups. A post hoc Tukey multiple comparisons test was performed to find the comparison of grades between different pairs of ethnic groups. This test found that the Hispanic/Latinx subgroup had significantly lower average final course grades as compared to other subgroups. No significant differences were found in course grades for other ethnic subgroups.

Table 25
Grades by Ethnicity: ANOVA

	n	Mean	SD
Asian	37	7.11	4.06
Filipinx	16	7.25	3.40
Latinx	133	4.28	3.73
White	71	6.39	3.99
Total	257	5.46	4.01

Note. $F(3, 253) = 9.073$; $p < 0.001$. Note, course grades are coded from 0 = F to 12 = A^{+}

Associations between control variables. The weak positive correlation (r = .15, p<. 05) between HSGPA and gender (Male = 0, Female = 1), indicates females, on average, had higher prior achievement. Similarly, the moderately small negative correlation (r = -.24, p<.01) between HSGPA and generational status (first generation = 1, not a first generation = 0) indicates that first-generation students, on average, had lower prior achievement than non-first-generation students. Generational status and gender were not significantly correlated.

Multiple Regression Assumptions and Diagnostics

This section provides a description of testing multiple regression assumptions to diagnose potential problems in the data and to strengthen statistical conclusion validity. First, all variables were checked to make sure that the values on the file are valid and reasonable. Then, a multiple regression was conducted to check assumptions for each research question. The diagnostic information, including predicted values, residuals, Cook's values, estimates of partial influence and collinearity statistics, was obtained. These were further examined to test the assumptions of linearity, homoscedasticity, multicollinearity, and normality of residuals. Some multicollinearity issues were found in the regression model for those research questions where a cross-product variable was entered into the sequential regression. An alternative approach, explained later, that does not require use of cross-products, was taken to continue with investigations of potential moderating effects (RQ 2 – RQ 4). Diagnostics were used to spot problematic data points focusing on three characteristics: distance, leverage, and influence (Keith, 2006). Details of the regression assumptions and diagnostics are available in Appendix A. The checks revealed that application of multiple linear regression was reasonable and no cases were removed from the analyses pertaining to College A.

Main Analysis for College A

This section presents the regression analysis for each of the four research questions for College A.

Regression model for RQ 1(College A). The sequential multiple regression for RQ 1 was done in two blocks. The results are displayed in Table 26

Table 26
Sequential Multiple Regression of Course Grades on Type of Course Controlling for Prior Academic Achievement, Generational Status, Ethnicity, and Gender

	b	**SE_b**	**β**	**t**	**R^2**	**ΔR^2**
Block 1					0.102	0.102^*
Prior Academic Achievement (1 = HSGPA $\geq$ 2.7)	0.26	0.56	0.01	0.09		
Gender (Male=0, Female =1)	-0.26	0.52	-0.04	-0.58		
Generation Status (1 = First gen, 0 = Non-first gen)	-0.66	0.59	-0.08	-1.05		
Asian	0.97	0.79	0.09	1.24		
Filipinx	0.97	1.06	0.06	0.92		
Hispanic/Latinx	-1.72	0.66	-0.22	-2.60^{**}		
Block 2					.118	$.016^*$
Course Type (1 = Corequisite, 0 = Prerequisite)	+ 1.23	0.57	0.13	2.15^*		

$^*p < 0.05$, $^{**}p < 0.01$
Note: b, SE_b, β, and t values are based on the final model with all variables included.
Note: Course grades are coded from 0 = F to 12 = A^+

Prior achievement, generational status, ethnicity, and gender were controlled in the regression by entering these in Block 1 of the regression model. The independent variable, ‘Course Type, was entered into the model in Block 2. As we can see from the table, the *t-value* in Block 2 is statistically significant (t = 2.15, p <.05). This suggests that the type of course accounts for unique variation in course grades. The change in R^2 (ΔR^2) in Block 2 indicates how much variation (1.6%) in the data is explained by adding the new variable 'Course Type, in the second block. A statistically significant change in R^2 ($\Delta R^2 = .016, p < .05$) in Block 2 suggests that after controlling for the independent variables of prior achievement, gender, generational status, and ethnicity, the type of course results in statistically significant results and accounts for an additional 1.6% of the variance in course grades. Due to the coding where 1= corequisite, and 0 = prerequisite, the positive coefficient (b = 1.23) for the type of model (in Block 2) implies that being in a corequisite course increases the course grade level on average (above that earned taking the course as a prerequisite) by 1.23 points on a continuum of grades from 1 through 12 (F = 0, D - = 1, D = 2, D + = 3, and so on……. . up to A+ = 12).

Since the *t-value* for the type of model is significant, and the regression coefficient *b* for the type of model is positive, the answer to RQ 1 is yes. In summary, average course grades in a STEM gateway math course are different for those who completed the corequisite model than those who completed it with the traditional model after controlling for prior academic achievement, gender, generational status, and ethnicity.

Regression model for RQ 2 (College A). Research Question 2 focuses on whether the generational status of a student moderates the effect of type of course delivery model on course grades. To check the interaction effect between the generational status and the type of course model, a cross product variable between generational status and type of course was created. As explained in the methodology section of this dissertation, the interaction variable was added to the regression in Block 3, after controlling for prior academic achievement, ethnicity, and gender in block 1, and entering the independent variable, Course Type, along with the variable Generational Status in Block 2. Unfortunately, this model did not satisfy all the assumptions of multiple regression. A very high correlation (0.85) was found between the interaction term and the generational status. There were threats of multicollinearity with tolerance (TOL) for the interaction term as low as .18 and for generational status just .19. Thus, an alternate approach that does not require the use of cross-products was employed. Specifically, regressions are run separately for each subgroup, then the confidence intervals for the regression coefficient, b, are compared to see whether they are non-overlapping. This alternative method for assessing variation in the effect across subgroups (in other words, a moderating effect) is used here since multicollinearity statistics suggested application of standard multiple linear regression was not warranted. This approach was adopted throughout analyses related to research questions two through four, for consistency in presentation of the findings.

Descriptive statistics for course grades broken down by generational status and type of course is provided in Table 27 below. It can be noted that, prior to controlling for other background variables (gender, prior academic achievement, and ethnicity) the difference in course grades for those taking the corequisite versus prerequisite offering appears to be greater for first-generation college students (4.68 vs. 3.11) than for non-first-generation college students (6.32 vs. 5.68).

Table 27
Course Grades by Generational Status and Type of Course

	Corequisite			**Prerequisite**			**Effect Size**
	n	Mean	SD	n	Mean	SD	d
First gen	81	4.68	3.85	19	3.11	3.54	0.41
Non-first gen	113	6.32	3.96	44	5.68	4.04	0.16

To see if the relationship between course grades and the type of model might vary based upon different generational status, separate regressions were run for first-generation students and non-first-generation students. Table 28 presents a summary of the regression results for each subgroup and also for the group as a whole. The confidence intervals for *b*, the regression coefficient associated with type of course, overlapped. This suggests that generational status of a student does not moderate the effect of a corequisite model on course grades. In fact, although the type of course was significantly associated with course grades for the group as a whole, it was not for each group separately.

It is recognized that hypothesis testing alone can be misleading since statistical significance is impacted by sample size. Thus, effect size estimates, using Cohen's *d* (Cohen, 1988) are also provided in Table 27. Values of .2, .5, and .8 in magnitude are general guidelines used when describing effects as small, medium, and large, respectively. Hence, Table 27 suggests type of course has a small to medium effect for first generation college students but does not meet the guidelines to call the effect even a small one for the non-first-generation students. Specifically, on average, first-generation students in College A perform better when taking the corequisite course (as compared to the prerequisite one), $d = 0.41$.

In summary, based on traditional hypothesis testing, the answer to RQ 2 is no; in other words, the impact of the developmental education model (traditional vs. corequisite) on course grades in a STEM math gateway course does not vary by the generational status of a student after controlling for their gender, ethnicity and prior academic achievement. For both groups, the regression coefficient was positive and the confidence intervals overlapped. However, the effect size estimates suggest that the course type matters for first-generation students, but has a negligible effect for non-first-generation students.

Table 28
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Generational Status (Controlling for Gender, Prior Academic Achievement, and Ethnicity).

	n	b	SE_b	CI (. 95)	t	p
First-gen	100	1.59	1.01	(-.42, 3.60)	1.57	.120
Non-first gen	157	1.05	.71	(-.35, 2.46)	1.48	.141
All	257	1.22	.57	(.09, 2.34)	2.12	. 035*

Regression model for RQ 3 (College A). The RQ 3 tests for prior academic achievement as a moderator for the effect of type of course delivery model on course grades. Descriptive statistics for course grades broken down by prior academic achievement and type of course are provided in the Table 29. It can be noted that, prior to controlling for other background variables (gender, prior academic achievement, and ethnicity) the difference in course grades for those taking the corequisite versus prerequisite offering appears to differ depending on the prior academic achievement level of the student. For those with lower prior achievement, precalculus grades were better, on average, in the prerequisite model than the corequisite model (5.75 versus 4.91) whereas the opposite was found for those with higher prior achievement where precalculus grades were better, on average, in the corequisite model than the prerequisite model (6.02 versus 4.78). However, caution must be exercised since only eight students with low prior academic achievement were in the prerequisite model sample. Cohen's *d* effect size estimates (-0.22 and 0.30 for lower and higher prior achievement subgroups, respectively) suggest the effect of course type is small for both groups, but in opposite directions.

Table 29
Course Grades by Generational Status and Type of Model

	Corequisite			**Prerequisite**			**Effect Size**
	n	Mean	SD	n	Mean	SD	d
HSGPA< 2.7	67	4.91	3.78	8	5.75	4.33	-0.22
HSGPA > = 2.7	127	6.02	4.06	55	4.78	4.04	0.30

Like in Research Question 2, similar issues with multicollinearity were observed, and it was decided to go with the alternate approach to perform separate regression analyses for the two subgroups of prior academic achievement (HSGPA < 2.7 and HSGPA> = 2.7). The results of the separate analyses are presented in Table 30.

Table 30
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Prior Achievement (Controlling for Gender, Generational Status, and Ethnicity).

	n	b	SE_b	CI (. 95)	t	p
HSGPA < 2.7	75	-.99	1.45	(-3.89, 1.89)	-.69	.493
HSGPA > = 2.7	182	1.38	.64	(.130, 2.64)	2.18	$.031^{*}$
ALL	257	1.18	.56	(.07, 2.29)	2.10	$.037^{*}$

In this case, the t-value for low prior achievement was not significant while the high academic achievement produced statistically significant results. A positive coefficient (b = 1.38) for high achievers suggests that being in a corequisite model enhances their final course grade by approximately one level. In other words, a corequisite model may enhance a B^- grade to a B, or a B grade to a B^+. It is unclear whether the non-significant finding for those with low prior academic achievement is due to insufficient power (with just eight students in the prerequisite group) or validly reflects that the type of course has little bearing upon the precalculus performance of students with low prior achievement. The standard error for the regression coefficient was over twice as large for the low prior achievement group than for the high prior achievement group. In summary, it appears that the answer to Research Question 3 is yes since for one group (the high achieving group) the type of model seems to matter, whereas for the other (the low achieving group) it does not. On the other hand, the separate confidence intervals for the unstandardized regression coefficient, b, overlap, and this would suggest that the answer to RQ 3 is no. As noted above, the effect of course type is small for both groups, but in opposite directions. Thus, this qualitative difference suggests that the answer to RQ3 is yes.

Regression model for RQ 4 (College A). Descriptive statistics for course grades broken down by different ethnic groups and type of course is provided in Table 31. It can be noted that, prior to controlling for other background variables (gender, prior academic achievement, and ethnicity) the precalculus course grades were higher for those taking the corequisite versus prerequisite courses and this pattern was consistent across all four ethnic subgroups. The difference was most pronounced among the Filipino subgroup (8.00 vs. 5.60). Cohen's *d* effect size estimates (ranging from 0.18 to 0.72) are small for the Latinx and White students, but large for the Filipinx students.

Table 31
Course Grades by Ethnic Groups and Type of Model

	Corequisite			**Prerequisite**			**Effect Size**
	n	Mean	SD	n	Mean	SD	d
Asian	22	7.41	3.84	15	6.67	4.47	0.18
Filipinx	11	8.00	3.32	5	5.60	3.29	0.72
Latinx	107	4.51	3.65	26	3.31	3.95	0.32
White	54	6.65	4.16	17	5.59	3.37	0.27

As we have seen earlier, ethnicity having four different subgroups was dummy coded differently (See Table 9). Based upon different ethnic subgroups, three new dummy variables, Asian, Filipinx, and Latinx were introduced, White being the reference group. To study the moderating effects of ethnicity on course grades from corequisite or prerequisite type of courses, three interacting variables Asian × Course Type, Filipinx × Course Type, and Latinx × Course Type were introduced in the third block of regression. Similar to RQ 2 and RQ 3, there were multicollinearity issues; therefore, separate regressions for each of the ethnic subgroups were performed. A summary of the regression analysis results for each ethnic subgroup is given in Table 32.

The impact of the course type was non-significant for all the ethnic subgroups except for Filipinx group. Although the regression assumptions were met, this finding is based on a very small sample size so care should be exercised when interpreting the Filipinx results. There were only 16 (6.2% of all) Filipinx students in this subgroup. A positive b coefficient of 3.54 suggests a 3.5 level increase in the course grades by being in the corequisite model. Given that the regression coefficients, across the various ethnic subgroups, are all positive and that the individual confidence intervals all overlap, the answer to RQ4 is no; that is, the impact of the type of model on course grades in a STEM math course does not vary by the ethnicity of a student after controlling for their gender, generational status and prior academic achievement.

Table 32

Regression of Course Grades on Course Type Analyzed Separately for Each Subgroup in Ethnicity (Controlling for Gender, Generational Status, and Prior Academic Achievement).

	n	b	SE_b	CI (. 95)	t	p
Asian	37	0.12	1.48	(-2.90, 3.14)	0.08	0.94
Filipinx	16	3.54	1.52	(0.18, 6.89)	2.32^{*}	0.04
Latinx	133	1.36	0.84	(-0.30, 3.03)	1.62	0.11
White	71	0.99	1.15	(-1.30, 3.28)	0.89	0.39
All	257	1.00	0.58	(-0.14, 2.15)	1.73	0.09

Analysis for College B

This section presents an analysis of the non-repeaters' data from Spring 2017 through Spring 2019 from College B, which uses the semester system. As explained in the beginning of this chapter, the cases from Fall 2016, Summer 2017, and Summer 2018 have been ignored. The sample demographics of the remaining 875 cases are presented in Table 33.

As can be seen from the table, there are cases with unknown gender, unknown generational status, unknown HSGPA, unknown ethnicity, and one or more ethnicities. The regression analysis in this study controls for gender, generational status, prior achievement, and ethnicity of a student. So, all the unknown and ambiguous cases that are not relevant to this study will be deleted from the data set. Additionally, the ethnic subgroup of American Indian/Alaskan Natives, having just one participant in the large data set, will also be deleted from the main analysis.

Table 33
Demographic Characteristics of All Non-Repeater Participants from College B

Demographic Characteristics		n	%
Gender	Male	552	63.1%
	Female	317	36.2%
	Unknown	6	0.7%
Generation Status	First- Gen	319	36.5%
	Non-First Gen	499	57.0%
	Unknown	57	6.5%
Prior Academic Achievement	Low (HSGPA<2.7)	49	5.5%
	High (HSGPA >=2.7)	87	9.9%
	Unknown HSGPA	739	84.5%
Ethnicity	African American	33	3.8%
	Asian	34	3.9%
	Filipino	21	2.4%
	Hispanic/Latinx	314	35.9%
	White	416	47.5%
	American Indian/Alaskan Native	1	0.1%
	Two or More	55	6.3%
	Unknown	1	0.1%
Course Type	Corequisite	286	32.7%
	Prerequisite (Traditional)	589	67.3%

A problematic issue with this data set is that there is a very large number (84.5%) of students who did not report their HSGPA, and deleting all these cases resulted in a very small data set. With the result, it was decided to analyze College B data with two separate approaches.

Two cases for College B data analysis are explained below.

- *Approach I:* After deleting all the unknown HSGPA cases, the sequential regression is followed on a small dataset by controlling for gender, generational status, prior achievement, and ethnicity. All four research questions are addressed in this case.
- *Approach II:* Keeping all the known and unknown HSGPA cases, the regression analysis controls for gender, generational status, and ethnicity. It is to be noted here that prior achievement will not be controlled in this case. Consequently, RQ 3 will not be addressed.

College B: Approach I

In this section, College B data will be analyzed for those cases where students' HSGPA is known.

Preliminary analysis and sample demographics. Deleting all the unknown GPA cases from College B's dataset resulted in a very small dataset to work with. Surprisingly, there were no students in corequisite precalculus courses from African American, Asian and Filipino ethnic subgroups. Consequently, African American, Asian, and Filipino subgroups were deleted from the dataset. Latinx and White were the only ethnic groups used for this College B, Case I data analysis. The student demographics in both the corequisite and traditional courses for all the cases to be included in the main analysis are displayed in Table 34.

Table 34
Demographic Characteristics of the Participants from College B Going into Main Analyses

Demographic Characteristics		Corequisite		Prerequisite	
		n	%	n	%
Gender	M	21	70.0%	24	70.6%
	F	9	30.0%	10	29.4%
Generation Status	First-Gen	15	50.0%	11	32.4%
	Non-First-Gen	15	50.0%	23	67.6%
Prior Achievement	Low (HSGPA<2.7)	5	16.7%	5	14.7%
	High (HSGPA >=2.7)	25	83.3%	29	85.3%
Ethnicity	Hispanic/Latinx	13	43.3%	12	35.3%
	White	17	56.7%	22	64.7%

Associations and relationships between variables. This section explains the correlations and associations with all different type of variables. Chi-squared test of association and Pearson's correlation coefficients are used to study these associations and relationships.

Differences between and associations with the independent variable (type of course model). Table 34 shows a higher proportion of first-generation students (15/26) enrolled in corequisite courses than the proportion of non-first-generation students (15/38) did. The majority of prerequisite students (68%) were from the non-first-generation group. On comparing students in prerequisite and corequisite courses based upon their prior academic achievement, it was noticed that low achieving students were equally distributed in these courses, and the group of high achieving students had only a slightly higher proportion (29/54) in prerequisite courses. A Chi-squared test of association was performed to check the association of each of the control variables with the independent variable - Course Type. None of the control variables gender $(\chi^2(1, N = 64) = .00; p = 0.95)$, generational status $(\chi^2(1, N = 64) = 2.\ 06; p = 0.15)$, prior achievement $(\chi^2(1, N = 64) = .05; p = 0.83)$, and ethnic subgroup Latinx $(\chi^2(1, N = 64) = \ .43; p = .51)$ were found to be significantly associated with the choice of course type.

Differences between and associations with the dependent variable (precalculus course grades). Correlations between course grades and the rest of the independent and control variables used in the study were calculated. Table 35 shows the correlation coefficients between all the variables used in this study. Being Latinx was found to have a significant correlation (r = -.26, p < .05*)* with final course grades. A moderately negative correlation suggests lower course grades for Latinx students than for the reference group (Whites, coded 0). None of the other variables showed a significant relationship with the final course grades.

Table 35

Correlation between All Variables Including the Ethnic Group Latinx

	Course Grade	Gender	Generational Status	Prior Achievement	Latinx	Course Type
Course Grade	1					
Gender	0.03	1				
Generational Status	-0.13	0.16	1			
Prior Achievement	-0.02	0.28*	-0.08	1		
Latinx	-0.26*	-0.10	0.19	-0.10	1	
Course Type	0.00	0.01	0.18	-0.03	0.08	1

Note. *p<.05, ** p < .01 N = 64. Dummy coding assigned the higher code of 1 to the corequisite, female, Latinx, and first-generation subgroups and lower code of 0 to the prerequisite, male, white, and non-first-generation subgroups.

Associations between control variables. A moderate and positive significant correlation (r = .28, p < .05) between prior achievement and gender suggesting female students (coded 1) had higher HSGPA, on average, than males (coded 0). Interestingly, a similar result was obtained for College A. No significant correlations were observed between the other control variables.

Multiple Regression Assumptions and Diagnostics

Similar to checking of multiple regression assumptions in case of College A, these assumptions were tested for College B data as well. This was done to diagnose potential problems in the data and to strengthen statistical conclusion validity. All variables were checked to make sure that their values are valid and reasonable. Then, a multiple regression was conducted to check assumptions for each research question. The diagnostic information, including predicted values, residuals, Cook's values, estimates of partial influence and collinearity statistics, were obtained. These were further examined to test the assumptions of linearity, homoscedasticity, multicollinearity, and normality of residuals. Diagnostics were used to spot problematic data points focusing on three characteristics: distance, leverage, and influence (Keith, 2006). Details of the regression assumptions and diagnostics are available in Appendix B. The checks revealed that application of multiple linear regression was reasonable. The presence of multicollinearity in some cases where an interacting variable was used was resolved by adopting alternative approaches of sequential regression on separate subgroups of the concerned variable. Overall, the assumptions were validated and no cases were removed from the analyses pertaining to Approach I for College B.

Main Analyses for College B: Approach I

This section presents the regression analysis for each of the four research questions pertaining to College B in Approach 1 (i.e., prior achievement was available and could be controlled).

Regression model for RQ1 (College B: Approach I). The first research question (RQ 1) used the sequential multiple regression to study the impact of a corequisite model (as compared to a prerequisite model) on precalculus (a STEM math gateway course) course grades. Regression was used in two blocks where the impact of gender, generational status, prior achievement level, and ethnicity were controlled by entering these in the Block 1 of the regression model. The variable ‘Course Type was entered into the regression in Block 2. The results are as shown in Table 36.

Table 36

Sequential Multiple Regression of Course Grades on Type of Course Delivery Model Controlling for Prior Achievement, Generational Status, Ethnicity, and Gender

	b	**SE_b**	**β**	**t**	**R^2**	**ΔR^2**
Block 1					0.079	0.079
Prior Achievement (1 = HSGPA ≥ 2. 7)	-.60	1.29	-.06	-.47		
Gender (Male = 0, Female =1)	.26	1.04	.03	.25		
Generation Status (1 = first-gen, 0 = non-first-gen)	-.71	.96	-.09	-.74		
Latinx	-1.82	.94	-.25	-1.94		
Block 2					.081	.001
Course Type (1 = Corequisite, 0 = Prerequisite)	.27	.91	.04	.30		
$^*p < 0.05$, $^{**} p < 0.01$. Note: b, SE_b, β, and t values are based on the final model with all variables included. Course grades are coded from 0 = F to 12 = A^+						

Although the control variables explained 8% of the variation in course grades, no individual control variable was significant. Moreover, the *t*-value for the variable Course Type is not statistically significant, with the ΔR^2 being less than one percent. This means there is insufficient evidence that the type of course (corequisite versus prerequisite) in precalculus made a difference in the final course grades. Due to the sample size (*n = 64)* in this case being very small, caution is needed when interpreting these results. While there may truly not be a difference due to the type of course, it is also possible that the non-significant findings reflect an underpowered analysis. In short, the answer to RQ 1 is no (based on a college using the semester schedule, and using cases where all control variables, including prior achievement, are available).

Regression model for RQ 2 (College B: Approach I). This research question tests for generational status as a moderator of the effect of type of model on course grades. A description of course grades with course average and standard deviation for students in corequisite and prerequisite types of precalculus courses based upon their generational status is displayed in Table 37. Cohen's *d* effect size values suggest the impact of course type is negligible, regardless of generational status.

Table 37
Course Grades by Generational Status and Type of Course

	Corequisite			**Prerequisite**			**Effect Size**
	n	Mean	SD	n	Mean	SD	d
First-gen	15	5.73	2.96	11	5.36	3.23	0.12
Non-first-gen	15	6.53	4.39	23	6.48	3.64	0.01

From Table 37, it can be observed that prior to controlling for gender, prior achievement, and ethnicity, both first-generation and non-first-generation students showed slightly better average course grades in corequisite precalculus courses as compared to average grades in prerequisite courses. For example, the first-generation students course average in corequisite and prerequisite courses was 5.73 versus 5.36 respectively. For non-first-generation students, this average course grade comparison between corequisite and prerequisite courses was 6.53 versus 6.48.

Further, to check if generational status of a student moderates the effect of course type on precalculus course grades, a new cross product variable 'Generation Status × Course Type' was created. This interaction (cross-product) variable was entered in Block 3 of the regression model, after controlling for prior achievement, ethnicity, and gender in Block 1, and entering the independent variable for type of course and generational status in Block 2. Generally, an interaction variable in regression analysis results in multicollinearity issues showing high correlation with its interacting variables. The current regression model showed slightly higher correlation between the interaction variable 'Generation Status × Course Type' and the control variables Generational Status and Course Type. The correlations of the interaction variable with generational status and type of course were 0.67 and 0.59 respectively. These correlations, though slightly high, are not alarming. The minimum value for TOL was .32 (greater than .17) and the maximum value for VIF was 3.10 (less than 6). These values for TOL and VIF were well within the permissible range (Keith, 2006). So, a slightly high correlation was not perceived as a threat to multicollinearity. Hence, sequential regression was performed in three blocks as planned earlier. The results for the sequential regression testing for generational status as a moderator for the effect of type of model on course grades are shown in Table 38.

Table 38
Testing for Generational Status as a Moderator of the Effect of Type of Model on Course Grades after Controlling for Gender, Prior Academic Achievement, and Ethnicity.

	b	SE_b	β	t	R^2	ΔR^2
Block 1					·072	.072
Prior Academic Achievement (1 = HSGPA ≥ 2.6)	-.61	1.30	-.06	-.47		
Ethnicity (0 = White) Latinx	-1.82	.95	-.25	-1.92		
Gender (1 = Female)	. 28	1.03	.04	.26		
Block 2					.081	.009
Type of Course (1 = Corequisite)	.09	1.20	.01	.08		
Generation Status (1 = 1^{st} gen)	-.94	1.36	-.13	-.69		
Block 3					.082	.001
Generation Status × Course Type	.44	1.90	.05	.24		

The regression results from this model were statistically non-significant. The *t*-values for the Course Type and for the interacting variable were both statistically insignificant. In other words, this regression model suggests that there is an insufficient evidence to conclude that generational status moderates the effects of the type of a precalculus course on final course grades.

Further, it was decided to run a separate analysis for each generational group, parallel to what was done for College A. The table below (Table 39) presents the results of the separate regression analysis for each subgroup of generational status. The separate regression analysis for each student subgroup based on their generational status showed insignificant results for each of the subgroups.

Table 39
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Generational Status (Controlling for Gender, Prior Achievement, and Ethnicity).

	n	b	SE_b	CI (. 95)	t	p
First-generation	26	. 653	1.195	(-1.833, 3.139)	.546	.591
Non-first-generation	38	.120	1.333	(-2.592, 2.833)	.090	.929
All	64	.162	.893	(-1.625, 1.950)	.182	.856

Moreover, the overlapping confidence intervals for the coefficient *b* also suggest a non-moderating effect for the generational status on course grades based upon the course type. Thus, in summary, the answer to RQ 2 is no. There is insufficient evidence to conclude that the generational status of a student moderates the effects of the type of a precalculus course on final course grades.

Regression model for RQ 3 (College B: Approach I). The regression model for RQ 3 tests for level of prior academic achievement as a moderator of the effect of type of course delivery model on course grades. Table 40 provides descriptive statistics for course grades broken down by both prior academic achievement and type of model. A small effect (Cohen's *d*= -0.28) is found for type of course on precalculus grades for students with low prior academic achievement (HSGPA < 2.7). The impact of course type is negligible, however, for students with higher prior academic achievement.

Table 40
Course Grades by Prior Academic Achievement and Type of Course

	Corequisite			Prerequisite			Effect Size
	n	Mean	SD	n	Mean	SD	d
HSGPA < 2.7	5	5.60	5.23	5	7.00	4.64	-0.28
HSGPA >= 2.7	25	6.24	3.46	29	5.97	3.35	0.08

In this case, prior to controlling for other background variables (gender, generational status, and ethnicity) the course grades seem to differ for students from corequisite or prerequisite types of courses based upon their prior achievement level. Students with lower prior achievement had better grades, on average, in the prerequisite type as compared to the corequisite type of precalculus classes (7.00 versus 5.60) whereas the opposite was true for those with higher prior achievement. Students in the group HSGPA >= 2.7 had better precalculus grades, on average, in the corequisite type of classes when compared to their average grades in the prerequisite type (6.24 versus 5.97). Interestingly, similar results were noticed for the College A data.

To check the moderating effects of the course type on the course grades based upon the prior academic achievement, a new cross product variable, ‘Prior Achievement × Course Type’, was created and entered in Block 3 of the regression model. This was done after controlling for gender, generational status, and ethnicity in Block 1, and entering the variables for prior achievement and type of course in Block 2. The interaction variable was found to be highly correlated with the type of course variable (*r* = .86*)*. Also, the collinearity statistics showed out of range values for tolerance and VIF. Two values for tolerance (.15 and .14) were less than .17 and two values for VIF (6.48 and 7.35) were greater than six. Such values for TOL and VIF signify presence of multicollinearity among the variables, resulting in misleading results (Keith, 2006). Therefore, this regression model was rejected and the alternate approach of regression analysis for the separate subgroups of HSGPA < 2.7 and HSGPA > = 2.7 was followed through. For each subgroup, the sequential regression was done in two blocks. Block 1 controlled for background variables of gender, generational status, and ethnicity. The independent variable, Course Type, was entered in to regression in Block 2. The regression results for each of the subgroups of HSGPA are presented in Table 41.

Table 41
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Prior Achievement (Controlling for Gender, Generational Status, and Ethnicity).

	n	b	SE_b	CI (.95)	t	p
HSGPA < 2.7	10	-2.44	2.47	(-8.49, 3.60)	-0.99	0.36
HSGPA > = 2.7	54	0.49	0.96	(-1.44, 2.42)	0.51	0.61
ALL	64	0.28	0.90	(-1.53, 2.08)	0.31	0.76

Interestingly, while running this analysis, it was found that gender had missing correlations with other variables. On closer inspection it was found that all the students in the low achieving group (HSGPA < 2.7) were males. Comparing two groups where one group has only males and the other has both males and females may pose a selection threat. To avoid this threat, another analysis was done by deleting all the female students from the higher achieving group and then comparing both the groups (having only male students) as regard to their grades in corequisite or prerequisite precalculus courses. The following table presents the new findings.

Table 42

A Summary of the Regression Results for Each Subgroup with Only Male Students

	n	b	SE_b	CI (.95)	t	p
HSGPA < 2.7	10	-2.44	2.47	(-8.49, 3.60)	-.99	.36
HSGPA > = 2.7	35	1.21	1.25	(-1.34, 3.75)	.97	.34
ALL	45	.68	1.15	(-1.64, 2.99)	.60	.56

In Table 41 and Table 42, all the *t-values* were found to be statistically insignificant. Confidence intervals for coefficient *b* are overlapping. Also, if we look closely at the results from either of the two tables, the negative coefficient (*b* = -2.44) for the group HSGPA< 2.7 may indicate lower course grades for low achieving students in corequisite courses (as compared to prerequisite courses). The positive *b* value for the group with HSGPA >=2.7, might be indicative of corequisite courses helping students in the group with higher prior academic achievement. Looking at the small sample size for the group HSGPA< 2.7, the Cohen's *d* was calculated to see the effect size. Cohen's *d* for the low-achieving group was found to be -0.28 after correction for the small sample, which is a small effect. The Cohen's *d* for the higher achieving group was .08, which is no discernible effect. So, despite the low achievement group being not statistically significant (as expected due to the very small sample), and although caution is necessary in interpreting the results, these results suggest that the corequisite format may not be helping — and may possibly be hurting — students who had low levels of prior achievement (based on HSGPA < 2.7).

Regression model for RQ4 (College B: Approach I). In Research Question RQ 4, ethnicity is tested as a moderator of the effect of the type of course on course grades. Due to the specific ethnic composition of the state of California, in the region where College B is located, the majority of students were of Latinx or White ethnicity. Therefore, just these two ethnic groups were considered for regression analysis in this case. The variable for ethnicity was dummy coded with 1= Latinx and 0= White. The descriptive statistics for course grades broken down by ethnicity and type of course model are provided in Table 43. The effect size estimates show moderate to large effects of course type on course grades for both the Latinx (*d* =-0.65) and White (*d* =0.49) students, but in opposite directions. On average, the unadjusted means (prior to controlling for other background variables) reveal that the Latinx students performed better in the prerequisite courses, whereas the white students performed better in the corequisite courses.

Table 43
Course Grades by Ethnicity and Type of Model

	Corequisite			Prerequisite			Effect Size
	n	Mean	SD	n	Mean	SD	d
Latinx	13	3.92	3.40	12	6.08	3.29	-0.65
White	17	7.82	3.03	22	6.14	3.69	0.49

To study the interaction effects between the ethnicity and the type of course, a new variable 'Latinx x Course Type' was introduced, and the regression was performed in three blocks. Block 1 controlled for gender, prior achievement, and generational status of a student. The variables for type of course and ethnicity were entered in Block 2. Finally, the cross-product variable was entered in the third block. This model showed a slightly high correlation between the interaction variable and the variables it interacted with. For example, the correlation between 'Latinx x Course Type' and 'Latinx' was .63, and the correlation between the interaction variable and 'Course Type' was .54. Collinearity diagnostics showed a maximum VIF = 2.80 (less than 6) and all values for tolerance (TOL) > .17, maximum TOL being .97. Thus, the values for VIF and TOL were within the permissible range, and a presence of multicollinearity was safely ruled out. With all the regression assumptions met, it was decided to run the sequential regression model as planned. The results of this model are shown in Table 44. This regression model showed statistically significant results. The *t-value* for the cross-product variable and ΔR^2 in Block 3 were statistically significant. A significant *t-value* for the variable 'Latinx x Course Type' suggests that ethnicity (Latinx versus White) moderates the effects of course type on final course grades. In other words, the impact of the type of course on precalculus grades varies based on the ethnicity of a student. The model further suggests a reduction in course grades for Latinx students by studying in a corequisite model (b = -3.83).

The statistically significant value for ΔR^2 =.068 in Block 3 implies that an additional 6.8% of the variation in course grades is explained by the interaction of Latinx ethnicity and choice of course type. So, the answer to RQ 4 is yes (that is, ethnicity does moderate the impact of course type on course grades) for students in College B (when considering Latinx versus White students for whom prior academic achievement can be controlled). It should be noted that the moderating effect result shown in Table 43 is the largest one found in this study, across multiple analyses.

Table 44

Testing for Ethnicity as a Moderator of the Effect of Type of Model on Course Grades

	b	SE_b	β	t	R^2	ΔR^2
Block 1					.021	.021
Prior Academic Achievement	-.341	1.260	-.035	-.270		
Generational Status (1 = First-gen)	-.668	.932	-.093	-.717		
Gender (1 = Female)	.422	1.015	.054	.416		
Block 2					.081	.060
Type of Model (1 = Corequisite)	1.780	1.131	.251	1.573		
Latinx	.072	1.275	.010	.057		
Block 3					.149	.068 *
Latinx × Course Type	-3.834	1.801	-.436	-2.129*		
* p < 0.05, ** p < 0.01						

Alternately, looking at the regression analysis for separate subgroups for ethnicity, the following results are obtained (Table 45).

Table 45
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Ethnicity (Controlling for Gender, Generational Status, and Prior Academic Achievement).

	n	b	SE_b	CI (. 95)	t	p
Latinx	25	-2.24	1.41	(-5.18, .70)	-1.59	.13
White	39	1.65	1.12	(-.63, 3.92)	1.47	.15
All	64	.19	.93	(-1.67, 2.05)	.21	.84

None of the *t-values* were significant, but the coefficient for the course type in case of Latinx students continued to be negative (b = -2.24). The confidence intervals in this case are overlapping. The negative *b* indicates a reduction in grade by being in a corequisite model. The Cohen's *d* calculations showed an above medium negative effect for Latinx students (d = -0.65) and a positive medium effect for White students (d = .49). In a nutshell, the results point toward a negative effect of the corequisite STEM math gateway course on Latinx students.

College B: Approach II

In this section, College B data will be analyzed after retaining all the known and unknown HSGPA cases. Since the number of unknown HSGPA cases are very large in this dataset, the prior academic achievement will not be controlled to study the impact of the type of course delivery model on precalculus course grades. Only the research questions RQ1, RQ2, and RQ4 will be answered in Approach II for College B.

Preliminary analysis and sample demographics. With the exception of prior achievement (HSGPA), which was not used in these Approach II analyses, after deleting the unknown and ambiguous cases for each variable, and running the chi-squared tests of association of ethnicity with the type of course, it was found that a very small number of Asian (4) , Filipino (7), and African American students (7) were in the corequisite model of precalculus courses, while the number of Latinx and White in corequisite courses were much higher (99 and 101 respectively). The number of students in the three ethnic subgroups (Asian, Filipino, and African American) in prerequisite model of courses was only marginally better (21, 11, and 14), but still too low when compared with the number of Latinx and White students in prerequisite courses (139 and 214 respectively). After observing the low representation by these ethnic subgroups, it was decided to drop the Asian, Filipino, and African American students from the data set for the main analysis. A crosstab analysis of the remaining categories of control variables and the independent variable of course type going into the main analysis is shown in Table 46.

Table 46

Demographic Characteristics of the Participants Going into Main Analyses

Demographic Characteristics		Corequisite		Prerequisite	
		n	%	n	%
Gender	Male	128	64.0%	222	62.9%
	Female	72	36.0%	131	37.1%
Generation Status	First- Gen	82	41.0%	141	39.9%
	Non-First Gen	118	59.0%	212	60.1%
Ethnicity	Hispanic/Latinx	99	49.5%	139	39.4%
	White	101	50.5%	214	60.6%

Associations and relationships between variables. This section explains the correlations and associations with all different type of variables. The Chi-squared test of association and Pearson’s correlation coefficients are used to study these associations and relationships.

Differences between and associations with the independent variable (type of course model). The Chi-squared test of association was performed to check the association of each of the control variables with the independent variable, Course Type. Out of all the control variables, only ethnicity showed statistically significant results for association with the type of course $(\chi^2(1, N = 553) = 5.34; p = 0.02)$. It was interesting to note that a higher proportion of students in the Latinx subgroup (99/238) chose the corequisite model of a precalculus course as compared to the ethnic subgroup of White students (101/315). Table 47 shows the Pearson's correlation coefficients between all the variables used in the study. The correlation coefficients reiterated the result that ethnicity (Latinx vs. White) is related with the independent variable of course type (r = .10, p <.01) which is small in magnitude but significant due to the large sample size.

Table 47
Correlation Between All the Variables Used in the Main Analysis

	Course Grade	Gender	Generational Status	LATINX	Course Type
Course Grade	1				
Gender	.01	1			
Generational Status	-.06	.09*	1		
Latinx	-.18**	.01	.18**	1	
Course Type	-.04	-.01	.01	.10**	1

Note. *p<.05, ** p < .01 N = 553. Dummy coding assigned the higher code of 1 to the corequisite, female, and first-generation subgroups and the lower code of 0 to the prerequisite, male, and non-first-generation subgroups.

The positive correlation between the variables ethnicity and course type shows that being Latinx ethnicity is associated with the corequisite type of precalculus courses, given the coding used for the two dichotomous variables. The other two control variables, gender and generational status, did not show any statistically significant association with the choice of course type.

Differences between and associations with the dependent variable (precalculus course grades). Ethnicity was found to be significantly correlated with the dependent variable as well ($r = -.18$, $p < .01$). On average, Latinx students received lower grades in a precalculus course than White students. The rest of the variables did not show a significant correlation with the final course grades.

Associations between control variables. Ethnicity and generational status are significantly correlated ($r = .18$, $p <.01$). A higher proportion of Latinx students are first-generation than the proportion of White students who are first-generation. The positive significant correlation between gender and generational status ($r =.09$, $p < .05$) indicates a larger proportion of females are first-generation than males.

Multiple regression assumptions and diagnostics. This section provides a description of testing multiple regression assumptions for Approach II of College B. After checking for valid and reasonable values of all variables, a multiple regression was conducted to check assumptions for each research question. As in the prior two cases, predicted values, residuals, Cook's values, estimates of partial influence, and collinearity statistics were obtained. These were further examined to test the assumptions of linearity, homoscedasticity, multicollinearity, and normality of residuals. Diagnostics were used to spot problematic data points focusing on three characteristics: distance, leverage, and influence (Keith, 2006). Details of the regression assumptions and diagnostics are available in Appendix C. The checks revealed that application of multiple linear regression was reasonable and no cases were removed from the analyses pertaining to Approach II of College B.

Main analysis for College B: Approach II. This section presents the regression analysis for three of the four research questions pertaining to College B. Sequential regression is used to answer questions RQ1, RQ2, and RQ4. Since the prior academic achievement is not controlled here, RQ3 will be ignored in this case.

Regression model for RQ1 (College B: Approach II). In this research question, the sequential multiple regression was used to study the impact of a corequisite model in a precalculus class. Regression was used in two blocks where the impact of gender, generational status, and ethnicity were controlled by entering these in Block 1 of the regression model. The variable course type entered into the regression in Block 2 gave the results shown in Table 48.

The *t*-value for course type in this regression model was not statistically significant. This suggests insufficient evidence to conclude that the type of course made a difference in the performance of students in a STEM math gateway course. So, similar to Case I of College B, the answer for RQ 1 is no. It is interesting to note that the only variable with a significant *t*-value is ethnicity (the ethnic subgroup Latinx is coded 1 with White coded 0). As we have seen in earlier cases, its coefficient for course type continues to remain negative (b = -.15*)*, suggesting that Latinx students have decreased performance in corequisite (as compared with prerequisite) types of STEM math gateway courses.

Table 48
Sequential Multiple Regression of Course Grades on Type of Course Delivery Model Controlling for Gender, Generational Status, and Ethnicity

	b	**SE_b**	**β**	**t**	**R^2**	**ΔR^2**
Block 1					0.032	0.032
Gender (Male = 0, Female =1)	.09	.29	.01	.31		
Generation Status (1 = first-gen, 0 = non-first-gen)	-.19	.29	-.03	-.65		
Latinx	-1.13	.29	-.17	-3.95**		
Block 2					.032	.000
Course Type (1 = Corequisite, 0 = Prerequisite)	-.15	.29	-.02	-.50		

*p < 0.05, ** p < 0.01
Note. b**,** SE_b, β, and t values are based on the final model with all variables included. Course grades are coded from 0 = F to 12 = A^+

Regression model for RQ 2 (College B: Approach II). This research question tests for generational status as a moderator of the effect of type of model on course grades. A description of course grades with average and standard deviation in corequisite and prerequisite courses based upon their generational status is given in Table 49. Cohen's *d* values suggest that type of course has a small effect (-0.31) for first-generation students, but a negligible one (0.08) for non-first-generation students.

Table 49
Course Grades by Generational Status and Type of Course

	Corequisite			**Prerequisite**			**Effect Size**
	n	Mean	SD	n	Mean	SD	d
First-gen	82	6.35	3.19	141	7.33	3.15	-0.31
Non-first gen	118	7.51	3.28	212	7.24	3.42	0.08

First-generation students show a slightly better course grades on average (7.33) in a prerequisite type of course as compared to the average course grade (6.35) in a corequisite course, while non-first-generation students show a slightly better performance in the corequisite type of precalculus courses.

To check the interaction effect between the generational status and the type of course, a new cross product variable 'Generation Status × Course Type' was entered in Block 3 of the regression model. In this case, entering the cross-product variable did not show multicollinearity issues. The correlations between the cross-product variable with the variables it was interacting with were marginally higher. The correlation of the interacting variable with Generational Status was 0.51, while its correlation with Course Type was 0.55. The tolerance (TOL) and VIF for all the variables were also checked. The minimum value for TOL was .44 and two of its values were equal to one. According to Keith (2006), "Tolerance can range from zero (no independence from other variables) to one (complete independence); larger values are desired" (p. 201). The maximum value for VIF was 2.29, which is acceptable, being less than six (Keith, 2006). To keep the results parallel with the prior analyses, the regression will be performed with both approaches: the sequential regression by entering an interaction variable in Block 3, and the separate regression analysis for each subgroup of the generational status. The results for the sequential regression by entering the interacting variable generational status X course type in Block 3 are shown in Table 50. The *t-value* for the course type and the interacting variable of course type with generational status were statistically non-significant. The ethnic group Latinx continued to show significant results with a negative coefficient (b = -1.08). To summarize, the generational status does not seem to modify the course grades based upon their enrollment in a corequisite or a prerequisite type of precalculus course

Table 50

Testing for Generational Status as a Moderator of the Effect of Type of Model on Course Grades.

	b	SE_b	β	t	R^2	ΔR^2
Block 1					.031	.031
Gender (1 = Female)	.09	.29	.01	.30		
Latinx	-1.08	.29	-.16	-3.78**		
Block 2					.032	.001
Course Type (1 = Corequisite)	.26	.37	.04	.70		
Generation Status (1 = first-gen)	.17	.36	.03	.49		
Block 3					.038	.005
Generation Status × Course Type	-1.01	.59	-.11	-1.72		

*p < 0.05, ** p < 0.01

Note. b, SE_b, β, and t values are based on the final model with all variables included.

Note: Course grades are coded from 0 = F to 12 = A^+

Alternate approach for RQ 2. Separate analyses for each subgroup based on generational status of a student are shown in the table below. The results are similar to the above approach. None of the *t*-values are statistically significant. The overlapping confidence intervals for the two subgroups suggest a non-moderating effect of the generational status on course grades based upon their choice of course type. As has been seen above, Cohen's *d* for the first-generation group (-0.31) and for the non-first-generation group (0.08) show opposing results (Table 49). The course type seems to matter for one group (small effect) but not the other (negligible effect). This aspect can be explored further in a future research project, as it might be indicative of a pattern that the two groups are affected differently by the choice of course type.

Overall, we will conclude based upon the regression results that there is insufficient evidence to conclude that generational status moderates the effect of choice of course type on precalculus course grades.

Table 51
Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Generational Status (Controlling for Gender and Ethnicity).

	n	b	SE_b	CI (. 95)	t	p
First-generation	223	-.75	.44	(-1.89, -.20)	-1.70	.091
Non-first-generation	330	.26	.38	(-.49, 1.02)	.68	.497
ALL	553	-.14	.29	(-.71, .43)	-.50	.619

Regression model for RQ 4 (College B: Approach II). In Research Question 4, ethnicity was tested as a moderator for the effect of the course type on course grades. Since the majority of students were in the subgroups Latinx and White (1 = Latinx, 0= White), only the Latinx variable was entered in to the regression model.

The descriptive statistics for course grades broken down by ethnicity and type of course model is provided in Table 52. It can be noted that prior to controlling for other background variables (gender and first-generational status), Latinx students performed better in the prerequisite type of STEM math gateway courses. The White subgroup had a better course average in the corequisite type of courses. Using Cohen's *d*, we find the effect was small for the Latinx students (-0.28) and more than negligible, but still small, for the White students (0.18).

Table 52
Course Grades by Ethnicity and Type of Course Model

	Corequisite			Prerequisite			Effect Size
	n	Mean	SD	n	Mean	SD	d
Latinx	99	5.97	3.46	139	6.94	3.42	-0.28
White	101	8.07	2.74	214	7.53	3.23	0.18

To study the interaction effect between Latinx and the course type, the cross-product variables Latinx x course type was introduced. The regression was performed in three blocks. After controlling for background variables of gender and generational status in Block 1, the type of course and ethnic subgroup Latinx were entered in Block 2. Finally, the cross-product variable was entered in to regression in the third block. As noticed in previous cases, the correlations of the cross-product variable Latinx x course type, with its interacting variables Latinx (.54) and course type (.62), were slightly on the higher side. The collinearity statistics ..showed a minimum value of tolerance (TOL) as .38 (maximum being .99) and the maximum value of VIF as 2.61. These values for TOL and VIF were within the permissible range. Even though the threat to multicollinearity is not strong, the regression analysis was done by both approaches: using the interacting variable and using the separate analysis for each subgroup. The results of the regression model using the interacting variable are shown in Table 53.

Table 53

Testing for Ethnicity as a Moderator of the Effect of Type of Course on Course Grades.

	b	SE_b	β	t	R^2	ΔR^2
<u>Block 1</u>					.003	.003
Gender (1 = Female)	.12	.29	.02	.41		
Generational Status (1 = First-gen)	-.13	.29	-.02	-.43		
<u>Block 2</u>					.032	$.029^{**}$
Course Type (1 = Corequisite)	.54	.39	.08	1.38		
Latinx	-.58	.36	-.09	-1.64		
<u>Block 3</u>					.044	$.012^{**}$
Latinx × Course Type	-1.50	.58	-.17	-2.58^{**}		
$^{*}p < 0.05$, $^{**}p < 0.01$						

This regression model showed statistically significant results. The ΔR^2 values for Block 2 and Block 3 are statistically significant. For Block 2 and Block 3 these values are given by

$\Delta R^2 = .029$ and $\Delta R^2 = .012$. This means that after controlling for gender and generational status, entering the variables for the Latinx group and the type of course explains 2.9 % additional variability in the course grades of the STEM math gateway course. Entering the interacting variables explains another 1.2% of the variation in course grades.

The *t-value* for the interacting variable 'Latinx x course type' is statistically significant ($t = -2.58$, $p < .01$) and it has a negative coefficient ($b = -1.50$). As per this regression model, corequisite precalculus courses are not helping Latinx students. Being a Latinx student in a corequisite STEM math course decreases course grades by 1.5 levels (recall that the coding of course grades was 0 = F, going up to 12 = A+). Going down by 1.5 levels means going down from a B+ to a B-, or from a B to a C+. In short, statistically significant results for the cross-product variable for Latinx students suggests that ethnicity moderates the effects of course type on final course grades in a precalculus class. In other words, the impact of the type of course in a STEM math gateway course on grades varies by the ethnicity of a student. The findings suggest that a corequisite type of precalculus class may actually be hurting Latinx students, on average. The answer to RQ 4 is yes.

Alternate approach for RQ 4 (College B: Approach II). We will now look at RQ 4 by doing a separate analysis for both Latinx and White ethnic subgroups. Table 54 shows a significant *t*-value for the course type in case of the Latinx group. This is consistent with the results from the prior approach. In particular, being a Latinx student in the corequisite type of course in a STEM math gateway course is associated with a decrease in course grades, on average. The sample shows an advantage to White students by being in a corequisite course, but the result is statistically insignificant for White students. In short, we can say that the answer to RQ 4 is yes.

Table 54

Regression of Course Grades on Type of Course Analyzed Separately for Each Subgroup in Ethnicity (Controlling for Gender, and Generational Status).

	n	b	SE_b	CI (. 95)	t	p
Latinx	238	-.96	.46	(-1.86, -.07)	-2.11^*	.036
White	315	.54	.38	(-.20, 1.28)	1.44	.152
All	553	-.26	.29	(-.83, .32)	-.88	.379

Summary of Findings

Table 55 below summarizes the key findings across data sources by research question and specific subgroups, as applicable. The general pattern of results to be observed is that — regarding RQ1 — overall, the type of course (corequisite versus prerequisite) does not matter much when all cases are used. Less than two percent of the variation in precalculus course grades are accounted for knowing the type of course taken in College A; essentially no variation is explained in College B. When questions regarding moderating effects are addressed, the impact of the type of course on course grades is more nuanced. In College A (where the quarter system is used) the corequisite model, on average, seems to be associated with better course performance for some subgroups. However, in College B (where the semester system is used) the prerequisite model seems to be associated with better course performance for some subgroups.

Table 55

Summary of Effect Size Indices Across Colleges, Research Questions, and Types of Approaches (With and Without Prior Achievement).

College	RQ	Approach	Source (Prior Table)	Subgroups (if applicable)	Change in R Squared (for Type of Course)	Cohen's d Effect Size	Better Course Grades, on average, obtained in.
A	1			N/A: All Cases	.016	0.18	
	2		27	First-gen		0.41	Coreq.
				Non-first-gen		0.16	

(Table 55 Continued)

	3			HSGPA< 2.7		-0.22	Prereq.
				HSGPA > = 2.7		0.30	Coreq.
	4			Asian		0.18	
				Filipinx		0.72	Coreq.
				Latinx		0.32	Coreq.
				White		0.27	Coreq
B	1	I		N/A: All Cases	.001	0.00	
	2		37	First gen		0.12	
				Non-first- gen		0.01	
	3		40	HSGPA < 2.7		-0.28	Prereq.
				HSGPA >= 2.7		0.08	
	4		43	Latinx		-0.65	Prereq.
				White		0.49	Coreq.
B	1	II		N/A: All Cases	.000	-0.08	
	2		48	First -gen		-0.31	Prereq.
				Non-first- gen		0.08	
	4		51	Latinx		-0.28	Prereq.
				White		0.18	

Note. College A uses the quarter system; College B uses the semester system. Cohen's d effect size values of .2, .5, and .8, are considered small, medium, and large, respectively, and they are coded light blue (small), light green (medium), and darker green (medium-large).

Chapter Summary

This chapter presented the results of data analysis from two different community colleges. These colleges, one from northern California and the other from southern California, follow different academic systems. One college uses the quarter academic term, while the other college uses the semester system. Due to this difference in term lengths, the data for each college was analyzed separately. Data for each college was cleaned to include only those terms where both corequisite and prerequisite (traditional) types of precalculus courses were offered. Also, data for the students who repeated the course one or more times and in different possible patterns were deleted. Only the non-repeater students' data was considered to keep uniformity in the type of participants going into the analysis process.

The chapter provided descriptive statistics, including sample demographics, and associations and correlations between all the variables. Sequential regression was used to answer four research questions about the impact of a corequisite model on course grades in a STEM math gateway course. The impact of the corequisite model was studied after controlling for the background variables of gender, first generational status, HSGPA, and ethnicity. The control variables, first-generational status, HSGPA, and ethnicity, were tested for their role in moderating the effect of corequisite model on course grades. Unfortunately, College B had a very large number of students (85%) who did not report their HSGPA, so data for College B was analyzed with two different approaches: first, after deleting all cases with unknown HSGPA and controlling for all the four control variables; second, with keeping all cases for known or unknown HSGPA and controlling for the other control variables (ignoring the HSGPA). The dataset in the first approach for College B turned out to be very small; the analysis was nevertheless done for all the four research questions. However, in the second case for College B, HSGPA could not be used as a control variable; therefore, only three research questions (RQ1, RQ2, and RQ4) were addressed.

College A showed significant findings for RQ1, suggesting that the corequisite model of courses in a precalculus course impact overall student grades in a positive way. In the case of College B, there was insufficient evidence to conclude that corequisite STEM math gateway courses are influencing course grades in any significant way. As they relate to the other research questions, the moderating effects were noticed for some non-traditional student populations with differences found as to how course grades varied by their choice of course type. In College A, students with higher prior academic achievement, first-generation students, Filipinx, Latinx, and White were found to perform better in corequisite courses, while students with lower HSGPA performed better with the prerequisite type of courses. RQ3 results for College A and B were consistent in finding that students with lower prior achievement (HSGPA) performed worse, on average, in corequisite precalculus courses. Additionally, College B showed significant findings in the case of RQ4. The results showed a medium-large effect (d= -0.65) of Latinx students performing worse, on average, in corequisite precalculus courses. However, students at College A, regardless of ethnicity, performed better, on average, in the corequisite classes, and the effect sizes ranged from small to medium-large across the ethnic groups. A detailed discussion of the findings, implications for practice/policy, and the recommendation for future research are presented in Chapter 5.

CHAPTER 5: DISCUSSIONS

With implementation of AB 705 in California since Fall 2019, all community colleges in the state are devising new types of courses to replace remedial education with accelerated education. Corequisite courses in English and mathematics are two of the more popular kinds of accelerated courses adopted by California community colleges. This study focused on the effect of corequisite courses on academic performance in precalculus, a STEM math gateway course. The following research questions were addressed in this study.

> Research Question One (RQ1): Are average course grades in a STEM gateway math course better for those who completed the corequisite model than those who completed it with the traditional model after controlling for prior academic achievement, gender, generational status, and ethnicity?
>
> Research Question Two (RQ2): Does the impact of the type of model on course grades in a precalculus course vary by the generational status of a student after controlling for their gender, ethnicity and prior academic achievement?
>
> Research Question Three (RQ3): Does the impact of the type of model on course grades in a precalculus course vary by the prior academic achievement level of a student after controlling for their gender, ethnicity and generational status?
>
> Research Question Four (RQ4): Does the impact of the type of model on course grades in a precalculus course vary by the ethnicity of a student after controlling for their gender, generational status and prior academic achievement?

The following sections will include a brief summary of the results found in Chapter 4, a discussion on these results, implications for policy and practice, limitations of the study, and suggestions for future research.

Summary of Findings

The findings from data analysis of the two colleges in this study showed some mixed results. College A, following a quarter system, showed more positive results, overall, of the corequisite type of precalculus courses when compared with those from College B, which follows a semester system. Results from College A showed that, after controlling for gender, generational status, prior academic achievement, and ethnicity, corequisite courses in a STEM math gateway course produced better course performance. The positive trend of corequisite courses with varying degrees of effects, in College A, was also evident in some student subgroups, like those with prior higher achievement (HSGPA>=2.7), Filipinx, Latinx, and White students. White students performed better in corequisite courses across both colleges. The other result consistent with both colleges was that the students with lower prior achievement (HSGPA<2.7) showed a better performance in prerequisite (traditional) types of courses. A statistically significant result from College B showed negative effects of corequisite precalculus courses on Latinx students' success. A detailed discussion of the results for each of the research questions are presented in the next section.

Discussion of Findings

Corequisite courses have been found to be effective in English and non-STEM math courses (Edgecomb,2011; Bailey et al., 2015; Logue, Watanabe-Rose, & Douglas, 2016; Kashyap and Mathews 2017). A recent report by California Acceleration Project (based upon Multiple Measures Assessment Project, statewide data from 2007-2014, and corequisite data from 2016-2018) reported positive results of the corequisite model of courses on all type of math courses (The Campaign for College Opportunity, Dec. 2019). This study focused on finding the effects of a corequisite model in a STEM math gateway course by controlling some variables. The effect of corequisite courses on precalculus course grades were studied by controlling for gender, first-generational status, prior academic achievement, and ethnicity. The data was obtained from two California community colleges, one of which follows a quarter system, while the other follows a semester system. Findings for each of the four research questions are discussed next.

Discussion of Research Question 1 Findings

Research Question 1 is the main research question of the study, comparing the course grades between corequisite and prerequisite types of precalculus courses. The comparison is done after controlling for all the above-mentioned covariates: gender, first-generational status, prior academic achievement, and ethnicity. Results found from Colleges A and B were different in nature.

College A showed an overall improvement in precalculus class grades with a corequisite model of classes. Though the variation explained and the effect size are small, the results suggest 1.2 points of possible increase in the grade earned by taking a corequisite type of precalculus course. This means that, on average, for example, a student at a B grade level in a prerequisite course could earn a B+ in a corequisite course. Similarly, for example, a B+ student in a prerequisite course could earn an A- in a corequisite course. In other words, a student's grade will increase by one level by being in a corequisite course. These positive results regarding corequisite courses in College A are in alignment with the available research on positive results of such courses in English and non-STEM math courses, as was discussed in Chapter 2 (Edgecomb, 2011; Logue, Watanabe-Rose, & Douglas, 2016; Belfield, Jenkins, & Lahr, 2016; Kashyap and Mathews, 2017).

In the case of College B, statistically significant results were not obtained as regards to course type affecting course grades in a precalculus class. College B data was analyzed with two different approaches producing similar results. The effect sizes were negligible in both analyses.

The reason for the difference in results for College A and B is not very clear, but it definitely raises some questions to think about. The difference in results may be due to the different academic systems of the colleges (quarter versus semester schedules), or it may be that College A is doing a better job with the implementation of the new model (it is to be noted here that both colleges are using the cohort model of corequisite courses). The quality of instruction and students' motivation levels could also be possible causes of differences in results. Neither of these factors were controlled in this study. As discussed further below, more research is needed to explore the cause for the differences found between the two colleges.

Discussion of Research Question 2 Findings

RQ2 focused on finding any possible moderating effects of generational status of students on course performance in a precalculus course based upon their choice of a corequisite or prerequisite type of course. Research suggests that first-generation students are at a disadvantage in gaining access to and succeeding in college (Berkner & Chavez, 1997; Chen & Carroll, 2005; War-burton, Bugarin & Nunez, 2001). So, it is important to study how the new AB 705 college education rule will affect this student population.

The regression analysis from both colleges found insufficient evidence to conclude that generational status moderates the effect of course type on precalculus course grades. Statistically significant results were not found in any of the analyses run separately by generational status, suggesting that the generational status of a student does not moderate the effects of course type on student grades in a STEM math gateway class.

However, by focusing on effect size indices, differences were found, by generational status, as to how course performance may be impacted by the type of course the student takes. First generation students at College A perform better, on average, in corequisite courses where evidence of a small to medium effect (d =.41) was found. In contrast, at College B (in the second analysis involving more students since HSGPA was unavailable and left uncontrolled) the opposite was found. Although the effect was small, (d= -0.28) first-generation students at College B performed better, on average, in prerequisite courses. For the non-first-generation students, regardless of college (or type of analysis), the effect size for course type was negligible.

In this case, we also find that College A corequisite courses are helpful at least to one student subgroup, raising questions about the cause of the difference in results from College A to College B. Is it the difference in the academic systems of the two colleges, or there is a difference in the implementation of the corequisite model in two colleges? It is interesting to note that the opposite effects were found in course type among first-generation and non-first-generation students. This means that the type of course matters for first-generation students but does not matter for non-first-generation students. Differences in educational experiences between first-generation and non-first-generation students have been found in prior research. A study on experiences and outcomes of first-generation students in community colleges found these students less participative in academic activities and less likely to complete a college degree when compared with non-first-generation students (Pascrella, Wolniak, Pierson and Terenzini, 2003; NCES, 2005). The differentiated results between first-generation and non-first-generation students are discussed more when suggestions for further research are offered.

Discussion of Research Question 3 Findings

This research question looked at moderating the effects of prior academic achievement on course grades due to a choice of a corequisite or a prerequisite type of a precalculus course. Some research suggested that corequisite courses work only for students who are close to the cut-off score for remedial placement (Boatman and Long, 2018). The findings for RQ3 were consistent for both Colleges A and B with those of other studies, which found that the corequisite model of courses may not serve the needs of all students — especially those in high need of remediation (Kezar & Lester, 2007; Kashyap & Mathew, 2017). In this study, prior academic achievement was divided into two subgroups: HSGPA< 2.7 and HSGPA>=2.7. This GPA cut-off was chosen based upon a combination of the state guidelines (2.6, see Table 4) and the cut-off used by one of the sample colleges (College B).

Significant findings from both colleges pointed towards the fact that low-achieving students did better, on average, in prerequisite courses when compared to those corequisite precalculus courses, with generation status and ethnicity controlled.

In College A, a small effect (d= -0.22) was found in which the *lower-achieving* students performed better, on average, in prerequisite courses. In contrast, a small to medium effect (d = 0.30) was found in which *higher achieving* students performed better in corequisite courses. Similar results were observed for College B where a small effect (d= -0.28) was found in which the lower-achieving students performed better in prerequisite courses.

The results, focusing on the effect sizes, are consistent across both colleges where the corequisite courses may not be helping students with low prior achievement histories (that is, HSGPA < 2.7). This important finding is discussed below, as it has implications for policy and practice.

Discussion of Research Question 4 Findings

Research Question 4 is about the role of ethnicity in moderating the effect of course type on precalculus course grades. Community colleges serve more students of color than any other sector of higher education (Mullin, 2012). A study by Horn & Nevill, (2006) found nearly 30% of community college students as Black or Hispanic. Studies also talk about a very small percentage of Hispanic, Native Americans, and African Americans earning a certificate or college degree (Berkner & Choy, 2008). An important goal of AB 705 is to improve the success rate of community college students. Thus, it is important to study how this new law affects students from different ethnic subgroups. RQ4 attempts to study the effect of corequisite courses, promoted AB 705, on the performance of students from racial minority subgroups. Unfortunately, small samples for many ethnic subgroups made it impossible to produce findings that would be valid statistically due to insufficient power; therefore, those analyses were not performed. The dataset obtained from College A (with repeaters removed) had students from Asian, Filipinx, Hispanic/Latinx, and White backgrounds, while only Latinx and White subgroups were sufficient in size from College B — even when a second analytic approach was used which did not control for prior academic achievement in high school, as that information was missing for a large proportion of students at that college. Based on regression analyses performed on data from College A separately for each ethnic subgroup, performance by Filipinx students was found to be much higher in the corequisite courses, on average, than the prerequisite courses. The positive coefficient ($b = 3.54$) suggested a 3.5 point increase in the grade level of a Filipinx student by being in a corequisite group (recall that the coding of course grades was 0 = F, going up to 12 = A+). A 3.5 increase in the course grades means Filipinx students earning B's in a prerequisite course, on average, are expected to earn A's or A+'s in a corequisite course. This medium-large effect size ($d = 0.72$) was the largest found among all analyses performed in this study. Small effect sizes were also found at College A for Latinx ($d = 0.32$) and White ($d = 0.27$) students, with those in the corequisite course performing better, on average, than those in a prerequisite course. Interestingly, statistically significant regression results were also found from both analytical approaches in College B. A negative value of the coefficient (b = -3.83) for type of course, in the first approach of College B analysis, showed that corequisite courses are possibly not helping Latinx students. It showed a decrease of course grades by almost four points; which means a student of Latinx ethnicity earing a B grade, for example, in a prerequisite type of course is expected to go down to a C- by being in a corequisite course. The effect sizes for Latinx (d = -0.65) in Case I for College B (the second largest effect size found in the overall analysis for all subgroups), also suggested that Latinx students did better, on average, in prerequisite courses. On the other hand, the effect size for White students (d = 0.49) showed an advantage by being in a corequisite course. Very similar results were observed from the second analytical approach for College B. The above results from College A and B, though not exactly similar, do show some similarities in the pattern. Findings from both colleges suggest that ethnicity moderates the effect of course type on grades in a STEM math gateway course. While College A showed some positive effects of the corequisite model on some ethnic groups, the results from College B seem to be aligned with previous research that the effects of the corequisite courses on racial minority students (Latinx) may not be all positive (Berkner and Choy, 2008). The findings from this section will be further discussed when suggestions for future research are offered.

Implications for Policy and/or Practice

Corequisite courses are recommended by the state to accelerate the process of college completion by reducing the time taken to complete a college-level course. The long sequence of remedial courses has been found to be providing too many opportunities for students to drop out (Hern, 2010). Researchers have argued that by reducing the number of courses prior to taking a gateway course may expedite the process of degree completion in general (Bailey et al., 2010; Hayward & Willet, 2014). Positive results of corequisite courses in English and non-STEM math courses have also been established by prior research (Edgecomb, 2011; Hagedorn & Kuznetsova, 2016; Logue, Watanabe-Rose, & Douglas, 2016). Findings of this study indicate that the impact of enrolling in corequisite courses, as compared to prerequisite ones, may be different for STEM math gateway courses, which are more math-intensive courses. The results from this study suggest that although corequisite courses in a STEM math gateway course are helping students in some cases, these courses may not be helping everyone equally. At one (sometimes both) of the colleges whose data were analyzed in this study, corequisite courses were found to be associated with lower (rather than higher) course performance, on average, for students with low prior academic achievement and students from some racial minority groups. Community colleges are known to serve a large number of nontraditional student populations, some of whom come to fulfill their long-lost dream of receiving a college education after a gap of several years. It is possible that such students need more support in math concepts and a gradual progression towards college-level math courses. Findings from both colleges in this study suggested that corequisite courses in STEM math may not be helping students whose prior academic achievement levels are low (as defined by HSGPA < 2.7). Also, results from one college showed a strong negative effect of corequisite courses on Latinx students. It is to be noted here that STEM math gateway courses, like precalculus, are math-intensive and require a solid algebraic background. It is quite possible that the extra support received in the corequisite courses at the sample colleges may not be sufficient to prepare lower-achieving students for a precalculus course. In that sense, the results of this study support putting a policy in place to offer developmental courses for those students who need support and cannot keep up with the rigor of a college-level STEM-math course, along with learning the basic math concepts (as found in corequisite models) in a short academic term. On the other hand, it may not be wise to base policy decisions on the basis of just one research project. Further research is needed to come to a definite conclusion on whether corequisite courses are actually hurting lower-achieving students and Latinx students, or if there are some other unseen factors causing the results found in this study. Since AB 705 is already in place, further research might help to find ways for this law to be more successful.

One big implication of this study points towards lack of consistency in data reporting across California Community colleges. There were many inconsistencies in the data obtained from the two sample colleges. Data obtained from one college was organized and categorically reported the repeat status of a student, while the data from the other college was conspicuous with the absence of a student's course repeating pattern and status. The data was reported with masked student ID's and, for the research purposes, a student's repeat status was created by looking at the student ID and the number of times it was repeated in the given data set. Additionally, due to lack of an explicit statement about the repeat status of a student, it was not possible to identify a student's status for their first academic term, as there was no prior data to compare with in the obtained data set. Due to this lack of clarity, data from the initial academic term was ignored, resulting in a smaller data set and, therefore, less potential for some of the statistical tests in this study. Having good data is important for doing good research. Therefore, it is vital to have good and consistent data reporting techniques across community colleges statewide and nationwide.

The findings from this study also suggest some implications for practice. Different results found between the colleges used in this study make us ponder the cause behind this disparity. Is this difference due to separate academic systems of the two colleges? Or, it is due to a variance in implementation of corequisite courses? Or, are there other factors which are not yet apparent? One implication for practice may be the need for greater communication and sharing across campuses as to what each is doing with the implementation of corequisite courses. Sharing of best practices multiplies the good outcomes in any set-up, and even more so in an educational set-up, where knowledge is shared to produce a better future for students — and society as a whole.

Suggestions for Further Research

This study suggests that many opportunities for further research exist, using both quantitative and qualitative studies individually or in combination.

The results from this study have limited generalizability, given that just two colleges were used. With the implementation of AB 705 in California, almost all colleges have now adopted corequisite courses in English and math gateway courses. Additional studies on STEM math corequisite courses should be done using a larger sample of colleges.

The findings of this study showed different effects of corequisite precalculus courses on students from two different colleges. College A showed more positive results of corequisite precalculus courses when compared to College B. More research is required to go deeper into the possible causes of such differences. Future studies could explore the differences brought in by varied implementation processes of a corequisite model. Both colleges in this study used the cohort type of corequisite model in a precalculus class. As per AB 705, colleges have freedom to choose from a variety of types of corequisite support. After the passing of this law, there are some colleges which have decided to adopt different formats of corequisite support in all math classes. For a future study, it might be interesting to compare the results of corequisite support in precalculus classes offered in different styles.

Future research could focus on the differences created due to academic systems of colleges, their geographical locations in-state or out-of-state, and differences due to teaching styles at different institutions. A study very similar to the current one could be done by controlling for the academic term length or investigating whether it is itself a factor that moderates the effect of course type on course performance.

Case studies looking into how corequisite courses are implemented across colleges would be illuminating, as would phenomenological studies where students enrolled in corequisite courses are interviewed to directly capture their experiences of such courses. Another interesting qualitative study could compare faculty experiences through interviews. Mixed-methods studies would also be invaluable to better understand the implementation and consequences of the state law AB 705.

In this research, while studying the moderating effects of student subgroups on their performance in corequisite or prerequisite courses, opposite results were found for some subgroups. For example, the generational status of a student in both colleges (College A and Case II of College B) showed different effects of course type for first-generation and non-first-generation students. A small to medium effect for the type of courses were found for first generation students, while this effect for non-first-generation students was negligible. Since this pattern was noticed in both colleges, further studies are needed to determine whether generational status continues to moderate the impact of course type on course performance.

This research did not include students who repeated prerequisite or corequisite precalculus courses. Future research may include course repeater students. There could be several patterns of repeating a course. For example, a student repeating a corequisite course, or a prerequisite course, may be affected differently from a student who chooses to repeat a prerequisite course after failing a corequisite course, or vice versa. A future study on the effects of different repeat patterns may yield interesting differences.

One important point of consideration is that sometimes students drop a course well into the 14^{th} week of a semester and earn a "W" on their transcript. These students may reenroll into the course in the future without being identified as a repeat student. It is interesting to note here that students who elect to withdraw from the course with a "W" may have been exposed to two-thirds of the course and therefore would not be at the same level of exposure as the student who is taking the course for the very first time. Research data obtained from colleges is usually silent about such students. Future research may consider this fact and find a way to parse out "W" cases for a study on non-repeater students.

Corequisite courses, being new, are still in the experimental stage. Several colleges are developing new corequisite courses and experimenting with different styles of such courses. Further research in this area is desirable and will be instrumental in improving the system of education in the state of California — and nation as a whole.

Conclusion

This final chapter discussed the findings for each research question in this study. All findings from both Colleges A and B were analyzed and compared. The results obtained suggest that, overall, there is a positive impact of enrollment in a corequisite precalculus course on course grades at College A. Less positive results were seen for College B. Although AB 705 proponents feel that corequisite courses benefit all types and subgroups of students, a key finding of this study found at both colleges was that corequisite courses in precalculus may not be helping students with lower levels of prior achievement (based on high school grade point average). In addition, although based on a very small sample, both the statistical significance test and the effect size estimate indicate that corequisite courses at College B might be hurting Latinx students. Disparity of results from both colleges in this study prompt deeper investigations of causes behind the obtained results.

Although more studies are needed to determine the extent to which our findings are generalizable, it will be interesting to further explore what could be done to make corequisite courses effective for all types of student populations at community colleges. The study also indicates the need for increased participation in workshops and communities of practice where faculty from different colleges could meet to share and discuss strategies for successful implementation of a corequisite model. Meanwhile, it seems wise for policymakers and higher education administrators to proceed cautiously before completely abolishing developmental education opportunities, as some students may need more rigorous assistance to complete a STEM math gateway course. Finally, future studies are needed to delve deeper into the experiences and performance of some non-traditional student subgroups in a corequisite type of a precalculus class. This will help to understand the impact of AB 705, and will educate us as to how to make practices based on the law which will be more beneficial in the long run to diverse student communities from two-year colleges.

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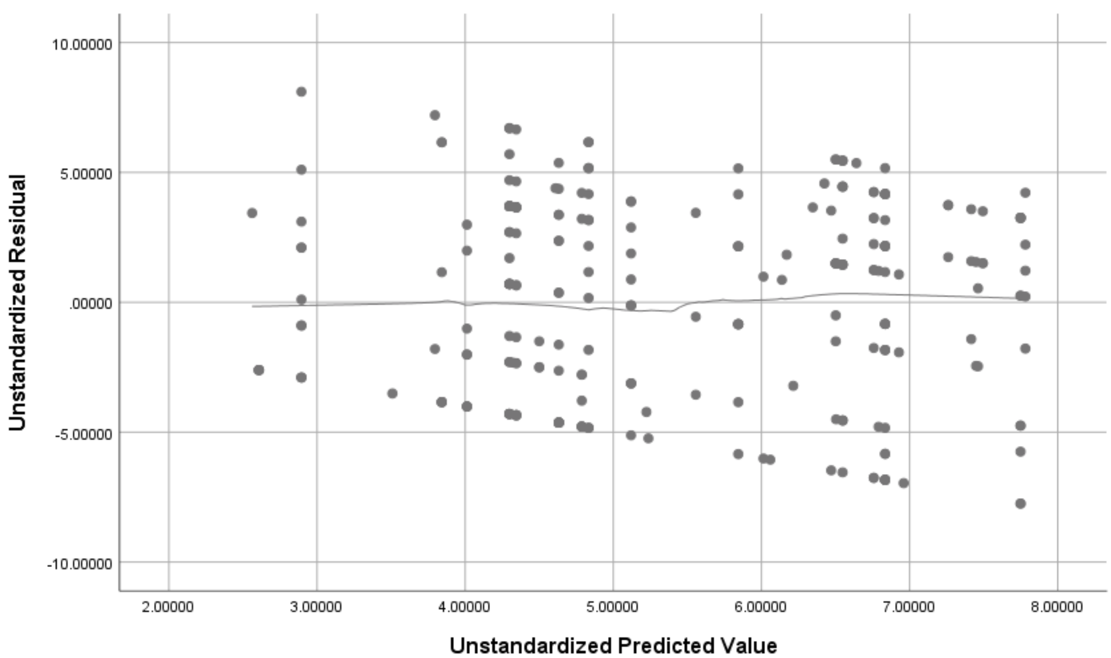
APPENDIX A: CHECKING FOR MULTIPLE REGRESSION ASSUMPTIONS FOR COLLEGE A

Linearity

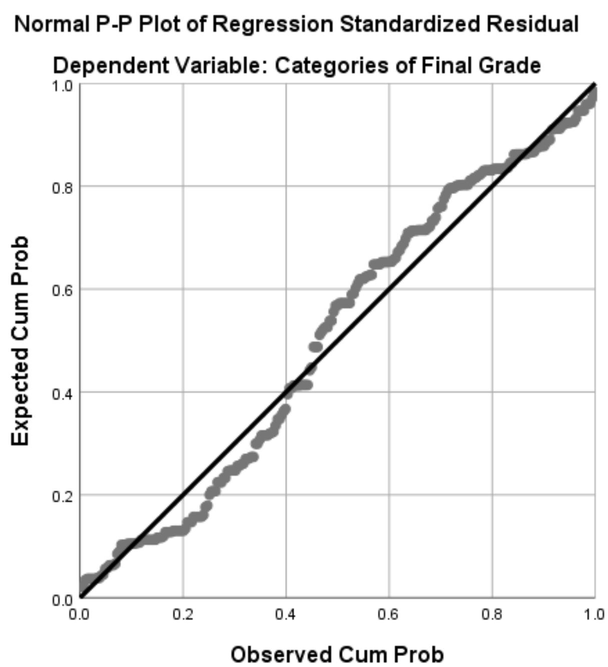
The assumption for linearity checks if there is a linear relationship between the outcome variable and the other independent variables used in the study. A series of scatterplot were created plotting the unstandardized residuals against the predicted values and the unstandardized residuals against the independent variable and each of the control variables. This was done for each of the research questions. The scatterplots did not indicate lack of homoscedasticity, given their rectangular shape. A loess line of fit, representing the best fitting non-parametric line, was added to each of the scatterplots (Keith, 2006). The loess lines resembled straight lines at heights near zero, as assumed.



The independent variable and all the control variables being dichotomized, the scatterplots were not curvilinear. Thus, for all the research questions, the scatterplots did not show a significant departure from linearity or a curvilinear relationship between the dependent and independent variables.

Normality of Residuals

A histogram and a p-p plot of standardized residuals were generated for each of the regressions to test for normal distribution of errors (Keith, 2006). The plotted values of the residuals varied slightly from the normal curve superimposed on the histogram. The normal p-p plot of standardized residual for the outcome variable showed slight variation from the straight line superimposed on the plot. Due to the large sample size, this slight divergence from the normal distribution was not interpreted as a concern for violation of the assumption of normality of distribution.



Multicollinearity

Multicollinearity info was obtained by checking the measure of tolerance (TOL) and variance inflation factor (VIF). According to Keith (2006), “small values for tolerance and large values for VIF signal the presence of multicollinearity” (p. 201). Values for tolerance range from 0 to 1 with higher values indication greater independence among influence variables. Values for VIF greater than 6 or 7 are indicators of concern for multicollinearity (Keith, 2006). For example, for RQ 1, the maximum value for VIF = 1. 929 and smallest value for TOL= 0. 518 (RQ1), neither of these coefficients are a cause of concern. In research questions 2, 3, & 4, there was a high concern for multicollinearity due to very high correlation between some variables. Each of the research questions RQ2, RQ3, and RQ4 used one or more interacting variables in the regression analysis planned in the beginning. These regression results showed a correlation of. 8 or more with at least one control variable. This was taken care by removing the interacting variables and modifying the regression approach.

Homoscedasticity

This assumption checks that the variance of errors around the regression line is fairly consistent across levels of the independent variable (Keith, 2006). Both numeric and graphic information was examined. The scatterplots used above to determine linearity showed a rectangular spread of variability in the residuals across levels of predicted grades rather than a fan shape distribution which is an indicator of heteroscedasticity (Keith, 2006). To further test the assumptions of homoscedasticity, the predicted values for course grades (outcome) were collapsed into five equal groups and a bar graph was created with these five groups and the variance of the residuals. This graph showed more of a rectangular shape with not too much variation in the bar lengths. The largest variance, for RQ 1, being 15. 080 and the smallest as 13.

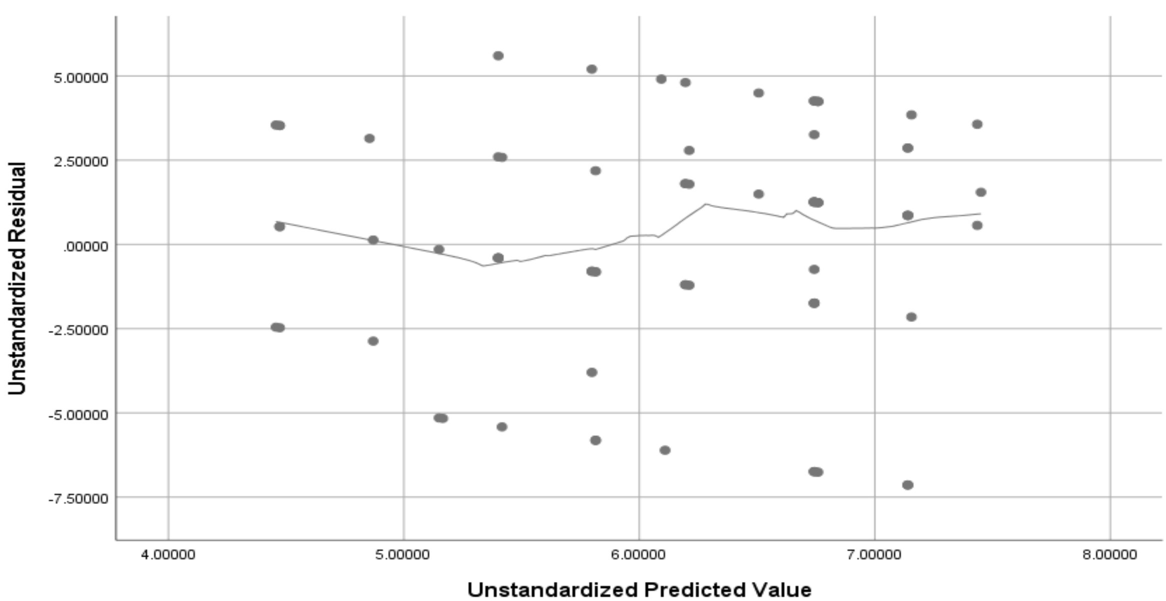
261, the ratio of largest to smallest variance was not more than 10. Similarly, for other research questions this ratio did not exceed 10. Considering this rule of thumb from Keith (2006), the assumption of homoscedasticity was not violated in any of the regression. **Problematic Data**

Keith (2006) cites three general characteristics – distance, leverage, and influence – as areas of focus for identifying problematic data points through regression diagnostics. Distance was examined by looking at the values of the standardized residuals for each regression. The large positive or negative standardized residuals were noted. For example, in RQ1, the smallest value for the standardized residuals being -2. 0533 and the largest being 2. 02747. In all the research questions, neither of these absolute values were significantly greater than 2. Values for leverage indicate an "unusualness of a pattern of independent variables, without respect to the dependent variable" (Keith, 2006 p. 197). Values for leverage range from 0 to 1 and are generally acceptable if they do not exceed twice the value of (k +1)/n where k is the number of independent variables in the regression model (Keith, 2006), and n is the sample size. For example, k =7 in RQ4, since there are seven independent variables used for the regression. The cases exceeding this range (k +1)/n) were noted down. Influence refers to cases whose values are prominent in determining regression line (Keith, 2006). Cases with large Cook's distance and standardized DF Beta values in comparison to other cases were highlighted as potentially problematic. Case numbers 29, and 229 were determined to regularly exert high influence on the regression lines. Upon checking these cases, nothing was found unusual about them and therefore the regression was continued with them included in the data set.

APPENDIX B: CHECKING FOR MULTIPLE REGRESSION ASSUMPTIONS FOR COLLEGE B: APPROACH I

Linearity

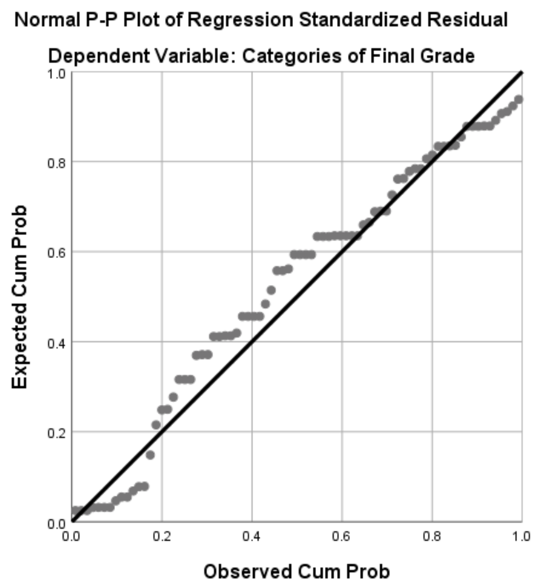
The model of multiple regression assumes a linear relationship between the outcome variable and the other independent variables. Scatterplots of unstandardized residuals against the outcome variable and all independent variables including the control variables were created. This was done for each of the research questions. A loess line of fit, added to the the regression scatterplots (Keith, 2006), was not too far from the straight line of regression. In this way, the model did not show a significant departure from linearity or a curvilinear relationship between the dependent and independent variables.



All the rest of the independent variables being dichotomized with values of either ‘0’ or ‘1’ do not pose a threat to the linearity assumption.

Normality of Residuals

As seen in the figure normal p-p plot of standardized residual for the outcome variable showed slight variation from the straight line superimposed on the plot. The slight divergence was not a threat for violation of normality assumption.



Multicollinearity

No multicollinearity was detected for RQ 1. The maximum correlation coefficients had the absolute value of 0. 271. All values for the measure of tolerance (TOL) were close to 1, the minimum being 0.893. The maximum value for the variance inflation factor (VIF) was 1. 142, which was below the cut-off mark (VIF < 6). The high correlation between variables in some cases where cross-product variables were introduced, showed presence of multicollinearity. This issue was addressed by removing the cross-product variable and resorting to separate regression analysis for each subgroup of the control variables.

Homoscedasticity

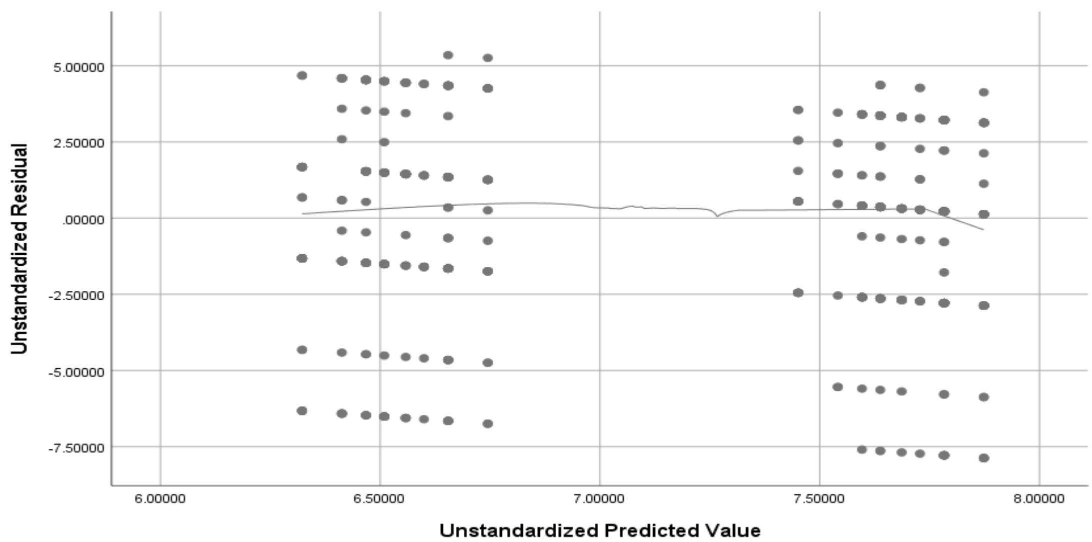
The scatterplot between the unstandardized residuals and the predicted grades were checked. The variance of the residuals was roughly the same across the values of the independent and the control variables. Further, the predicted values for course grades (outcome) were collapsed into five equal groups. A bar graph created with these five groups and the variance of the residuals did not show too much variation in the bar lengths. For each of the research question, the ratio of largest variance to smallest variance was not more than 10. For example, for the research question 1, the largest variance was 12 and the smallest was 8. The ratio of the largest variance to smallest variance was not more than 10. Thus, the assumption of homoscedasticity was verified for all regression questions.

Problematic Data

To identify any problematic data points distance, leverage, and influence were checked through regression diagnostics. Distance was examined by looking at the values of the standardized residuals. All the standardized residuals were with in the range -2 and +2. For example, in RQ1, the smallest value for the standardized residuals was -1. 962 and the largest was 1. 538. In all the research questions, neither of these absolute values were significantly greater than 2. Values for leverage were checked by calculating (k +1)/n, k being the number of independent variables in the regression model. The cases exceeding this number were noted down. Cases with large Cook's distance and standardized DF Beta values in comparison to other cases were highlighted as potentially problematic. Case numbers 26, and 101 were found to be repeated in the list of noted down case numbers. These cases were examined in the data set. Case 26 was a Hispanic male with low HSGPA, non-first-generation, and earned an F grade in a corequisite model of class. Case # 101 was a Hispanic female with a high HSGPA, not a first generation, and was awarded an A grade in a traditional precalculus class. These results were not dropped and the regression was continued with them in the data set.

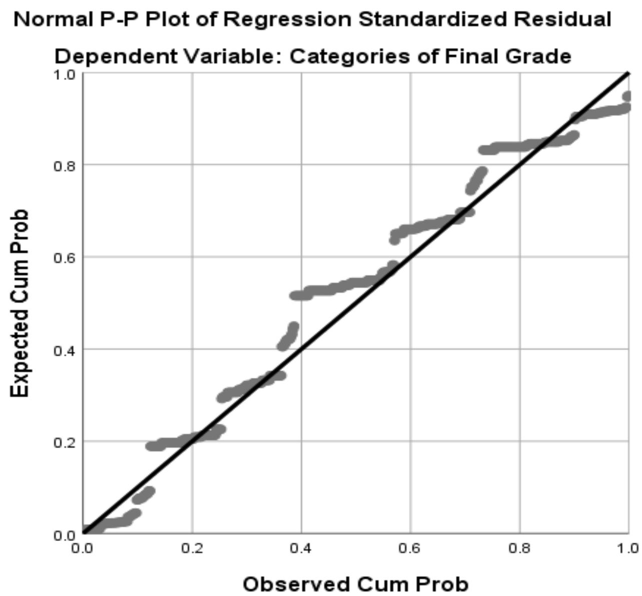
APPENDIX C: CHECKING FOR MULTIPLE REGRESSION ASSUMPTIONS FOR COLLEGE B: APPROACH II

Linearity: To check for linearity, scatterplot of unstandardized residuals was graphed against the predicted dependent variable of course grades. The scatter plot shown in the graph below is corresponding to RQ1. Similar graphs were observed in case of rest of the research questions. The line of loess is relatively horizontal at Y = 0 (since the mean of residuals = 0). Since, the graph is not a fan shaped, and line of loess is close to the horizontal line Y = 0, linearity assumptions are satisfied in this case.



Normality of Residuals

With the large data set (n = 553) in this case residuals should be approximately normal. The normal p-p plot of standardized residual for the outcome variable were graphed. As is seen from the graph, there is a slight variation from the straight line superimposed on the plot. This slight divergence was not a threat for violation of normality assumption. This p-p plot corresponds to RQ1. Similar p-p plots were observed in case of other research questions. Normality of residuals can be assumed in this case.



Multicollinearity

Multicollinearity was checked by observing the correlations between variables, and checking for VIF, and TOL values. The correlation coefficients were all fine with maximum absolute value of the correlation as 0.179. All values for the measure of tolerance (TOL) were close to 1, the minimum being 0. 959. The maximum value for the variance inflation factor (VIF) was 1. 04, which is below the cut-off mark (VIF < 6). Slightly high correlations between the interacting variables in case of RQ2 and RQ4 were observed, but TOL and VIF were within the range. So, multicollinearity was not an issue in this case.

Homoscedasticity

The scatterplot between the unstandardized residuals and the predicted grades (Figure above) did not show a fan shape distribution. It was more of a rectangular spread of data points.

As in the case of college A, the predicted values for course grades (outcome) were collapsed into five equal groups. A bar graph was created with these five groups and the variance of the residuals. This graph did not show too much variation in the bar lengths. For each of the research question, the ratio of largest variance to smallest variance was not more than 10. For example, for the research question 1, the largest variance was 15. 8 and the smallest was 8. 596. The ratio of the largest variance to smallest variance was not more than 10. Thus, the assumption of homoscedasticity was not violated in any of the regression.

Problematic Data

To identify problematic data points through regression diagnostics, distance, leverage, and influence were checked. Distance was examined by looking at the values of the standardized residuals for each regression. The large positive or negative standardized residuals were noted. For example, in RQ1, the smallest value for the standardized residuals being -2. 417 and the largest being 1. 641. In all the research questions, neither of these absolute values were significantly greater than 2. 5. Values for leverage indicate an "unusualness of a pattern of independent variables, without respect to the dependent variable" (Keith, 2006 p. 197). Values for leverage range from 0 to 1 and are generally acceptable if they do not exceed twice the value of $(k+1)/n$ where k is the number of independent variables in the regression model (Keith, 2006), and n is the sample size. In this case maximum number of predictors used was 6. With $k=6$, the maximum acceptable value for leverage is $2*(k+1)/n) = .0253$. None of the leverage values exceeded this specified range. Influence refers to cases whose values are prominent in determining regression line (Keith, 2006). Cases with large Cook's distance and standardized DF Beta values in comparison to other cases were noted down. In this approach of College B, no pattern was observed and none of the cases was observed repeatedly as a problematic data.