2021

# THE EFFICACY OF ACCELERATING UNDERPREPARED COMMUNITY COLLEGE STUDENTS USING A COREQUISITE LIBERAL ARTS MATHEMATICS COURSE

Drew Wilkerson
*University of Kentucky*, drew.wilkerson@kctcs.edu
Author ORCID Identifier:
https://orcid.org/0000-0001-6679-3830
Digital Object Identifier: https://doi.org/10.13023/etd.2021.005

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Drew Wilkerson, Student

Dr. Willis Jones, Major Professor

Dr. Jane Jensen, Director of Graduate Studies

# THE EFFICACY OF ACCELERATING UNDERPREPARED COMMUNITY COLLEGE STUDENTS USING A COREQUISITE LIBERAL ARTS MATHEMATICS COURSE

---

DISSERTATION

---

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Education in the College of Education at the University of Kentucky

By

Drew Wilkerson

Lexington, Kentucky

Co-Directors: Dr. Willis Jones, Associate Professor of Educational Policy Studies and Evaluation
and Dr. Jane Jensen, Professor of Educational Policy Studies and Evaluation

Lexington, Kentucky


https://orcid.org/0000-0001-6679-3830

ABSTRACT OF DISSERTATION

THE EFFICACY OF ACCELERATING UNDERPREPARED COMMUNITY COLLEGE STUDENTS USING A COREQUISITE LIBERAL ARTS MATHEMATICS COURSE

Every year, millions of first-time students enroll in community colleges underprepared for college-level work in mathematics. Typically, these students are referred to a sequence of developmental courses designed to remediate their skills and prepare them for college-level work. Recently, educators and policy makers have questioned the efficacy of these courses, especially since most students assigned to remedial courses never complete the sequence and enroll in college-level courses. Calls to reform developmental mathematics have included changes to how institutions determine whether students are college-ready and the elimination of the remedial course sequences themselves. The corequisite model, in which students enroll in a college-level course in the same semester as a developmental or support course, has shown much promise to increase the rate at which students complete a credit-bearing mathematics course that counts towards graduation.

This study examined success in a corequisite liberal arts mathematics course at a large community college in the southeastern United States in which underprepared students enrolled simultaneously in a liberal arts mathematics course and a support course. The study first investigated success in the corequisite course in comparison to the historical rate at which similar students, placed into a prerequisite, developmental sequence, completed a college-level mathematics course. It then used a multiple regression to investigate predictors of success in the corequisite course. Finally, the study used a propensity score design to investigate how students performed in the corequisite course compared to those in the standalone version of the course deemed college ready.

The results showed that, overwhelmingly, more students completed a college-level mathematics course using the corequisite compared to first enrolling in a prerequisite developmental course or course sequence. Within the corequisite, high school GPA, socioeconomic status, and sex were the biggest predictors of course grade, while ACT and the placement test used were poor predictors. There was also an achievement gap for underrepresented minority students. When comparing students in the corequisite to similar students in the standalone, there was no difference in course grade.

This study has practical significance not only to the institution at which it was conducted, but also the broader landscape of corequisite education.

*Keywords:* corequisite model, corequisite mathematics, developmental mathematics, multiple measures, placement policy

Drew Wilkerson

November 19, 2020
Date

THE EFFICACY OF ACCELERATING UNDERPREPARED COMMUNITY COLLEGE STUDENTS USING A COREQUISITE LIBERAL ARTS MATHEMATICS COURSE

By

Drew Wilkerson

Dr. Willis Jones
Co-Director of Dissertation

Dr. Jane Jensen
Co-Director of Dissertation

Dr. Jane Jensen
Director of Graduate Studies

November 19, 2020

To my wife Jenny, for your love, patience, and support.

ACKNOWLEDGEMENTS

Two months after starting this doctoral program in January 2015, I was asked to serve as the bishop of my church congregation, a lay ministry position that typically lasts four to five years. Already feeling overwhelmed as a husband and father of four children, full time professor and chair of the mathematics department, and now part-time student, I thought that God must have a sense of humor. Never one to turn down an opportunity to serve, I gladly accepted. What followed was a period of time in which I have never been more challenged or pushed to my limit, especially in regards to time, but also one in which I have seen the greatest blessings in my life and seen the hand of God at every turn. I will be forever grateful for the journey and for the things I learned about myself over the last six years.

There are so many people who helped me get to this point and deserve my thanks. First, to my family. I could not have done this without my wife Jenny who has been my rock for the last 15 years. She has supported me in all my various pursuits and responsibilities and stepped up at home when I've had to step back. Thank you for your love and patience while I chased dreams and tried to make a better life for us. To my wonderful children—Molly, Gabe, Lincoln, and Simon—for the missed soccer games and days we didn't get to see each other much. It's all for you. To my mom, who has always pushed me to perfection and taught me to have the highest expectations for myself. To my dad who would have read every single page of this manuscript, if he was still here, and then would have wanted to talk about the details for hours on end.

I want to thank Dr. Willis Jones for sticking with me after his job change and through all the times when I was slow to make progress. It took me longer than either of us thought it would, but I will be forever grateful to you for lending your expertise and helping me become a scholar. Thank you for believing in me and your enthusiasm for my work. I also want to thank Dr. Jane Jensen for seeing me through from the beginning of our cohort program to the very end. Your willingness to join my committee and then switch to the co-director role, when that became necessary, without hesitation will not be forgotten. A thank you to the other members of my committee as well—Dr. Molly Fisher and Dr. David Royster—for your insights that helped shape this study. Also, a thank you to Dr. Derek Lane for serving as my outside examiner.

Finally, a thanks to the IERP staff and all the talented faculty, staff, and students at Jefferson Community and Technical College. You provide the "why" in my professional efforts and made this study possible.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# CHAPTER 1: INTRODUCTION

Every year, millions of students begin their studies at institutions of higher education, most of whom are underprepared for college-level work. This is especially true in community colleges which serve students of all backgrounds and education levels because of their open-access nature (Armstrong, 2000). As many as two-thirds of all community college students enter lacking the academic skills needed to be successful in college-level work (Bailey, 2009). Historically, institutions predominantly responded to this lack of preparation by placing students into remedial, more commonly called today developmental or transitional, education courses to help students learn the necessary skills to be successful in college-level course work[1]. These courses generally focus on mathematical skills taught in the secondary school curriculum or even the middle or elementary school curriculum. It is common for institutions to have as many as two or three, sometimes more, levels of developmental education that are taught in a sequence.

Developmental mathematics has been a topic of great debate, particularly over the last 20 to 25 years. On the one hand, some argue that developmental education is an essential part of higher education that helps remediate the skills of underprepared students who would otherwise be excluded from higher education or marginalized in college-level courses (Bettinger & Long, 2005). On the other hand, many argue that developmental mathematics is ineffective at remediating the skills needed to be successful and therefore serves as a roadblock to higher education (Scott-Clayton &

[1] While some authors make a distinction between the two, the terms developmental and remedial education will be used interchangeably throughout this paper. Either term will refer to any course designed to teach skills that should have been learned in the high school, or even the middle or primary, curriculum and serve as prerequisites to entry-level college courses.

Rodriguez, 2014). Studies on the efficacy of developmental mathematics have shown mixed results. While some have found that developmental education has a positive effect on students' academic outcomes (Bettinger & Long, 2005, 2009; Hughes & Scott-Clayton, 2011), others have shown no significant or even a negative impact (Bailey, 2009; Boatman & Long, 2010; Martorell & McFarlin Jr., 2011; Ngo & Kwon, 2015; Scott-Clayton & Rodriguez, 2014). In addition, most students who begin in developmental mathematics courses do not persist and never get the chance to enroll in the college-level course for which they are preparing. Some argue that any positive impact is overshadowed by the fact that, overwhelmingly, students never get to enroll in the courses they are being prepared to take (Scott-Clayton & Rodriguez, 2014).

The current environment in higher education places ever-increasing pressure on institutions to increase retention and graduation rates. Studies have shown there is a correlation between success in mathematics and retention and graduation in college (Parker, 2005). With a lack of evidence to support the notion that developmental mathematics is definitively able to improve outcomes for underprepared students, many educators and policy makers have called for serious reforms. Some have questioned the widespread use of placement tests to determine college readiness while others have questioned the very idea of prerequisite, developmental courses. Research has shown that while most institutions use placement tests to determine whether students are college-ready, the tests are relatively ineffective at predicting student outcomes and success in college-level courses (Belfield & Crosta, 2012; Gerlaugh, Thompson, Boylan, & Davis, 2007; Hughes & Scott-Clayton, 2011; Marwick, 2002; Parker, 2005; Scott-Clayton, 2012). Other metrics, such as high school GPA or multiple measures have been shown to be more predictive (Armstrong, 2000; Belfield & Crosta, 2012; Marwick, 2002; Scott-Clayton, 2012).

At the same time, some have called for an end to traditional developmental mathematics course sequences and have advocated recently for most students who are underprepared to enroll in a corequisite mathematics course (Bailey, Jeong, & Cho, 2010; Saxon & Morante, 2014; Vandal, 2014). While the model has several variations, the general concept is that students enroll in a gateway mathematics course and developmental education course in the same semester (Atkins & McCoy, 2016). The idea behind this setup is that students can attempt a credit-bearing course right away and receive the support they need to be successful. The corequisite model could take the form of a college-level course paired with a developmental support course, mandatory tutoring, or sequenced courses (Vandal, 2014).

One reason the corequisite model has become so popular is that it decreases the amount of time it takes for students to complete a college-level course. With traditional developmental education usually spanning multiple semesters, there are too many exit points in which students could leave the developmental education pipeline. The longer the pipeline, the more likely it is that students will leave college before finishing, or even attempting, a college-level course (Henry & Stahl, 2017).

While placement policy is a perennial topic in the literature, corequisite mathematics is a recent phenomenon and is still somewhat limited to relatively few institutions and states. Further research is needed to establish the efficacy of corequisite mathematics courses and to determine predictors of success so that institutions may set appropriate placement policies for the courses. Jefferson Community and Technical College (JCTC) provided an opportunity for such a study.

**Problem Statement**

It is possible that corequisite mathematics courses can serve as a better alternative to the developmental model. Early studies have shown optimism that corequisite courses can be successful (Golson, 2009; Moening, 2016; "Texas proposal narrative statements," 2011). Whether these courses can be successful on a larger scale outside of a select few institutions or state-systems is yet to be completely established as the literature on corequisite mathematics is still somewhat limited. Further, whether all students can be successful in a corequisite model or whether some would benefit from a standalone developmental course has yet to be established empirically.

**Purpose of the Study**

The purpose of this study was to analyze the relationship between the corequisite model and student success, particularly, a passing grade in the college-level course. It sought to establish the efficacy of the corequisite model compared to a traditional sequence of developmental mathematics courses. The study also analyzed predictors of student success in a corequisite course, as measured by a passing grade in the college-level course, particularly, placement test score, ACT score, high school GPA, age, sex, socioeconomic status, and race.

**Research Questions**

The following questions served as a guide to this study:

1. How does success compare for students placed into the corequisite course compare to the historic rate at which students who placed into developmental

courses completed their developmental math course or courses and college-level course?

2. What are the best predictors of success in the corequisite course?
3. How does success in the corequisite course compare to students deemed college-ready and placed into the college-level course with no support?

**Significance of the Study**

This study has practical significance for JCTC and the Kentucky Community and Technical College System (KCTCS). As required by Kentucky's Council on Postsecondary Education, KCTCS fully implemented a corequisite model in the fall 2019 semester. JCTC had already moved towards the corequisite model prior to the Council's mandate and fully implemented a liberal arts corequisite course in fall 2018. This study could provide a baseline for what level of long-term success might be expected from a corequisite model and be useful in determining whether the model developed by JCTC should be continued locally, or even replicated across the state. Another aspect of implementing the corequisite model across the KCTCS is determining whether placement measures are appropriate for which students should be placed directly into a standalone college-level course, corequisite course, or single semester developmental course.

This study also adds to the growing, but still limited, literature on corequisite mathematics. It has the potential to add confidence that the model can help underprepared students successfully complete a college-level liberal arts mathematics course. The study extends the literature to a large community college, on both an urban and suburban campus, which serves a diverse group of students. The analysis of the relationship between student demographics and success also has the potential to provide guidance in placement policies for other institutions. Unlike some studies, a wide range of student abilities, as determined by placement test score, were placed into the corequisite course rather than only students just below the cutoff score.

**Definitions**

College-Level Course – academic course that provides credit towards graduation and fulfills the mathematics requirement for a degree or credential. Synonymous in this study with credit-bearing course and gateway course.

Corequisite Course Model – developmental education model in which underprepared students enroll in a college-level mathematics course and developmental education support course in the same semester (Complete College America, 2016).

Corequisite Course – refers to the college-level course that is paired with a developmental level support course for students deemed underprepared for college-level mathematics. When referencing "success" in a corequisite course, it should be taken as success in the college-level portion of the course pairing.

Corequisite Student – a student enrolled in a college-level course simultaneously with a support course.

Corequisite Support Course – a developmental course paired with a college-level course for student deemed underprepared for college-level mathematics. The support course provides the development of non-cognitive skills, such as growth mindset, study skills, and time management skills, just in time remediation, and in-class time to work on problems.

Credit-Bearing Course – academic course that provides credit towards graduation and fulfills the mathematics requirement for a degree or credential. Synonymous in this study with college-level course and gateway course.

Cut Score – a set score on a placement test which scoring below requires a student take a developmental course and scoring at or above places the student into a college-level course.

Developmental Education/Courses – a noncredit bearing course or sequence of courses designed to remediate the skills of underprepared college students, which serve as prerequisites to college-level courses. Synonymous in this study with remedial education/courses.

Gateway Course – entry-level mathematics course that is high enrollment and high-risk (large number of students who are, historically, unsuccessful) (John N. Gardner Institute, 2017). Synonymous in this study with college-level course and credit-bearing course.

Just in Time Remediation – providing remediation to students in a support course just before they will need to use the skill in the college-level course (Berryman & Short, 2010).

Liberal Arts Mathematics Course – a credit-bearing course designed to meet the mathematics requirement for students in non-STEM fields through an emphasis on quantitative reasoning rather than algebraic manipulation. Within KCTCS, this course is titled Contemporary College Mathematics.

Remedial Education/Courses - a noncredit bearing course or sequence of courses designed to remediate the skills of underprepared college students, which serve as prerequisites to college-level courses. Synonymous in this study with developmental education/courses.

Stand-Alone Course – an analogous course to that of the college-level course in the corequisite, but without the support course. This course is intended for students deemed college ready.

STEM Course/Pathway – a college-level course that emphasizes algebraic manipulation, such as college algebra or precalculus, and is designed to prepare students in STEM fields for further study in Calculus and beyond.

Student Success – for purposes of this study, student success will be defined as completion of a college-level mathematics course with a grade of A, B, or C.

**Summary**

Most community college students arrive on campus unprepared for college-level work. Generally, the response to this issue has been to place students in standalone developmental courses or sequences of courses to remediate the mathematical skills lacking per a placement test. However, very few students complete their developmental course sequence and enroll in a gateway course, let alone complete one. Many have argued that because of this, developmental education is a failure despite any positive effect it may have. In response, there is currently a nationwide movement to adopt the corequisite model. In the corequisite model, most underprepared students are enrolled directly into a college-level course and a support course in the same semester.

The purpose of this study was to establish the efficacy of the corequisite model compared to a traditional developmental course sequence. It also analyzed the relationship between ACT score, placement test score, high school GPA, age, sex, socioeconomic status, and race with success in a corequisite mathematics course.

# CHAPTER 2: LITERATURE REVIEW

## Purpose and History of Developmental Education

**Purpose of developmental education.** Every year, millions of students identified as underprepared enroll in community colleges. Estimates range anywhere from half to two-thirds of students are underprepared. In a study conducted in Florida, less than half of all entering community college students successfully passed pretests in mathematics, reading, and writing (Parker, 2005). Bailey (2009) determined that 59% of students were underprepared for college based on the number of students enrolled in developmental education courses and argued that it could be as high as two-thirds when accounting for students who were judged as “college-ready” but struggled in their college-level courses. Greene and Forster (2003) determined that only 32% of students left high school prepared for college study based on the number of students who completed three objectives: 1) graduated high school, 2) took certain college prep classes while in high school, and 3) demonstrated basic literacy skills. More recently, Chen and Simone (2016) found that 68% of students starting at community colleges were underprepared for college study, based on enrollments in developmental education courses, and that the rate was even higher for minorities and lower-income students.

The theoretical framework of developmental mathematics is simple. Institutions assess students’ academic skills, most commonly using a placement test, to determine whether they meet the minimum level of proficiency needed to enroll and be successful in a college-level mathematics course (Calcagno & Long, 2008). The institution then places students with skills below the minimum level into remedial courses. These courses are intended to develop the skills needed for success in college-level courses (Breneman, Abraham, & Hoxby, 1998). In its most common form, and the one under critique in this paper, developmental education is a semester long course which covers material that could have been learned in high school or earlier (Breneman et al., 1998) and is like that of a college-preparatory course (Martorell & McFarlin Jr., 2011). Usually a student transitions from the developmental level to the college level by either passing their developmental course or series of courses. It is common for institutions to have up to as many as three levels of developmental mathematics, such as pre-algebra, beginning algebra, and intermediate algebra, and some may have as many as five (Marwick, 2002).

The instructional techniques used in a developmental classroom can vary greatly from institution to institution. There is no consensus amongst colleges on topics taught in any remedial course or what skills a student must possess to be college ready. Even courses that bear the same name, such as “basic algebra”, could vary greatly in the skills taught. While some courses may focus entirely on mathematical skills, others may take a wider breadth and help develop non-cognitive abilities such as study or time management skills. Instructional strategies could also vary with some preferring a “skills and drills” approach in which basic skills in the content area are learned through repetition and practice, while others take a student-centered approach in which learning is more personalized to the needs of individual students (Martorell & McFarlin Jr., 2011).

**History of developmental education**. Despite the recent attention, developmental education is not a new practice in higher education. While many jaded educators might lead one to believe that students arrive at college more underprepared than ever before, developmental education has a long history. There has never been a so-called “golden age” in which all students enrolling in higher education were college-ready (Phipps, 1998). In fact, Arendale (2002) identified six phases of American developmental education dating back to the mid-seventeenth century. Each phase was unique in the kinds of activities used to provide remediation and saw an increase in the subpopulations served by remedial education as socio-political factors changed the makeup of the student body.

Early remediation from the seventeenth to nineteenth centuries took the form of tutoring, where at places like Harvard, underprepared students received help in Latin and Greek (Arendale, 2002; Phipps, 1998). As enrollment in and the mission of higher education slowly began to expand, the need became even greater. The focus of high schools during the late nineteenth and early twentieth centuries was on preparing people for life, not preparing them for university study. In fact, around 1900 the College Board was created in part to help bridge the gap between high school and college and establish universal standards of college readiness (Schudson, 1972). Remedial education became college preparatory programs during this time and was fully integrated into institutions throughout the mid-1900s (Arendale, 2002). The literature indicates that around 80% of institutions have offered remedial education for a little more than 100 years (Boylan & Bonham, 1994; Canfield, 1889).

**Effects of Remediation**

Despite the prevalence of developmental education and an abundance of research the past two decades, there are still many questions surrounding the efficacy of developmental mathematics courses (Chen & Simone, 2016). The hope is that students placed into developmental mathematics will perform better in college-level courses than they otherwise would have. This should lead to higher retention and graduation or transfer rates (Scott-Clayton & Rodriguez, 2014). The literature is mixed on whether that happens. Some studies have shown that developmental mathematics has a positive effect on student outcomes, while many others have shown little to no effect or even a negative effect on student outcomes, especially for those near the cutoff for college-level courses. Critics of developmental mathematics use the latter to argue that it is in effective in remediating marginalized students and therefore acts as a barrier to college-level mathematics rather than a gateway (Calcagno & Long, 2008).

**Positive effects.** Bettinger and Long (2005) conducted a study of first-time freshman who enrolled in one of 19 two-year colleges in Ohio in fall 1998. The longitudinal study tracked students until 2003. Overall, students in the study who placed into developmental education performed worse than students in college-level classes. Students in remediation completed fewer credit hours, were more likely to have stopped out prior to completing a two-year or four-year degree and were less likely to have transferred to a four-year university than students who were college-ready and started in a college-level course. The authors argued that this was expected, as students placed into remediation are less academically prepared than students placed into college-level courses.

To study the effects of development mathematics and control for the level of academic preparation, Bettinger and Long took advantage of varying placement policies in colleges across Ohio that would place some students into developmental mathematics at some institutions while at others it would place similar students into college-level courses. This allowed them to compare students with similar placement test scores and high school preparation placed into both developmental and college-level courses. Taking this into account, the outcomes were much different than when comparing developmental students to all students placed into college-level courses. Students placed into developmental education were 15% more likely to transfer to a four-year university and took more credit hours than their similar peers placed into college-level courses. Students placed into developmental mathematics, completed on average ten more credit hours than their peers in college-level courses did. There was no difference in degree completion between the two groups.

Bettinger and Long (2009) extended their 2005 study to include first-time freshman entering Ohio four-year public colleges and those entering two-year colleges who indicated that they intended to transfer to a four-year. Like the 2005 study, the authors found that those placed into remediation had improved outcomes compared to those placed into college-level courses. Students in developmental mathematics were 10% less likely to drop out than similar students placed into college-level mathematics. The results were even stronger for students with higher ACT scores. Those in remediation nearer the high end of the ACT cut score were more likely to complete more credit hours, complete their degree, and transfer to a four-year college than students with the same ACT score placed into college-level courses.

Using the data from the National Educational Longitudinal Study (NELS:88), Attewell, Lavin, Domina, and Levey (2006) found generally positive results from remediation. The NELS:88 tracked students from 1988 to 2000. The data set yielded a large national sample of students who graduated high school and attended college within eight years of graduation. The authors created a comprehensive profile of each student with information such as high school performance. This allowed the authors to compare students with similar backgrounds and academic preparation enrolled in developmental mathematics courses and college-level courses.

Like Bettinger and Long, Attewell et al. found that compared to all students enrolled in college-level courses, students enrolling in developmental mathematics performed worse. However, just as with the studies by Bettinger and Long, when controlling for academic backgrounds, Attewell et al. found developmental education resulted in better outcomes compared to similar students enrolled in college-level courses. Students enrolled in remedial courses were less likely to complete 10 or fewer credit hours. There was no effect on a student’s likelihood of graduating or transferring to a four-year institution nor was it predictive of whether a student was likely to stay continuously enrolled or whether they would postpone enrollment by one or more semesters. Saying this another way, while remediation did not increase a student’s likelihood of graduating, it did not decrease it either. Despite what were generally positive effects, Attewell et al. did find one negative result for students enrolling in two or more developmental mathematics courses. These students were roughly three percent less likely to graduate with a two-year degree than their similar peers were. Taken as a whole, the authors found that besides students who enrolled in multiple levels of remedial courses, developmental mathematics at worst provided no effect and at best improved the likelihood of completing more credits.

While these studies indicated that developmental mathematics had a positive effect on student outcomes, the results are limited in several ways. First, the studies conducted by Bettinger and Long were from a single state and may not be generalizable to other states or individual colleges. While the data sets are large, differences in culture, secondary school preparation, matriculation, and state and institutional policy may mean that the results are not applicable outside of Ohio. Bettinger and Long (2009) also, at least partially, drew from four-year universities and the results may not be applicable to community college students. It is possible that students who begin at four-year colleges are fundamentally different from those who start at community colleges, such as in motivation, high school preparation, or academic or socioeconomic capital, and therefore might not be appropriate to compare to students who begin at community colleges. Attewell et al. (2006) found that remedial education had vastly different effects on outcomes for students in two-year colleges versus students in four-year colleges. While the sample used by Attewell was a large, national sample, it was restricted to students who self-reported high school and college transcript data, which could raise validity questions. Finally, these, and many other studies, are limited to students near the cutoff for remediation and can only be applied to a limited number of students. The effects of remediation on outcomes of students with academic preparation far below placement into college-level mathematics were left out of these studies because they did not have a comparable group in the college-level courses. It cannot be determined whether remediation has the same positive effect for these students as the ones in the studies near the cutoff scores. This is a significant limitation, one that this study hopes to address.

**Insignificant or negative effects.** While these and other studies found developmental mathematics had a positive effect on student outcomes, many others show an insignificant or even negative effect. It is studies such as the ones described below that have caught the attention of higher education policy makers as of late. Calcagno and Long (2008) evaluated the effect of developmental education on several student outcomes such as fall-to-fall persistence, graduation, and transfer. The sample was comprised of 98,000 first-first time college students who enrolled in one of 28 Florida community colleges. The authors used a regression discontinuity model to analyze the effect of developmental mathematics on students whose placement test score was just below the cutoff for college-level courses versus those with scores just above the cutoff score. The underlying assumption of the model is that those just above and below the cutoff are academically equivalent and therefore the causal effects of developmental mathematics can be determined by comparing like students placed into developmental mathematics courses versus college-level courses.

While Calcagno and Long (2008) found some positive effects, these were limited. The authors found that students who enrolled in remediation were slightly more likely to persist and enroll in the following fall semester. They also found that remediation had a positive effect on the number of credits completed. However, after controlling for credits that count towards graduation, there was no significant difference between students in remedial courses compared to college-level courses, meaning the increase in credit hours were the remedial courses themselves. The authors found that enrolling in remedial mathematics had no significant impact on the likelihood a student passed their first college-level mathematics course. It also had no impact on the likelihood of earning a two-year certificate or degree or transferring to a four-year institution. The results suggest that while developmental courses may have a small influence on persistence, it is more likely that they simply delay enrollment in college-level courses and that students may be just as likely to pass if placed in college-level courses right away as opposed to first completing a developmental mathematics course.

Scott-Clayton and Rodriguez (2014) studied first-time freshman who enrolled in one of six community colleges from a large urban community college system between 2001 and 2007. Like other studies, the research design relied on comparing students just below and above the cutoff for placing into remediation. While the sample did provide a large data set, the authors were careful to point out that students in the sample were not typical of first-time community college freshman nationally. Scott-Clayton and Rodriguez found some results like that of Calcagno and Long (2008). They found that developmental education had no effect, one-way or the other, on whether a student would graduate or transfer to a four-year institution. Students in the study who enrolled in developmental mathematics courses earned slightly more credits, but like Calcagno and Long, the additional credits were attributed to the remedial courses themselves and not college-level credits. The study also showed remediation had no effect on the likelihood of dropping out or the number of semesters enrolled.

Unlike Calcagno and Long (2008), Scott-Clayton and Rodriguez (2014) found remediation had no effect on persistence. They also found that students who enrolled in developmental courses were less likely to pass a college-level mathematics course and less likely to earn a C or better in a college-level mathematics course than comparable students who enrolled directly into college-level mathematics. While there is not enough evidence to claim remediation provided no benefit, this study raises questions about the worth of developmental mathematics, at least for students near the cutoff for college-level courses.

Boatman and Long (2010) found negative effects for students near the cutoff for remediation but extended their study to those two or three levels below college-level mathematics. The study was set in Tennessee and the sample was restricted to fulltime students who first enrolled in a public two-year or four-year college in fall 2000 and who took a placement test upon entering college. Students were tracked for three years. While the data set did include students enrolled in both two-year and four-year colleges, the authors controlled for institution type as part of their analysis. Boatman and Long looked at the effects of remediation through three levels of developmental mathematics. This was done by comparing students enrolled in one level to those enrolled in one level directly about the course, i.e. students two levels below college-level course were compared to students enrolled in a course one level below college level.

For students who enrolled in the highest level of developmental mathematics, the authors found that students completed on average eight fewer courses by year three than comparable students who enrolled in the college-level course. Students in remedial mathematics were also less likely to complete a degree within six years. Developmental mathematics had no effect on persistence during the first or second year. Students who enrolled in the middle-level developmental mathematics (two levels below college-level) completed 6.8 fewer college-level credits in the first three years compared to their like peers who enrolled in the highest-level of developmental mathematics. However, there was no statistically significant difference in six-year graduation rates between students who enrolled in the middle-level course compared to those enrolled in the highest-level course. When comparing students in the lowest-level developmental course to those in the middle-level course, the results were less exaggerated. Students in the lowest level completed on average three less college-level credits compared to those in the middle-level course. The authors also found no statistically significant difference in six-year graduation rates of students in the lowest level compared to the highest-level. For all three levels, the authors found no statistically significant difference in a student's grade in their first college-level mathematics class compared to their like peers who started one level higher. This study suggests that students could likely be successful in a course one level higher than the one in which they were placed and that a careful examination of how students are placed into course might be needed.

Martorell and McFarlin Jr. (2011) studied entering freshman at Texas two-year and four-year colleges between 1991 and 1992 and again between 1999 and 2000. As with other designs, the study focused on students just below the cutoff on the placement test. The authors found that the likelihood of completing the first year of college is six percentage points lower for students who barely fail the placement test compared to those who barely pass. Students who barely placed into remediation completed 2.5 less college-level credits than students who barely placed into college-level courses. They found no effect on the likelihood of graduating in four, five, or six years. Therefore, while remediation does not cause a delay in graduation, it does not improve the likelihood of it either.

While these findings are troubling, the research designs limit them to students near the edge of remediation and not the most underprepared students with the weakest academic abilities. The effect of remediation is likely different for students just below the college level compared to students well below it.

Possibly the most convincing evidence used by opponents of developmental mathematics is completion rates of the developmental sequence and eventual success in the college-level course. This is especially true at the lowest levels of developmental mathematics where only a small proportion of students enroll in and eventually pass college-level mathematics (Ngo & Kwon, 2015). While there is some evidence that students who pass all their remedial courses have better outcomes than those who never take remedial courses, as few as 30% of students pass all their remedial courses (Attewell et al., 2006). Gerlaugh et al. (2007) found that 68% of students passed their highest-level developmental course, of whom 58% went on to complete their first college-level mathematics course. This means that less than 40% of students enrolled in the highest-level developmental mathematics course went on to complete the first college-level mathematics course. In addition, this measure fails to consider that most institutions have multiple levels of developmental mathematics and that students could place two or even three levels below college-level mathematics. If one assumes similar pass rates in those courses and subsequent courses, less than 28% of students in the middle-level mathematics course and less than 20% of students in the lowest-level mathematics course went on to complete the first college-level mathematics course. Boatman and Long (2010) reported high failure and withdraw rates, 45%-50%, for students in developmental mathematics, meaning most students never even make it to their college-level mathematics course. While most students passed their developmental mathematics course, less than half and as few as one-third passed the entire developmental sequence to which they were assigned. More troubling, between 60% and 70% of students failed to complete the sequence despite having passed all developmental courses in which they enrolled.

One study often cited by critics was conducted by Bailey et al. (2010). This study used a sample of over 250,000 first-time credential-seeking students taken from 57

Achieving the Dream colleges across 15 states. The study revealed glaring results of how students progressed through developmental mathematics. While most students passed the developmental mathematics course they enrolled in, there was a much more negative result when looking at the developmental mathematics sequence as a whole, that is, all the courses a student would need to complete in succession prior to enrolling in a college-level mathematics course. Overall, only one-third passed the entire developmental sequence to which they were assigned. Looking specifically at the three levels of developmental mathematics in the sequence, one can see that the likelihood of completing the sequence decreased with the level of remediation. Forty-five percent of students assigned to the highest-level developmental mathematics course completed the sequence, 32% of students assigned to the middle-level completed the sequence, and just 17% of those assigned to the lowest level completed the sequence. Of those who did not complete their sequence, an average of 29% exited the developmental mathematics sequence after failing or withdrawing from a course across each level. Again, the percentage increased the further down the level: 17% for the highest-level, 32% for the middle-level, and 44% for the lowest level. More despairing is that on average, 11% of students failed to complete the sequence despite having passed all developmental courses to which they enrolled, the highest percentage being found in the lowest-level where almost one-quarter of students failed to complete the sequence despite never failing a course. Just less than one-third of students failed to complete the sequence because they failed to enroll in a developmental course.

When looking at pass rates in the first college-level course, Bailey et al. found what on the surface appear to be some positive results. Pass rates were nearly 80% for developmental mathematics sequence completers who enrolled in the gatekeeper, with virtually no difference in pass rates for students who started at the three levels. However, as the authors pointed out, passing the college-level course necessitates that a student enrolls in it. Only two-thirds of students who completed the developmental sequence ever enrolled in the gatekeeper course, and surprisingly, those who started in and completed the highest-level developmental course had the lowest enrollment rate in the gatekeeper course.

Looking at all students, only 20% of students referred to developmental mathematics ever completed a college-level mathematics course. As expected, those starting in the lowest levels of remediation were the least likely to complete the gatekeeper course. Just 10% of students referred to the lowest level, 20% of those referred to the middle level, and 27% of those referred to the highest level completed a college-level course.

Supported by evidence like that presented here, critics paint a pale picture of developmental mathematics. The evidence suggests that, for students near the cutoff, developmental mathematics acts as a barrier to higher education. It also suggests that, at least as is currently practiced, developmental mathematics is ineffective at helping students complete a college-level course. Any benefit seen from remediation is overshadowed by the fact that so few developmental students ever enroll in a college-level course.

Recently, developmental education has caught the attention of policy makers across the country. Thanks to efforts from policy advocacy groups such as Complete College America, reforms to improve developmental mathematics are taking place at state and institutional levels. Many policy makers and educators have begun to question whether the traditional sequence of remedial courses should be done away with all together. To this end, the corequisite model is gaining much attention. In this model, rather than placing underprepared students into a sequence of remedial courses, most students are instead enrolled directly into their college-level course and are provided additional support. For those with the weakest preparation, a single developmental course could be used to remediate skills just enough to be successful in the college-level course with the support course.

At the same time, some question the placement policies used to determine whether students are college ready. If developmental mathematics is not increasing the likelihood of success in college-level courses, perhaps it is because the wrong students are being assigned to it. In many states and institutions, there is interest about whether high school metrics, especially high school GPA, could better predict whether students should be considered college-ready compared to using placement tests (Ngo & Kwon, 2015).

## The Corequisite Model

Many have concluded that developmental mathematics, as a sequence of courses, is not very effective, in large part because most students never make it to their college-level course (Bailey et al., 2010). Some have called for accelerating developmental course sequences or even eliminating them entirely (Saxon & Morante, 2014). One model that has shown promise is the corequisite model[2]. In the corequisite model, most

[2] Note, there is a disagreement in the literature on the spelling with some authors preferring “co-requisite” while others favor “corequisite”. The latter will be used throughout this paper as I have found to be more common in recent literature and is the nomenclature used within KCTCS where this study took place.

underprepared students enroll in the college-level mathematics course without first having to complete prerequisite developmental courses. Students in the corequisite model are provided support to be successful in their college-level course (Vandal, 2014). This support comes in different forms, from credit-based options in which students enroll in support courses alongside their college-level course to non-credit based options such as mandatory tutoring (Atkins & McCoy, 2016). The support work might be generic for all students (Moening, 2016) or customized to provide the support needed by each individual student (Golson, 2009).

One reason the corequisite model has become so popular is that it decreases the amount of time it takes for students to complete a college-level course. With traditional developmental education usually spanning multiple semesters, there are too many exit points in which students could leave the developmental education pipeline. The longer the pipeline, the more likely it is that students will leave college before finishing, or even attempting, a college-level course (Henry & Stahl, 2017). The problem is not whether good instructional techniques are used or even whether students can do the work in the developmental classes. Even with a good success rate, say 80%, in each course, when looking at the entire sequence the “multiplication principle” means that at best 64% of students one-level down, 51% of students two-levels down, and 41% of students three-levels will go on to complete a college-level course (Hern & Snell, 2010). The actual numbers are much lower because these theoretical ones do not consider students who leave college between semesters whether for academic or external reasons, such as family and employment issues. These external issues often impact low-income students disproportionately (Hern & Snell, 2014).

The corequisite model first emerged as early as the 1990s (Adams, Gearhart, Miller, & Roberts, 2009), but really gained momentum in 2007 with the launch of the Accelerated Learning Program (ALP) at the Community College of Baltimore County and the subsequent studies on its effectiveness (Cho, Kopko, Jenkins, & Smith Jaggars, 2012; Jenkins, Speroni, Belfield, Smith Jaggars, & Edgecombe, 2010). In the ALP model, students who placed into the highest level of developmental writing instead enrolled into English 101 with a support course. ALP students were more likely to complete English 101 and 102, more likely to be retained, and completed more courses than students enrolled in developmental writing.

Part of the theoretical framework used by the ALP, and generally shared by other corequisite models, involved mainstreaming, cohort learning, and acceleration (Adams et al., 2009). Mainstreaming and cohort learning help students avoid isolation, which Tinto (1988) said can lead a student to drop out or stop-out. By mainstreaming students into college-level courses, students see themselves as part of the college community rather than as subordinate (Glau, 1998). Students perform college-level work and do not just redo high school content (Edgecombe, 2011). By grouping students into cohorts in the support course and college-level course, students can form familial and emotional ties with one another (Lei, Gorelick, Short, Smallwood, & Wright-Porter, 2011).

The corequisite model is also supported by the work of Henry Levin and the Accelerated Schools Program. Levin (1989) found that by accelerating learning for at-risk students, the achievement gap could be closed more quickly than with more traditional remedial education, which often emphasizes basic skills over application, slows down the pace of instruction, and reduces expectations. Acceleration also reduces the number of exit points in which a student could fail out, or simply not enroll in the next course (Bailey et al., 2010; Edgecombe, 2011).

While the literature on the efficacy of the corequisite model is still young, preliminary studies show great promise. While not specifically on the corequisite model, the study by Bailey et al. (2010) showed support for the corequisite model. In this study, 17% of students referred to remedial mathematics ignored their placement recommendation and enrolled instead in a college-level course, with 72% of them passing. When considering all students in the study referred to the remedial sequence, only 27% of students eventually completed the college-level course by enrolling first in a developmental course. This study adds support that students deemed underprepared can be much more successful by enrolling directly into their college-level course.

A study conducted at Austin Peay University in Tennessee implemented two corequisite courses, statistics and a liberal arts mathematics course. While the pass rates in these courses were slightly lower than the historic rate for students who first completed the two-course remedial sequence, it was more than double when considering all students referred to remedial courses. While traditionally only 33% and 23% of students who first enrolled in the developmental sequence completed liberal arts math and statistics, respectively, 71% and 54% completed it in the corequisite model (Golson, 2009).

At Texas State University-San Marcos, students one-level below the college level were instead enrolled in a corequisite experience. In the prerequisite model, only 37.4% of students who first enrolled in developmental course went on to complete the college-level course. In the corequisite model, 88% completed the college-level course in one semester in the summer 2008 pilot and 73.9% completed it in the summer 2010 pilot ("Texas proposal narrative statements," 2011).

In a study of a corequisite model over five semesters, Moening (2016) found that overall the corequisite model improved student pass rates in the college-level mathematics course compared to a traditional developmental sequence. While the results varied by certain demographics, such as age, gender, race, and Pell status, in general all students benefited from the corequisite model. Further, students just below the placement test cutoff score performed better in the college-level course by enrolling in the corequisite model than students just above the cutoff score who enrolled in a standalone college-level course.

In a study by Logue, Watanabe-Rose, and Douglas (2016) at three community colleges in the City University of New York system, students who tested at the elementary algebra level were randomly placed into either an elementary algebra course, elementary algebra course with workshop, or college-level statistics course with workshop. That study showed that students placed into statistics passed at a higher rate than students in elementary algebra. After one year, the students who first completed statistics had completed more credits than students who first completed elementary algebra. The authors also noted that completing the statistics course resulted in a more positive attitude towards mathematics compared to elementary algebra and therefore might encourage a student to remain or become a STEM student.

**Placement Policy**

Placement policy is another area of current reform. If developmental education is not successful, perhaps the method used to determine whether students are college-ready is not sufficient. Further, if the corequisite model is used, how should it be determined who takes a standalone college-level course, corequisite course, or maybe even a one semester developmental course?

**How placement tests are used.** For the most part, community colleges determine college-readiness using a standardized placement test (Marwick, 2002). Historically, colleges commonly used national tests, such as ACCUPLACER and COMPASS, though COMPASS was recently discontinued. Still, many colleges use other mathematical tests besides the standard, national ones (Fields & Parsad, 2012). In Kentucky, for instance, institutions can use the University of Kentucky developed Kentucky Online Testing (KYOTE) exam as their placement test. Gerlaugh et al. (2007) found that assessment was mandatory at approximately 92% of institutions, though Fields and Parsad (2012) found that closer to 100% of public, two-year institutions used a mathematics test for placement. Most community colleges use placement tests as the sole measure of college-readiness. Less than 30% of institutions use criteria other than placement tests to determine academic preparedness (Fields & Parsad, 2012).

Placement tests generally assess a student's ability in algebra and other basic mathematical skills. Tests such as ACCUPLACER offer multiple tests to assess various mathematical concepts. Specifically, ACCUPLACER offers three tests: an Arithmetic Test, an Elementary Algebra Test, and a College-Level Math Test (2014). These tests are used to determine proficiency and whether a student needs to be remediated. Conceptually, the placement test assesses the knowledge and skills a student has accrued through years of schooling. If a student possesses a certain mathematical skill, he/she will get its corresponding question correct on the test, and if he/she does not possess the skill, he/she will get the question wrong. The test provides a cumulative score, which is associated with an institutional or statewide placement policy that associates a range of scores to either the college-level course or one of the levels of developmental mathematics. Missing enough questions on the placement test will lead to placement lower than college-level courses. It may even mean that a student's skills are too poor for developmental mathematics courses taught by the college and must go to other state sponsored programs for remediation, such as Adult Basic Education. Generally, there are firm cut scores giving little flexibility for students who just miss placing into a higher-level course. In this way, the placement test acts as a high-stakes assessment and a gatekeeper to the college-level courses.

**Validity of placement tests**. Placement tests are so prevalent because they are cost- and time-effective, but it is not clear whether they do what they are conceptually believed to do. It is possible through pure chance, that a student can guess correct answers to enough questions so that he/she place into a course more difficult than he/she can complete. On the other hand, if a student does not perform to the highest level to which he/she is capable, he/she may be placed into a course lower than the highest level in which he/she could be successful. If students can be placed into higher-level courses without increasing the risk of failure, they may be more likely to persist and complete their credential (Marwick, 2002).

Unfortunately, it seems likely that students underperform on placement tests. According to Safran and Visher (2010), college advisors reported that entering students often take placement tests without realizing the impact the tests have on course placement and that students often take the test without any preparation. Venezia, Bracco, and

Nodine (2010) found that students were relatively uninformed about placement tests and that some did not even know they would be required to take a placement test. For many students, placement was something they experienced for the first time when they arrived on campus. Still, others viewed placement tests as a measure of what they remembered on the day of the test without the benefit of any review. It is possible that many students who are assigned to low-level developmental courses could have performed better on the placement test if they understood the high-stakes nature of the placement test and did a small amount of review (Gordon, 2006).

**Relationship between placement tests and student outcomes**. While some students may not realize the gravity of placement tests, that alone does not necessarily mean that placement tests are ineffective in assigning students to their appropriate mathematics course. Belfield and Crosta (2012) found some positive association between placement test score and student outcomes. They found a weak, but positive, association between placement test score and cumulative college GPA. The study also revealed a positive association between placement test score and the number of college credits completed. Parker (2005) found a positive association between placement test score and graduation. The higher the placement score, the more likely a student was to graduate. Despite these positive associations with student outcomes, the primary use of the placement test at a community college is to determine whether a student will be successful in the first college-level mathematics courses and not as a predictor of overall college success.

An abundance of evidence suggests that placement tests are not very effective in placing students into mathematics courses. Despite the positive associations, Belfield and

Crosta (2012) found that using placement test cutoff scores resulted in what they called high “severe error rates”. This metric was calculated by looking at the number of students predicted to earn a B or better in the college-level mathematics course but instead were assigned to developmental mathematics, combined with the number of students assigned to the college-level course despite having a high likelihood of failing.

Likewise, while Scott-Clayton (2012) found that using placement tests reduced the severe error rate of simply placing all students into the college-level course, they found the placement test was a better predictor of who did well in the college-level class, but not who would fail it. This leaves open the possibility that some students were excluded from the college-level course despite being likely to pass it with a satisfactory grade.

Armstrong (2000) found that the correlation between placement test scores and course grades were generally weak, and was the weakest for the lowest-level courses. Parker (2005) concluded that placements tests were only useful for placing students into STEM math courses such as college algebra or pre-calculus and that using placement tests as the sole method to place students resulted in students placed into courses lower than which they could be successful.

The research suggests uncertainty concerning the effectiveness of using placement tests to assign students to mathematics courses. It is likely that many students are assigned to remediation when they in fact could be successful in college-level courses.

**Alternative placement methods**. Other characteristics, such as academic preparation in high school, could be as good or better predictors of success in college-level mathematics and college in general than are placement tests. High school GPA, the number of high school honors classes, the number of math classes completed in high school and the highest mathematics course completed in high school might serve as effective placement metrics (Belfield & Crosta, 2012; Hughes & Scott-Clayton, 2011; Saxon & Morante, 2014; Zientek, Yetkiner Ozel, Fong, & Griffin, 2013). While using other measures besides placement tests is a current area of debate amongst scholars and policy makers, it is by no means a new idea; it was first suggested at least 45 years ago. Sheldon questioned if data from high school transcripts and high school GPA, even if self-reported, would place students more effectively than standardized tests (as cited in Armstrong, 2000). The literature suggests that high school metrics, high school GPA in particular, may be better at placing students, or at the least, should be combined with placement test scores to make placement decisions.

Belfield and Crosta (2012) found positive associations between high school transcript data and student outcomes in college. They found high school GPA to be highly predictive of success in college and other high school transcript data to be less so. On average, a student's college GPA was one letter grade lower than their high school GPA. They suggested that if success in college is defined to be a C or better, a student with a high school GPA of C+ or higher is likely to be successful in college and it might be appropriate to waive the placement test requirement for the student. They also found that using high school GPA placed half as many students into remedial mathematics who could have been successful in college-level mathematics and placed fewer students in college-level mathematics who were likely to fail. Further, the authors found that creating a placement policy using a combination of high school GPA and placement test score was less predictive than high school GPA alone.

Likewise, Scott-Clayton (2012) found that using only high school GPA to place students reduced severe error rates compared to using only placement tests. Creating a metric using placement test and high school GPA provided little improvement to the severe error rate, but did make a small, statistically significant difference.

Ngo and Kwon (2015) found high school GPA to be more predictive of college persistence and success than placement tests and suggested that institutions consider its use in placement decisions.

While there is evidence that high school GPA is more effective at placing students than placement tests alone, others have found that placement policies combining multiple metrics place students into higher-level courses than single metrics alone while not hurting their chances of success (Parker, 2005). For instance, one college gave a multiple measures point boost in which additional points for a high school GPA in the A or B grade ranges were added to the placement test score (Ngo & Kwon, 2015).

Marwick (2002) urged caution in adopting policies that make placement decisions using single metrics. She found that when placing students using only placement test or using only high school GPA, some students would be placed in a lower-level course who could have otherwise been successful in a college-level course. Instead, Marwick suggested setting cutoffs for both metrics and using them together to place students. Her study showed that students did just as well in the higher-level class when the metrics disagreed on which level to place the student. This result suggests that it may be beneficial to create a placement policy in which high school GPA and placement test scores are used together to make placement decisions. Even considering other results that indicate high school GPA alone is sufficient, considering the two together may at worst provide no improvement.

Many institutions and state-systems are implementing multiple measures to increase student success and graduation rates and reduce the number of students assigned to remediation. California adopted the practice of using multiple measures in the early 1990s in response to claims that placement tests disproportionally placed minority students into remedial courses (Ngo & Kwon, 2015). Other states, like North Carolina, New Jersey, and Connecticut began as early as the late 2000s moving towards multiple measures placement policies using high school GPA for students in the "grey area" just below the cutoff for college-level courses (Burdman, 2012). In 2013, the state of Florida passed legislation that made placement tests optional for students, relying instead on their abilities from having graduated from a Florida high school (Nix, Bertrand Jones, Brower, & Hu, 2020). In fall 2016, the KCTCS for the first time allowed its member institutions to consider high school GPA as a placement metric, but this was only on a trial basis.

### Summary

Conceptually, developmental education is simple. Institutions place students who are underprepared for college-level study into developmental education courses to learn the mathematical skills necessary for college-level study. Developmental education has existed in higher education for quite some time and has been a part of nearly 80% of institutions for at least the last 100 years. It is not entirely clear whether developmental education is successful in accomplishing its purpose. While some studies show positive effects for students who enroll, others show no or even negative effects. This is especially true for students near placement cutoff scores. Further, very few students who enroll in developmental education courses ever persist to the college-level course for which they are preparing to take. Critics argue that since most students never reach the course they are preparing to take, developmental education, as we know it, is a broken system.

Recent calls for reform have suggested the use of the corequisite model in which most students enroll in a credit-bearing course at the same time as a support course. Preliminary studies suggest the model has great promise when comparing the number of students who pass the college-level course in the corequisite model compared to the number of students who complete a developmental sequence and then pass a college-level course. There is also a movement to reform placement policies on college campuses. Studies have shown that placement tests are poor predictors of success and that metrics such as high school GPA or multiple measures are much better predictors. Further research is needed on the efficacy of the corequisite model as well as the predictors of success in such a course.

# CHAPTER 3: METHODOLOGY

This study sought to establish the efficacy of the corequisite model in a liberal arts mathematics course in the community college setting. While the model has existed on a small scale for the last two decades, it gained the most attention and momentum in the latter part of the 2010s, including in Kentucky. The corequisite was fully implemented for liberal arts mathematics at JCTC in 2018 and statewide for all KCTCS in 2019. This study has practical significance for both JCTC and KCTCS and contributes to the literature on the corequisite model.

This chapter provides the details of the research design and setting for this study. It also sets forth the specific methods used to analyze the data to answer the research questions and provides the ethical considerations made by me as the researcher.

## Research Questions

1. How does success compare for students placed into the corequisite course compare to the historic rate at which students who placed into developmental courses completed their developmental math course or courses and college-level course?
2. What are the best predictors of success in the corequisite course?
3. How does success in the corequisite course compare to students deemed college-ready and placed into the college-level course with no support?

The study defined student success as passing the college-level course with an A, B, or C, while students who earned grades D or E or who withdrew (W) were considered unsuccessful. While it is true that a student who earned a D grade received credit towards graduation, for purposes of this study, any such student was considered unsuccessful. It is difficult to consider a student a success with achievement at such a low level, especially considering that a pattern of performance at this level will likely lead to ramifications for the student, such as financial aid probation, or academic probation or suspension from the college. This level of achievement might also affect long-term success, such as the student transferring to a four-year university or applying to a selective admissions program, such as nursing. No students audited the course or had an incomplete grade (I) at the time the data was collected, so there were no cases of a student being excluded from the study due to course grade.

**Setting**

Jefferson Community and Technical College (JCTC) is a large community college in the Southeastern Region. It has six campuses, two urban campuses, one suburban campus, and three rural campuses. Data for this study was from the main urban campus, suburban campus, and one rural campus. Three others were excluded because they did not offer the corequisite course during the semesters included in this study. JCTC is part of a large statewide system, KCTCS. Yearly enrollment at JCTC ranged roughly between 12,000-15,000 students over the last six years with approximately 11,776 students enrolled in the fall 2018 semester, of which 1,703 were first-time freshman. In fall 2018, 29% of students were full-time and 76% identified as a credential-seeking student. The student body was approximately 55% female, 41% male, and 4% unknown gender. Approximately 59% of the student body was white, 20% black or African American, 9% Hispanic, and 4% two or more races. The College considered 33% of the student body as underrepresented minorities. The median student age was 21, with approximately 64% of the student body under the age of 25. Sixty-six percent of students were Pell Grant eligible (Jefferson Community and Technical College, 2020). In comparison, the national average for all community colleges included students who were 37% full time, 56% female, 46% white, 13% black or African American, 25% Hispanic, 34% Pell Grant eligible, and with a median age of 24 (American Association of Community Colleges, 2020a). While JCTC was close to the national average in many areas, it is not necessarily representative of all institutions.

**Research Design**

In 2018, Kentucky's Council on Postsecondary Education mandated that all public postsecondary institutions adopt the corequisite model by the fall 2019 semester. Prior to this, JCTC had already piloted a liberal arts corequisite course in the 2017/2018 academic year. Following the successful pilot, JCTC fully implemented the liberal arts corequisite model in the fall 2018 semester, a year ahead of the Council's mandate. It is the 2018/2019 academic year, the first full year of implementation, over which this study is set.

The College paired a liberal arts mathematics course with a supplemental course. Students registered in both courses for a total of five credit hours, three of which were the credit-bearing, college-level course and two were the supplemental course. The same instructor taught the college-level course and the supplemental course. The College offered eleven corequisite sections each in the fall 2018 and spring 2019 semesters, eight at the urban campus, two at the suburban campus, and one at a rural campus. In fall 2018, all sections at the urban and suburban campuses were setup with a maximum possible enrollment of 25 students in which all students in a section placed below college level. All students in the college-level course enrolled in the same supplemental course. The corequisite course at the rural campus was a split format in which college-ready and corequisite students enrolled together in the same college-level class, similar to that of the ALP in Baltimore. Half of the 30 students were corequisite students and took a supplemental class together, while the other 15 college-ready students only took the college-level class. The spring 2019 semester used a similar enrollment structure, with two split sections at the urban campus and one at the rural campus. The other eight corequisite sections at the urban and suburban campuses were ones in which all students enrolled were corequisite students.

JCTC also offered standalone sections of the liberal arts course for students deemed college ready. The maximum enrollment in the standalone sections was 30-35 students. The content of the standalone course was identical to the corequisite sections. Some of the instructors for the standalone sections also taught the corequisite versions, but not all taught both. Many aspects of the course were standardized, such as the course schedule, textbook, homework problems, group projects, and exams, but some aspects of the course were flexible for individual instructor preference such as daily learning activities. An active learning environment was expected in all sections and instructors participated in professional development to learn effective strategies.

The corequisite support course was frontloaded with soft skills, such as time management skills, study skills, and growth mindset, for the first several weeks of the course. Time in the support course was spent reemphasizing topics in the college-level course with additional lecture, group work, or other learning activities, and working on assignments independently or in groups with guidance from the instructor as needed. Students earned a separate grade for the support course from the college-level course.

However, only grades in the college-level course were of interest for this study as the goal of the corequisite was to help students pass the college-level course.

JCTC used a combination of the ACT test and a placement test to determine whether students were college ready. At the time of the study, statewide policy stipulated that students who scored a 19 or above on the ACT mathematics test were college ready for liberal arts mathematics courses. At JCTC, students who scored below a 19, did not have an ACT score, or whose ACT score was more than two years old were required to take a placement test. JCTC used a non-national placement test developed by the University of Kentucky called the Kentucky Online Testing (KYOTE) exam. A score range of 6-21 on the KYOTE Math College Readiness test placed a student at the corequisite level. Students who scored at or above 22 were placed into the standalone version of the course. Students who scored below a 5 were not placed into any course offered by the college but were instead referred to Adult Basic Education Services. Prior to the implementation of the corequisite model, a score from 6 to 21 placed students into one, two, or three levels of developmental education. Students at the lowest level of developmental education had to complete three courses over three semesters before they were eligible to take a college-level course.

The KCTCS placement policy chart allowed for comparison on national standardized placement tests such as Compass and Wonderlic. Scoring 21 or below on the KYOTE placement test correlated to 49 and below on the Compass Algebra Domain and below 3330 on the Wonderlic Quantitative, for example (Kentucky Community and Technical College System, 2018). Table 3.1 below provides a comparison between KYOTE and common national placement tests.

While a grade of D or higher in a course was needed to earn graduation credit at JCTC, for reasons explained above, success in the college-level course was considered an A, B, or C. This corresponded to earning a 70% or better. All sections used the same grading scale and criteria (i.e. assignments, projects, and tests).

**Data Collection**

The JCTC Office of Institutional Effectiveness, Research, and Planning collected and provided the data for the study. First, data was provided about each student enrolled in the liberal arts mathematics course for fall 2018 and spring 2019. A total of 735 students were included in the sample. Students under the age of 18 were excluded. The data collected for each student included: semester enrolled, delivering campus, class section number, final course grade in liberal arts mathematics course, race/ethnicity, Pell Grant status, age, sex, cumulative high school GPA, major, full/part time enrollment status, ACT mathematics score, and KYOTE placement test score. High school graduation year and high school name were also reported, but this data was incomplete for too many students to be of value. Assigned to each student was a nondescript, proxy ID. The course section number was needed to identify whether a student was in the corequisite course or the standalone course, as the College used a standard convention to distinguish between the two. The analysis did not use the grades for the supplemental support course since the research is concerned with how the students perform in the college-level course.

The second set of data was on all first-time students enrolled during the fall 2012 semester and was publicly available. This data set centered on students who enrolled in a developmental math class during the fall 2012 semester, specifically MAT 55 Pre-

Algebra, MAT 65 Basic Algebra or MAT 85 Intermediate Algebra, and tracked over six years their completion of the developmental mathematics sequence and then a college-level course. This data provided a historic baseline for the rate at which students who placed below college level went on to complete a college-level mathematics course. While this data set was convenient because it was readily available, it also allowed for a fuller picture of how students might complete developmental mathematics and a college-level course. The time frame acknowledged that many students fail courses, do not enroll in developmental courses right away, do not enroll in the next course or repeat a failed course in the subsequent semester, or temporarily stop out of college altogether and then return. A six-year snapshot allowed the data to track student progression through developmental mathematics.

**Data Analysis**

This study relied on quantitative data and analysis. Quantitative analysis was appropriate for this study as the main purpose was the relationship between several variables (Creswell, 2014). Univariate analysis was conducted for each variable. The first research question was explored using a two proportions z-test. The second research question was investigated using a multiple linear regression. The third research question used propensity score matching to simulate an experimental design. A two-sample t-test was then used to compare the mean course grade in the corequisite course with that of the standalone course.

**Research Question 1:** The first research question asked how success in the corequisite course compared to the historic rate at which students assigned to developmental mathematics completed a college-level mathematics class. Since students who placed into the corequisite course historically would have been placed into the developmental course sequence, this comparison had significant value. The study compared the success rate in the corequisite course to the rate at which first-time JCTC students who enrolled in a developmental mathematics course in the fall 2012 semester went on to complete a college-level mathematics course. In both samples, students earning final course grades of A, B, or C in the college-level course were considered successful, while students earning grades D, E or W were considered unsuccessful.

A one-tailed, two proportion z-test was used to answer the first research question because this type of analysis was able to determine whether any significant difference existed between the two population proportions (Triola, 2018). The hypothesis test was run using StatCrunch at the $\alpha = 0.05$ significance level. StatCrunch is a recognized statistical software capable of computing powerful statistical analysis (Triola, 2018; West, Wu, & Heydt, 2004). It was chosen for this part of the analysis because of its ability and ease in conducting hypothesis testing using data summaries as opposed to raw data. The fall 2012 data was available in summary only.

Since prior research indicated that the corequisite model increased a student's chance of completing a gateway mathematics course, a one-tailed test was used. The null hypothesis was that the difference in the proportion of students who passed the corequisite course and the proportion of students who enrolled in developmental mathematics and went on to pass a college-level course was zero. This could be written as $H_0\colon p_1 - p_2 = 0$, where $p_1$ was the proportion of students who passed the corequisite course and $p_2$ was the proportion of developmental students who went on to complete a college-level course. The alternative hypothesis was that the proportion of students who passed the corequisite course was greater than the proportion of students who enrolled in developmental mathematics and went on to pass a college-level course. This can be written as $H_1: p_1 > p_2$.

Three assumptions must be met in order to conduct a two proportion z-test (Triola, 2018). First, the proportions must come from a simple, random sample. Second, the samples must be independent. Finally, for each of the samples, it must be the case that $np \geq 5$ and $nq \geq 5$. Before conducting the hypothesis test, it was verified that the samples met these conditions.

**Research Question 2**: The second research question was explored using a multiple linear regression model. A multiple linear regression was appropriate since this type of analysis shows the relationship between multiple independent variables and a dependent variable (Lewis-Beck & Lewis-Beck, 2016). This analysis showed which predictors had the strongest relationship with student success. Another advantage was that multiple regression removed the influence of the independent variables on each other from the model.

SPSS was used to run the regression analysis. The dependent variable in the model was the final course grade (GRD). College-level course letter grades were converted to discrete numerical values as shown in Table 3.2. Failing grades and withdraw grades were given the same discrete value since they both represented an unsuccessful attempt at the course. No students in the sample audited the course or received an incomplete grade (I).

The primary tool JCTC used to place students into the corequisite course was the KYOTE math placement test (KMATH) score. A small number of students in the data set were missing a KMATH score. For these students, the KCTCS placement chart (Table 3.1) was used to assign a KMATH score based on an equivalent placement test. In all cases, a median KMATH score was assigned from each range for which a student had a comparable placement score. Ten of the students who were missing a KMATH score had one generated based on their ACT Math score. Another 12 students had a KMATH score generated using a Compass score. Five students had no placement test data and were excluded from the regression analysis.

Other independent variables used in the regression analysis included ACT Math score (ACTM), high school cumulative GPA (GPA), and age (AGE). There has been much research on the relationships between placement tests and high school GPA with success in mathematics courses. Prior research also indicates that there may be differences in success in mathematics based on a student’s age (Gupta, Harris, Carrier, & Caron, 2006; Wolfle, 2012).

The analysis also included several indicator variables as independent variables. Socioeconomic status was considered using the Pell Grant indicator variable (PELL). This variable indicated whether a student was eligible to receive a Pell Grant, with a value of 1 indicating a student was eligible and a value of 0 indicating a student was not eligible. Low-income students are particularly at-risk in education (Mamiseishvili & Deggs, 2013)

The underrepresented minority indicator variable (URM) considered race. As defined by the Kentucky Council on Post-Secondary Education, underrepresented minorities included someone whose racial or ethnic makeup was from one of the following: African American or black, Hispanic or Latinx, Native American or Alaskan Native, or two or more races (*Kentucky Public Postsecondary Education Policy for Diversity, Equity, and Inclusion*, 2016). While other criteria or ethnic makeups, such as Asian, are often considered underrepresented minorities, the ones used in this study matched those used at JCTC and throughout Kentucky. The indicator variable assigned students who met the definition of an underrepresented minority a value of 1, while those who did not were assigned a value of 0. While significant improvements have been made recently, a gap in the graduation rates between underrepresented minority and non-underrepresented minority students at JCTC. Given the relationship between achievement in mathematics and graduation rates, this is an important variable to include (Parker, 2005). Further, prior studies indicate that race/ethnicity may have a relationship with success in college mathematics (Walker & Plata, 2000; Ward, 2006)

The female indicator variable (FEM) considered a student's sex. The indicator variable assigned students identifying as female a value of 1, while those identifying as male, and the 13 students with unknown gender, were assigned a value of 0. Female students were much more likely to place into the corequisite than were male students. Also, prior research suggests that female students may have greater anxiety about mathematics which could affect their performance in the class (Betz, 1978)

The semester a student took the class was taken into account using the fall semester indicator variable (FALL), with a value of 1 indicating that a student took the class in the fall semester and a value of 0 indicated the class was taken in the spring semester. This variable was added to explain any difference between course delivery between fall and spring semester, such as different professors teaching the course, and the possibility of any difference in ability for students who chose to take the class in the fall compared to the spring.

The campus at which the class was delivered was also considered in the model to explain any differences that may exist between campuses. The Downtown Campus indicator variable (DTCAMPUS) assigned a value of 1 if a student took the class at the Downtown Campus and a value of 0 if a student took the class at the Southwest or Shelby County Campuses. Historically, students at the Downtown Campus do not perform as well as those at other campuses, but it is possible that this difference is explained by other variables.

Finally, differences explained by a student's major were considered using the TRANSFER indicator variable. The associate in science and associate in arts degrees are primarily intended for students who intend to transfer to a four-year institution. Including this variable allowed the analysis to account for any difference between students on a transfer pathway compared to students enrolled in a terminal technical program. The indicator variable assigned a value of 1 to students whose declared major was associate in science or associate in arts, and 0 otherwise. Table 3.3 below summarizes the variable names and descriptions.

A significant number of students were missing ACT or GPA data because it was either not collected or recorded by the College as part of the admissions process. In the case of the ACT, it was also possible that a student never took the ACT. Of the 454 students included in the regression analysis, 266 were missing an ACT Math score and 297 were missing a cumulative high school GPA. These numbers include 223 students who were missing both an ACT Math score and cumulative high school GPA. To account for the missing data, several regression models were built to attempt to maximize the sample size as well as to determine the effect that variables had on the model. The first model included all the independent variables from Table 3.3 except for ACTM and GPA. The analysis included all 454 students. The second model included ACTM as an independent variable along with the others from the first model. This model included only 188 students in the analysis. The third model included GPA as an independent variable along with the others from the first model. This model included only 157 students in the analysis. The fourth and final model included all the variables from Table 3.3 and thus included only 114 students in the analysis.

For each of the four models, course grade was the dependent variable. Several versions of each model were generated to test the effect of the various independent variables on the model. The independent variables were inputted in three blocks, with each successive version of the model adding an additional block. The first block included the student's academic background: KMATH, GPA, and ACTM. Depending on the model, this block may have only contained one or two of the variables. The second block included the student's demographic characteristics: AGE, PELL, URM, and FEM. The third and final block included the student's enrollment data: FALL, DTCAMPUS, and TRANSFER. Analysis was provided on the performance of each model and how the inclusion of additional blocks affected the model.

A reliable regression model must satisfy several assumptions (Lewis-Beck & Lewis-Beck, 2016). First, there should be no specification error. The second assumption that should be met is that there are no measurement errors. Finally, several assumptions need to be met concerning the error term: 1) the sum of the residuals must be zero; 2) the variance of the residuals must be constant for all values of the independent variables; 3) the residuals should have a normal distribution; 4) the condition of no autocorrelation must be met.

According to Lewis-Beck and Lewis-Beck (2016), there are varying views on how serious any violations to these assumptions are for the regression model. They noted that some assumptions are less affected by violations than the others are. Violations of homoscedasticity and no autocorrelation are relatively minor, while violations of the normality assumption can be ignored completely if the sample size is large enough to apply the Central-Limit Theorem. Other violations can be more serious, such as measurement errors or omission of relevant variables. As part of the analysis, any violations of the assumptions as well as their potential impact on the results were noted.

**Research Question 3:** The final research question sought to determine how students in the corequisite course performed compared to their college-ready peers in the standalone course. To attempt to establish a causal relationship, propensity score matching was used to generate two comparison groups. The propensity score is defined as the conditional probability of a student placing into the corequisite course given various covariates (Rosenbaum & Rubin, 1983). Students with similar scores had roughly the same probability of being placed into the corequisite course. Using propensity scores allowed for a comparison of students in the corequisite course to similar students enrolled in the standalone course and allowed the analysis to more closely resemble an experimental study design instead of an observational study design (Oakes & Johnson, 2006). Comparing students who were similar based on propensity score could allow for more confidence in inferring that the corequisite influenced outcomes, and not some other covariate.

A logit model was used to generate propensity scores (Oakes & Johnson, 2006). The dependent variable for the logit model was enrollment type, with enrollment in the corequisite course coded as 1 and enrollment in the standalone course coded as 0. The covariates used in the model were some of the ones included in the multiple regression for question 2, including: ACTM, GPA, PELL, URM, AGE, and FEM. KMATH was not included because too few students in the standalone course had recorded KMATH, ACTM, and GPA scores, inclusive. A better sample size was achieved excluding KMATH as a covariate. Students with missing data were excluded from the logit model.

The propensity scores were then used to match students in the corequisite course to students in the standalone. A "nearest neighbor within calipers" approach was used for direct matching with replacement, with the caliper width set to 0.05 (Oakes & Johnson, 2006). Each corequisite propensity score was matched to the standalone propensity score closest to it, but within 0.05. After matching, a standalone propensity score was replaced and could be matched to another corequisite propensity score.

Using the matched samples, course grades were compared between the standalone course and the corequisite course using a two-sample t-test. This method was appropriate because the use of a test allowed for the comparison of two population means, such as the mean course grade (Triola, 2018). The hypothesis test was run using StatCrunch at the $\alpha = 0.05$ significance level. The null hypothesis was that the difference in courses grades between the standalone sample and corequisite course was zero. This could be written as $H_0: \mu_1 - \mu_2 = 0$, where $\mu_1$ and $\mu_2$ were the mean course grades of the standalone and corequisite course, respectively. The null hypothesis was that the difference in courses grades between the standalone sample and corequisite course was not zero. This could be written as $H_0: \mu_1 - \mu_2 \neq 0$.

In order to conduct a two-sample t-test, three assumptions must be met (Triola, 2018). First the, two samples must be independent. The samples must also come from simple random samples. Lastly, the samples must both be large ($n > 30$) or come from populations having normal distributions. Before conducting the hypothesis test, it was verified that the samples met these conditions.

**Ethical Considerations**

As with any research, it was crucial to be aware of the potential ethical issues of this study. Since I had no direct contact with human subjects in this quantitative study, potential ethical issues primarily surrounded collecting and analyzing the data and distributing the results. Since the researcher held faculty rank and was a full time administrator at JCTC, extra care was taken throughout the study to avoid any potential conflicts of interest. Creswell (2014) identified five areas for which ethical considerations should be given: prior to conducting the study, at the beginning of the study, collecting and storing the data, analyzing the data, and reporting and sharing the data. Ethical considerations in these five areas are discussed below.

**Ethical issues prior to conducting the study.** Before beginning this study, I sought and received approval from both the KCTCS and the University of Kentucky. The Institutional Research, Effectiveness, and Planning (IREP) Office at JCTC was consulted prior to submitting IRB applications to both KCTCS and the University of Kentucky.

In addition, I need to acknowledge that the study was conducted at the institution where I was, and still am at the time of publication, employed as a fulltime administrator, also holding faculty rank. During the time of the development and implementation of the corequisite, I was a member of and chair of the Mathematics Division at JCTC. While the setting was one of practicality and convenience in which I was familiar with the course offerings and had easy access to data, it was also an ideal setting for the study. As described above, JCTC was similar to the demographics in the national sample of community colleges. It was also part of a statewide system that required the implementation of corequisite mathematics by fall 2019. This study provided significant practical relevance for the college and state, as well as other institutions wishing to implement a corequisite model.

**Ethical issues at the beginning of the study**. The college advising staff enrolled students based on placement test scores published in the KCTCS catalog and according to the graduation requirements of the students major. There were no other selection criteria. Further, this was an observational study only and did not rely on an experimental design.

It is also important to note, considering my position at the college, that no attempt was made to influence course outcomes, such as course grades. Instructors teaching the course received no reward nor repercussion for positive or negative student outcomes. Further, though I was a mathematics faculty member at the time, I did not teach the corequisite or standalone course.

**Collecting and storing the data.** Since sensitive academic information about students was collected, care was taken with data collection and storage so FERPA regulations were not violated. The JCTC IREP Office provided the data used in the regression analysis from the College's student information system, while data from the fall 2012 semester came from a public source. Further, individual student identifiers, such as name and student ID number, were not reported or kept by me as the researcher. Sensitive information, such as grades placement scores, and class section in which a student enrolled, were collected for this study. A password-protected computer was used to keep all data secure.  While it may have been possible to identify an individual student through a combination of data points, it was highly unlikely.

**Analyzing the data**. Potential ethical issues in analyzing the data were avoided by following standard statistical methods and hypothesis testing. Results from the statistical tests were reported completely and I did not underrepresent data that could be looked on unfavorably by some parties, while at the same time did not overrepresent data that could be looked on favorably by other parties. I was forthcoming about any potential limitations to the statistical analysis and violations of assumptions.

**Reporting and sharing data**. This area had greatest potential for ethical issues. Since I was a full-time administrator and held faculty rank at the college where the study is taking place, great care was taken to avoid any potential conflicts of interest. This study had no bearing or influence on my administrative role at JCTC. The study also had no bearing on my tenured faculty status. There was no benefit for positive results and no consequences for negative results. This allowed the analysis of the data and recommendations from the results to be reported unbiasedly.

It is important that others can be confident that the research was conducted objectively and that stakeholders are confident that the data has not been skewed to advance any particular viewpoint on developmental education. This was especially important in an environment in which many faculty members at the college are still skeptical of corequisite education and view its implementation as forced from the top down to the faculty, while many administrators long for an increase in retention and graduation rates. While I acknowledge my own internal belief that developmental education is a broken system as practiced and that corequisite education shows great promise, the discussion of the results was done from a neutral position.

Being a solo researcher, there was no concern with ordering authorship. Those who have assisted in the development of the study and the research, including the doctoral committee and IREP Office staff, were acknowledged.

**Summary**

This study was conducted using data from Jefferson Community and Technical College, which fully implemented a corequisite liberal arts mathematics model during the fall 2018 semester. JCTC is a large community college with both urban, suburban, and rural campuses. The makeup of the student body is close to the national average. The corequisite course was offered at three of the six campuses.

The study explored three research questions to help better understand corequisite mathematics:

1. How does success compare for students placed into the corequisite course compare to the historic rate at which students who placed into developmental courses completed their developmental math course or courses and college-level course?
2. What are the best predictors of success in the corequisite course?

3. How does success in the corequisite course compare to students deemed college-ready and placed into the college-level course with no support?

Univariate analysis was provided for each variable. A two-proportion z-test was used to analyze the effectiveness of the corequisite model compared to students who historically enrolled in a developmental math sequence. Multiple linear regression was used to analyze the best predictors of success in a corequisite course. For the third research question, propensity score matching was used to simulate an experimental design and provide similar comparison groups of students who took the corequisite and standalone versions of the course. Using these matched samples, a two-sample t-test was used to compare course grades for each course.

Table 3.1 Comparison of KYOTE Scores to Common National Tests

| **KYOTE** | **ACT** | **SAT** | **ALEKS** | **COMPASS** | **ASSET** | **Wonderlic** |
|---|---|---|---|---|---|---|
| 22-31 | 19-21 | 500-559 | PPL 30 | Algebra Domain 36-49 | El. Alg. 41-45<br>Int. Alg. 39-42 | Quantitative 288-329 |
| 18-21 | 17-18 | N/A | N/A | Algebra Domain 31-35 | El. Alg. 39-40<br>Int. Alg. 36-38 | Quantitative 265-287 |
| 12-17 | 16 | N/A | N/A | Algebra Domain 16-30 | El. Alg. 27-38<br>Int. Alg. 26-35<br>N. Skills 38-55 | Quantitative 250-264 |
| 6-11 | 14 | N/A | N/A | Pre-algebra Domain 24-41 | N. Skills 25-37 | Quantitative 200-249 |

Table 3.2 Letter Grade Numeric Conversion

| Final Course Letter Grade | Numerical Value |
|---|---|
| A | 4 |
| B | 3 |
| C | 2 |
| D | 1 |
| E or W | 0 |

Table 3.3 Multiple Regression Model Variable Descriptions

| Variable | Description |
|---|---|
| GRD | Final course grade in the liberal arts mathematics course. This was the independent variable in the model. |
| KMATH | KYOTE math placement test score. |
| ACTM | ACT Math score. |
| GPA | Cumulative high school grade point average. |
| AGE | Student’s age at the time of enrollment. |
| PELL | Indicator variable for whether a student was eligible for a Pell Grant. |
| URM | Indicator variable for whether a student was an underrepresented minority. |
| FEM | Indicator variable for whether a student was female. |
| FALL | Indicator variable for whether a student took the course in the fall. |
| DTCAMPUS | Indicator variable for whether a student took the class at the Downtown Campus |
| TRANSFER | Indicator variable for whether a student was an associate of science or arts major |

# CHAPTER 4: DATA ANALYSIS AND RESULTS

This chapter presents the results of the analysis for this study. The data used in the analysis came from two sources. The first data set was provided by the JCTC IREP Office. It contained data about students enrolled in the liberal arts mathematics course for fall 2018 and spring 2019, which included both students enrolled in standalone sections of the course and students enrolled in the corequisite. A total of 735 students were included in the sample, 463 students in the corequisite and 272 students in the standalone course. The data provided for each student included: semester enrolled, delivering campus, class section number, final course grade in liberal arts mathematics course, race/ethnicity, Pell status, age, high school graduation year, high school name (including GED), full time enrollment status, cumulative high school GPA, major, ACT score, and placement test score.

The second source of data was publicly available and came from the Jefferson Community and Technical College Voluntary Framework of Accountability Public Profile published by the American Association of Community Colleges (American Association of Community Colleges, 2020b). This provided data on all first time at Jefferson students who enrolled in the fall 2012 semester. The data included a breakdown of the number of students who required and enrolled in developmental mathematics, as well as the number who completed the developmental mathematics sequence and went on to complete a college-level mathematics course. This data set provided a baseline to compare the rate at which students in the corequisite completed a college-level course to the historic rate at which similar students, who were placed into a developmental mathematics course or sequence, completed a college-level course.

The two data sets were used to answer three research questions. First, how success in the college-level course for corequisite students compared to the historic rate at which students placed into developmental courses completed a college-level course. This question was answered using a one-tailed two-proportion z-test. The second question explored the best predictors of success in the college-level course for corequisite mathematics students. The analysis for this question used a multiple regression with variables that included math placement test score, ACT math score, high school GPA, age, socioeconomic status, semester the class was taken, underrepresented minority status, campus at which the class was taken, and major. The third question asked how success in the college-level course for students placed in the corequisite course compared to students deemed college-ready and placed into the college-level course with no support. The answer to this question was explored by first using propensity score matching to generate comparable samples. Using the matched samples, a two-sample t-test was used to compare the mean course grade for corequisite versus standalone.

This chapter begins with a summary of the two samples, including descriptive statistics for the fall 2018 and spring 2019 liberal arts mathematics sample. The chapter then provides the results of the analysis of the data for each research question.

**Description of the Sample**

Data for this study came from two sources. The first was data from all students enrolled in the liberal arts mathematics course during the fall 2018 and spring 2019 semester. This data was further broken down according to whether a student took the corequisite version of the course or a standalone version. Three of the campuses at the College did not offer the corequisite course and were not included in the sample.

Likewise, students under the age of 18, most of whom were high school dual credit students, were not included in the sample. Twelve students took the course in both the fall and spring semesters. For these twelve students, only their fall semester attempt was included in the sample. The total sample size was 723 students, of which 459 students enrolled in the corequisite course and 264 students enrolled in the standalone course.

Table 4.1 below provides a summary of the demographics and pass rates for the overall sample and separately for corequisite and standalone parts of the sample. By far, the majority of students enrolled in a corequisite course as opposed to the standalone course. The A/B/C pass rate was higher in the standalone courses compared to the corequisite courses. For both the corequisite and standalone, more students enrolled in the fall than the spring, but a higher percentage of students enrolled in the standalone in the fall compared to the corequisite in the fall. The enrollment rate for underrepresented minorities in the corequisite course was much higher than the enrollment rate in the standalone course, as was the rate for Pell Grant eligible students. Female students were more likely to enroll in the corequisite course than the standalone course. Those with undisclosed gender enrolled in the corequisite and standalone courses at very similar rates.

Most students enrolled were part-time students. However, part-time students were more likely to enroll in the corequisite course than the standalone course. The enrollment rate in the corequisite course was higher than the standalone course at the Downtown Campus, while the rate was higher in the standalone course at the Southwest and Shelby County Campuses. For both the corequisite and standalone courses, most students who enrolled were an associate of arts major, followed by other and then associate in science.

Compared to the College as a whole, the underrepresented minority student enrollment rate was higher in both the corequisite course and standalone course, nearly double in the corequisite course. Likewise, the enrollment rate in the corequisite course was higher for Pell Grant eligible students compared to the College rate. Enrollment in the standalone course for Pell eligible students was the same as the College rate. Female student enrollment was higher in both courses than the College rate. Students with unknown gender enrolled in both courses at a slightly lower rate than the overall College rate. Fulltime student enrollment in both courses was higher than the overall College rate.

Tables 4.2 below provides descriptive statistics for the discrete and continuous variables for the overall combined sample, corequisite sample, and standalone sample. The mean grade and standard deviation were very similar for the corequisite sample and standalone sample, 2.05 and 1.500, and 2.18 and 1.498, respectively. The mean KYOTE Math score and ACT Math score were higher in the standalone course than the corequisite course, but this result is not surprising, as the score on these tests determined placement into each course. The standard deviations for the KYOTE Math and ACT Math scores in the standalone course were also higher than those in the corequisite course.

The second data set used for this study came from the Voluntary Framework for Accountability (VFA) Jefferson Community and Technical College Public Profile, published by the American Association of Community Colleges (American Association of Community Colleges, 2020b). This source provided a baseline for the historic completion rate for developmental education at JCTC. Specifically, the data tracked developmental education completion over a period of six years for all students who first entered JCTC in the fall 2012 semester. Of the 2,981 students who first entered JCTC in fall 2012, 1,243, or 41.7%, required developmental mathematics education. When looking only at first time in College students, that rate increases to 49.3% who required developmental mathematics.

For first time at JCTC students referred to developmental mathematics, 886 students, or 71.3%, actually attempted a developmental mathematics course within six years, 275 students, or 22.1%, finished their developmental mathematics course sequence and became college ready, and only 160 students, or 12.9%, went on to successfully complete a college-level mathematics course. These rates take into account students assigned to developmental mathematics but never enrolled, so are not a measure of success for students who actually enrolled in a developmental mathematics course. When looking only at the 886 students who actually attempted a developmental mathematics course, 31.0% of students completed their developmental course sequence and became college ready, and 18.1% went on to successfully complete a college-level mathematics course. While the success rates improved when looking only at those who attempted a course, they are still very low. These numbers were similar to those found by Bailey et al. (2010). This data is summarized in Table 4.3 below.

**Research Question 1: Corequisite Success Compared to Historic Rate**

The first research question asked how success in the corequisite course compared to the historic rate at which students assigned to developmental mathematics completed a college-level mathematics course. This study compared the success rate in the corequisite course to the rate at which first-time JCTC students who enrolled in a developmental mathematics course in the fall 2012 semester went on to complete a college-level mathematics course. In both samples, students earning final course grades of A, B, or C in the college-level course were considered successful, while students earning grades D, E or W were considered unsuccessful.

A one-tailed, two proportion z-test was used to answer the first research question because this type of analysis is able to determine whether any significant difference exists between two population proportions (Triola, 2018). For the fall 2018/spring 2019 corequisite sample, the sample size was $n_1 = 459$ and the success rate was $\widehat{p_1} = 65.142\%$. For the fall 2012 sample, the sample size was $n_2 = 886$ and the success rate was $\widehat{p_2} = 18.1\%$.

The three assumptions to run a two proportion z-test were met for both samples (Triola, 2018). First, the proportions came from simple, random samples. While students were not enrolled randomly in either sample, it was assumed that there was enough randomization in overall student enrollment that this condition was met. Second, the samples were assumed independent given the amount of elapsed time between the semesters observed in the samples. Third, for each sample, $np \geq 5$ and $nq \geq 5$. For the corequisite sample, $n_1\widehat{p_1} = 299$ and $n_1\widehat{q_1} = 160$. For the fall 2012 sample, $n_2\widehat{p_2} = 160$ and $n_2\widehat{q_2} = 726$.

The hypothesis test was run using StatCrunch. The test was run at the $\alpha = 0.05$ significance level. The null hypothesis was that the difference in the proportion of students who passed the corequisite course and the proportion of students who enrolled in developmental mathematics and went on to pass a college-level course is zero. This can be written as $H_0: p_1 - p_2 = 0$. The alternative hypothesis was that the proportion of students who passed the corequisite course was greater than the proportion of students who enrolled in developmental mathematics and went on to pass a college-level course. This can be written as $H_1: p_1 > p_2$.

From the StatCrunch output, $z = 17.267$ and $p < 0.0001$. Since $p < 0.0001 < \alpha = 0.05$, the null hypothesis is rejected. There is statistical evidence that the pass rate in the corequisite course is greater than the college-level mathematics course completion rate for developmental mathematics students.

### Research Question 2: Predictors of Success

The second research question explored predictors of success in the corequisite course. This question was explored using multiple linear regression. Multiple linear regression was appropriate since this type of analysis shows the relationship between multiple independent variables and a dependent variable (Lewis-Beck & Lewis-Beck, 2016). SPSS was used to run the regression analysis. The dependent variable in the model was the final course grade (GRD). College-level course letter grades were converted to discrete numerical values (see Table 3.2). Failing grades and withdraw grades were given the same discrete value since they both represented an unsuccessful attempt at the course. No students in the sample audited the course or received an incomplete grade (I).

KMATH score was the primary tool used by JCTC to place students into the corequisite course. However, a small number of students in the data set were missing a KMATH score. For these students, the KCTCS placement chart (Table 3.1) was used to assign a KMATH score based on an equivalent placement test. In all cases, a median KMATH score was assigned from each range for which a student had a comparable placement score. Five students had no placement test data and were excluded from the regression analysis.

Other independent variables used in the regression analysis included ACT Math score (ACTM), high school cumulative GPA (GPA), and age (AGE). The analysis also included several other factors as indicator variables. The PELL indicator variable considered socioeconomic status. The URM indicator variable took into account race. The female indicator variable (FEM) considered a student's sex.

Differences in the semester a student took the course were accounted for using the FALL indicator variable. The campus at which the class was delivered was also considered to account for any differences that may exist between campuses. The DTCAMPUS indicator variable was used to distinguish whether a student took a class at the downtown campus, or the other two, nonurban, campuses.

Differences attributed to a student's major were also considered using the TRANSFER indicator variable. This indicator variable considered whether a student was an associate of science or associate of arts major or if they instead declared a terminal technical program as their major. All independent variable names and descriptions were summarized in Table 3.3.

A significant number of students were missing ACT or GPA data because it was either not collected or recorded by the College as part of the admissions process. In the case of the ACT, it is also possible that a student never took the ACT. Of the 454 students included in the regression analysis, 266 were missing an ACT Math score and 297 were missing a cumulative high school GPA. These numbers include 223 students who were missing both an ACT Math score and cumulative high school GPA.

To account for the missing ACTM and GPA data, several regression models were built to attempt to maximize the sample size as well as to determine the effect that variables had on the model. For each of the four models, course grade was the dependent variable. Several versions of each model were generated to test the effect of the various independent variables on the model. The variables were added in blocks, with each successive version of the model adding an additional independent variable block. The first block included a student's academic background: KMATH, GPA, and ACTM. The second block included a student's demographic characteristics: AGE, PELL, URM, and FEM. The third and final block included a student's enrollment data: FALL, DTCAMPUS, and TRANSFER. Analysis was provided on the performance of each model and how the inclusion of each additional block affected the model.

While an attempt was also made to include GED status as an indicator variable, it could not be because of too much missing data. This data would have been collected during the admissions process. Data reported in the sample included high school name or stated "GED" for students who earned a GED instead of a high school diploma. Less than half of students had high school/GED data, and only 19 students were reported in the sample as having earned a GED. This, along with missing data points for GPA and ACTM, would have given too small a sample size. Complicating things further, students who earned a GED did not have a GPA reported. In a trial run of the regression model that included GED, there was no significant relationship between a student earning a

GED and final course grade, so excluding it as a variable in the models should have minimal impact.

Likewise, an attempt was made to include a student's enrollment intensity, that is, part time or fulltime enrollment status. However, all students that had an ACTM score or GPA were part time students. This resulted in a meaningless variable in the regression and was thus excluded. As with GED, a trial run of the regression model was made to determine what impact, if any, there would be from excluding enrollment intensity. In the trial run, there was not a significant relationship between enrollment intensity and course grade, and including it had little impact on the relationship of the other variables with course grade. Excluding enrollment intensity as a variable may have little impact on the reliability of the model.

The first model included all the independent variables from Table 3.3 except for ACTM and GPA. The analysis included all 454 students. The second model included ACTM as an independent variable along with the others from the first model. This model included only 188 students in the analysis. The third model included GPA as an independent variable along with the others from the first model. This model included only 157 students in the analysis. The fourth and final model included all the variables from Table 3.3 and included only 114 students in the analysis.

A reliable regression model must satisfy several assumptions (Lewis-Beck & Lewis-Beck, 2016). First, there should be no specification error. This means that there should be a linear relationship between the dependent and independent variables, and that no relevant x's have been excluded and no irrelevant x is included. Each of the independent variables included theoretically have an impact on student success, so it was not believed that irrelevant variables were included in the model.  For each continuous independent variable, a scatterplot was generated to determine whether a linear relationship existed with course grade.  Figures 4.1, 4.2, 4.3, and 4.4 below show the relationships between KMATH, ACTM, GPA, and AGE with GRD. There seemed to be, at best, a very weak positive linear relationship between KMATH, ACTM, and AGE with GRD.  This could affect the reliability of the model. There was a moderate positive linear relationship between GPA and GRD.

Due to the nature of this study, there were certainly independent variables that possibly had a bearing on student success but were excluded from the model, such as problems with transition and incorporation into college (Tinto, 1988), self-efficacy and stress (Zajacova, Lynch, & Espenshade, 2005), and whether a student cared for dependents (Fralick, 1993). Due to this, the study was only able to determine correlation and not causation. Non-cognitive abilities or soft-skills, such as self-control, self-confidence, persistence, grit, optimism, and time-management, might also have had a bearing on student success, however, these are of lesser concern, in terms of specification error, since soft-skills are a part of the support course curriculum and because GPA captures, at least some, non-cognitive ability (*Indicators of future success: GPA and noncognitive skills*, 2015).

The second assumption that needed to be met was that there were no measurement errors. While this could not be confirmed case by case, it was assumed that there was no data entry errors into the student information system for student grades or student historical data and placement scores. As stated previously, there were issues with missing GPA, ACTM, and high school data, but it was assumed that there was no deliberate bias by records office staff to exclude this data.

Finally, several assumptions need to be met concerning the error term. First, the sum of the residuals needed to be zero. This was not a concern because ordinary least squares regression ensures that the residuals sum to zero. It was also assumed that the condition of no autocorrelation was met since it most frequently occurs with time-series variables. There was no reason to believe that there are any correlations between the error terms.

The variance of the residuals needed to be constant for all values of the independent variables. To verify this condition, plots were generated of the residuals versus the predicted values to ensure homoscedasticity, which is that the errors were evenly scattered and centered on zero across all predicted values of the independent variable. Lastly, the residuals needed to have a normal distribution. This condition was verified by generating a histogram of the residuals to determine whether they were roughly normal and centered at zero. These final two assumptions were verified only for the best performing regression model and are included below with the results for Model 4.

According to Lewis-Beck and Lewis-Beck (2016), there are varying views on how serious any violations to these assumptions are for the regression model. They noted that some assumptions are less affected by violations than the others are. Violations of homoscedasticity are relatively minor, while violations of the normality assumption can be ignored completely if the sample size is large enough to apply the Central-Limit Theorem, which this data set was.

**Model 1:** The regression analysis for model 1 included all independent variables except for ACTM and GPA. For the first iteration of model 1, KMATH was used as the only independent variable. It was found, on average, that a one-point increase in KMATH score was associated with a 0.035-point increase in course grade, which was significant at the 5% level. KMATH score explained only 1.3% of the variance in course grade.

In model 1b, the student demographic variable block was added to the model. This block controlled for AGE, PELL, URM, and FEM. All variables in the model were significant at the 5% level except for PELL. Adding the student demographic block to the model had no effect on the significance of KMATH or its relationship with course grade. On average, a one-point increase in KMATH score was associated with a 0.035-point increase in course grade. A one-year increase in age was associated with a 0.021-point increase in course grade. On average, underrepresented minority students received course grades that were 0.441 points less than nonminority students did. Female students received course grades that were, on average, 0.314 points more than male students and students with unknown gender were. Students who received a Pell Grant earned course grades that were 0.221 points less than students who did not, but again, this result was not significant at the 5% level. Together, KMATH score, age, socioeconomic status, race, and sex explained 5.8% of the variance in course grade. Adding the student demographic variable block resulted in a model that performed better than the previous model. The adjusted $r^2$ increased while the average residual error decreased. Despite performing better, the model still explained very little of the variance of course grade.

The final iteration of the model added the enrollment data block: DTCAMPUS, TRANSFER, and FALL. This block controlled for the campus at which a student took the class, the student's major, and the semester in which the class was taken. Adding the enrollment data block resulted in FEM no longer being significant at the 5% level but had no effect on the significance of KMATH or the other variables in the demographics block. In this model, KMATH, AGE, URM, and DTCAMPUS were all statistically significant at the 5% level, while PELL, FEM, FALL, and TRANSFER were not. The relationship to course grade was about the same for KMATH. A one-point increase in KMATH score was associated with a 0.034-point increase in course grade. The relationship between AGE and course grade decreased slightly. A one-year increase in age was associated with a 0.018-point increase in course grade. The relationship between PELL and course grade increased slightly, with Pell Grant recipients receiving course grades that were 0.184 points less than students who did not receive a Pell Grant. The relationship between course grade and underrepresented minority status also increased slightly, with underrepresented minority students receiving course grades that were 0.393 points less than nonminority students were. The relationship between FEM and course grade decreased. On average, female students received course grades that were 0.298 points higher than male students and students with unknown gender did. Students who took the corequisite class in the fall semester received course grades that were, on average, 0.025 points less than students who took the class in the spring semester were. Grades at the downtown campus were 0.365 points less than at the nonurban campuses. Students whose majors were coded as TRANSFER earned course grades that were 0.253 points higher than students with other majors were.

The third model was the best performing model, with the highest adjusted $r^2$ and lowest average residual error. Together, KMATH, AGE, PELL, URM, FEM, FALL, DTCAMPUS, and TRANSFER accounted for 7.5% of the variance in course grade. The regression model can be written: $\widehat{grd_i} = 1.464 + 0.034KMATH_i + 0.018AGE_i - 0.184PELL_i - 0.393URM_i + 0.298FEM_i + 0.025FALL_i - 0.365DTCAMPUS_i + 0.253TRANSFER_i$. Also note, VIF (Variance Inflation Factors) measures were checked for the final model to determine any issues with multicollinearity. Judging from the VIF measures, there does not appear to be any multicollinearity issues with any of the variables. The results of the regression analysis for Model 1 are shown in Table 4.4.

**Model 2:** The regression analysis for model 2 included all independent variables except for GPA. Due to missing ACT data, not all students were included, and the sample size was much smaller than model 1. The number of students included in the analysis was 188. The academic background data block was first inputted into the regression model and included KMATH and ACTM. In this model, neither KMATH nor ACTM were significant at the 5% level. It was found, on average, that a one-point increase in KMATH score was associated with a 0.021-point increase in course grade. The relationship between ACTM and course grade was similar, but slightly higher, with a one-point increase in ACTM score associated with a 0.035-point increase in course grade. KMATH score and ACTM score, together, explained 1.2% of the variance in course grade.

The second iteration of the model added the demographic variable block to the model. Adding this block to the model had no effect on the significance of KMATH and ACTM, and only AGE and FEM were significant at the 5% level. The slope of the relationship between KMATH and course grade increased, while the slope of the relationship between ACTM and course grade decreased. On average, a one-point increase in KMATH score was associated with a 0.035-point increase in course grade. A one-point increase in ACTM score was associated with a 0.011-point increase in course grade. A one-year increase in age was associated with a 0.071-point increase in course grade. On average, students who received a Pell Grant earned course grades that were 0.338 points less than students who did not. Underrepresented minority students received course grades that were 0.334 points less than nonminority students did. Female students received course grades that were, on average, 0.584 points more than male students and students with unknown gender were. Together, KMATH, ACTM, AGE, PELL, URM, and FEM explained 10.1% of the variance in course grade. Adding the student demographic variable block resulted in a model that performed better than the previous model. The adjusted $r^2$ increased while the average residual error decreased. The model also explained nearly 10 times the amount of variance in course grade compared to the previous model.

The final iteration of the model added the enrollment data block. This block controlled for the campus at which a student took the class, the student's major, and the semester in which the class was taken. Adding the enrollment data block had no effect on the significance of the variables compared to the previous model. In this model, only AGE, FEM, and TRANSFER were statistically significant at the 5% level. The relationship between KMATH and course grade decreased compared to the previous model. A one-point increase in KMATH score was associated with a 0.028-point increase in course grade. The relationship between ACTM and course grade increased, with a one-point increase in ACTM score associated with a 0.026-point increase in course grade. The relationship between AGE and course grade decreased slightly. A one-year increase in age was associated with a 0.069-point increase in course grade. The relationship between PELL and course grade increased, with Pell Grant recipients receiving course grades that were 0.283 points less than students who did not receive a Pell Grant. The relationship between course grade and underrepresented minority status decreased slightly, with underrepresented minority students receiving course grades that were 0.348 points less than nonminority students did. The relationship between FEM and course grade decreased. On average, female students received course grades that were 0.503 points higher than male students and students with unknown gender did. Students who took the corequisite class in the fall semester received course grades that were, on average, 0.084 points less than students who took the class in the spring semester. Grades at the downtown campus were 0.180 points less than at the nonurban campuses. Students with a TRANSFER major earned course grades that were 0.465 points higher than students with other majors were.

The third model was the best performing model, with the highest adjusted $r^2$ and lowest average residual error. Together, KMATH, ACTM, AGE, PELL, URM, FEM, FALL, DTCAMPUS, and TRANSFER accounted for 12.8% of the variance in course grade. The regression model can be written: $\widehat{grd_i} = -0.267 + 0.028KMATH_i + 0.026ACT_i + 0.069AGE_i - 0.283PELL_i - 0.348URM_i + 0.503FEM_i + 0.084FALL_i - 0.180DTCAMPUS_i + 0.465TRANSFER_i$. Also note, VIF measures were checked for the final mode to determine any issues with multicollinearity. Judging from the VIF measures, there does not appear to be any multicollinearity issues with any of the variables. The results of the regression analysis for Model 2 are shown in Table 4.5.

**Model 3:** The regression analysis for the third model swapped GPA for ACTM in the academic background data block and included all other covariates. Due to missing GPA data, not all students in the corequisite were included in the analysis. The number of students included in the analysis was 157. The first iteration of the model included the academic background data block, KMATH and ACTM. In this model, only GPA was significant at the 5% level. On average, a one-point increase in KMATH score was associated with a 0.037-point increase in course grade. The relationship between GPA and course grade was much stronger, with a one-point increase in GPA associated with a 0.692-point increase in course grade. KMATH score and GPA, together, explained 12.2% of the variance in course grade.

The demographic variable block was added to the second iteration of the model. Adding this block had no effect on the significance of KMATH or GPA. Most of the variables in this iteration were significant at the 5% level: GPA, AGE, PELL, and FEM. The slope of the relationship between KMATH and course grade decreased, while the slope of the relationship between GPA and course grade increased. On average, a one-point increase in KMATH score was associated with a 0.029-point increase in course grade. A one-point increase in GPA was associated with a 0.782-point increase in course grade. A one-year increase in age was associated with a 0.091-point increase in course grade. On average, students who received a Pell Grant earned course grades that were 0.608 points less than students who did not. Underrepresented minority students received course grades that were 0.283 points less than nonminority students did. Female students received course grades that were, on average, 0.682 points more than male students and students with unknown gender did. Together, KMATH, GPA, AGE, PELL, URM, and

FEM explained 24.3% of the variance in course grade. This was the best performing model yet, with the highest adjusted $r^2$ and the lowest average residual error.

The final iteration of the model added the enrollment data block: FALL, DTCAMPUS, and TRANSFER. Adding the enrollment data block had no effect on the significance of the variables compared to the previous model. In this model, GPA, AGE, PELL, and FEM statistically significant at the 5% level. The relationships between KMATH, GPA, and AGE with course grade all decreased compared to the previous model. On average, a one-point increase in KMATH score was associated with a 0.027-point increase in course grade. A one-point increase in GPA was associated with a 0.780-point increase in course grade. A one-year increase in age was associated with a 0.088-point increase in course grade. The relationships between PELL, URM, and FEM with course grade all increased some. Pell Grant recipients received course grades that were 0.556 points less than students who did not receive a Pell Grant. Underrepresented minority students received course grades that were 0.239 points less than nonminority students did. On average, female students received course grades that were 0.685 points higher than male students and students with unknown gender. Students who took the corequisite class in the fall semester received course grades that were 0.074 points more than students who took the class in the spring semester. Grades at the downtown campus were 0.269 points less than at the nonurban campuses. Students with a TRANSFER major earned course grades that were 0.005 points less than students with other majors were. This model explained 25.0% of the variance in course grade but had a lower adjusted $r^2$ and higher standard error of regression compared to the previous model.

The best performing iteration for Model 3 was the second iteration, which did not include the student enrollment data block. It had the highest adjusted $r^2$ and the lowest average residual error while accounting for nearly the same variance in course grade as the third iteration that included the student enrollment block. The regression model for Model 3b can be written: $\widehat{grd_i} = -2.409 + 0.029KMATH_i + 0.782GPA_i + 0.091AGE_i - 0.608PELL_i - 0.283URM_i + 0.682FEM_i$. Also note, VIF measures were checked for the final mode to determine any issues with multicollinearity. Judging from the VIF measures, there does not appear to be any multicollinearity issues with any of the variables. The results of the regression analysis for Model 3 are shown in Table 4.6.

**Model 4:** The regression analysis for the final model included all independent variables. Accounting for missing GPA and ACTM data, the number of students included in the analysis was 114. The first iteration of the model included the academic background data block: KMATH, GPA, and ACTM. In this model, only GPA was significant at the 5% level. On average, a one-point increase in KMATH score was associated with a 0.018-point increase in course grade. The relationship between GPA and course grade was sizeable. A one-point increase in GPA was associated with a 0.883-point increase in course grade. For ACTM, a one-point increase in score was associated with a 0.126-point increase in course grade. KMATH, ACTM, and GPA, together, explained 17.5% of the variance in course grade.

The second iteration of the model included the demographic variable block. Adding this block had no effect on the significance of KMATH, GPA, or ACTM. Only GPA and PELL were significant at the 5% level in this model. The slope of the relationships between KMATH, GPA, and ACTM with course grade all decreased slightly. On average, a one-point increase in KMATH score was associated with a 0.017-point increase in course grade. A one-point increase in GPA was associated with a 0.862-point increase in course grade. A one-point increase in ACTM score was associated with a 0.115-point increase in course grade. For the new variables, starting with AGE, a one-year increase in age was associated with a 0.161-point increase in course grade. On average, students who received a Pell Grant earned course grades that were 0.599 points less than students who did not. Underrepresented minority students received course grades that were 0.237 points less than nonminority students did. Female students received course grades that were, on average, 0.492 points more than male students and students with unknown gender did. Together, the academic background and demographic variable blocks explained 26.2% of the variance in course grade. This model performed better than any of the previous models, with the highest adjusted $r^2$ and the lowest average residual error.

The final iteration of the model added the enrollment data block and so included all the independent variables considered for this study. Adding the enrollment data block had no effect on the significance of the variables compared to the previous model. As with the previous iteration, only GPA and PELL were statistically significant at the 5% level. The relationships between KMATH, GPA, AGE, and FEM with course grade all decreased compared to the previous model, while the relationships between ACTM, PELL, and URM increased. On average, a one-point increase in KMATH score was associated with a 0.015-point increase in course grade. A one-point increase in GPA was associated with a 0.855-point increase in course grade. A one-point increase in ACTM score was associated with a 0.117-point increase in course grade. For AGE, a one-year increase was associated with a 0.157-point increase in course grade. Pell Grant recipients received course grades that were 0.587 points less than students who did not. Underrepresented minority students received course grades that were 0.220 points less than nonminority students were. On average, female students received course grades that were 0.446 points higher than male students and students with unknown gender did. Students who took the corequisite class in the fall semester received course grades that were 0.017 points more than students who took the class in the spring semester. Grades at the downtown campus were 0.061 points less than at the nonurban campuses. Students with a TRANSFER major earned course grades that were 0.269 points higher than students with other majors were. While this model explained 27.1% of the variance in course grade, more than the previous, this model did not perform as well as it had a lower adjusted $r^2$ and higher standard error of regression. This was similar to the outcomes observed in Model 3 and throws the value of the enrollment data block into question.

The best performing iteration for Model 4, in terms of the highest adjusted $r^2$ and the lowest average residual error, was the second iteration, which only included the academic background and demographic data blocks. This model accounted for 26.2% of the variance in course grade. This model also performed better than any of the previous iterations for Models 1, 2, 3, and 4. The regression model for Model 4b can be written: $\widehat{grd_i} = -5.499 + 0.017KMATH_i + 0.862GPA_i + 0.115ACT_i + 0.161AGE_i - 0.599PELL_i - 0.237URM_i + 0.492FEM_i$. Also note, VIF measures were checked for the final mode to determine any issues with multicollinearity. Judging from the VIF measures, there does not appear to be any multicollinearity issues with any of the variables. The results of the regression analysis for Model 4 are shown below in Table 4.7.

For the best performing model, assumptions about the error term were verified. The residuals were plotted versus the predicted values to ensure homoscedasticity. This result is shown below in Figure 4.5. From the plot, it seemed there was near constant variance and there is evidence of homoscedasticity. In addition, a histogram of the residuals was generated to determine whether they were roughly normal and centered at zero. This result is shown below in Figure 4.6. The residuals appeared to be somewhat skewed and did not follow the normal curve. As stated previously, since the central limit theorem can be applied, this is not a serious violation (Lewis-Beck & Lewis-Beck, 2016).

As a note, the final model was also run with students who withdrew from the course removed. It is possible that students who withdraw before the end of the semester are different than those who persist to the end and receive a failing grade. Then again, it is certainly possible that a failing student "disappeared" sometime during the semester without withdrawing and thus did not persist either. In any case, removing the W students decreased the sample size of the final model from 114 to 108 students. The resulting model accounted for just over one percentage point more of the variance with course grade. There was little change to the adjusted $r^2$ and the average residual error. The slopes of the relationships between the independent variables with course grade were similar to when the W students were included, however, removing the W students did cause age to become significant and socioeconomic status to become not significant.

**Summary of the Regression Analysis:** Of all the variables, high school GPA had the strongest relationship with course grade. It was significant at the 5% level in every iteration in which it was included. When adding GPA as a variable in Model 3, the first iteration outperformed every other previous model in terms of adjusted $r^2$ and average residual error, even without including other variables besides KMATH. In the best performing model, a 0.862-point increase in GPA was associated with a one-point increase in course grade, almost a one-to-one relationship.

The KYOTE math placement test proved to be a very poor predictor of final course grade. First, the relationship with course grade was only statistically significant in the first model, though it is possible that the reduced sample size in subsequent models caused KMATH to longer be significant. Disregarding significance, the relationship between KMATH and course grade was very weak. In the best performing regression model, a one-point increase in KMATH score was associated with only a 0.017-point increase in course grade. This equates to only about a quarter of a letter grade difference in the average predicted grades for the lowest and highest placed corequisite students. The highest slope observed between KMATH and course grade was 0.037 in Model 3a.

ACTM had a stronger relationship with course grade than did KMATH, but it was not significant in any of the iterations in which it was included. Comparing Models 1 and 2, adding ACTM as a variable did improve the model's performance. Comparing Models 2 and 4, which both included ACTM, ACTM was a better predictor when GPA was also included as a variable than when it was not. In the best performing regression model, a one-point increase in ACTM score was associated with a 0.115-point increase in course grade. With the corequisite level equating to an ACTM range of 14-18 on the KCTCS placement chart, this means that one could expect roughly a half a letter grade difference in average predicted course grades for the highest and lowest scores.

Age was statistically significant in Models 1, 2, and 3, but not Model 4. It seems likely that the decreased sample size of Model 4 affected the significance of this variable. In almost every instance, except for Model 1, age was a better predictor of course grade than KMATH and ACTM. On average, older students performed better than younger students in the corequisite course. The common notion in mathematics education that "you must use it or lose it" did not apply here. The best performing regression model also had the highest slope of the relationship between age and course grade. In that model, on average, a one-year increase in age was associated with a 0.161-point increase in course grade.

Socioeconomic status was the variable with the second strongest relationship with course grade. While not significant at the 5% level in every iteration, it was usually significant in models that included GPA, and was significant in the best performing model. In the best performing model, students who received Pell Grants received course grades that were 0.686-points less than students who did not.

The results showed underrepresented minority students to be at a disadvantage compared to non-underrepresented minority students. In every iteration in which URM was included as a variable, underrepresented minority students received course grades that were less than that of their non-minority peers. The difference ranged from 0.220 points less to 0.441 points less on the high end. In the best performing regression model, underrepresented minority students earned course grades that were 0.237 points less than non-underrepresented minority students. URM was only statistically significant at the 5% level in Model 1, possibly due to the decreased sample sizes in the subsequent models.

The analysis showed that female students had an advantage over male students, receiving higher course grades in every iteration. The average difference in course grades between male and female students ranged from 0.298 to 0.685 points in the various models. In the best performing regression model, female students earned course grades that were 0.492 points higher than male students and students with unknown gender. FEM was statistically significant in five out of the eight models in which it was included. It was not significant in either of the iterations of Model 4, possibly because of the sample size.

The variables in the enrollment data block—FALL, DTCAMPUS, and TRANSFER—had highly mixed results. These variables typically had very high p-values and were not statistically significant at the 5% level. The slopes of their relationships with course grade were also highly varied. In Models 3 and 4, including this variable block resulted in poorer model performance, with decreased adjusted $r^2$ and increased average residual error, compared to other models.

The semester in which a student took the corequisite course had a negligible effect on course grade. The average difference in course grade between the fall and spring semester was less than one-tenth of a point in all iterations. The FALL variable was never statistically significant in any model.

There was a small difference in course grade depending on which campus a student took the corequisite course. Students at the downtown campus received course grades that were less than students at the non-urban campuses, but the difference was small especially when ACTM was also considered in the model. At the high end in Model 1, students at the downtown campus received course grades that 0.365 points less than the other campuses, and only 0.061 points less on the lower end in Model 4. In the only other model that included ACTM and DTCAMPUS, Model 2, students at the downtown campus earned course grades that were only 0.180 points less than the other two campuses. DTCAMPUS was only statistically significant in Model 1.

Lastly, students who declared a transfer major earned higher course grades than students in technical majors, though this varied quite a bit. In Model 2, transfer students earned course grades that were, on average, 0.465 points higher than technical students, while the result was in the neighborhood of 0.25 in Models 1 and 4. In Model 3, transfer students earned course grades that were 0.005 points less than technical students, which seems to be an outlier considering the other results. The TRANSFER variable was only statistically significant at the 5% level in Model 2.

**Research Question 3: Corequisite vs. Standalone**

The final research question sought to determine how students in the corequisite course performed compared to their college-ready peers in the standalone course. To attempt to establish a causal relationship, propensity score matching was used to generate two comparison groups. The propensity score is defined as the conditional probability of a student placing into the corequisite course given various covariates (Rosenbaum & Rubin, 1983). Using propensity scores allowed for a comparison of students in the corequisite course to similar students enrolled in the standalone course. Comparing similar students in each group gave more confidence to whether the corequisite course had an effect on student outcomes.

A logit model was used to generate propensity scores. The dependent variable for the logit model was enrollment type, with enrollment in the corequisite course coded as 1 and enrollment in the standalone course coded as 0. The covariates used in the model were ones used in the multiple regression for question 2, including: ACTM, GPA, PELL, URM, AGE, and FEM. KMATH was not included because too few students in the standalone course had recorded KMATH, ACTM, and GPA scores, inclusive, because KMATH score was not required for placement into the standalone course if a student had a sufficient ACTM score. A better sample size was achieved excluding KMATH as a covariate. Students with missing data were excluded from the model. The sample included 86 students enrolled in the standalone course and 115 students enrolled in the corequisite course. Figure 4.7 shows the overlap in propensity scores for the students in the corequisite compared to the students in the standalone. While the interquartile range of the corequisite propensity scores is greater than that of the standalone propensity scores, the medians are similar in value and there is certainly overlap between the scores.

The propensity scores were then used to match students in the corequisite course to students in the standalone. Students with similar scores had roughly the same probability of placing into the corequisite course. A "nearest neighbor within calipers" approach was used for direct matching with replacement, with the caliper width set to 0.05 (Oakes & Johnson, 2006). Each corequisite propensity score was matched to the standalone propensity score closest to it, but within 0.05. After matching, a standalone propensity score was replaced in the sample and could be matched to another corequisite propensity score. Each score in the corequisite sample had a standalone nearest neighbor, but only about half of the standalone scores were used as a nearest neighbor. The matched samples included 115 students in the corequisite and 45 students in the standalone course.

A summary of the demographics of the two samples is shown in Table 4.8. The standalone course matched sample was 40% underrepresented minority students and 71.1% female, while 62.2% received a Pell Grant. The corequisite course matched sample was 49.6% underrepresented minority students and 72.2%% female, while 67.8% received a Pell Grant.

Descriptive statistics were also run for the continuous variables in each sample. Table 4.9 shows a summary of the descriptive statistics for each sample. While course grade was not included in the logit model, it is included here with the descriptive statistics as it was used later in the analysis. The mean value of each covariate in the standalone sample was similar to that of the corequisite sample. The standalone sample had a mean GPA of 2.953 while the mean of the corequisite sample GPA was 2.899. The mean ACTM score of the standalone sample was 16.978 compared to a mean of 16.313 in the corequisite sample. Lastly, the mean age of the standalone sample was 18.467 years while the mean of the corequisite sample was 18.809 years.

A desired outcome of propensity score matching is a reduction in the standardized difference[3] between the standalone and corequisite sample for each covariate (D'Agostino Jr., 1998). Using data from the full samples in Table 4.2 and data from the matched samples in Table 4.9, Table 4.10 shows the standardized difference for each covariate. The standardized differences for both GPA and ACTM dropped significantly, while the standardized difference for AGE unfortunately increased slightly.

[3] The mean difference as a percentage of the average standard deviation: $100(\bar{x}_1 - \bar{x}_2) \div \sqrt{(s_1^2 + s_2^2) \div 2}$, where for each covariate $\bar{x}_1$ and $\bar{x}_2$ are the means for the standalone and corequisite samples, respectively, and $s_1^2$ and $s_2^2$ are the variances for the standalone and corequisite samples, respectively.

Using the matched samples, course grades were compared between the standalone course and the corequisite course using a two-sample t-test. The assumptions for this test were met as the samples were independent, and propensity score matching simulated a simple random sample (Triola, 2018). In addition, since the sample size for each was larger than 30 students, there were no issues with consideration for normality.

The null hypothesis was that the difference in mean courses grades between the standalone sample and corequisite course was zero. This could be written as $H_0: \mu_1 - \mu_2 = 0$, where $\mu_1$ and $\mu_2$ were the mean course grades of the standalone and corequisite course, respectively. The null hypothesis was that the difference in mean courses grades between the standalone sample and corequisite course was not zero. This could be written as $H_0: \mu_1 - \mu_2 \neq 0$.

The hypothesis test was run using StatCrunch, with the mean course grade and standard deviation for each sample $\bar{x}_1 = 1.82$ and $s_1 = 1.482$, and $\bar{x}_1 = 1.97$ and $s_2 = 1.486$, respectively (see Table 4.9). The test was run at the $\alpha = 0.05$ significance level. From the StatCrunch output, $t = -0.575$ and $p = 0.5668$. Since $p = 0.5668 \gg \alpha = 0.05$, the null hypothesis was not rejected. There was not sufficient evidence to support the claim that there was a difference in course grade between the standalone and corequisite courses.

**Summary**

This section provided an analysis of the data in an attempt to answer the three research questions for this study. The analysis for the first question relied on data from the fall 2012 semester from the Jefferson Community and Technical College Voluntary

Framework of Accountability Public Profile published by the American Association of Community Colleges. It tracked the progression of developmental mathematics students from their developmental mathematics course sequence to their final college-level course. The average rate at which these students completed a college-level course was compared to the average rate at which students passed the corequisite course using a two-proportion z-test. There was evidence to suggest that students completed the corequisite course at a higher rate than the developmental mathematics sequence.

The second research question was explored using a multiple linear regression using covariates from the corequisite course data set. Due to large numbers of missing data—specifically high school GPA and ACT mathematics score—multiple models were generated to try to maximize the sample size while observing the interaction between variables. The best model included high school GPA, ACT mathematics score, age, sex, and socioeconomic status. The two variables with the greatest impact on course grade were high school GPA and socioeconomic status, specifically whether a student received a Pell Grant.

To answer the third and final research question, propensity score matching was first used to generate comparable samples in the corequisite and standalone courses since students were not placed by random assignment. Matching students using propensity scores allowed a comparison of students in the corequisite course who were similar to those in the standalone course. This gave more confidence in the ability to establish a causal relationship between the corequisite course and grade outcome. A two-sample t-test was used to compare the mean course grades of the corequisite and standalone matched samples. However, there was not sufficient evidence to conclude any difference in course grade between the two.

Table 4.1 Summary of Demographics and Pass Rates for Fall 2018/Spring 2019

| | Overall Sample | Corequisite Sample | Standalone Sample |
|---|---|---|---|
| N | 723 | 459 | 264 |
| A/B/C Pass Rate | 66.805% | 65.142% | 69.697% |
| D/E/W Rate | 33.195% | 34.858% | 30.303% |
| Enrolled Fall Semester | 57.399% | 54.248% | 62.879% |
| Enrolled Spring Semester | 42.600% | 45.752% | 37.121% |
| Underrepresented Minority | 54.772% | 61.438% | 43.181% |
| Non-Underrepresented Minority | 45.228% | 38.562% | 56.818% |
| Pell Grant Eligible | 70.954% | 73.638% | 66.288% |
| Not Pell Grant Eligible | 29.046% | 26.362% | 33.712% |
| Female | 68.050% | 70.588% | 63.636% |
| Male | 29.184% | 26.580% | 33.712% |
| Undisclosed Gender | 2.766% | 2.832% | 2.652% |
| Part-Time Student | 58.645% | 61.438% | 53.788% |
| Fulltime Student | 41.355% | 38.562% | 46.212% |
| Course Taken at Downtown Campus | 71.508% | 75.599% | 64.394% |
| Course Taken at Southwest Campus | 22.960% | 20.261% | 27.652% |
| Course Taken at Shelby County Campus | 5.533% | 4.139% | 7.955% |
| Students with Associate in Science Major | 21.992% | 23.747% | 18.939% |
| Students with Associate in Arts Major | 44.813% | 43.355% | 47.348% |
| Students with Other Major | 33.195% | 32.898% | 33.712% |

Table 4.2 Descriptive Statistics for the Overall, Corequisite, and Standalone Samples

| | Variable | n | Minimum | Maximum | Mean | SD |
|---|---|---|---|---|---|---|
| Overall Sample | GRD | 723 | 0 | 4 | 2.11 | 1.498 |
| | KMATH | 581 | 3 | 29 | 12.69 | 5.584 |
| | ACTM | 352 | 11 | 28 | 17.41 | 2.987 |
| | GPA | 250 | 1.43 | 4.00 | 2.81 | 0.641 |
| | AGE | 723 | 18 | 75 | 24.79 | 8.971 |
| Corequisite Sample | GRD | 459 | 0 | 4 | 2.06 | 1.498 |
| | KMATH | 432 | 3 | 28 | 11.43 | 4.618 |
| | ACTM | 188 | 13 | 26 | 16.27 | 2.039 |
| | GPA | 159 | 1.43 | 3.86 | 2.74 | 0.654 |
| | AGE | 459 | 18 | 68 | 25.50 | 9.254 |
| Standalone Sample | GRD | 264 | 0 | 4 | 2.20 | 1.496 |
| | KMATH | 149 | 4 | 29 | 16.34 | 6.483 |
| | ACTM | 164 | 11 | 28 | 18.73 | 3.348 |
| | GPA | 91 | 1.65 | 4.00 | 2.94 | 0.600 |
| | AGE | 264 | 18 | 75 | 23.57 | 8.330 |

Table 4.3 Summary of fall 2012 Developmental Mathematics Student Success

| Cohort | n | Finished Dev. Math Courses and Became College Ready | Completed College Math Course |
|---|---|---|---|
| First Time at JCTC Students Referred to Dev. Math | 1243 | 275<br>22.1% | 160<br>12.9% |
| Referred to Dev. Math and Enrolled in Course | 886 | 275<br>31.0% | 160<br>18.1% |

Table 4.4 Multiple OLS Regression Results for Model 1

| | Model 1a | Model 1b | Model 1c | VIF (Final Model Only) |
|---|---|---|---|---|
| **KMATH** | 0.035*<br>(0.014) | 0.035*<br>(0.015) | 0.034*<br>(0.015) | 1.080 |
| **AGE** | | 0.021*<br>(0.008) | 0.018*<br>(0.008) | 1.132 |
| **PELL** | | -0.221<br>(0.166) | -0.184<br>(0.167) | 1.153 |
| **URM** | | -0.441*<br>(0.148) | -0.393*<br>(0.150) | 1.151 |
| **FEM** | | 0.314*<br>(0.153) | 0.298<br>(0.153) | 1.037 |
| **FALL** | | | 0.025<br>(0.137) | 1.007 |
| **DTCAMPUS** | | | -0.365*<br>(0.165) | 1.082 |
| **TRANSFER** | | | 0.253<br>(0.151) | 1.080 |
| **Intercept** | 1.650<br>(0.182) | 1.332<br>(0.331) | 1.464<br>(0.354) | |
| **$r^2$** | 0.013 | 0.058 | 0.075 | |
| **Adjusted $r^2$** | 0.011 | 0.048 | 0.058 | |
| **Standard Error of Regression** | 1.489 | 1.461 | 1.453 | |

*Note*: N = 454; Standard error in parentheses; *$p < 0.05$

Table 4.5 Multiple OLS Regression Results for Model 2

| | **Model 2a** | **Model 2b** | **Model 2c** | **VIF (Final Model Only)** |
|---|---|---|---|---|
| **KMATH** | 0.021 (0.023) | 0.035 (0.023) | 0.028 (0.023) | 1.397 |
| **ACTM** | 0.035 (0.060) | 0.011 (0.059) | 0.026 (0.059) | 1.345 |
| **AGE** | | 0.071* (0.028) | 0.069* (0.028) | 1.061 |
| **PELL** | | -0.338 (0.235) | -0.283 (0.239) | 1.215 |
| **URM** | | -0.334 (0.221) | -0.348 (0.222) | 1.157 |
| **FEM** | | 0.584* (0.234) | 0.503* (0.235) | 1.082 |
| **FALL** | | | 0.084 (0.210) | 1.023 |
| **DTCAMPUS** | | | -0.180 (0.245) | 1.109 |
| **TRANSFER** | | | 0.465* (0.211) | 1.038 |
| **Intercept** | 1.212 (0.885) | -0.049 (1.097) | -0.267 (1.105) | |
| **$r^2$** | 0.012 | 0.101 | 0.128 | |
| **Adjusted $r^2$** | 0.001 | 0.071 | 0.084 | |
| **Standard Error of Regression** | 1.479 | 1.426 | 1.416 | |

*Note*: N = 188; Standard error in parentheses; $*p < 0.05$

Table 4.6 Multiple OLS Regression Results for Model 3

| | **Model 3a** | **Model 3b** | **Model 3c** | **VIF (Final Model Only)** |
|---|---|---|---|---|
| **KMATH** | 0.037<br>(0.023) | 0.029<br>(0.023) | 0.027<br>(0.023) | 1.180 |
| **GPA** | 0.692*<br>(0.178) | 0.782*<br>(0.184) | 0.780*<br>(0.185) | 1.271 |
| **AGE** | | 0.091*<br>(0.033) | 0.088*<br>(0.033) | 1.241 |
| **PELL** | | -0.608*<br>(0.268) | -0.556*<br>(0.276) | 1.288 |
| **URM** | | -0.283<br>(0.236) | -0.239<br>(0.242) | 1.258 |
| **FEM** | | 0.682*<br>(0.010) | 0.685*<br>(0.268) | 1.171 |
| **FALL** | | | 0.074<br>(0.219) | 1.031 |
| **DTCAMPUS** | | | -0.269<br>(0.248) | 1.121 |
| **TRANSFER** | | | -0.005<br>(0.221) | 1.032 |
| **Intercept** | -0.539<br>(0.526) | -2.409<br>(0.992) | -2.230<br>(1.033) | |
| **$r^2$** | 0.122 | 0.243 | 0.250 | |
| **Adjusted $r^2$** | 0.111 | 0.213 | 0.204 | |
| **Standard Error of Regression** | 1.428 | 1.343 | 1.351 | |

*Note*: N = 157; Standard error in parentheses; $*p < 0.05$

Table 4.7 Multiple OLS Regression Results for Model 4

| | **Model 4a** | **Model 4b** | **Model 4c** | **VIF (Final Model Only)** |
|---|---|---|---|---|
| **KMATH** | 0.018<br>(0.027) | 0.017<br>(0.027) | 0.015<br>(0.027) | 1.360 |
| **GPA** | 0.883*<br>(0.217) | 0.862*<br>(0.222) | 0.855*<br>(0.224) | 1.151 |
| **ACTM** | 0.126<br>(0.085) | 0.115<br>(0.084) | 0.117<br>(0.084) | 1.324 |
| **AGE** | | 0.161<br>(0.082) | 0.157<br>(0.084) | 1.077 |
| **PELL** | | -0.599*<br>(0.281) | -0.587*<br>(0.291) | 1.203 |
| **URM** | | -0.237<br>(0.266) | -0.220<br>(0.271) | 1.192 |
| **FEM** | | 0.492<br>(0.290) | 0.446<br>(0.296) | 1.149 |
| **FALL** | | | 0.017<br>(0.255) | 1.056 |
| **DTCAMPUS** | | | -0.061<br>(0.283) | 1.101 |
| **TRANSFER** | | | 0.269<br>(0.255) | 1.037 |
| **Intercept** | -2.897<br>(1.372) | -5.499<br>(2.241) | -5.480<br>(2.309) | |
| $\mathbf{r^2}$ | 0.175 | 0.262 | 0.271 | |
| **Adjusted** $\mathbf{r^2}$ | 0.153 | 0.214 | 0.200 | |
| **Standard Error of Regression** | 1.368 | 1.318 | 1.329 | |

*Note*: N = 114; Standard error in parentheses; $*p < 0.05$

Table 4.8 Summary of Demographics for Propensity Score Matched Samples

| | Standalone Matched Sample | Corequisite Matched Sample | Standalone Full Sample | Corequisite Full Sample |
|---|---|---|---|---|
| n | 45 | 115 | 264 | 459 |
| Underrepresented Minority | 40.0% | 49.6% | 43.2% | 61.4% |
| Female | 71.1% | 72.2% | 63.6% | 70.6% |
| Pell Grant Recipient | 62.2% | 67.8% | 66.3% | 73.6% |

Table 4.9 Descriptive Statistics for Propensity Score Matched Samples

| | Standalone | | Corequisite | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| GRD | 1.82 | 1.482 | 1.97 | 1.486 |
| GPA | 2.95 | 0.558 | 2.90 | 0.596 |
| ACTM | 16.98 | 2.083 | 16.31 | 1.698 |
| AGE | 18.47 | 0.694 | 18.81 | 1.544 |

Table 4.10 Standardized Differences Between Overall and Matched Samples

| | Full Samples Standardized Difference | Matched Samples Standardized Difference |
|---|---|---|
| GPA | 31.87% | 8.66% |
| ACTM | 88.75% | 35.32% |
| AGE | -21.92% | -28.40% |

Figure 4.1 Scatterplot of the Relationship Between KMATH and GRD

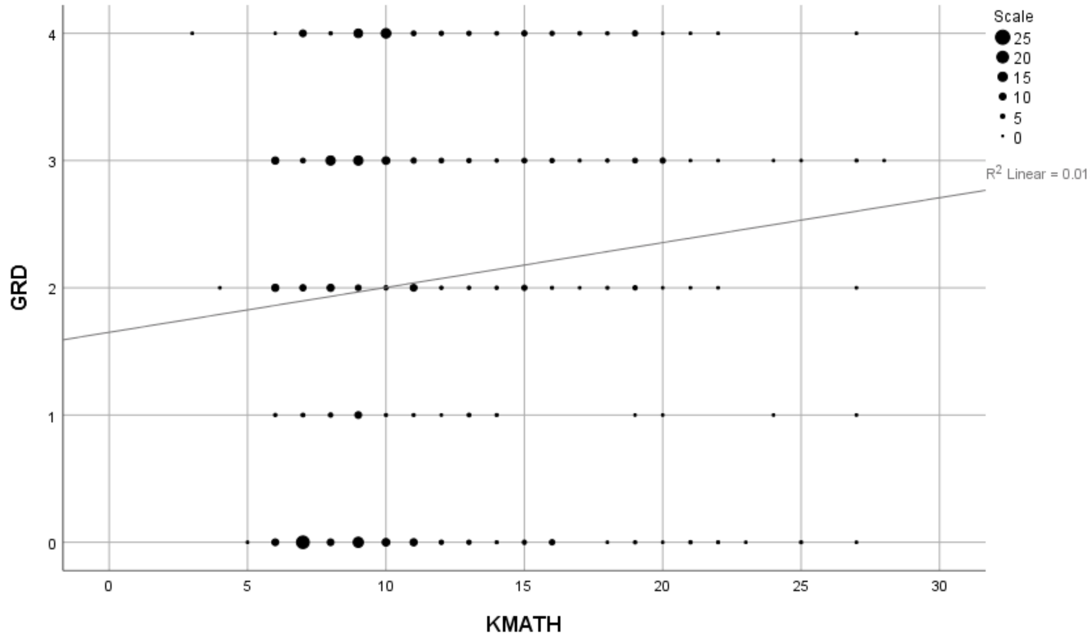


Figure 4.2 Scatterplot of the Relationship Between ACTM and GRD

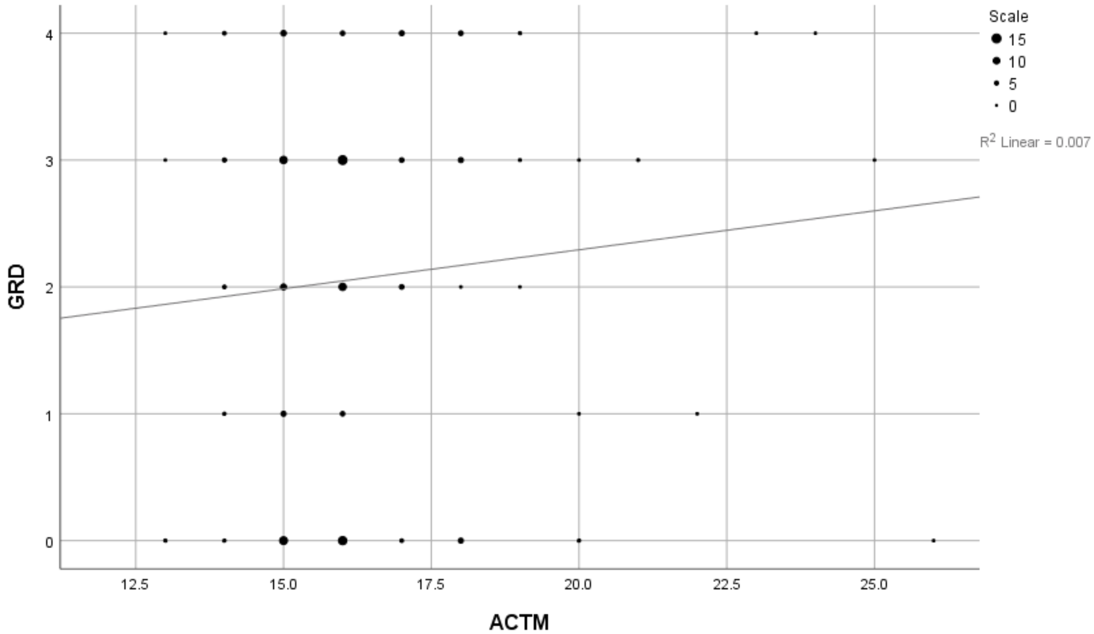


Figure 4.3 Scatterplot of the Relationship Between GPA and GRD

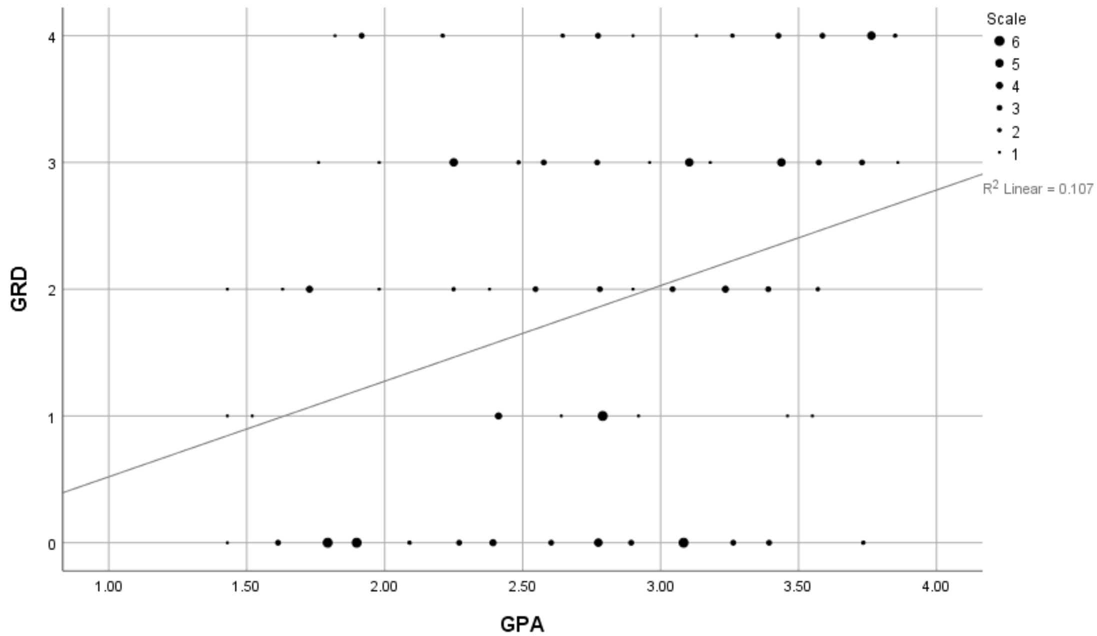


Figure 4.4 Scatterplot of the Relationship Between AGE and GRD

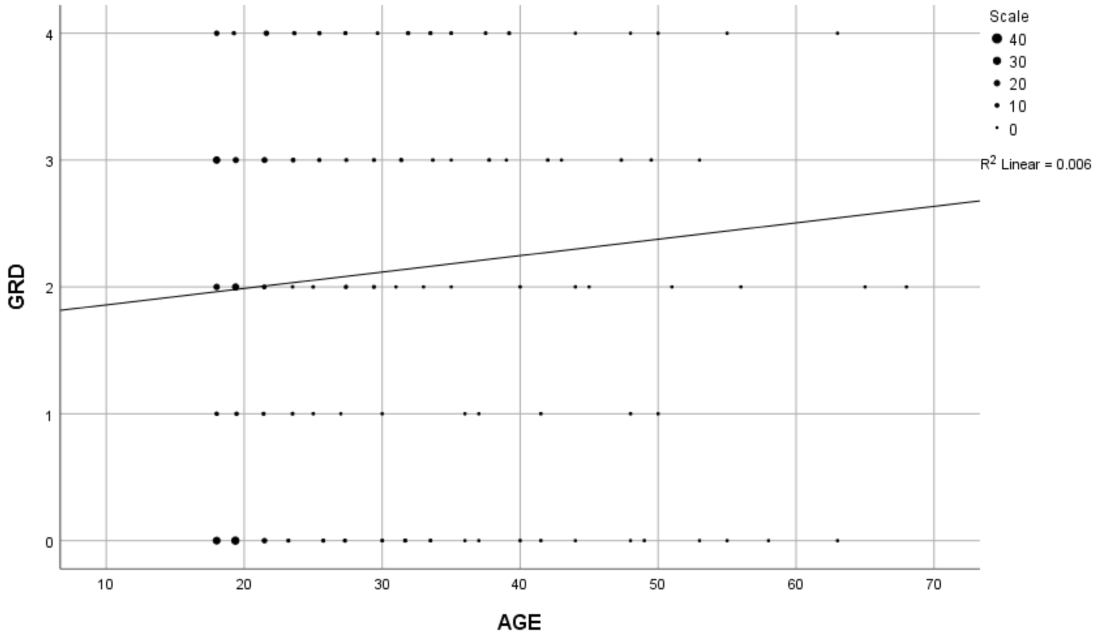


Figure 4.5 Residuals vs. Predicted Values

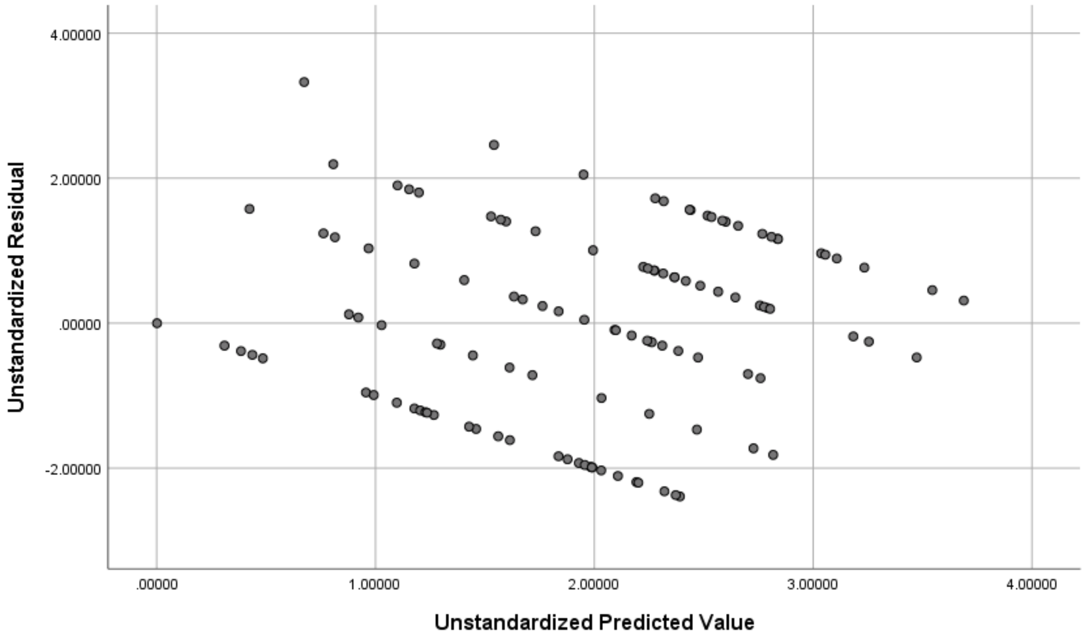


Figure 4.6 Histogram of the Residuals

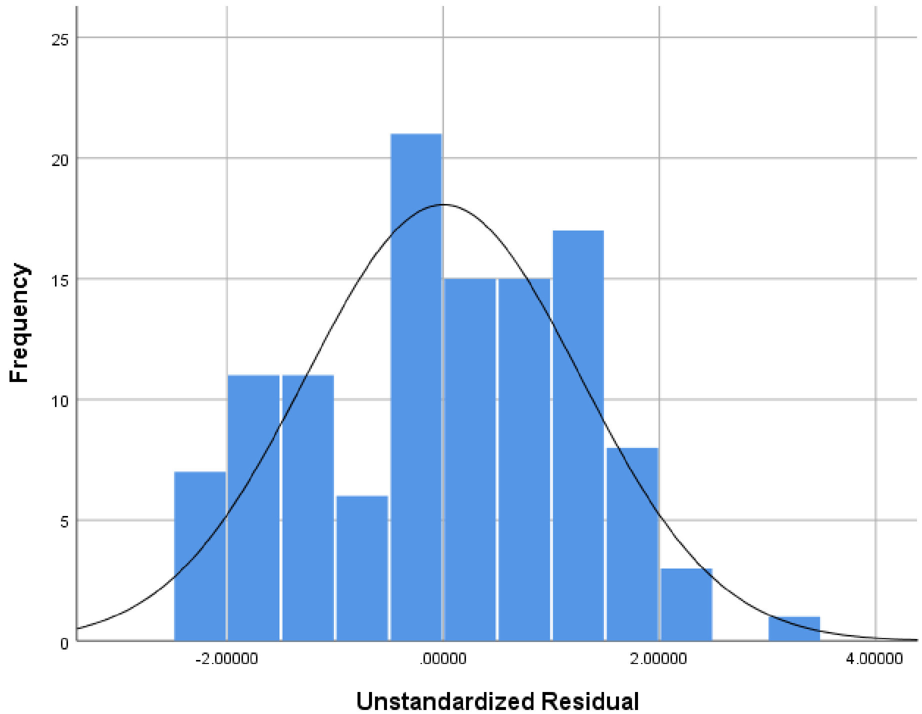
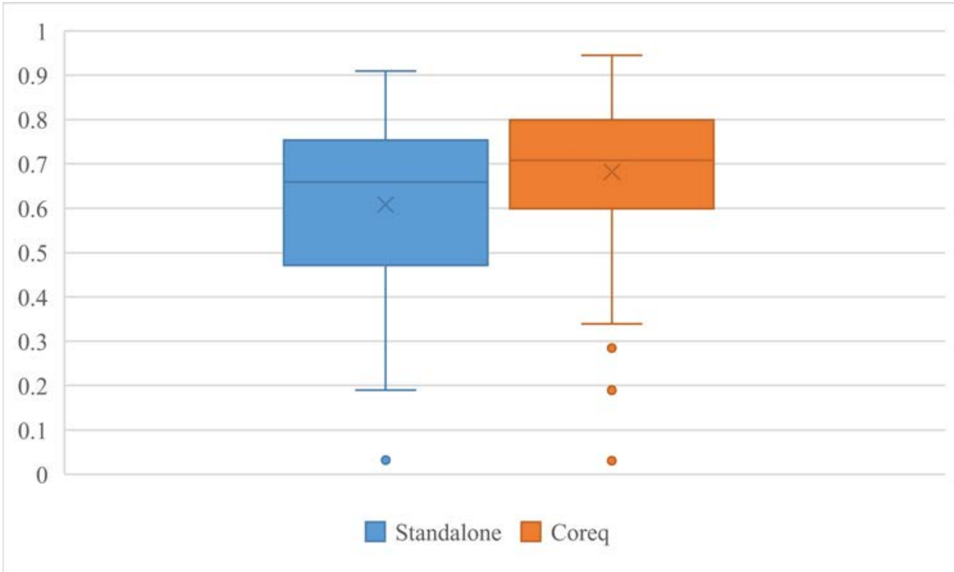


Figure 4.7 Overlap of Propensity Scores



# CHAPTER 5 CONCLUSIONS AND DISCUSSION

## Introduction

As many as two-thirds of students enter community college lacking the academic skills needed to be successful (Bailey, 2009). Institutions historically have responded to this lack of preparation by placing students into remedial education courses to help students learn the necessary skills to be successful in college-level course work. These courses generally focused on mathematical skills taught in the secondary school curriculum or even the middle or elementary school curriculum.

Developmental mathematics has been a topic of great debate, particularly over the last 20 to 25 years. On the one hand, some argue that developmental education is an essential part of higher education that helps remediate the skills of underprepared students who would otherwise be excluded from higher education or marginalized in college-level courses (Bettinger & Long, 2005). On the other hand, some argue that developmental mathematics is ineffective at remediating the skills needed to be successful and therefore serves as a roadblock to college-level courses and higher education (Scott-Clayton & Rodriguez, 2014). Studies on the efficacy of developmental mathematics have shown mixed results. While some have found that developmental education has a positive effect on students' academic outcomes (Bettinger & Long, 2005, 2009; Hughes & Scott-Clayton, 2011), others have shown no significant or even a negative impact (Bailey, 2009; Boatman & Long, 2010; Martorell & McFarlin Jr., 2011; Ngo & Kwon, 2015; Scott-Clayton & Rodriguez, 2014).

In addition to the large number of students referred to developmental education, most students who begin courses do not persist and never get the chance to enroll in the college-level course for which they are preparing, overshadowing any positive impact developmental education may have (Scott-Clayton & Rodriguez, 2014). If developmental education is not a pathway to college-level course completion, then it serves as a barrier and gatekeeper to college and earning a credential.

With a lack of evidence to support the notion that developmental mathematics is definitively able to improve outcomes for underprepared students, many educators and policy makers have questioned the idea of prerequisite, developmental courses (Bailey et al., 2010; Saxon & Morante, 2014; Vandal, 2014). Instead, the corequisite model is gaining traction because it offers students the chance to complete a college-level course right away and eliminates the numerous exit points that exist in the developmental education model. While the corequisite model has several variations, the general concept is that students enroll in a gateway mathematics course and developmental education course in the same semester, providing the opportunity to earn college credit right away (Atkins & McCoy, 2016).

The purpose of this study was to analyze the relationship between the corequisite model and student success, particularly, a passing grade in the gateway course. It sought to establish the efficacy of the corequisite model compared to a traditional sequence of developmental mathematics courses as well as analyze predictors of student success in a corequisite course, particularly, placement test score, ACT score, high school GPA, age, sex, socioeconomic status, and race. Statistical results of the analysis were presented in Chapter 4.

This chapter presents a discussion of the findings for each of the three research questions that guided this study. It provides insight into the findings' implications for developmental education and the corequisite movement, as well placement policy, for JCTC and KCTCS as well as the broader landscape. The chapter also provides recommendations for future research.

**Limitations of the Study**

There were several limitations to this study. First, the study was restricted to a single community college with both an urban and suburban setting. While the results had practical value to the institution at which the study was conducted, it is possible that they were unique to this institution and not generalizable to other colleges. Further, the results might not be typical of a four-year university due to inherent differences between community college and university students. The College also used a placement test developed within the state and not a national standardized placement test. While it was possible to develop a comparison to other placement tests, such as Compass and Wonderlic, the analysis of the relationship between placement test score and success might not be meaningful for institutions using a different placement test.

The sample size of the study was also somewhat limited because the data came from only the first two semesters of full implementation of the corequisite course. Missing ACT and GPA data complicated this further. Also, since the study was set over two semesters, the results may not be able to develop full confidence in the efficacy of corequisite mathematics. At the very least, the results might suggest the need for further research.

Another limitation caused by the reduced sample size was that all students included in the regression analysis were part-time students. That is, of students who had both a high school GPA and ACT Math score, all were part-time students. This could skew the results if there are differences between part-time and fulltime students.

The methods used to answer the first research question were observational only and not experimental, so a causal relationship between the corequisite and improved outcomes could not be established. Also, a determination could not be made as to whether all students benefitted equally from the corequisite, or whether some students had better outcomes by enrolling in traditional developmental education.

Regarding the methods used to answer the second research question, the regression analysis had specification error. While an attempt was made to include as many relevant variables as possible, the model most certainly inadvertently excluded relevant variables and left most of the variance in course grade still unexplained. In addition, while the literature indicated that these variables should be included, KMATH, ACTM, and AGE had only very weak linear relationships to course grade.

The college-level mathematics course in the study was a liberal arts mathematics course and not an algebra-based course. While there is a national push for colleges to develop math pathways, the predominant gateway mathematics courses across the nation and at JCTC are algebra based courses (Ganga & Mazzariello, 2018). The results of this study may not be generalizable to other math pathway corequisite courses such as a college algebra or statistics. No determination could be made as to whether a corequisite would be successful in these courses or whether the same covariates also predict course grade.

## Discussion of Results

As expected from the literature, implementing the corequisite model at JCTC led to significantly more students completing a college-level course than with the developmental model. More than three times the number of students completed a college-level course in the corequisite course than in the comparison group from 2012. While the full picture is incomplete because this study did not address students destined to take college algebra, the results of this study suggest there should be little concern with accelerating students needing to take a liberal arts mathematics using a corequisite model.

Along with others, this study found high school GPA to be a far better predictor of success than a placement test score. In fact, both placement tests investigated in this study proved to be very poor predictors of success in the corequisite model. It is concerning that the sole means of placing students predicted so poorly whether they would be successful. When looking at how students will perform, this study suggests that more emphasis should be placed on high school GPA than standardized placement tests.

Despite efforts in recent years at JCTC to improve outcomes for low-income and underrepresented minority students, this study showed that an achievement gap still exists for these two groups in the corequisite course. In the best performing model, underrepresented minority students earned course grades that were roughly a quarter of a letter grade less than their non-underrepresented minority peers. The difference was even worse for low-income students, with students who received a Pell Grant receiving course grades that were half a letter grade less than students who did not receive a Grant. This is especially concerning considering low-income and underrepresented minority students were more likely to place into the corequisite course than the standalone course. Reasons for these gaps are possibly attributed to external, non-academic factors, pedagogy and curriculum that does not connect to these groups of students. Another possible contributing factor was that the College lost TRIO services in 2016. While other programs were implemented to assist students, the TRIO grant provided significant funding and staffing resources.  Greater emphasis on interventions aimed at these two groups is necessary to close this equity gap.

Interestingly, although female students were more likely to enroll in the corequisite than the standalone course, the results from the regression analysis showed that they outperformed male students by as much as half a letter grade. The disparity between the enrollment trend and success in the course is concerning. It is possible that female students placed into the corequisite course could have been just as successful in the standalone version of the course and not needed to spend the extra time and tuition dollars by enrolling in the corequisite course. Increased math anxiety on algebraic placement tests could be a contributing factor to the enrollment in-balance (Betz, 1978). If that was the case, anxiety did not lead to effect performance in the class itself. Instead, the results of this study followed the national trend in which female college students outperform male college students (Goldin, Katz, & Kuziemko, 2006). While interaction terms were not included in the regression analysis due to sample size concerns, it is reasonable to think that low-income male students, low-income underrepresented minority students, and underrepresented minority male students could be at a particularly high risk as well.

Surprisingly, this study found that there was not a significant difference in course grade between similar students in the corequisite versus the standalone course, or in other words, the corequisite did not help students earn higher course grades. It is reasonable to have hypothesized that the additional instruction time and inclusion of soft skills would have led to high grades in the corequisite. It could be that soft skills, like those in the corequisite, were included just enough in the standalone course to provide students with similar remediation. The fact that most instructors who taught the corequisite also taught the standalone course makes this plausible. It could also be that the wrong students were served by the corequisite and some who were identified as high risk could have performed just as well in the standalone version of the course.

**Implications**

The results of this study have implications both locally within JCTC and KCTCS and contribute to the larger landscape of corequisite education nationally. Compared to students enrolling in a multi-course developmental education sequence, there seems to be no question from this study that the corequisite model is a better option in terms of students completing a college-level math course. While the methods used cannot fully establish a causal relationship, the drastic increase in achievement helps provide confidence in the corequisite model. This study supports the continued use of the liberal arts corequisite model at JCTC. In just one year, the rate at which students completed a college-level course was more than tripled, with roughly 65% of students passing the corequisite. This increase could have an effect on students' likelihood to persist resulting in an increase to the graduation rate (Parker, 2005).

The results of this study showed certain groups to be at-risk, specifically low-income and underrepresented minority students. Adding another demographic of concern, male students and students of unknown gender performed much worse than female students, nearly half a letter grade less (note though, only 13 students in the corequisite sample were identified as having unknown gender). These groups should be a continued area of focus and priority for intervention strategies.

In April 2019 near the end of this study, JCTC opened a student resource center called the Hub at the Downtown Campus. The purpose of the Hub is to eliminate non-academic barriers to success by providing students access to an on-campus food pantry to help eliminate food insecurity, connect students to campus and community resources, and facilitate and grant awards from a student emergency fund. This study suggests the continued need of resources such as the Hub as a possible means to close the achievement gap. Finding ways to proactively connect students to the Hub rather than students seeking services themselves could help overcome deficiencies in capital, especially considering low-income students and underrepresented minority students are often first-generation college students as well (Chen & Carroll, 2005; Karp, O'Gara, & Hughes, 2008).

Another promising development since the time of this study is the implementation of a promise scholarship for area students. Eligible students can attend JCTC with a last-dollar-in scholarship and students with family incomes under a certain level are also eligible to receive a stipend each semester. This could increase outcomes for low-income and underrepresented minority students by helping to eliminate financial barriers affecting student success.

While this study did not set out to specifically evaluate placement policy, it is difficult to evaluate the efficacy of corequisite without also discussing the methods for which students are directed to it via institutional policy. This study calls into question the placement policy used by JCTC and KCTCS, at least for liberal arts mathematics. Despite the KYOTE placement test and ACT being used as the primary methods to place students, the regression analysis showed that neither one was very predictive of course grade in the corequisite, especially KYOTE. While the study did not extend the results to the standalone course, it is reasonable to assume the findings might be similar. If GPA is such a better predictor of success, it should be considered as the primary means of placement, or at the very least, as a placement option. Placement policy should be amended to allow high school GPA as a placement metric.

Another area of the placement policy called into question by this study is the length of time tests are valid. Currently within KCTCS, math placement tests, including KYOTE and ACT, are valid for a maximum of four years. At JCTC, it is even more restrictive with tests valid for only two years. Outside of that time frame, students must retest. Students who delay entry to College after high school are generally affected the most by this policy as these tests are usually taken in high school initially. The results of this study showed a positive relationship between age and course grade. If older students perform better, it might not be necessary to impose a time limit on test scores. Further, if GPA is adopted as a means of placement, the results suggest there should be little concern using it for students who have been out of high school for some time. Whether there is a difference between students who graduated high school in the last, say, decade, compared to much older students was not investigated by this study. Whether the same can be said for algebra-based courses also needs to be determined.

### Recommendations for Future Research

The results of this study suggest several areas for further research that would not only benefit JCTC and KCTCS but contribute to the broader literature. While the results of this study showed positive outcomes for students in a liberal arts mathematics corequisite compared to a developmental sequence, it is not clear whether similar results should be expected from corequisites in other mathematics pathways, specifically college algebra and technical mathematics. JCTC and KCTCS more recently condensed the developmental mathematics sequence for college algebra to a single class, with some students enrolling in the developmental course and others enrolling in a corequisite, depending on placement score. Also implemented was a corequisite option for the technical mathematics course. In this pathway, similar to the liberal arts pathway, there is no longer a developmental prerequisite and students either enroll in the corequisite or a standalone course, depending on placement score. The efficacy of these two new curricular options needs to be examined to understand more fully the benefits and limitations of the corequisite model.

Further, while more students completed a college-level course using the corequisite, this study did not attempt to determine whether there were any positive effects on other student outcomes. Whether success in the corequisite has any effect on retention, the number of credit hours earned, the likelihood of transfer, or graduation rates are important factors, especially in the current environment. Prior studies have indicated a correlation between completing a college-level mathematics course and retention and graduation rates (Parker, 2005). A longitudinal study of corequisite students at JCTC could provide insight into whether these outcomes are improved or whether they are just as likely to stop-out or dropout.

This study showed high school GPA to be more predictive of course grade than the placement tests used at JCTC. Consideration should be given for policy change to include GPA as a placement option, either in addition to or instead of placement tests (Scott-Clayton, Crosta, & Belfield, 2014). Further research is needed to establish multiple measure placement policies and cutoffs for JCTC and KCTCS. In addition, whether high school GPA is suitable for algebra-based courses, such as college algebra or trigonometry, or higher-level courses like calculus, must be established. The 2020/2021 academic year provides an opportunity for such research as allowing high school GPA to be used for placement was part of the COVID-19 state-wide response from KCTCS.

The variables in the best model of the regression analysis only explained 26.2% of the variance with course grade. There is still much to learn about what influenced success in the corequisite course at JCTC. Additional studies using methods that account for self-efficacy and stress (Zajacova et al., 2005), whether a student worked full-time (Johnson & Rochkind, 2009), the occurrence of a medical issue or other significant life event during the semester, whether a student cared for dependents (Fralick, 1993), and attendance could explain more of the variance seen in course grade and allow for modifications and interventions to improve outcomes in the course.

Finally, while this study focused exclusively on mathematics, JCTC, and other institutions around the state and county, also recently implemented changes to developmental reading and English, including corequisite courses. From an overall policy lens, it is important to understand the success of these courses as well, and whether any similarities exist amongst the three.

## Summary

This study investigated the efficacy of a corequisite liberal arts mathematics course. The study found that compared to a traditional developmental course sequence, more students passed a college-level mathematics course using the corequisite. When looking at success in the corequisite itself, high school GPA was the strongest predictor of course grade. Socioeconomic status and sex also were also strong predictors, with Pell Grant recipients receiving lower grades than non-recipients, and female students receiving higher grades. Race and age also had an influence on course grade, but to a lesser extent than GPA, socioeconomic status, and sex. Placement test scores, ACT and the Kentucky Online Testing (KYOTE) exam, were poor predictors of course grade. When comparing course grades of students in the corequisite to ones in the standalone version of the course, there was no difference.

The findings of this study support the continued implementation of the liberal arts mathematics corequisite at JCTC. It suggests that placement policy be reconsidered to include GPA as one of the possible metrics, or even as the primary metric. It also suggests that students who were placed into the corequisite may have been successful in the standalone version of the course and that a review is needed of which students are placed into the corequisite. Additional interventions are needed to close the achievement gap for low-income, underrepresented minority, and male students. This study not only should guide decision making at JCTC and KCTCS, but also adds to the existing literature on corequisite mathematics.

## REFERENCES


Adams, P., Gearhart, S., Miller, R., & Roberts, A. (2009). The Accerlerated Learning Program: Throwing open the gates. *Journal of Basic Writing*, *28*(2), 50-69.

American Association of Community Colleges. (2020a). Fact Sheet. Retrieved from https://www.aacc.nche.edu/wp-content/uploads/2019/03/AACC-2019-Fact-Sheet-1.pdf

American Association of Community Colleges. (2020b). Jefferson Community and Technical College - Voluntary Framework of Accountability Public Profile Page. Retrieved from http://vfabi.aacc.nche.edu:8080/asp/Main.aspx?rn=/20200312083121433

Arendale, D. (2002). History of supplemental instruction (SI): Mainstreaming of developmental education. In D. B. Lundell & J. L. Higbee (Eds.), *Histories of Developmental Education*: The Center for Research on Developmental Education and Urban Literacy.

Armstrong, W. B. (2000). The association of student success in courses, placement test scores, student background data, and instructor grading practices. *Community College Journal of Research and Practice, 24*, 681-695.

Atkins, C., & McCoy, A. (2016). A co-requisite model for developmental mathematics: Innovative pathway leads to positive outcomes for education majors. *Educational Renaissance*, *5*(1), 13-25.

Attewell, P., Lavin, D., Domina, T., & Levey, T. (2006). New evidence on college remediation. *The Journal of Higher Education*, *77*(5), 886-924.

Bailey, T. (2009). Challenge and opportunity: Rethinking the role and function of developmental education in community college. *New Directions for Community Colleges, 145*, 11-30.

Bailey, T., Jeong, D. W., & Cho, S.-W. (2010). Referral, enrollment, and completion in developmental education sequences in community colleges. *Economics of Education Review, 29*, 255-270.

Belfield, C. R., & Crosta, P. M. (2012). Predicting success in college: The importance of placement tests and high school transcripts. CCRC Working Paper No. 42. *Community College Research Center, Columbia University*.

Berryman, T. G., & Short, P. M. (2010). Leading developmental education redesign to increase student success and reduce costs. *Enrollment Management Journal 4*(4), 106-114.

Bettinger, E. P., & Long, B. T. (2005). Remediation at the community college: Student participation and outcome. *New Directions for Community Colleges, 129*, 17-26.

Bettinger, E. P., & Long, B. T. (2009). Addressing the needs of underprepared students in higher education: Does college remediation work? *The Journal of Human Resources, 44*(3), 736-771.

Betz, N. E. (1978). Prevalence, distrution, and correlates of math anxiety in college students. *Journal of Counseling Psychology, 25*(5), 441-448.

Boatman, A., & Long, B. T. (2010). Does remediation work for all students? How the effects of postsecondary remedial and developmental courses vary by level of academic preparation. *National Center for Postsecondary Research Working Paper*.

Boylan, H. R., & Bonham, B. S. (1994). Seven myths about developmental education. *Research and Teaching in Developmental Education, 10*(2), 5-12. Retrieved from http://www.jstor.org.ezproxy.uky.edu/stable/42802461

Breneman, D. W., Abraham, A. A., & Hoxby, C. M. (1998). Remediation in higher education: Its extent and cost. *Brookings Papers on Education Policy, 1*, 359-383.

Burdman, P. (2012). Where to begin? The evolving role of placement exams for students starting college. *Jobs for the Future*.

Calcagno, J. C., & Long, B. T. (2008). The impact of postsecondary remediation using a regression discontinuity approach: addressing endogenous and noncompliance. *National Bureau of Economic Research Working Paper No. 14194,* 1-49. Retrieved from http://www.nber.org/papers/w14194

Canfield, J. (1889). The opportunities of the rural population for higher education. *National Council on Education*. Retrieved from www.books.google.com

Chen, X., & Carroll, C. D. (2005). First-generation students in postsecondary education: A look at their college transcripts. Postsecondary Education descriptive analysis report. *National Center for Education Statistics, NCES 2005-171*.

Chen, X., & Simone, S. (2016). Remedial coursetaking at US public 2- and 4-year institutions: Scope, experiences, and outcomes. Statistical analysis report. NCES 2016-405. *National Center for Education Statistics*.

Cho, S.-W., Kopko, E., Jenkins, D., & Smith Jaggars, S. (2012). New evidence of success for community college remedial English students: Tracking the outcomes of students in the Accelerated Learning Program (ALP). *Community College Research Center, 53*.

Complete College America. (2016). Transform remediation: The co-requisite course model. Retrieved from http://www.completecollege.org/docs/CCA%20Co-Req%20Model%20-%20Transform%20Remediation%20for%20Chicago%20final(1).pdf

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*: Sage publications.

D'Agostino Jr., R. B. (1998). Propensity score methods for bias reduction in the comparison of a treatmen to a non-randomized control group. *Statistics in Medicine 17*, 2265-2281

Edgecombe, N. (2011). Accelerating the academic achievement of students referred to developmental education. *Community College Research Center, 30*.

Fields, R., & Parsad, B. (2012). Tests and cut scores used for student placement in postsecondary education: fall 2011. *National Assessment Governing Board*.

Fralick, M. A. (1993). College success: A study of positive and negative attrition. *Community College Review, 20*(5), 29. doi:10.1177/009155219302000505

Ganga, E., & Mazzariello, A. (2018). Math pathways: Expanding options for success in college math. *Education Commission of the States*.

Gerlaugh, K., Thompson, L., Boylan, H. R., & Davis, H. (2007). National study of developmental education II: Baseline data for community colleges. *Research in Developmental Education*, *20*(4), 1-4.

Glau, G. R. (1998). *The "mainstreaming+" approach*. Paper presented at the Annual Meeting of the Conference on College Composition and Communication, Chicago, IL.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of American college women: The reversal of teh college gender gap. *Journal of Economic Perspectives, 20*(4), 133-156.

Golson, M. (2009). *Tennessee board of regents: developmental studies redesign initiative*. Retrieved from

Gordon, S. P. (2006). The shaky bridge connecting school and college mathematics. *The Mathematics Teacher, 100*(3), 174-178.

Greene, J. P., & Forster, G. (2003). Public high school graduation and college readiness rates in the United States. *Education Working Paper No. 3. Center for Civic Innovation*, 1-32.

Gupta, S., Harris, D. E., Carrier, N. M., & Caron, P. (2006). Predictors of student success in entry-level undergraduate mathematics courses. *College Student Journal, 40*(1), 97-109.

Henry, L. A., & Stahl, N. A. (2017). Dismantling the developmental education pipeline: Potent pedagogies and promising practices that address the college readiness gap. *Journal of Adolescent & Adult Literacy, 60*(6), 611-616.

Hern, K., & Snell, M. (2010). Exponential attrition and the promise of acceleration in developmental English and math. *Research and Planning Group of the California Community Colleges*. Retrieved from www. rpgroup. org/rpsearch/results/taxonomy% 3A17

Hern, K., & Snell, M. (2014). The California acceleration project: Reforming developmental education to increase student completion of college-level math and English. *New Directions for Community Colleges, 167*, 27-39.

Hodara, M., & Jaggars, S. S. (2014). An examination of the impact of accelerating community college students' progression through developmental education. *Journal of Higher Education, 85*(2), 246-276.

Hughes, K. L., & Scott-Clayton, J. (2011). Assessing developmental assessment in community colleges. *Community College Review, 39*(4), 327-351.

*Indicators of future success: GPA and noncognitive skills*. (2015). Retrieved from http://www.nea.org/assets/docs/Indicators_of_Success-BGH_ac5-final.pdf

Jefferson Community and Technical College. (2020). Fast facts. Retrieved from https://jefferson.kctcs.edu/about/college-at-a-glance/index.aspx

Jenkins, D., Speroni, C., Belfield, C., Smith Jaggars, S., & Edgecombe, N. (2010). A model for accelerating academic success of community college remedial English students: Is the Accelerated Learning Program (ALP) effective and affordable? *Community College Research Center, 21*.

John N. Gardner Institute. (2017). Gateway course definition. Retrieved from http://www.jngi.org/gateway-courses-definition/

Johnson, J., & Rochkind, J. (2009). With their whole lives ahead of them: Myths and realities about why so many students fail to finish college. *Public Agenda*.

Karp, M. M., O'Gara, L., & Hughes, K. L. (2008). Do support services at community colleges encourage success or reproduce disadvantage? An exploratory study of students in two community colleges. CCRC Working Paper No. 10. *Community College Research Center*.

Kentucky Community and Technical College System. (2018). Catalog 2018-2019. Retrieved from https://kctcs.edu/education-training/course-catalog/2018-2019-KCTCS-Catalog.pdf

*Kentucky Public Postsecondary Education Policy for Diversity, Equity, and Inclusion*. (2016). Retrieved from http://cpe.ky.gov/policies/academicaffairs/diversitypolicy.pdf

Lei, S., Gorelick, D., Short, K., Smallwood, L., & Wright-Porter, K. (2011). Academic cohorts: Benefits and drawbacks of being a member of a community of learners. *Education, 131*(3), 497-504.

Levin, H. M. (1989). Accelerated schools: A new strategy for at-risk students. *Consortium on Educational Policy Studies*

Lewis-Beck, C., & Lewis-Beck, M. (2016). *Applied regression: An introduction* (2 ed.). Thousand Oaks, California: SAGE Publications, Inc. .

Logue, A. W., Watanabe-Rose, M., & Douglas, D. (2016). Should students assessed as needing remedial mathematics take college-level quantitative courses instead? A randomized controlled trial. *Educational Evaluation and Policy Analysis, 38*(3), 578-598.

Mamiseishvili, K., & Deggs, D. M. (2013). Factors affecting persistence and transfer of low-income students at public two-year institutions. *Journal of College Student Retention, 15*(3), 409-432.

Martorell, P., & McFarlin Jr., I. (2011). Help or hindrance? The effects of college remediation on academic and labor market outcomes. *The Review of Economics and Statistics, 93*(2), 436-454. doi:10.1162/REST_a_00098

Marwick, J. (2002). Alternative methods of mathematics placement. *The Community College Enterprise, 8*(2), 41-50.

Moening, B. A. (2016). *The co-requisite model: A regression discontinuity.* (Doctor of Education). Ball State University, Muncie, Indiana.

Ngo, F., & Kwon, W. W. (2015). Using multiple measures to make math placement decisions: Implications for access and success in community colleges. *Research in Higher Education, 56*, 442-470.

Nix, A., Bertrand Jones, T., Brower, R. L., & Hu, S. (2020). Equality, efficiency, and developmental education reform: The impact of SB 1720 on the mission of the Florida College System. *Community College Review, 48*(1), 55-76.

Oakes, J. M., & Johnson, P. J. (2006). Propensity score matching for social epidemiology In J. M. Oakes & J. S. Kaufman (Eds.), *Methods in social epidemiology* (1 ed., pp. 364-386). San Fransisco, CA: Jossey-Bass.

Parker, M. (2005). Placement, retention, and success: A longitudinal study of mathematics and retention. *The Journal of General Education, 54*(1), 22-40.

Phipps, R. (1998). *College remediation: What it is, what it costs, what's at stake*. Retrieved from Washington, D.C.:

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects *Biometrika, 70*(1), 41-55.

Safran, S., & Visher, M. G. (2010). Case studies of three community colleges: The policy and practice of assessing and placing students in developmental education courses *National Center for Postsecondary Research Working Paper*.

Saxon, D. P., & Morante, E. A. (2014). Effective student assessment and placement: Challenges and recommendations. *Journal of Developmental Education, 37*(3), 24-31.

Schudson, M. S. (1972). Organizing the 'meritocracy': A history of the College Entrance Examination Board. *Harvard Educational Review*, *42*(1), 34-69.

Scott-Clayton, J. (2012). Do high-stakes placement exams predict college success? CCRC Working Paper No. 41. *Community College Research Center, Columbia University*.

Scott-Clayton, J., Crosta, P. M., & Belfield, C. R. (2014). Improving the targeting of treatment: Evidence from college remediation. *Educational Evaluation and Policy Analysis*, *36*(3), 371-393. Retrieved from https://journals.sagepub.com/doi/abs/10.3102/0162373713517935

Scott-Clayton, J., & Rodriguez, O. (2014). Development, discouragement, or diversion? New evidence on the effects of college remediation policy. *Education Finance and Policy*.

Texas proposal narrative statements. (2011). In *Complete College America*.

Tinto, V. (1988). Stages of student departure: Reflections on the longitudinal character of student leaving. *The Journal of Higher Education, 59*(4), 438-455.

Triola, M. F. (2018). *Elementary statistics* (13 ed.). Boston: Pearson.

Vandal, B. (2014). Promoting gateway course success: Scaling corequisite academic support. *Complete College America*.

Venezia, A., Bracco, K. R., & Nodine, T. (2010). *One shot deal? Students' perceptions of assessment and course placement in California's community colleges*. San Francisco, CA: WestEd.

Walker, W., & Plata, M. (2000). Race/gender/age differences in college mathematics students. *Journal of Developmental Education, 23*(3).

Ward, N. L. (2006). Improving equity and access for low-income and minority youth into institutions of higher education. *Urban Education 41*(1), 50-70.

West, W., Wu, Y., & Heydt, D. (2004). An introduction to StatCrunch 3.0. *Journal of Statistical Software, 9*(5).

Wolfle, J. D. (2012). Success and persistence of developmental mathematics students based on age and ethnicity *The Community College Enterprise, 18*(2), 39-54.

Zajacova, A., Lynch, S. M., & Espenshade, T. J. (2005). Self-efficacy, stress, and academic success in college. *Research in Higher Education, 46*(6), 677-706.

Zientek, L. R., Yetkiner Ozel, Z. E., Fong, C. J., & Griffin, M. (2013). Student success in developmental mathematics. *Community College Journal of Research and Practice, 37*(12), 990-1010.

## VITA

Drew Wilkerson

EDUCATION

University of Nebraska-Lincoln — Lincoln, NE
Master of Science — Graduated: 2010
Mathematics

Brigham Young University-Idaho — Rexburg, ID
Bachelor of Science — Graduated: 2006
Mathematics Education

PROFESSIONAL EXPERIENCE

| | |
|---|---|
| Jefferson Community and Technical College | Louisville, KY |
| Assistant Vice President of Academic Affairs | January 2019-present |
| Associate Professor of Mathematics, with Tenure | July 2016-present |
| Chair of Mathematics Division | July 2016-December 2018 |
| Mathematics Department Head | July 2011-December 2018 |
| Assistant Professor of Mathematics | July 2013-June2016 |
| Instructor of Mathematics | August 2010-June 2013 |
| University of Nebraska-Lincoln | Lincoln, NE |
| Graduate Teaching Assistant | August 2008-July 2010 |
| Highland High School | Gilbert, AZ |
| Teacher | January 2007-June 2008 |

Awards and Recognitions

- Appointed to the KCTCS Leader Enrichment and Development (LEAD) Academy (2018).
- Merit Award, Jefferson Community and Technical College (2012).
- Merit Award, Jefferson Community and Technical College (2011).
- Praxis Recognition in Excellence for Mathematics (2005).