

COMMUNITY COLLEGE DEVELOPMENTAL MATH REDESIGN
AND ITS EFFECT ON STUDENT OUTCOMES

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DEDICATION

To my parents, Samuel and Esther Yoon, emigrating with us from Korea, so their children would have access to all the higher education opportunities available in the United States. I hope we lived up to your expectations. Chun, Sue, and I definitely appreciate and love you very much!

To Anson, Alyssa and Ashlyn – I love you very and may you always pursue your dreams.

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ABSTRACT

President Obama's Blueprint for Keeping College Affordable and Within Reach for All Americans (2012), includes challenges to improve American higher education outcomes. One outcome that has drawn national concern is the low four- and six-year graduation rates of undergraduate students entering the nation's colleges and universities. The number of students entering degree-granting institutions has increased over the past decade, but nearly half of the students are leaving without a degree. This is not a new concern, as researchers begin studying student retention processes in the mid- 1970s.

The open-door policy of community colleges presents added challenges, as many of the students are currently under-prepared for college level work, especially in mathematics. *Achieving the Dream*, an initiative to help community college students to succeed, suggests that over 70% of college students are not ready for college-level math. Although research is beginning to address student success in developmental course sequences within community colleges, passing rates generally remain low and the programs' impact on student retention is mixed at best.

This study's purpose was to examine whether a curriculum redesign model could be applied to a developmental mathematics program in a community college setting to increase student success. More specifically, the study examined whether the redesigned developmental math (1) improved student performance in developmental courses so that more students passed, (2) increased student enrollment in subsequent developmental courses, and (3) increased student enrollment in college level mathematics courses. The research employed a regression discontinuity design, which represents a strong

alternative approach for estimating treatment effects in the absence of random assignment of individuals to treatment and control groups by using a covariate (i.e., a math placement test) to assign students. Student enrollment patterns and course outcome information were collected on students enrolled in developmental math courses from the Spring 2010, Fall 2010 and Spring 2011 semesters.

Findings indicated that the redesigned developmental math program had a positive impact on student achievement, with a greater percentage of students passing the redesigned developmental courses. In addition, more students enrolled in the subsequent developmental math course when they participated in the redesigned sequence. Finally, more students completing the redesigned sequence subsequently enrolled in college-level math than their peers in the traditionally-delivered math developmental courses. The results indicated that the particular redesigned developmental math curriculum investigated provides a process for applying the best practices of developmental math to create an educational environment for both academic and social integration--factors leading to successful student retention and persistence.

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CHAPTER 1: OVERVIEW OF THE RESEARCH PROBLEM

The National Center for Public Policy and Higher Education (2004) reports that only 60 of every 100 ninth graders actually graduate from high school. Of that subset of persisting students, 40 immediately enter college, 27 are still enrolled during their sophomore year, and only 18 complete any type of postsecondary education within 6 years of graduation from high school. This trend has revealed an educational pipeline that is “leaking.” Concerns with student academic preparedness for postsecondary education, student retention and eventual persistence to earn a degree during their undergraduate years, and rising costs of educating students, many of whom may not complete programs, has raised issues about accountability, funding, and productivity in higher education. More recent reports (NCES, 2011) continue to show that the numbers of students graduating from postsecondary institutions are not increasing.

While there are numerous barriers for students in making timely progress toward graduation, at community colleges, student preparedness for college-level work is a significant educational issue. About half of all first-time community college students are academically under-prepared and must enroll in at least one remedial/developmental math or English course. Many students drop out of these courses or the subsequent remedial/developmental courses due to a combination of academic and non-academic factors. In the past, remedial education was often referred to as preparatory or compensatory education, but these types of skill-related math, reading, and writing courses were later renamed and redefined as “developmental” to encompass both the academic and non-cognitive factors that influence student success (Clowes, 1982). For

the purpose of this study, these basic skill-related courses, or courses which are not part of degree programs but are aimed at ensuring student academic readiness for university-level math and English courses, will be referred to as developmental courses, as this is the designation used in most community colleges.

Most of the students participating in developmental programs report that it is their intention to earn an associate or baccalaureate degree (Knopp, 1996). A barrier to reaching a degree for many students is their preparedness for college. Previous research suggests students are less-prepared for college math based on the lower retention rates of completing similar types of developmental courses. Completion rates were 76% for reading, 73% for writing, and only 63% for math (National Center for Developmental Education, 2004). Another recent study confirmed that passing rates in math were also lowest at 58% versus 69% for reading and 64% for writing (Gerlaugh, Thompson, Boylan, & Davis, 2007). The challenge of completing developmental course sequences does not bode well for community college students who may be interested in, or preparing for, pursuit of science, technology, engineering and math (STEM) fields.

For Hawai'i, the situation is even worse than the reported national data. The outcome of the Hawai'i pipeline is below the national average, with only 13 out of 100 ninth grade students (versus 18) completing a postsecondary degree within 6 years of graduation from high school (University of Hawai'i, 2006). Similar to national trends, students seem to have a greater deficiency in math versus English based on the numbers required to enroll in math and English developmental courses. At the community colleges in the University of Hawai'i system, 74% of students who enroll are not ready

for college-level math, as indicated by math placement test results. Of those students placed into developmental math, only 61% actually enroll in the appropriate math course. In addition, of those students who enroll in developmental math courses, only 54% successfully complete the course (University of Hawai'i Community Colleges, 2007). This percentage remains fairly consistent over time, in that only 54% complete the next developmental math course and even when a course is repeated, of the repeating students, only a similar percentage succeed.

In Hawai'i, each of the community college campuses offers 3-4 courses in the developmental math sequence, with the entry point determined by the COMPASS Math Placement Test. If students must start with the basic math course, not only might it take 3 or more semesters to become "college ready" for studying math, but of 100 students who begin, only about 16 will be eligible, based on the 54% pass rate per course, to take college level math courses at the end of the sequence. For these students, in addition to the time and money associated with their developmental courses, they will be at a significant disadvantage if they wish to pursue STEM majors.

One effort that seems to have had success in improving passing rates in college courses is the course redesign efforts of the National Center for Academic Transformation (NCAT). The NCAT course redesign model uses information technology to redesign learning environments to produce better learning outcomes for students while reducing the cost of instruction (Twigg, 2005a). Traditionally, campuses have merely bolted on instructional technologies to existing courses without much pedagogical considerations. This has resulted in increased technology costs to the institution without

perceivable increases in students learning and progress toward degrees. The NCAT, in collaboration with 30 institutions, has created a course redesign methodology that increases student learning while reducing the cost of instruction (Twigg, 2003).

The basis of the NCAT redesign model relies on online tutorials, continuous assessment and feedback, increased interaction among students, on-demand support, and mastery learning. The course redesign projects focuses on large-enrollment, introductory courses since these reach significant numbers of students. These courses are also often known to be gatekeeper courses—that is, students need to pass them in order to enroll in subsequent courses required for their majors or to complete general requirements for their degrees. In the initial work of NCAT with the 30 institutions, 25 of the 30 projects showed a significant increase in student learning; 18 of the 24 projects measuring retention reported a decrease in drop-failure-withdrawal rates and an increase in course completion rates; and all reduced costs by 37% (ranging from 20%-70%) and produced a collective annual savings of about \$3 million (NCPPE, 2005; Twigg, 2003).

PURPOSE OF THE STUDY

A recent study conducted by the Conference Board of Mathematics found math enrollment up in all pre-college courses (Lutzer, Rodi, Kirkam, & Maxwell, 2007). As noted previously, about half of all first-time community college students nationally were academically underprepared and enrolled in at least one developmental math course. In a policy brief about *Achieving the Dream*, a national initiative on community college success, Biwas (2007) noted that in an analysis of 46,000 students enrolled in 27 participating institutions, over 70 percent were found not prepared adequately for college-

level math. Of those who started in developmental math, only 14 percent completed a college-level math course upon completing their developmental sequence. Many students dropped out of these developmental courses due to a combination of academic and non-academic factors (Boylan & Saxon, 2004).

Complicating the under preparedness issue is that the placement exam results, while measuring content knowledge, may be clouded by math anxiety. Apprehension about math performance has been shown to significantly reduce math performance, especially when the additional element of a timed test is a factor (Cates & Rhymer, 2003). Clouding results even further is the fact that when students internalize stereotypes regarding race and gender (e.g., “Girls aren’t good in math”), student performance suffers, masking a mere skill deficiency (Steele & Aronson, 1995).

In Hawai‘i, almost 75% of public high school graduates entering the University of Hawai‘i system begin in the community colleges (Heck, 2006). In the fall of 2005, based on their COMPASS Math Placement Test, 83% of students entering the community college were not prepared to take college level math (UHCC, 2007). Of these students, approximately 61 % enrolled in remedial/ developmental math and only 56% of the enrolled students successfully completed their course. The ramifications of the current situation are significant in that regardless of the particular reason for a student being placed into developmental math, students are not making satisfactory progress toward a degree. Almost 50% of existing developmental courses are being filled by repeat registrations (UHCC, 2007). Developmental math is currently a gatekeeper course and, therefore, a barrier for students, both financially and academically.

The facts and figures noted previously paint a grim picture of the environment around developmental math. Given the serious nature of students' lack of readiness to study college math and its impact on student persistence, the purpose of this study is to examine whether the course redesign process can be applied to a developmental math curriculum (versus just individual courses) in a community college setting to create a structure for teaching math that improves student performance as measured by grades and success in passing each course. In addition, this study will examine whether a redesigned sequence of community college developmental math courses leads to higher subsequent student enrollments over successive semesters in order for students to complete the sequence and enroll in college-level math.

CONCEPTUAL OVERVIEW

For the purpose of this study, student success will be discussed in terms of achievement in math and retention, which facilitates persistence in earning a degree. Early work on student retention centered on student involvement (Astin, 1985; Pascarella & Terenzini, 1991; Tinto, 1975, 1993). This previous research on student academic and social engagement and its positive relationship to undergraduate retention and eventual persistence forms the conceptual background for the current study. Findings from this work emphasized the importance of student involvement on a range of student outcomes (e.g., Austin, 1984, 1985; Pascarella & Terenzini, 1991). As a result, higher education institutions focused on students' transition to college and programs structured to increase their social integration in the form of expanded orientations, first-year programs, and a variety of extra curricular activities to promote student--student and student--faculty

interactions. This work fell on the shoulders of student affairs professionals seeking to provide students assistance to promote persistence (Barr, Desler, & Associates, 2000), and research showed that involvement mattered (Astin, 1984; Mallette & Cabrera, 1991; Nora, 1987; Terenzini & Pascarella, 1977). Unfortunately, in many of these programs, faculty participation was not integral, and the programs were viewed more as “add-ons” to university activities. In addition, further studies revealed that outcomes were different based on institutional settings; that is, residential versus non-residential, and between two-year and four-year institutions (Yorke, 1999).

A number of theories have been proposed to examine students’ likelihood to persist or leave college early (Bean, 1980; Bean & Metzner, 1985; Tinto, 1993). Tinto's Model of Institutional Departure (1993) identified three major sources of student departure from the institution including academic difficulties, inability to integrate educational and occupational goals, and failure to become engaged in the intellectual and social life of the institution. Tinto further noted the need for institutions to provide resources for program development, incentives for program participation and continual assessment of their actions with an eye toward improvement.

Building on this line of institutional action to help retain students, this study seeks to apply advances in the application of technology to impact student performance, focusing on academic integration and its relationship to successful performance. Tinto (1993) argues that if a student performs well in class, enjoys the subject or studying the subject, there is increased academic integration and therefore a reduced risk of dropping out. A few studies examining Tinto’s model in two-year community colleges have also

supported the importance of academic integration as a factor in student persistence (Bers & Smith, 1991; Fox, 1986; Pascarella, Smart, & Ethington, 1986). Although evidence is less consistent regarding social integration in a two-year setting, academic integration consistently had a beneficial direct and indirect influence on student persistence (Bers & Smith, 1991). Compared with four-year residential institutions, social networks within community colleges are less likely to develop, because students are more often commuter students who do not spend much time on campus, outside of classes, to build social networks, which may result in the higher rates of early (first semester) dropouts or stop-outs (temporary withdrawal) at community college campuses (Bers & Smith, 1991; Tinto, 1993).

Findings in support of Tinto's (1993) student integration model are also generally consistent with Bean and Metzner's (1985) assertion that if students had confidence in their academic ability, there would be less likelihood of dropping out. Bean and Metzner proposed a student attrition conceptual model for examining traditional and non-traditional student attrition, with likelihood to leave primarily associated with academic and psychological outcomes, background variables, and environmental variables. Student motivation (e.g., relevance and satisfaction) has also been found to affect persistence and to be highly correlated with various course-related issues such as instructional design, instructors' facilitation, and interaction (Shea, Pickett, & Pelz, 2003).

Despite personal student characteristics upon entering college or institutional type (i.e., two- or four-year college), research has shown that the quality of student effort does impact student learning (Kaufman & Creamer, 1991; Ory & Braskamp, 1988; Pace,

1984). The more students engage in their learning, the more effort they will exert, which will result in greater learning. Studies on classroom activities (Volkwein, King, & Terenzini, 1986) have shown that student learning is enhanced when students are actively involved in their learning process, which could lead to greater investment of effort. Unfortunately, regardless of institution type, all students seem to experience a similar learning environment--the classroom. In these classrooms, students are relatively passive participants (Fischer & Grant, 1983).

Studies have also shown that learning occurs over extended period of time as a result of active engagement with the material (Felder & Brent, 1996). Therefore, learners cannot be limited to listening to lectures and depending primarily on textbooks. Evidence collected in a number of studies regarding course structure, however, indicates that the primary learning method presented to students is visual in which faculty lecture and present material (Lemire, 1998). This seems to be a direct contrast to studies that show that the use of a variety of instructional methods increases the chance of success for under-prepared college students (Casazza & Silverman, 1996). In the area of mathematics education, for under-prepared college students, because of the possible compounding factor of math anxiety which leads to lower achievement, the lecture method may impose additional difficulties, since math concepts are learned through actively doing math (Twigg, 2005b).

Higher education has traditionally valued individual faculty practice, allowing faculty latitude in course development and delivery, while standardizing the student learning experience. This assumes that all students in a course have similar learning

needs, interests, skills, and knowledge. Redesigned courses treat students as individual learners with differing needs and standardize faculty practice in moving students from passive note-taking to active learning. The active learning components include the following: on-line tutorials, which are interactive and provide students with needed practice and greater engagement with the material in order to fully learn the material; continuous assessment and feedback that enables both repetition and frequent feedback that research shows enhances student learning (Pellegrino, Chudowsky, & Glaser, 2001; Moore, Walsch, & Risquez, 2008); on-demand support that provides students with assistance from a variety of people that provide not only differing perspectives, but a sense that the student is a part of a community; and mastery learning that provides flexibility for students but are not self-paced, where student progress is organized by the need to master specific learning objectives according to scheduled milestones for completion.

In developmental courses, due to the variety of leaning needs of students, the integration of technology in the form of course redesign may provide a powerful tool for academic integration. Not only can technology be used to mediate the content, but may also be used to provide continuous assessment and individualized feedback, which may not be feasible in most classrooms.

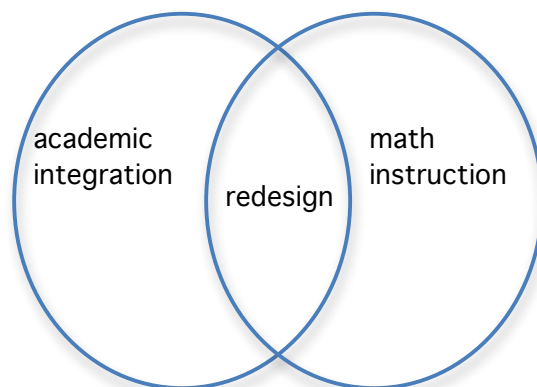
Math Course Redesign

Developmental math courses seem to be a logical candidate for redesign. While students are not ready for college-level math as evidenced by a placement exam, they have varying levels of math knowledge or competence. In addition, students may actually

possess a higher level of knowledge, but during the test process this knowledge was masked by math anxiety, or they were merely rusty due to a break in taking courses between graduating from high school and enrolling in higher education. Therefore, in a traditional developmental course, there may be several types of students: those who are not prepared; those who know some of the material; and those who know most of the material but were misplaced due to math text anxiety or from not having had math recently.

Mastery learning is one aspect of course redesign. Therefore, in a developmental math course, this model provides students who know most of the material to quickly review what they know and spend additional time on what they may have forgotten and then be prepared to move on to the next course. For students who know some of the material, they can quickly review what they know and then spend the remainder of the semester learning the new material in order to be prepared for their next course. Finally, for the group of students who are poorly prepared, the redesigned course can help them learn at their own pace, receive continuous feedback about their understanding and knowledge of the content, and access additional support from faculty. It would seem that the redesign method lends itself to students' success in learning course content and their likelihood to complete subsequent courses in the sequence. In Figure 1, the essential elements of student academic integration, math instruction, and course redesign are summarized.

Figure 1.1: Addressing academic integration through redesigned math instruction.



The redesign model provides a means to take what is known about mathematics instruction and strategies for academic integration (e.g. active learning, frequent assessment, immediate feedback), and using technology, provide individualized instruction, which could improve learning outcomes.

Technology-Based Applications

While there are numerous computer resources available from both textbook publishers and computer application vendors, currently in the developmental math arena, there are two technology-based applications which are widely used: MyMathLab (www.mymathlab.com) and ALEKS (www.aleks.com). MyMathLab is a product of Pearson, a publisher of numerous math textbooks. The software is easily customizable and provides direct connections to Pearson math textbooks. The tools include interactive homework exercises, lessons correlated to the textbook at the objective level; a Personalized Study Plan, generated when students complete a test or quiz; multimedia learning aids, such as video lectures, animations, and a multimedia textbook; an Assessment Manager which allows faculty to assign media resources (such as a video

segment or a textbook passage), homework, quizzes, and tests; a gradebook, designed to automatically tracks students' results; and a MathXL Custom Question Builder, which allows faculty to create static and algorithmic exercises for assignments.

ALEKS is an application developed by a team of software engineers, mathematicians, and cognitive scientists with the support of a multi-million-dollar grant from the National Science Foundation at New York University and the University of California at Irvine. While the tools of ALEKS are similar to MyMathLab, the underlying structure of ALEKS is an iterative process that assesses a student's knowledge state and delivers targeted instruction on the topics that a student is most ready to learn. In ALEKS, faculty select the content areas that a student is required to master and the application manages the required content to facilitate student learning and completing the required content.

NEED AND SIGNIFICANCE OF THE STUDY

As with any new curricular approach in education, evidence of impact is needed, so that others may decide whether a particular approach will work in various institutional settings. Many studies on developmental education are descriptive and provide simple comparisons between students receiving remediation course work and students who do not receive this type of course work (Bettinger & Long, 2005). This study proposes, using rigorous analysis, to examine whether the redesigned developmental math sequence using ALEKS can improve student learning, reduce time to reaching college-level math preparedness, and improve student persistence in math. If students are successful in each of the redesigned developmental math courses, this may provide them with enough

confidence to complete their program or transfer to a four-year institution. If students succeed at a greater rate in the redesigned developmental courses, this would have financial implications for both students and the institutions. For the student, passing the developmental courses will mean not having to continue to pay tuition for non-college level courses. For institutions, having fewer students repeating courses is a savings in both financial and physical resources. Success may also pave the way for coordinated conversations about how other community college campuses teach developmental math. Finally, if student learning improves, there may be additional implications of applying the redesign model to other large enrollment, gatekeeper classes, throughout the entire University of Hawai'i system.

RESEARCH FOCUS

In order to address the problems of college preparedness in math, improve student learning, and improve persistence through a course sequence, a small group of developmental faculty at one community college in the University of Hawai'i System embarked on not only a redesign of a particular developmental course but, rather, the redesign of the entire developmental math sequence. The goal of this project was to reduce the amount of time for students to develop proficiency in math, in order to be ready for college level math, while insuring student mastery of necessary skills and concepts. Previous projects of the NCAT have shown a positive correlation between redesigned math courses and improved student outcomes. These initial projects support the view that student learning and success in completing courses can be increased

through careful attention to what students are learning and how they learn within each course.

Research Questions

This study addresses three primary research questions:

1. Is there a difference in learning outcomes as measured by “passing” developmental courses between students in traditional face-to-face and redesigned courses?
2. Is there a difference in persistence rates as measured by enrollment in subsequent developmental math courses between students in traditional face-to-face and those in redesigned courses?
3. Is there a difference in persistence rates of students enrolling in college level math between traditional and redesigned courses?

The first question seeks to explore the structure of developmental math, based on the academic integration model. This model recognizes the need for more student-focused instruction, in which the individual student learning needs are what shape the delivery of the curriculum. It also recognizes that not all students in one course are at the same level of math deficiency. The traditional face-to-face course seems to be structured on the premise that all students are at the same knowledge level, and therefore, learn as a group, being introduced and working through the content together. In contrast, the redesigned course allows students to progress through the material at their own pace. The course begins with a diagnosis by the software to determine students’ areas of strength and weaknesses in the course (i.e. Pre-Algebra). During the course of the

semester, students will work through all parts of the course content, but will spend less time on areas that they know or learn quickly, and more time on new material or areas of difficulty. The software tracks students' progress, so faculty can monitor and can provide additional instruction or encouragement. Therefore, most of the students should be successful in mastering the content, resulting in passing the course and being prepared for subsequent courses. The difference in a redesigned course is the amount of time students are required to spend on each of the content areas – individual knowledge and proficiency driven, versus being determined by faculty and their syllabus.

The second and third questions examine persistence as a consequence of successful completion of the initial developmental course and enrollment in the next math course, including college level math. Current national statistics state that only about 58% of the students are successful in their developmental math course (Gerlaugh et al., 2007). This statistic remains consistent whether the students in the course are students new to the course or are students who are repeating the course. In the redesign model, greater number of students should be able to pass as the course is structured around individual students' deficiencies. Their success in their initial course should result in enrollment of their next math course. If students' progress to their next course and it also has been redesigned, higher success rates should be achieved. Therefore, students who take a sequence of redesigned courses should be college-math ready at a higher rate than students in traditional face-to-face courses, and register for the 100 level math course.

CHAPTER 2: REVIEW OF THE LITERATURE

This chapter outlines three broad strands of literature that are relevant to this study. The integration of these components creates a comprehensive view of college students' successful academic performance in developmental math. The first strand summarizes key research on student engagement, retention and persistence, which increase students' likelihood for success in postsecondary education. The second strand concerns research on the role of remedial and developmental education, particularly in the community colleges. The third strand is focused more specifically on developmental math programs.

THEORIES ON STUDENT ENGAGEMENT, RETENTION AND PERSISTENCE

In a recent national study of high school sophomores, the National Center for Educational Statistics (2004) reported that nearly 75% planned to attend college after high school. The Condition of Education (NCES, 2011) reported that over the past 40 years, "total undergraduate enrollment in degree-granting postsecondary institutions increased from 7.4 million students in fall 1970 to 13.2 million in fall 2000 and to 17.7 million in fall 2009" (p. 34). Unfortunately, while the number of students enrolling in higher education has increased, nearly half of the students who enter two- and four-year colleges leave without earning a degree (NCES, 1996 & 2002; Tinto, 1993). Some of this can be attributed to the student's lack of adequate academic preparation. For example, in 1994 only a little more than half of the students graduating from high school completed a college preparatory curriculum (NCES, 1996). Moreover, although the open-access mission of community colleges has resulted in increased enrollments, it has also resulted

in the admission of many students who were not adequately prepared, as evidenced by the proliferation of remedial or developmental courses during the past decade (Boylan, 1999; Gerlaugh et al., 2007; Higbee, Arendale, & Lundell, 2005).

Research has found that college attendance patterns and graduation rates can vary for different groups of students (e.g., by race/ethnicity, social class, gender) and by the type of institution they first enter (two-year or four-year). In addition, students of color and students from low socioeconomic backgrounds are at the greatest risk for dropping out or stopping out of college regardless of whether they begin at a community college or four-year institution (Tinto, 1993). These findings raise concerns regarding student attrition. In response, research on retention has focused on the initial period of students' transition to college, their involvement and engagement academically and socially, and their eventual persistence (Austin, 1984; Bean 1985; Tinto, 1993).

Beginning in the mid 1970s, Tinto (1975) began writing about dropping out of higher education and proposed theories to examine students' likelihood to persist or leave college early. Tinto's early works (1975, 1982) and subsequent book *Leaving College* (1993) began to look at connections between the academic and social systems within higher education that might impact students' decision regarding continuing. His Model of Institutional Departure (1975) identified three major sources of student departure from higher education: academic difficulties, inability to integrate educational and occupational goals, and failure to become engaged in the intellectual and social life of the institution. His Student Integration Theory suggested that the lack of congruency between students and institutions creates a climate for student attrition. It is the matching

of the student's academic ability and motivation to the institution's academic and social characteristics that shape the student's decision to stay or leave. Tinto's theory put emphasis on the concept of integration and the patterns of interactions between the student and others (e.g., peers, professors) and between students and components of the educational system (e.g., institutional type, curriculum, major). This model argues the importance of both social and academic integration.

Influenced by Tinto's work, postsecondary institutions turned attention to aspects of student social integration by developing activities and programs focused on increased student involvement (Bean, 1980; Bean & Metzner, 1985; Tinto, 1993). Qualitative studies showed that students who were involved on their campuses, engaged in activities with other students, and involved in extracurricular events, especially where faculty were also present were more likely to continue (Astin, 1984; Pascarella, 1980; Terenzini, Lorang, & Pascarella, 1981). This work of increasing social integration fell largely to student affairs professionals. The results were found in extended or expanded orientation programs, development of freshmen seminars, and a variety of extracurricular activities. However, these types of efforts often did not lead to real integration in the student's academic life. While programs were developed, they were add-ons, in which faculty members were not always present, and students could not see the programs' role in their academic goals (Tinto, 1982). More importantly, the evidence regarding social integration and student retention was not always consistent (Bers & Smith, 1991).

Academic integration focuses on the learning experience as being central to student retention, in particular, the learning that happens in classrooms and labs. If a

student performs well in class, enjoys the subject or studying the subject, there is increased academic integration, and therefore a reduced risk of dropping out. According to Tinto (1998), the conditions for academic success include having clear and high expectations of students in the classroom and providing frequent feedback to students about their performance. A few studies examining Tinto's model in two-year community colleges have also supported the importance of academic integration as a factor in student persistence (Bers & Smith, 1991; Fox, 1986; Pascarella et al., 1986). Although evidence is less consistent regarding social integration in two-year settings, academic integration has been shown consistently to be beneficial as both a direct and an indirect influence on student persistence (Bers & Smith, 1991). The finding that academic integration is more important in community colleges is not surprising, since community colleges are often commuter campuses and therefore provide few opportunities for social integration (Bers & Smith, 1991; Tinto, 1993). Compared with four-year residential institutions, social networks within community colleges are less likely to develop and students are less likely to be connected with people and events on the campus (Cross, 2000).

Findings in support of Tinto's (1993) student integration model are also generally consistent with Bean's student attrition model (1980). Bean proposed an alternative to Tinto's model to explain the college persistence process. His model built on models of organizational turnover and models of attitude-behavior interactions. The student attrition model asserts that behavior is shaped by process where beliefs shape attitudes, and in turn attitudes influence behavioral intentions (Bean, 1985). Therefore, students' beliefs are affected by their experiences, and their intentions are shaped by these beliefs and

experiences (Cabrera, Nora, & Castaneda, 1993; Nora, 1987). Studies have largely supported that student attrition is linked with students' likelihood to leave primarily associated with academic and psychological outcomes, background variables, and environmental variables (Bean & Metzner, 1985; Bean, Partanen, Wright, & Aaronson, 1989). In addition to students' confidence in their academic ability and the environmental factors supporting students, Bean and Vesper (1990) found that family factors also contribute both directly and indirectly. Bean and Metzner provided a conceptual model for examining both traditional and non-traditional student attrition. They noted that non-traditional students were more likely than traditional students to be influenced by changing conditions in the external environment.

A number of studies based on this model examined the interaction between student beliefs and their performance in the classroom. These studies showed that student motivation (i.e., relevance and satisfaction) affected persistence and was also highly correlated with various course-related issues such as instructional design, instructors' facilitation, and classroom interactions (Shea et al., 2003). Importantly, despite various student background characteristics upon entering college, the quality of student effort was noted to impact student learning which, in turn, impacts persistence or attrition (Kaufman & Creamer, 1991; Ory & Braskamp, 1988; Pace, 1984). While the theories of Tinto and Bean address issues of retention and attrition, and the type of work higher education professionals need to engage in to assist students graduate, student preparedness for college cannot be overlooked. Recent studies report that nearly 62 of every 100 well-prepared high school graduates who enter college after high school earned

a baccalaureate degree; however, only three of every 100 underprepared students did so (Adelman, 1999; Cabrera, LaNasa, & Burkum, 2001). A report by the Advisory Committee on Student Financial Aid (2008) showed that among the 1992 high school graduate cohort, only 26% of college-qualified low-income students actually attained a bachelor's degree by 2000. Although the percentage was higher among more economically advantaged students (56%), they also faced challenges in obtaining bachelor's degrees. The report by the Advisory Committee on Student Financial Aid (2008) identified three critical transition points for students: enrollment, persistence and transfer. Barriers faced by students at these transition points which prevented their attainment of the bachelor's degree, included academic, social, informational complexity, and financial difficulties.

Community colleges have become a more popular entry point for students of various economic backgrounds, and even more students are turning to community colleges due to economic constraints. In addition, with their open-door policy admission policies, more students are beginning at community colleges for their college career, with plans to transfer to obtain their bachelor's degree. While not all students enroll in community colleges to obtain an associate degree or to transfer to a four-year institution, the persistence rates of those intending to earn a degree or transfer are not impressive (Driscoll, 2007). For example, 2006 data showed that after three years, 45% of first-time community college students were not enrolled in any type of institution and had not received a degree (NCES, 2007). While community colleges were designed to be a pathway to degree attainment, evidence points otherwise. Students who are not college

ready are less likely to persist (Giegerich, 2006; Grimes, 1997). Completing developmental requirements, passing college level math, and earning a year of college-level credits seem to be critical milestones toward eventual degree attainment (Adelman, 1999; Calcagno, Costa, Bailey, & Jenkins, 2006). In addition to inadequate academic preparedness were competing pressures of work and family, which limit time for academics for community college students (Schmid & Abell, 2003; Tinto, 1993). Due to the difficulties faced by community college students, the need for academic and social integration seems to be a greater challenge for institutions.

REMEDIAL AND DEVELOPMENTAL EDUCATION

Remedial Education

The preparation of under-prepared students for college has been the purpose of remediation in higher education. This is not a recent development. For example, in the 17th century, Harvard College assigned tutors to underprepared students studying Greek and Latin (Phipps, 1998). The University of Wisconsin offered remedial programs in reading, writing, and arithmetic in 1849 (Breneman & Haarlow, 1998). With the establishment of the G.I. Bill after World War II, remediation was necessary to assist adult students entering college after a break in their education. With the development of community colleges and their open-door policy, the need for remediation increased (Boylan & Saxon, 2004; Cohen & Brawer, 1989; Knopp, 1996). Although this increased need can be attributed partly to greater numbers of students who enter postsecondary education, remediation continues to be an important issue in higher education, and demand continues to increase (NCES, 2011). According to a National Center for

Educational Statistics (1996) study, 99% of America's public community colleges offer remedial courses in one or more subject areas. Concerns about remediation have grown as college and states have devoted substantial resources to this area (Breneman & Haarlow, 1998).

Early studies, mainly conducted by Roueche and his colleagues at the University of Texas–Austin, focused on effective learning techniques for successful remediation (Roueche, 1968; Roueche & Wheeler, 1973). Learning theory drew primarily on behaviorist techniques favored at that time, which tended to produce positive results with remedial students. Of particular importance was establishing clear and carefully defined goals and objectives for improved student performance (Donovan, 1974; Kulik & Kulik, 1991; Roueche, 1968; Roueche, 1973). A high level of structure, with all requirements and standards clearly stated, allowed academically under-prepared students to know exactly what was to be expected. These students may not have learned either the organizational skills to understand the concepts or time management skills to allow for adequate time for learning (Boylan & Bonham, 1998; Cross, 1976). One behaviorist approach for creating an environment for clearly defined goals with a high degree of structure was mastery learning (Bloom, 1968; Carroll, 1963). Mastery learning utilizes small units of instruction with frequent testing, requiring students to master the material before moving on to the next unit. Therefore, this high degree of structure helps compensate for the student's lack of skill by modeling the appropriate method for organizing information (Cronbach & Snow, 1977). In addition, a variety of teaching methods other than the lecture approach was encouraged (Canfield, 1976; Lemire, 1998),

as the lecture approach had likely not worked for these students in their previous school environments.

Positive results have been observed when the remediation programs have included more than just skills development (Calcagno & Long, 2008; Greene & Foster, 2003; Tinto, 2004). In remedial courses, as students are insufficiently prepared, academic support becomes a key role in retention and success (Tinto, 2005). An example of an academic support that seems to be successful is study groups. This can serve as both social and academic integration criteria for retention (Astin, 1993; Tinto, 2005). In addition, where remedial programs are successful, they are seen as an essential part of the campus academic community and are considered part of the campus planning activities (Kiemig, 1983; Roueche & Baker, 1987; Roueche & Roueche, 1993). This could explain the lack of remedial courses at many four-year institutions, as they are not an essential part of the campus academic community.

Developmental Education

With an increasing number of students requiring remediation (McCabe & Day, 1998) and the variety of instructional methods needed to address this demand, the area was renamed and redefined as developmental education to encompass both the academic and non-cognitive factors that influence student success (Clowes, 1982). This perspective was based not only on the research of Tinto (1993) and Bean (1980), but also on the revised Student Personnel Point of View (American Council on Education, 1998), which included a section on the need for academic assistance programs and noted that it was the responsibility of colleges and universities to provide counseling and other services to

assist student in developing the skills and attitudes necessary for success. Developmental courses therefore focus on student strengths and address both cognitive and affective development in order to provide skills for success.

Developmental education includes not just instruction on academic content, but also involves motivating students to learn and participate in activities so they will remain engaged and persist (Tinto, 1993). This places a greater responsibility on faculty teaching these courses. Community college students are often less “engaged” than their peers at four-year institutions in all aspects of pursuing their academic goals. Therefore, their faculty may be the student’s main means of understanding opportunities for engagement and assistance with setting educational goals. As previously mentioned, students who have clear goals are more likely to persist (Tinto, 1993).

Studies suggest that for success, courses need to be delivered by faculty who are an integral part of the campus academic community (Kiemig, 1983; Roueche & Baker, 1987; Roueche & Roueche, 1993). These professionals know, understand, and take action based on research on developmental courses and the types of students in these programs (Boylan, Bliss, & Bonham, 1997; Maxwell, 1997). Unfortunately, staffing patterns indicate that among all institutions and all subjects, 72% of those teaching developmental courses are “part-time” faculty (Boylan, Bonham, Jackson, & Saxon, 1994). Cross (1976) observed that the lack of achievement was more than a simple cognitive issue, but also a factor of the selection of instructors who work with this special population of students.

Essential Components of Developmental Courses

Concerns around staffing of developmental courses were informed by a 30 year review of research in developmental education which identified 20 characteristics of successful programs (Boylan & Bonham, 1998). Eight of these characteristics directly relate to teaching. These include utilizing a variety of teaching methods, sound cognitive theory-based courses, computer-based instruction to supplement regular classroom activities, classroom and laboratory integration, developmental course exit standards which are consistent with entry standards of subsequent courses, strategic learning that teaches students skills to monitor their comprehension, and think strategically about learning, professional training for faculty, and critical thinking (Boylan et al., 1997; Starks, 1994). These encompass the “Seven Principles for Good Practice in Undergraduate Education” (Chickering & Gamson, 1987; Chickering & Reisser, 1993), which are fundamental to developmental programs. Included in these guidelines are practices that encourage faculty-student contact, promote cooperation among students, encourage active learning, give prompt feedback, emphasize time on task, communicate high expectations, and respect student’s diverse talents. Through a review of both research and current practices, several structures for implementation of developmental programs seem to be in practice, which enhance student success.

Solely measuring student outcomes without looking at the elements of the developmental course may not present a clear picture (King, Morris & Fitz-Gibbon, 1987). Effective developmental programs appear to incorporate both the characteristics of successful programs and the “Seven Principles for Good Practice in Undergraduate

Education” (Smittle, 2003). Many of these characteristics of good practice can be summarized as instructional techniques. These effective instructional techniques include regular testing, frequent and timely feedback, and the use of active learning strategies (Gerlaugh et al., 2007). Tinto’s (2005) findings on study groups, whether they are created by faculty or self-generated by students, also seem to yield positive results. This may be due to the additional time on task and the integration of students with the course material and with their fellow students. In addition to the activities in a classroom, there has also been an increase in other support services such as tutoring and academic advising that have been found to be successful (Boylan et al., 1995; Gerlaugh et al., 2007).

The increased use of computers has also been associated with improved classroom learning. An analysis of computer-based instruction at 123 colleges and universities found that the use of the computer as a tutor designed to supplement regular instruction had positive effects (Kulik & Kulik, 1986). The use of computers for students to do writing assignments and as a tutor in math contributed to student success in developmental courses (Roueche & Roueche, 1999). The effectiveness of computer-based instruction declined, however, when it was used as the primary delivery tool in developmental education (Bonham, 1992).

Administration and organization of developmental education is also important for success. As mentioned previously, developmental programs that are seen as an essential part of the campus academic community and are considered part of the campus planning activities are successful (Kiemig, 1983; Roueche & Baker, 1987; Roueche & Roueche,

1993). This emerges from a commitment from the institution regarding the importance of developmental education (Boylan, 1999). With a student-centered and holistic view of the student, this type of program recognizes that students may not only be taking courses, but also may be working, parenting or in other developing relationships. Therefore, support services can be developed to support students within the broader context of their academic, economic, and social lives. This organization recognizes that the student's progress or lack of progress in developmental courses may be the result of issues outside the classroom, which prevents them from spending sufficient time on the subject (Schmid & Abell, 2003; Tinto, 1993). Good developmental programs also have explicit goals and objectives, including what is expected not only from faculty and students but, also, from the staff involved in support programs (Boylan et al., 1997; Kiemig, 1983).

A third key area of for success is the faculty. For many students, especially at community colleges, the classroom may be only place where they meet with each other and the faculty (Tinto, 2005). Therefore, what happens in the classroom and the involvement of the student in the classroom may impact not only what the student learns, but also have an impact on their view of education, which may impact retention. Volkwein and Cabrera (1998) suggest that the single most important factor in affecting multiple aspects of student growth and satisfaction is what happens in the classroom. Stated differently, the developmental program and support structures that an institution designs are important, but how the faculty interacts with the students may have significant impact on student success. This might help explain why despite the existence of developmental programs, students continue to struggle.

Higher education has traditionally valued individual faculty practice, allowing faculty latitude in course development and delivery, while standardizing the student learning experience. This assumes that all students in a course have similar learning needs, interests, and skills. However, some students might have had very little math experience, some had difficulty learning math in high school, some might have done well but forgot (Phipps, 1998), and some may have had problems understanding the placement exam and have been misplaced. Therefore, successful programs have faculty who have the ability to teach a diverse student population and understand their different learning styles (Smittle, 2003). However, many faculty members continue to teach the way they were taught, using the lecture format. This method may be the least effective with students in developmental courses, as this may have been the method used in their previous educational setting. Students in developmental courses are most likely to succeed when a variety of instructional methods are used that promotes active student involvement (Casazza & Silverman, 1996; Cross, 2000).

It is encouraging that the field of developmental education is employing the strategies outlined in this section (Gerlaugh et al., 2007). Data is beginning to suggest that with appropriate assistance under-prepared students can be as successful in higher education as their better-prepared classmates (Bettinger & Long, 2005; Boylan 1999; Smittle, 2003). As noted previously, passing developmental requirements seems to be the first critical milestones toward degree attainment of underprepared students (Adelman, 1999; Calcagno et al., 2006). However, an initial research in retention rates in these programs reveals they are still not adequate: 76% for reading, 73% for writing, and 63%

for math (Boylan, 2002). In addition, pass rates in math were also lower at 58% versus 69% for reading and 64% for writing (Gerlaugh et al., 2007).

DEVELOPMENTAL MATH AND COURSE REDESIGN

Before looking at developmental math more specifically, one area of consideration is the math placement exam. Apprehension about math performance has been shown to significantly reduce math performance, especially when the additional element of a timed test is also involved (Cates & Rhymer, 2003). While placement exams measure content knowledge, the results may be clouded by math anxiety.

Ajzen's Theory of Planned Behavior (2002) suggests that behavior is the result of two factors: intention for the behavior and the actual behavioral control. In the academic setting, students believe that if they work hard, they can be successful. And along with this positive attitude, if students experience a positive attitude about their success from significant others, there is higher predictability for success. This theory is consistent with Bean's (1985) Student Attrition Model, which asserts that behavioral intentions are shaped by a process in which beliefs shape attitudes, and attitudes influence behavior intentions. Similarly, the reverse is true, and math anxiety results from repeated negative experiences related to math (Kogelman, Nigro, & Warren, 1978). This negative attitude can become a self-fulfilling prophecy (Shields, 2007).

Student attitudes and perceptions about expected level of performance could be a better predictor of future performance than actual past performance; that is, performance may be mediated by self perceptions of capability or in the case of math, lack of capability (Bandura, 1997). Research on math anxiety has shown that performance is

related more to an affective deficiency than a cognitive one (Ho, Senturk, Lam, & Zimmer, 2000; Martinez & Martinez, 1996; Meece, Wigfield, & Eccles, 1990). More specifically, academically stronger students have a stronger sense of self-confidence, attributing success and failure to their own efforts (Hall & Ponton, 2005), while developmental students tended to have more external locus of control, attributing success or failure to fate or luck (Grimes, 1997). Additionally, when students internalize stereotypes regarding race and gender, performance suffers even further, masking a mere skill deficiency (Juang & Silbereisen, 2002; Steele & Anderson, 1995). It is suggested, therefore, that developmental math programs need to integrate the best instructional practices with attitudinal support systems for students (Burley, Butner, Anderson, & Siwatsu, 2009).

Developmental Math

What Works in Remediation by Hunter Boylan (2002) has been the standard or best practice in developmental education since its publication. Based on this work, additional documents have emerged for looking at the research in this area, as well as ideas for implementation, especially as they relate to developmental math (Gabriner, 2007; Schwartz & Jenkins, 2007; US DOE, 2005). It seems that developmental math in U.S. community colleges follows two major pedagogical patterns in teaching and learning (Walker, 2008). One is skill efficiency, defined as the accurate, smooth and rapid execution of mathematics procedures. The other is conceptual understanding, defined as the mental connections among math facts, procedures and ideas. While there is agreement about the importance of computational fluency and conceptual

understanding, there remain issues about procedural fluency and conceptual math reasoning (Epper & Baker, 2009), which has resulted in issues about which skills should be taught and in what order. Stated another way, while there are trends in terms of methods and techniques that characterize effective teaching in developmental courses, there is also the need to address program components, as well as organizational components. In addition, research suggests that one reason students drop out of math courses is the perceived poor quality of instruction and the lack of active engagement with their faculty and the course material (Hora, 2011; Seymour & Hewitt, 1997). On the other hand, when students invest in their learning, the more effort they will exert, which typically will result in greater learning.

Student achievement in developmental math has been positively linked to motivation and active engagement (Gunthorpe, 2006; Tinto, 2005). In these studies, there is recognition of the different learning styles of students and, therefore, different instructional methods are utilized. This is consistent with studies on classroom activities which have shown that learning is enhanced when students are actively involved their learning (Hora, 2011; Volkwein, King, & Terenzini, 1986). However, it seems that regardless of institution type, most students experience similar learning environments in the classroom. While classrooms can be dynamic environments, students are more often described as passive participants (Fischer & Grant, 1983). In these classrooms, students spend most of their time listening to lectures or observing demonstrations. This allows them to be unengaged cognitively, while physically present. And if they are not frequently assessed, it may lead to failure in the course. Fortunately, successful

programs, even in traditional classrooms, use frequent assessment to help students learn (Coe, 2006; Cross, 2000; DiMuro, 2006). Emerging from this research is the need for a learning environment that uses a mix of instructional methods, challenges students with questions beyond just memorization, provides for continuous assessment and prompt feedback, and allows students to talk about mathematics (Boylan & Saxon, 1998; Casazza & Silverman, 1996; Johnson, 1996; Lemire, 1998; Perkins, 1993; Waycaster, 2001).

Developmental math courses are specifically designed to bridge the gap between the student's previous math experience and what is expected in college level math (Boylan, Bonham, & White, 1999; Lesik, 2006). Despite some positive results when appropriate instructional methodologies are implemented, the evidence that these programs are successful is mixed (Baxter & Smith, 1998; O'Conner & Morrison, 1997). One of the reasons may rest with the classroom environment and the faculty teaching developmental math courses.

Math Redesign

Although there is considerable variability in how developmental courses are conceptualized and delivered, the majority consists of semester-long classes taught in traditional classrooms (Bailey & Cho, 2009). As mentioned previously, studies have shown that learning occurs over extended period of time as a result of active engagement with the material (Felder & Brent, 1996). Therefore, learners cannot be limited to listening to lectures and depending on math textbooks. However, evidence collected in a number of studies of college students indicates that the primary learning methods used

are visual and auditory (Lemire, 1998). This seems to be a direct contrast to studies that show that the use of a variety of instructional methods increases the chance of success of under-prepared college students (Casazza & Silverman, 1996). The teacher of college-ready students can encourage active learning to achieve desired student outcomes, but developmental education faculty must structure and lead the activities to teach developmental students to become independent learners (Smittle, 2003). Boylan (1999) argues that appropriate developmental education should be student oriented, that is, with the student placed at the center of the learning experience. Research has suggested scenarios for success, but colleges have been slow to adopt and adapt to these successful programs. One reason for this could be the role of faculty, as previously mentioned. Higher education has traditionally encouraged the “academic freedom” of individual faculty practice. It is clear, however, that developmental education may require some standardization of faculty support roles and techniques used in delivering instruction successfully.

Course redesign attempts to change the way course content is delivered. With support from the Pew Charitable Trusts, the National Center for Academic Transformation and 30 postsecondary institutional partners developed a course redesign methodology that uses technology to improve student learning while reducing cost (Twigg, 2003). Key elements of course redesign include redesigning the entire course versus individual sections, encouraging active learning, providing students with individualized assistance, building in ongoing assessments and prompt feedbacks, and ensuring sufficient time on task and monitoring student progress. These can be achieved

through employing computer-based learning resources, mastery learning, on-demand assistance, and staffing alternatively (replacing high cost faculty labor with less costly labor and technology where appropriate).

Course redesign proposed six models: Supplemental Model, Replacement Model, Emporium Model, Fully Online Model, and the Buffet Model. Briefly, the supplemental model retains the basic structure of the traditional course while supplementing lectures and textbooks with technology-based, out of class activities or changes what goes on in the class by creating an active learning environment inside the classroom. The replacement model reduces the number of in-class meetings with out-of-class, online, interactive learning activities. The emporium model replaces lectures with a learning resource center featuring interactive computer software and on-demand personalized assistance. The fully online model replaces all in-class meetings with online, web-based, multi-media enriched resources. The buffet model customizes the learning environment for each student based on learning preferences and desired learning outcomes. Utilizing one of these six course redesign models, among the 30 initial institutional participants, 25 showed significant increases in learning, and 18 of the 24 institutions who measured retention showed increases (Twigg, 2005a). While the initial effort was not targeted at developmental courses, it has been applied to developmental courses in several community colleges with success (Twigg, 2008).

Redesigned courses treat students as individuals and standardize faculty practice, moving students from passive, note taking to active learning. The active learning components include on-line tutorials, which are interactive and provide students with

needed practice and greater engagement with the material in order to fully learn the material. Continuous assessment and feedback that enables both repetition and frequent feedback are key to redesign and lead to enhanced student learning (Angelo & Cross, 1993). On-demand support provides students with assistance from a variety of people, which provides not only differing perspectives, but also a sense that the student is a part of a community. Mastery learning provides flexibility for students, in that learning is organized around the need to master specific learning objectives according to scheduled milestones for completion. Many of these components are delivered using technology in order to provide not only consistent, but continuous feedback.

Developmental math courses lend themselves to redesign due to the emphasis on students as individual learners. While students are not ready for college level math as evidenced by a placement exam, they have varying levels of math knowledge or competence (Lesik, 2006; Phipps 1998). In addition, they may actually possess a higher level of knowledge, but it was masked by math anxiety during the placement testing process (Kogelman et al., 1978). Therefore, in a traditional developmental course, there may be several types of students including those who really are not well prepared, those who know some of the material, and those who know most of the material but were misplaced due to math test anxiety or from not having had math recently.

In contrast, a redesigned developmental math course provides students who know most of the material, to quickly review what they know and spend more time on what they are unfamiliar with, learn the material and move on to the next course. For students who know some of the material, they can review and spend the remainder of the semester

learning the material in order to be well prepared for their next course. Finally, for the group of students who are poorly prepared, the redesigned course can help them learn at their own pace, receive continuous feedback about their mastery of the content, and have additional support from faculty.

Computer-Assisted Math Redesign

As noted earlier, an analysis of computer-based instruction at 123 colleges and universities found that the use of the computer as a tutor designed to supplement regular instruction had positive effects (Kulik & Kulik, 1986). Therefore, in developmental courses, due to the variety of learning needs of students, technology application in the form of course redesign may provide a powerful tool for academic integration.

Reviews of the course redesign method for developmental math provide preliminary evidence of positive results. For example, at Tennessee's Cleveland State Community College, several hours of class time each week was replaced by an hour of computer instruction and two hours in the computer lab. Reports from the college show positive learning gains by students (Squires, Faulkner & Hite, 2009; Twigg 2005b). This is consistent with previous research, which stated that the effectiveness of computer-based instruction declined, however, when it was used as the primary delivery tool in developmental education (Bonham, 1992).

In the redesign of developmental math, the NCAT's partner institutions have found that the Emporium Model has consistently produced gains in student learning. The two computer applications most frequently used by redesign programs are MyMathLab provided by Pearson Education and ALEKS (NCAT). The respective Pearson Education

(2012) and ALEKS (2012) websites of these products suggest they provide initial diagnostics of the student's math knowledge, support the learning styles and the instructional needs of the student, provide for measurable course objectives, emphasize frequent assessment and feedback, and have grade book features for ease of course management.

The ALEKS software, which is featured in this dissertation study, was developed out of research collaboration between the New York University and the University of California at Irvine. ALEKS is based on Knowledge Space Theory, which utilizes assessment of student initial knowledge from which to develop a practical implementation tool for learning using Internet based tools.

SUMMARY OF LITERATURE

Theories regarding student engagement, retention and persistence point the way for successful developmental programs. From the work of Tinto (1993) and Bean (1980), the importance of both academic and social integration and student behavior provide both a theoretical framework, as well as practical application of these theories in the classroom. Despite the philosophy and learning techniques underpinning developmental education, however, these programs were often found to be ineffective (Grubb & Associates, 1999). For example, a study conducted by the Conference Board of Mathematics found math enrollment continued to be high in all pre-college courses, both due to the number of underprepared students and students not passing these developmental courses (Lutzer et al., 2007).

Developmental education has attempted to identify the characteristics of successful programs (Boylan & Bonham, 1998). However, the implementation of these programs has not produced consistent results regarding student learning and continued research is encouraged (Duranczyk, 2007; Higbee et al., 2005). Results of developmental programs at four-year colleges found that students in these programs did not perform any worse than similar students who did not enroll in developmental courses. Moreover, math remediation appeared to improve some student outcomes, but a large number continue to struggle (Bettinger & Long, 2005). This could be the result of continued emphasis on the individuality of faculty, versus the individuality of each student.

Results of course redesign for developmental math courses suggest increases in student learning, and reports from publishers of computer software are supportive. However, rigorous research is not yet readily available as most are descriptive studies (US DOE, 2012). This study attempts to provide research results using a strong research design to add to the field of developmental math education in community college settings.

CHAPTER 3: METHOD

RESEARCH SETTING

The study was conducted at a large community college within the University of Hawai‘i System. At the larger community colleges in Hawai‘i, with student headcounts greater than 2,000, an average of 75 developmental math sections are offered each semester. Therefore, if only 58% of students successfully pass developmental math courses (UHCC, 2007), of the approximately 75 courses offered, mathematically, almost 37 of the courses could be filled with students repeating the course. These percentages are also consistent at the community colleges with smaller headcounts. Unfortunately, these passing percentages are consistent in each subsequent course, if students persist.

The four courses in the developmental math sequence at this community college in Hawai‘i are Essential Mathematics for Algebra (Math 1), Introductory Algebra (Math 22), Algebraic Foundations I (Math 73) and Algebraic Foundations II (Math 83). Increasing students’ successful completion of developmental courses by even a small percentage, could mean a cost savings to both the institution (by not having to offer numerous sections which are frequently filled with students who did not pass previously) and for the student (making faster progress through the math sequence, as well as not spending more time and money in non-transfer level courses). In addition, if taking a redesigned course could increase the percentage of students enrolling in the next course in the math sequence, this could result in larger numbers of students reaching their academic goals.

The current developmental math sequence is Math 1, Math 22, Math 73 and Math 83, each awarding 3 credits. In these courses, students meet with faculty for a total of 150 minutes each week, either three times per week in 50-minute sessions or twice a week in 75 minute sessions. The courses meet in a traditional lecture classroom. The textbook used by the traditionally delivered courses have a supplemental math software (MyMathLab) that student have access to but are not required to use. Students are also encouraged to use the math lab to access tutors or their MyMathLab software for supplemental assistance.

Math Redesign (Treatment)

The redesigned course sequence included conversations with faculty in college-level math courses (Math 100, 103, 111 and 115) to determine what concepts and skills faculty expected students to have when entering their courses. This resulted in the creation of new redesigned math courses: Whole Number Skills - Math 9 (1 credit), Essential Math for Algebra - Math 18 (3 credits) and Accelerated Algebraic Foundations - Math 82 (4 credits). Math 18 is equivalent to Math 22, and Math 82 is equivalent to Math 73 and 83. The redesigned courses use an online instructional tool to help guide student learning and track student progress. In the redesigned model, each student spends at a minimum of three sessions (50 minutes each = equivalent to 150 minutes) “doing” math. Students are required to do the following: attend one class session where they work on math under guidance of the student’s faculty in the math lab; attend one mandatory lab session in the math lab with math faculty/tutor (not necessarily the students’ course faculty) present for assistance; and participate in a third session either in

the math lab or at another location of the student's choosing but using the math software. During the semester, faculty members monitor student progress during weekly classroom interactions.

The faculty at the community college where this study took place evaluated both the MyMathLab and ALEKS software and selected ALEKS because it provided students the greatest opportunity to manage student learning and their progress. Due to the artificial intelligence in ALEKS, the software provides learning components based on the student's answers to her or his answers on the previous problems presented (ALEKS.com). In addition, it was the most flexible in integrating with all major textbooks used for developmental math, regardless of publisher.

In the application of ALEKS to the developmental math redesign, faculty first identified the content topics required for mastery of each of the redesigned math courses. Then upon placement in a developmental course, via the COMPASS Placement Test, students are given an initial assessment using ALEKS, containing approximately 30 problems that cover all of the topics in the course. This diagnostic test allows ALEKS to generate a customized learning plan for each student. After the initial assessment, students are presented with "pies." These pies contain "slices" which modularize the topics/content included in the entire course syllabus. Since the initial diagnostic assessment covers the entire course rather than a smaller amount of material (such as a chapter), both the faculty and the student receive a clearer picture of how many of the course topics the student is familiar with and how many of the course topics the student will need to work on in order to meet the course learning outcomes. As the entire

developmental math sequence is redesigned, students who master the content in one course are able to move onto the subsequent math course, even during the same semester. This self-mastery aspect of redesign can help mediate the findings that the more semesters of developmental education a student is required to complete, the less likely it is for that student to complete a college level math or English course successfully or to earn a degree (Hern, 2010).

In addition to the ALEKS software, developmental math faculty produced short videos to further illustrate concepts, using examples that students in Hawaii might be more familiar with. These were linked to the ALEKS content using the learning management software used by the college. This provided students another perspective of the material, as well as providing a faculty face, as student interaction with faculty is an important component of academic integration (Tinto, 1975).

The redesign of each of the courses in the developmental sequence was structured with the student as the focus. The computer software provided the means of providing individualized learning based on the students' learning needs. Due to the ongoing assessment and immediate feedback, the students' understanding of math was continually monitored. In addition, since students were not spending time listening to lectures on a particular topic, they spent much more time on task; that is, doing math versus hearing about math. All of these are features of the redesign model supported by the work of the National Center for Academic Transformation (Twiggs, 2008). In addition to the content mediated by the ALEKS software, the classroom was structured so groups of students

could get together to work on problems together or the faculty could explain to groups of students who may be working on similar concept.

Subjects

The subjects in this study were students at one community college who took the COMPASS Math Placement Test prior to the Spring 2010 semester through the start of Spring 2011 semester and subsequently enrolled in developmental math courses during Spring 2010, Fall 2010, and/or Spring 2011 semesters. Due to Math 9 redesign not being completed by Spring 2010, students in Math 1 and Math 9 were not included in this study. Table 3.1 shows the number of students who were part of this study. The redesigned math courses will be designated as T for treatment from this point forward.

Table 3.1. Student enrollments in developmental math.

Course	Sp '10	Fall '10	Sp '11
18/97 (T)	73	132	93
22	221	319	195
73	431	392	356
82/98 (T)	127	131	164
83	413	381	297
Total	1265	1355	1105

DESIGN

The purpose of the research is to ascertain whether the introduction of a redesigned math curriculum has an effect on students' achievement in math, as measured by receiving a passing grade (85%) in the developmental course in which they enrolled. In the redesigned course, if students achieved an 85%, they received credit for the course.

The faculty decided that grading would be Credit/No Credit, as these courses are non-transferable courses. Three student cohorts were involved in this study: students enrolled in Spring 2010, Fall 2010, and Spring 2011.

Design Concerns

Concerns have been raised about previous studies concerning the impact of developmental education due to weaknesses in their research designs (Boylan & Saxon, 2000; Moss & Yeaton, 2006). One of the concerns has been ability to document program effects that eliminate alternative explanations (Moss & Yeaton, 2006; Weiss, 1998). The most common research designs used in developmental education have been one-group, pretest and post-test design, which is of little usefulness because it does not provide a control group, and the post-test only with nonequivalent groups design (Moss & Yeaton, 2006). As Moss and Yeaton note, this latter type of design uses placement scores, but then uses high-scoring students who do not need the developmental course work as a comparison group. This approach suffers from selection bias, since the two groups are not equivalent and the selection process is not modeled as part of the analysis. Moreover, because the low pretest group, which receives the treatment, is compared to a high pretest group, the design is often likely to result in findings of no effect (Moss & Yeaton, 2006).

Regression Discontinuity

Regression discontinuity (RD) is a type of treatment and control group design. It is a pre- and post-test comparison group design (Cook & Campbell, 1979). It represents an alternative approach for estimating treatment effects in the absence of random assignment of individuals to treatment and control groups. Thislethwaite and Campbell

(1960) first proposed RD, which is a type of quasi-experimental design, as a legitimate alternative to the randomized experiment, because its advantage is that it can provide unbiased estimates of a treatment effect when it is not practical to undertake a randomized experiment. The design therefore provides a strong, reliable alternative to the randomized experiment (Shadish, Cook, & Campbell, 2002), since the impact of a treatment can be assessed accurately by establishing a precise criterion for assigning students to treatment and control groups. As Cain (1975, in Pedhazur & Schmelkin, 1991) noted, “the critical difference for avoiding bias is not whether the assignments are random or nonrandom, but whether the investigator has knowledge of and can model this selection process” (p. 304). Therefore, estimation bias may be avoided in the RD design, not because of random assignment of subjects, but because the covariate used to assign subjects is known beforehand (Pedhazur & Schmelkin, 1991).

The design is described as follows:

O	C	X	O
O	C		O

The O suggests the students are measured prior to instruction and the C denotes that the groups are assigned by a conditional factor (i.e., participants scoring above or below a specific cut score). The first group receives the redesigned course (X) and the second group receives the traditional course. Finally, students are measured in terms of some type of outcome. Regression discontinuity makes it possible to assess the impact of a treatment accurately by establishing the precise criteria for assigning students to the

treatment and the control groups (Pedhazur & Schmelkin, 1991; Thistlethwaite & Campbell, 1960; Trochim, 1984).

Subjects above the established cut point can be assigned to one group, those below to another, and the treatment assigned to either group. This procedure was followed in the current study, where individuals were alternatively assigned to treatment and control groups based on higher or lower math pretest scores.

The RD design allows the researcher to utilize a line of best fit, or a regression line, to represent the outcomes for the treatment and control groups, instead of just solely relying on group composition. If students who are placed in the upper group are learning more (i.e., receive higher grades) it indicates a “discontinuity” due to something other than the “pretest” effect. This discontinuity (or break in the regression line between the pretest and posttest) is indicative of a treatment effect. If the treatment has no effect, a single regression line would be expected. If the treatment is effective, a discontinuity in the regression line reflects the size of the treatment effect (Shadish et al., 2002). The anticipated effect can be shown in Figure 3.1 for the probability that a student passes a given math course $P(Y=1)$. The pretest is anticipated to affect student likelihood to pass in either group and the discontinuity is the result of a treatment effect.

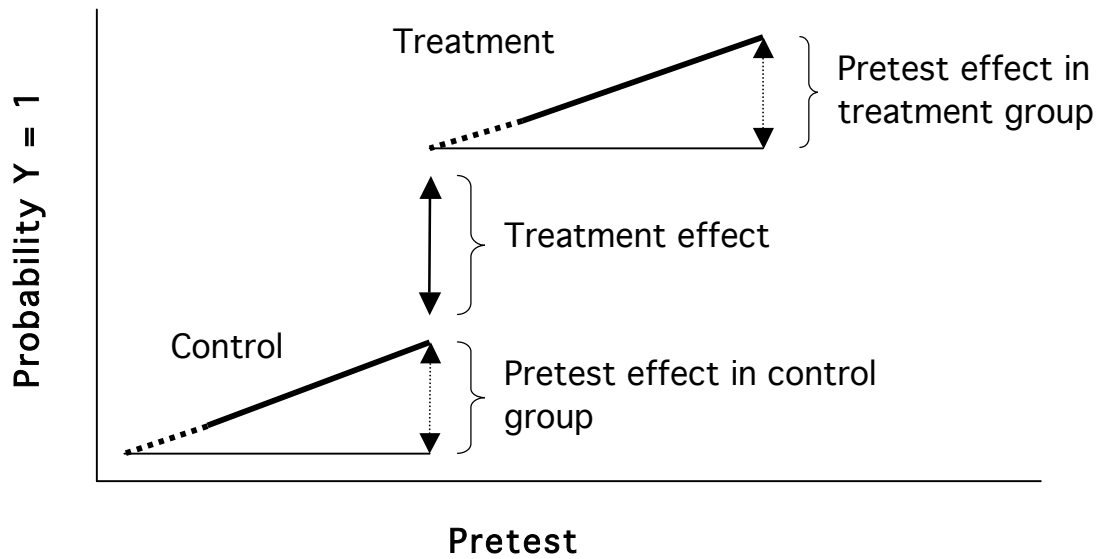


Figure 3.1. Relationship between pretest, instructional group, and probability of passing course.

Several advantages and cautions have been noted for the RD design (Cook & Campbell, 1979; Luyten, 2006). First, RD can produce an unbiased causal inference, if it is precisely implemented with correct modeling of the relation between the assignment criterion (i.e., pretest) and the dependent variable (i.e., specified outcome). The major strength of the design is that it does not require group equivalence before instruction begins. This is because the major assumption is that in the absence of a treatment effect, the groups should be the same on the post-test measure (i.e., those immediately above and below the cut score would have no reason to score differently in terms of the outcomes). Its major drawback, however, is the possibility that effects may be biased if the relationship between the assignment covariate and the outcome variable is incorrectly modeled (i.e., if possible nonlinear relationships or possible interactions are ignored).

These possibilities were checked, however, in preliminary analyses following Moss and Yeaton's (2006) suggestions.

Second, RD allows for an assessment of the size of the treatment effect. An estimate of zero (0) would indicate that the difference in likelihood to pass a given math course between the groups taking the traditional course versus the redesigned course can be attributed solely to prior ability and not to taking the course. There is the possibility of selection bias (Campbell & Cook, 1979), since groups are comprised on the basis of differing skills in math. In some situations, prior ability may not be an optimal means of assigning students to treatment and control groups. For example, motivation and other factors might intervene with prior ability in influencing success in passing a course. This possibility is diminished in the current study since student choice also entered into their assignments to the treatment and control groups.¹ Moreover, students were also sometimes assigned to the treatment and control groups based on lower prior ability and sometimes on higher ability.

A third advantage is that, in principle, controlling for student background to assess the effect of the treatment is not required. This is because the exact criterion of assignment to treatment or control group is known, and its effect is accounted for in the analysis. The approach does depend on relative equality of cohort samples, however,

¹ Results are presented for students who were assigned based solely on their pretest score. A second set of results are presented which included students who also "chose" to enroll in a treatment or control course despite their pretest score. In these instances, where eligible and non-eligible individuals are examined, respectively, it can be shown that results from RD designs in a neighborhood of the threshold for eligibility regardless of whether or not students self-select into the treatment (e.g., Moss & Yeaton, 2006).

especially in studies with small sample sizes. As noted, misclassification can sometimes be a problem, since other factors besides pretest score can influence student assignment.

A fourth advantage is that because the manner of assignment of individuals to treatment and control groups can be modeled as a known process (i.e., a specific cut point), this degree of control minimizes the bias to the estimation of the treatment (Shadish et al., 2002). Shandish and colleagues (2002) note that the design is sometimes criticized by those who think it is implausible that RD can yield unbiased estimates of treatment effects, since it is not a true randomized experiment. More specifically, because RD is based on using a cut point, it does not seem that it can yield unbiased estimates of treatment effects. Shadish and colleagues argue that this level of control is equivalent to randomized experiment because the selection process is completely known and perfectly measured:

In a randomized experiment, the assignment mechanism is completely known and is equivalent to a coin toss. It is also fully known for RD [regression discontinuity], as it consists of whether the score on assignment variable is above or below the cut point. In both cases, the assignment mechanism can be perfectly measured and implemented – that is, the researcher records correctly whether the coin came up heads or tails, or whether a person’s score is above or below the cutoff. (p. 224)

It is possible that the treatment may interact with the pretest measure. A significant interaction would suggest different treatment effects at different levels of student previous learning (as captured by the pretest score). This would be shown by different

slopes for the treatment and control regression lines (Moss & Yeaton, 2006). In this study, this possibility was diminished by actually modeling the possible treatment-pretest interactions. Hence, by positing a particular type of results in the absence of the program effect and by comparing the actual results to the expected pattern of “no results,” the RD design controls selection bias and is as strong in terms of internal validity as its experimental counterparts (Shadish et al., 2002; Trochim, 1990).

Data Collection

In the RD approach for examining differences in program outcomes, student prior ability can be used as a criterion to assign individuals to the control and treatment groups to determine the effect of being in the redesigned courses versus traditional courses on likelihood of passing (as well as future behavior). Participants included in the study therefore must be assigned due to their similar ability range as their peers, as determined by their pretest at program entry. In this study, cut-off scores were determined ahead of time for students entering courses requiring certain skill levels.

Student COMPASS Math Placement Test scores, student enrollment in developmental math course, and student achievement, as measured by their grade in the courses (or receiving Credit) were extracted from the University’s student information system. All students with valid records were selected for Spring 2010, Fall 2010 and Spring 2011. The data set includes all students with a COMPASS Math Placement Test score and who register for a developmental course(s) during the research period- spring semester 2010 through spring semester 2011. Students were able to select the pre-algebra or algebra placement test. Their results were modeled separately, as placement test results

direct student to different courses within the developmental sequence. The pre-algebra test is used primarily for the lower-level traditional or redesigned course, but depending on the score, it could lead to the higher-level algebra courses. Based on the placement test results, students are directed to the appropriate developmental course. However, because the student information system does not prevent students from enrolling in a lower-level course, students who did not enroll in the course specified by placement test results, were excluded in the preliminary set of data analyses. Subsequently, analyses were also conducted which included these self-selecting, or misclassified students.

Three student cohorts were involved in this study. Students in the first cohort were followed for 3 academic semesters: Spring 2010 = math course enrollment and grade earned, Fall 2010 = math course enrollment and grade earned, Spring 2011 = math course enrollment and grade earned. The analysis was replicated on a second cohort of students, Cohort B. These students were also followed for 2 academic semesters: Fall 2010 = math course enrollment and grade earned; and Spring 2011 = math course enrollment and grade earned. For the third cohort of students, only their Spring 2011 course enrollment and grade earned were examined.

Student Assignment to Groups

The information regarding student placement test scores, enrollment, and grades was extracted from the University of Hawai'i's Banner student information system. Students were recommended to take either the pre-algebra or algebra COMPASS Math Placement Test based on their most recent math course taken. However, students were able to select either test type. Based on their scores, students were placed into one of four

courses (see Figure 3.2). The letter T (treatment) denotes a redesigned math course, while C (control) denotes a traditionally delivered math course. These are only used for clarification and not part of the University's official course designation. Math 103 and 130 are shown in Figure 3.2 merely for placement score purposes and were not part of this study.

COMPASS pre-algebra test:		COMPASS algebra test:	
Score	Course registration	Score	Course registration
		0-29	Math 73 C
21-30	Math 18 T	30-39	Math 82 T
31-46	Math 22 C	40-61	Math 83 C
47-66	Math 73 C	62-74	Math 103
67-100	Math 82 T	75-100	Math 130

Figure 3.2. Assignment of students to groups.

In the pre-algebra test, students with lower scores were placed into Math 18T (with the cut scores being 30 and 31) while those with higher scores are placed into Math 22C. In the upper ranges of the pre-algebra test scores (with the cut scores being 66 and 67), those scoring 47-66 were placed into Math 73C, while those with 67-100 were placed into Math 82T. For those students who selected the algebra test, scores of 0-29 were placed into Math 73C, while those with 30-39 were placed into Math 82T, and those with 40-61 were placed into Math 83C.

In either sequence, students had the option of enrolling in a class lower than their placement results, but not higher (i.e., a student with a score of 49 in the pre-algebra sequence could enroll in Math 22C instead of Math 73C, but not in 82T). Students who

selected the algebra test scoring 62 or higher are eligible for college level math, and were not part of this study. College-level math courses were only used for enrollment purposes, to test students' persistence in math courses, as all associate of arts degrees at the community colleges require a 100-level math course for graduation.

During this pilot phase of redesigning developmental math courses, students were allowed flexibility in registering for redesign or traditional courses. Therefore, for this study, all students who enrolled in courses not designated by their COMPASS Placement Test scores were removed from the initial analyses presented. Removing these students likely reduces some selection bias in these analyses. As a check on this, however, a second set of analyses is presented, where the possible effects of misclassified students were investigated by also including those students who "chose" to enter a particular control or treatment course despite their pretest score. This allows for testing the strength of the treatment in the presence of a "strict" versus "loose" assignment criterion (Yeaton & Moss, 2006).

Course Structure

In the traditional math courses, classes met for a total of 150 minutes, either three times per week in 50-minute sessions or twice a week in 75-minute sessions. The textbook used by the traditionally delivered courses had supplemental math software (MyMathLab) that student had access to, but were not required to use. Students were also encouraged to use the math lab to access tutors and/or their MyMathLab software for supplemental assistance. Students could also access MyMathLab software on their computers at any time.

Redesigned math courses, the treatment courses, were offered during Spring 2010, Fall 2010, and Spring 2011 semesters. In the final redesigned courses, each student spent at a minimum of three sessions (50 minutes each, equivalent to 150 minutes) “doing” math as there were no lectures associated with the courses. All sessions used the ALEKS software. Students spent one session under guidance of their faculty of record, as published in the schedule of courses, in the math lab/classroom. Therefore, all the students in one session were those who placed into a particular developmental math course and enrolled for the specific course section. Students spent a second mandatory lab session in the math lab with a math faculty/tutor, but at a time of their choice. Therefore, the faculty/tutor available for assistance in the math lab might not necessarily be the students’ course faculty member, and the other students in the math lab could be enrolled in other redesigned (treatment) developmental math courses. For the third session, students could select to work on their math in the math lab or at another location of the students’ choosing with access to a computer. Choice was dependent on student progress. If students were performing at the 85% rate based on homework and quizzes, faculty allowed students the choice. If they were not at this level, students were required to be at a math lab for their third session. The ALEKS software provided faculty continuous feedback of the student’s progress. Faculty had access to student progress via the ALEKS software or through the campuses learning management system.

At the beginning of the semester, all students started with an assessment using ALEKS, which covered all the content of the specific course. This provided students with a plan of what content areas the student needed to master for the specific course. The

ALEKS software delivered the content mediating the student's learning, as well as the assessment, which provided students immediate feedback regarding progress; reinforcing prior knowledge, while introducing new content. In this way, students monitored their own progress with clear goals. The ALEKS software was also integrated into the college's learning management system (Sakai), in which faculty produced short videos providing further instruction. Videotapes were produced by several developmental faculty, so that students would be familiar with multiple faculty members, as they would not always see their faculty of record in the math lab for their second or third session. Finally, faculty closely monitored student progress during weekly classroom interactions, as well as reviewing reports generated by ALEKS. All of these factors should enhance the quality of the developmental math program and result in improved student learning. It should be noted that in the Spring 2010 semester, this final structure was not completely in place. Students in the redesigned courses did not have required, scheduled course meetings in the lab/classroom. Students were allowed to work through their math course using the ALEKS software at any location of their choosing. A possible limitation to keep in mind in the research design as implemented, therefore, was that students in the redesigned sequence had different combinations of instructors in the lab (in addition to their assigned course instructor), while students in the control courses were assigned to one instructor. The number of students taking developmental courses during each semester and the number of course sections offered, however, tends to diminish the effects of any particular instructor on the outcomes. Moreover, some of the instructors assigned to redesigned courses also taught traditional (control) sections.

Regardless of the specific course students completed (i.e., traditional or redesign; control or treatment), all students took the same final exam. However, it should be noted that grading was different. More specifically, in the traditional courses, students received letter grades (A-F). In the redesigned courses, students were given Credit/ No Credit only, with Credit being set at 85%. This criterion is slightly above the traditional criterion for achieving a B grade (80%) in the traditional course. As courses in developmental course sequence do not factor into a students' overall transfer GPA, the decision was made to provide only Credit/No Credit option for the redesigned courses. It is more important for students to learn the material and be prepared for the next course, versus passing with a C grade and having a lower chance of success in the next course of the math sequence.

Course Offered by Semester

Figure 3.3 provides a summary of the courses offered over the three semesters of this study. They include minor adjustments in the course numbers since in the first semester of the redesign project, the courses were in pilot phase and so were assigned “experimental” course numbers.

Spring 2010

Introductory Algebra: Math 97 (T) and Math 22 (C)
 Algebraic Foundations I: Math 73 (C) and Math 98 (T)
 Algebraic Foundations II: Math 98 (T) and Math 83 (C)

Fall 2010 and Spring 2011

Introductory Algebra: Math 18 (T) and Math 22 (C)
 Algebraic Foundations I: Math 73 (C) and Math 82 (T)
 Algebraic Foundations II: Math 82 (T) and Math 83 (C)

Note: T = Treatment (Redesign), C = Control (Traditional)

Figure 3.3. Traditional and redesigned courses offered by semester.

VARIABLES IN THE MODELS

Outcomes

Pass or not pass. Students' grades were used as a measure of whether they successfully passed the traditional or re-designed math course they enrolled in for each semester. Students had to receive a grade of B or A to pass (coded 1). Students who received grades of C or lower (or withdrew for various reasons) were considered as not passing (coded 0). It should be noted that "pass" was described as a B (score of 80%) in the traditional courses; however, receiving an equivalent B grade in the redesigned courses required a score of 85%, making it slightly easier to pass the traditional course. This might contribute to some unavoidable bias favoring greater likelihood to pass in the traditional sequence.

Subsequent Enrollment. Student persistence was monitored between Spring 2010, Fall 2010, and Spring 2011. For students who passed either the redesigned (treatment) or traditional (control) course, students who subsequently enrolled in another course during this period were coded 1 and students who did not were coded 0.

Enrollment in a 100-level course. For students who successfully completed the developmental sequence (between Spring 2010 and Spring 2011), if they enrolled in a 100-level math course (including having registered for Fall 2011), they were coded 1 and those who did not enroll were coded 0.

Predictors

Treatment effect. This variable is simply an indicator of the student being assigned to the control group (coded 0) or the treatment group (coded 1).

Pretest. Pretest represents the transformed measure of the student's pretest in relation to the cut point for group assignment. Student COMPASS Math Placement Test scores were used for purposes of assignment to the traditional or redesigned course sequence. The highest score at the cut point was coded 0, which with respect to the intercept in the model equation, represents the achievement of the students with most prior ability in either the control or treatment group (depending on whether individuals at and below the cut point were assigned to the control group or treatment group).

ANALYSIS

Steps in the Regression Discontinuity Analysis

Preliminary analyses. In the RD approach, an important first step is to determine the functional relationship between the assignment variable (i.e., the student's math placement test) and the outcome variable (i.e., probability of passing) (Shadish et al., 2002). Determining the functional relationship (i.e., whether it is linear or curvilinear) between the assignment and outcome variable is important in order to ensure unbiased treatment effects (Shadish et al., 2002). This can be accomplished by initially including higher-order (i.e., quadratic, cubic) assignment (pretest) effects and possible interactions with the treatment and then removing non-significant effects (Moss & Yeaton, 2006). In this case, after eliminating possible higher-order interactions (quadratic, cubic), the treatment x pretest interaction was retained, in the analyses since there were a couple of occasions when the results indicated that the treatment worked differentially for students with differing levels of prior math ability.

Analyses of treatment effects. After determining the initial functional relationship, one can proceed with the analysis of treatment effects. The preliminary math test students take and the pre-established cut score are critical independent variables because placement into a particular treatment (traditional or redesigned) is determined by students' preliminary math score in relation to a cut-point, which would be different for each level of developmental math courses examined. One of the advantages of the study is that the placement into redesigned versus traditional courses is rotated over the course of the study (i.e., sometimes lower test scores are assigned to the treatment and sometimes to the control).

Assumptions of the RD design. As Trochim (1984) notes, interpreting results of studies using the RD design depends on the support of three assumptions. These assumptions were met in conducting the analyses presented in the following chapter.

1. *The assignment of participants according to the cut score must be followed.*

Models were first examined with incorrectly assigned students excluded. Those models demonstrated program effects at both the lowest level math courses and the second level. Follow-up analyses included students who self-selected into the treatment or control groups were included. Follow-up analyses were also conducted examining subsets of these two sets of analyses (e.g., comparing students who self-selected into the control group and students who did not self-select into the control versus students assigned to the treatment).

2. *The pattern of pretest scores must be specified correctly by the statistical model used.* Models were tested initially for possible higher order polynomial effects related to

the pretest scores (i.e., quadratic, cubic) and for interactions between the higher order polynomials and the treatment. As Cook and colleagues (2002) note, if interactions or nonlinear effects are suspected, the analysis should be conducted with the higher order terms in the model and then non-significant terms should be dropped from higher to lower order. When there is doubt, the terms should be kept in the model because this over-fitting will yield unbiased coefficients (p. 233).

3. *There is no coincidental factor at the chosen cut score that would result in program effects.* This assumption is supported by conducting the study over a repeated number of semesters, with situations where students above the cut score were assigned to the treatment group, and with situations where students above the cut score were assigned to the control group. Moreover, different cut scores were used for assignment to lower and higher developmental course situations of the study. Similarly, two different pretests were used to formulate the treatment and control groups. There might be concern of a possible instructor effect. However, the number of sections (approximately 75 per semester) and faculty involved (approximately 20) reduce this possible concern substantially. Moreover, several taught in both the treatment (redesign) and the control (traditional) courses.

Specifying the RD Model

Defining the model for dichotomous outcomes. Because the outcomes in the study are dichotomous (0 = did not pass, 1 = pass; 0 = did not enroll subsequently, 1 = enrolled subsequently), a slightly different type of quantitative model is required from the commonly used multiple regression model for continuous outcomes. The generalized

linear model (GLM) consists of three components needed to specify the relationship between the categorical dependent variable Y and a set of independent X variables (McCullagh & Nelder, 1989). First is the underlying *random component* that describes the sampling distribution of the dependent variable. Because the dependent variable in this case can take on only one of two possible values, its expected values (or mean) will follow a binomial distribution.

The probability of selecting a student who passes a particular developmental course then is simply the proportion of students who pass (often denoted by π to refer to a population and p within a sample), and the probability of selecting a student who does not pass is $1-\pi$. The expected value, or mean (μ), is then the population proportion ($\mu = \pi$). For example, if the probability of passing is 0.60 and the probability of not passing is 0.40 ($1-0.60$), then the odds of success (or passing the course) are defined as $0.60/0.40$ or 1.5 to 1.

Second is a *link function*. Because the relationship between the effects of the predictors on a dichotomous dependent variable are not be linear in nature, a link function is required to transform the expected value of the outcome so that a linear model can be used to model the relationship between the predictors and the transformed outcome. For dichotomous outcomes, the logit link function is most often used, since it represents a fairly easy transformation of the expected values of Y by taking the log of the probabilities of each event occurring. Because the expected values of Y , for a given X , cannot extend beyond the boundaries 0 and 1, they must be transformed, so they are constrained to lie within the interval of 0 to 1. The logit link function assumes a

dichotomous dependent variable Y with probability π , where for individual i the ratio of the probability of passing versus not passing is defined as follows in equation 3.1.

$$\eta = \log\left(\frac{\pi}{1-\pi}\right), \quad \text{Equation 3.1}$$

Here, \log refers the natural logarithm, which is approximately 2.71828. The logit coefficient (η) is the log of the odds of the event coded $Y=1$ as opposed to $Y=0$. Logits can take on any negative value when the probability is less than 0.5 and any positive value when the probability is greater than 0.5. Therefore, although the predicted value for the transformed outcome, η , can take on any real value, the probability $Y = 1$ will always vary between 0 and 1.

Third is a *structural component* that refers to a linear combination of independent variables that is used to predict values of the outcome. This is the part that specifies the set of predictors that are used to model students' likelihood of passing a course. Taking the log of the odds of success provides a means of representing the additive effects of a set of predictors (X) on the outcome. The structural model can then be expressed as a linear logit equation, where the log odds for the likelihood of individual i being passing a course can be expressed in terms of the underlying variate (η), which is defined by the logit transformation of $\pi/(1-\pi)$:

$$\eta = \log\left[\frac{\pi}{1-\pi}\right] = \beta_0 + \beta_1 pretest + \beta_2 treatment + \beta_3 treatment * pretest . \quad \text{Equation 3.2}$$

The intercept β_0 is the value of η when the value of all independent variables is zero. The slope coefficients (β) representing the effects of the pretest, treatment, and possible interaction between the treatment and previous ability can be interpreted as the predicted change in the natural log of the odds that $Y = 1$ (versus $Y = 0$) for a 1-unit increase in X , holding the other predictors constant. It should be noted that a key characteristic of a logistic function (which represents a type of S-curve) is that the slope is the steepest halfway between 0 and 1 ($\pi = 0.5$), indicating the maximum effect of a unit change in X on the probability $Y = 1$. Since the variance of the outcome in a logistic regression model is a function of the population proportion (π), there is no separate error term included in Eq. 3.2 (McCullagh & Nelder, 1989).

Because log odds are not an easy metric to interpret, they are often transformed into odds ratios (e^β), where $e = 2.71828$. Odds ratios express the change in the ratio of the odds of passing versus not passing associated with a unit change in the predictor X , while holding the other variables constant. The odds ratios can be used to determine the predicted probability that a student will pass a course. We can rearrange the log odds equation to predict the probability $Y = 1$ (the student passed the course) for given levels of a predictor. We use the following equation where π is the probability $Y = 1$. In particular, the inverse transformation of the logit link function is a logistic function of the form as seen in Equation 3.3.

$$\pi = \frac{\exp(\beta)}{1 + \exp(\beta)}. \quad \text{Equation 3.3}$$

For example, if the odds ratio is 3.0 favoring passing, using Eq. 3.3, the probability of passing a course will then be calculated as $3/(1+3)$ or 0.75.

Specifying the RD model. Following Cook and colleagues (2002), a preliminary model was first specified to check whether there might be higher order polynomial effects and interactions. Quadratic and cubic terms were included in the model and then non-significant terms should be dropped from higher to lower order. In all cases, these higher order terms were found to be non-significant. Equation 3.4 represents the reduced RD model examined after testing for higher order treatment effects and higher order treatment*pretest interactions:

$$Y_i = \beta_0 + \beta_1(x_i - x_0) + \beta_2z_i + \beta_3(x_i - x_0)z_i \quad \text{Equation 3.4}$$

where:

- Y_i = failing (0) or passing (1) score for student i
- x_i = transformed pretest score of student i ($x_i - x_0$)
- x_0 = the required cut score for assigning student i
- z_i = the treatment for student i (0 if control; 1 if treatment)
- β_0 = probability of passing for the control group
- β_1 = coefficient for pretest effect
- β_2 = coefficient for treatment effect
- β_3 = interaction between pretest and treatment effect

It should be noted that in the RD equation, x_0 represents the cut-point or highest score that will separate the groups, which is transformed to 0 and x_i represents the placement score which is transformed to an integral value with reference to the cut point, and the

difference $x_i - x_0$ represents the distance from the cut point each individual student scores. The coefficients β_1 and β_2 represent the effect of the pretest and the effect of the treatment, respectively. The effect of the pretest is assumed linear for this illustration, and it is also assumed that there is no significant interaction (β_3) between the treatment and pretest (which is tested in tested model).

Other Analyses

After the RD examination of passing or failing courses, the next part of the analysis examined whether there were differences in likelihood to enroll subsequently by whether students passed the treatment or control course. The analyses were conducted using the chi-square test to determine whether there was a non-chance relationship between course enrollment and passing either the treatment or control course. It should be reiterated that the structure of course redesign in developmental math allows for students to move more quickly through the content, based on prior knowledge and proficiency (Twigg 2008). Although a few students in this study did complete both of the redesign courses in one semester, the numbers were too small for meaningful analysis.

Finally, a similar analysis was used to examine whether completing either the treatment or control sequence of developmental courses led to different likelihoods of enrolling in a Math 100 series course at the end of the study (e.g., Fall 2011).

Significance levels for evaluating effects. Because this was preliminary research where variables were likely not measured optimally, results are presented based on significance at the traditional $p < .05$ and $p < .10$. This is recommended for evaluating effects in preliminary studies (Pedhazur & Schmelkin, 1991).

CHAPTER 4: RESULTS

This chapter presents the results of the study. First, information is presented comparing the redesigned and traditional courses and enrollment patterns for the semesters considered within the study. Second, the analyses are presented to examine the treatment effects on students' likelihood to pass or fail courses within the math developmental sequence. Third, evidence is presented on students' likelihood to enroll in a subsequent developmental course if they passed a redesigned or traditional course. Finally, preliminary evidence is presented on whether successfully completing the developmental math sequence leads to a greater likelihood of enrollment in 100 level math courses.

Course Enrollments

Preliminary data were examined according to the semester the student enrolled in a remedial/developmental math course and the level of the course. Spring 2010 was the pre-pilot year for the course redesign project. The numbers of students who enrolled in the developmental math sequence are summarized in Table 4.1.

Table 4.1. Student enrollment in developmental math courses.

Course	Spring '10	Fall '10	Spring '11
97/18 (T)	73	132	98
22 (C)	221	319	207
73 (C)	431	392	357
98/82 (T)	127	131	164
83 (C)	413	381	299
Total	1265	1355	1125

T = treatment, C=control

Table 4.1 suggests large numbers of students enrolled in the developmental courses each semester. It is important to note that the student information system did not

prevent students from enrolling in either the redesign (treatment) or the traditional (control) course, based on their COMPASS Math Placement test results, since these courses were equivalent. Therefore, students considered for the first set of analyses presented include only those students who correctly enrolled in the developmental class as classified by their placement score. These are the correctly classified students. Unless stated, only students who were correctly classified will be used in the analyses. However, when the analysis includes students who were misclassified into either the treatment or control set of courses, the results will be identified as including “misclassified” students. As previously noted, for Spring 2010, the first semester of this study, the course numbers of 97 and 98 reflect the assignment by the community college’s curriculum committee.

**RESEARCH QUESTION 1: DOES REDESIGN LEAD TO A
GREATER LIKELIHOOD TO PASS VERSUS FAIL A COURSE?**

Table 4.2 provides an initial examination of students’ likelihood of passing or failing a math course during the initial semester of the course redesign. Of the 1265 enrolled students, we can see that students in the redesigned courses (i.e. 97 and 98) were more likely to have greater observed passing numbers than would be expected given the number of students enrolled. For example, in Math 97, 42 students passed against the expected pass number of 22 students. Similarly, in Math 98, 47 students passed against the expected number of 38.5. In contrast, for the traditional courses at the Algebraic Foundation I & II, fewer students passed the courses than the expected numbers. Students in the traditional (or control) Introductory Algebra also passed at a greater number than

would be expected. This could be due to the student's previous knowledge or placement test biases.

Table 4.2. Student likelihood to pass versus fail in initial Spring 2010 semester.

Variables		Fail	Pass	Total
97 (T)	count	31.0	42.0	73.0
	expected	50.9	22.1	73.0
22	count	129.0	92.0	221.0
	expected	154.1	66.9	221.0
73	count	340.0	91.0	431.0
	expected	300.5	130.5	431.0
98 (T)	count	80.0	47.0	127.0
	expected	88.5	38.5	127.0
83	count	302.0	111.0	413.0
	expected	288.0	125.0	413.0
total	count	882.0	383.0	1265.0
	expected	882.0	383.0	1265.0

T = treatment (redesign)

In Table 4.3 the significant chi-square coefficient 61.314, 4 df, $p < .001$ suggested there was a non-chance relationship between course enrolled in during Spring 2010 and probability of passing or not. The contingency coefficient, which estimates the strength of the association (for nominal data) between group membership and likelihood to pass was 0.22 ($p < .001$), suggests a weak but statistically significant relationship.

Table 4.3. Test of association between enrollment and likelihood of passing-Spring 2010.

	Value	df	<i>p</i> -value
Pearson Chi-Square	61.314	4	.000
Likelihood Ratio	59.224	4	.000
Linear-by-Linear Association	3.426	1	.064
N of Valid Cases	1265		

This pattern is also observed in the combined data for Fall 2010 presented in Table 4.4. Of the 1355 students enrolled, we can see that students in the redesigned courses (Math 18, Math 82) have higher numbers of students who passed than would be expected given course enrollment. In contrast, once again, in the traditional Algebraic Foundations I and II courses, lower numbers of students who passed than would be expected, given course enrollments.

Table 4.4. Student likelihood to pass versus fail in Fall 2010 semester.

Variables		Fail	Pass	Total
18 (T)	count	53.0	79.0	132.0
	expected	78.5	53.5	132.0
22	count	181.0	138.0	319.0
	expected	189.8	129.2	319.0
73	count	275.0	117.0	392.0
	expected	233.2	158.8	392.0
82 (T)	count	35.0	96.0	131.0
	expected	77.9	53.1	131.0
83	count	262.0	119.0	381.0
	expected	226.6	154.5	381.0
total	count	806.0	549.0	1355.0
	expected	806.0	549.0	1355.0

T=Treatment (redesign)

The increase in passing rates for the redesigned developmental courses is likely the result of the structural changes made during Summer 2010. Beginning Fall 2010, students were required to attend a minimum of two sessions in the math lab, one of which was supervised by their instructor of record. Once again, in Table 4.5 the chi-square coefficient (111.314, 4 df, $p < .001$) suggests the relationship between passing and course enrollment was not due to chance and the contingency coefficient of 0.28 ($p < .001$)

indicates a substantial association. Once again, students in Math 22 (traditional) continue to pass at a rate higher than would be expected.

Table 4.5. Test of association between enrollment and likelihood of passing-Fall 2010.

	Value	df	<i>p</i> -value
Pearson Chi-Square	111.314	4	.000
Likelihood Ratio	112.000	4	.000
Linear-by-Linear Association	13.370	1	.000
N of Valid Cases	1355		

This same initial pattern of results was repeated exactly in Spring 2011, so the results are not tabled ($\chi^2 = 124.83$, 4 df, $p < .001$; contingency coefficient = 0.32).

Readers should keep in mind, however, that these initial results include all students; that is, those who took the course they were supposed to take and those who chose to take a different course. Therefore, while initial results look promising, they depend on the combinations of students enrolled in each course and do not control for the process of assigning students to the treatment or control groups, one of the specific advantages associated with the regression discontinuity design (Shadish et al., 2002).

Regression Discontinuity Models to Explain Passing

The initial research question asked if there is a difference in learning outcomes between students in traditional and redesigned courses. The results presented indicate a difference, but might there be a relationship between prior math ability, membership in the treatment or control group, and probability of passing the math course? In this case,

we use three background predictors: pretest, treatment (coded 1) versus control (0), and the possible interaction between the pretest and treatment. The results are presented in as odds ratios in Table 4.6.

Table 4.6: Odds ratios explaining likelihood of passing Math18(T) and Math 22(C).

Variables	Prelim	Spring10	Fall10	Spring11
Intercept	0.154**	0.495*	0.645**	0.485**
Pretest	1.436	1.084*	1.033*	1.015
Treatment	11.492**	3.232*	5.116*	7.158*
Treatment*Pretest	0.412	0.954	1.195*	1.133
Pretest ²	1.011			
Treatment*Pretest ²	0.770			
Pretest ³	0.998			
Treatment*Pretest ³	0.980			
Student N	172	172	315	177
Correctly Classified	66.3	58.7	60.0	64.4

Note: ** $p < .10$; * $p < .05$; Treatment = redesign

In the first column, the preliminary results show that there were no higher-order nonlinear effects or interactions that might bias the treatment effects. Therefore, these effects were subsequently dropped from further analyses presented (although they were tested for each subsequent occasion). Notice that when the misclassified students were removed from the analysis ($N = 122$, see Table 4.2), there were 172 students included in this analysis.

The intercept odds ratio for Spring 2010 was 0.495. This can be interpreted as the odds of passing the course when all the other variables are zero. For the person who is at the cut score on the pretest (0), and in traditional instructional group, the odds of passing are just about half (0.495) compared with not passing. Another way of looking at this is that an odds ratio of 0.5 to pass the course would be the same as an odds ratio of 2.0

favoring not passing ($1/0.5 = 2.0$). With respect to the treatment, the odds ratio was 3.232, which suggests that for individuals in the redesigned curriculum the odds of passing were multiplied by a factor of 3.232 compared with individuals in the control group. This result is statistically significant, since the significance level is below $p = .05$. Another way of expressing this is to say that the odds of passing were about 3.2 times higher for individuals in the treatment group than for individuals in the control group, holding the pretest and possible interaction between the treatment and pretest constant. For each added point on the pretest, the odds of passing were also significantly increased by a factor of 1.084 ($p < .05$), or about 8.4%, holding other variables in the model constant.

Table 4.6 also shows significant treatment effects associated with the redesigned course for Fall 2010 and Spring 2011. For Fall 2010, the odds ratio was 5.116 ($p < .05$), and for Spring 2011 it was 7.158 ($p < .05$). These all indicate sizable advantages for passing associated with enrolling in the redesigned math course, compared with enrollment in the traditional course, holding other variables constant. The significant interaction between the treatment and pretest (Fall 2010) suggests that being in the redesigned course enhanced the likelihood of passing ($OR = 1.195, p < .05$) for students with higher prior ability as defined by pretest scores. One assessment of the model's fit to the data is the percentage of individuals correctly classified as passing or failing. In table 4.6, the treatment students had lower pretest scores, so on previous skills alone, they likely would not have passed. Hence, the percent correctly classified is modest (61%).

For Fall 2010, the treatment (or discontinuity) effect is illustrated in Figure 4.1. Notice that students lower pretest scores were assigned to the treatment, and as a group they had higher predicted probability of passing. is clearly seen in Figure 4.3.

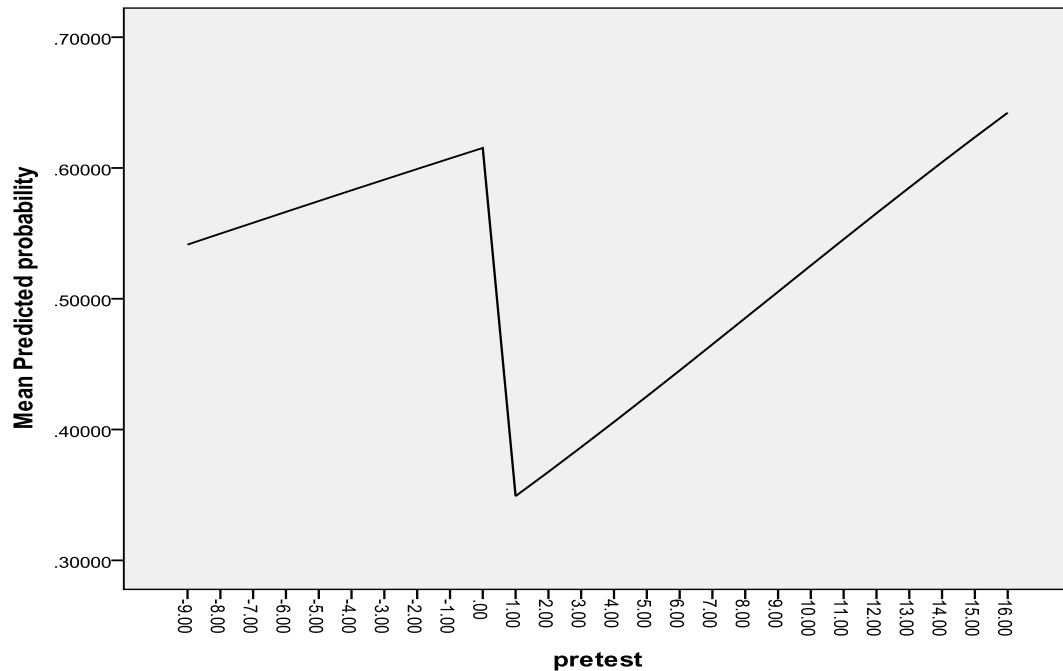


Figure 4.1. Illustrating the treatment effect (Math 18T) vs. control group (Math 22C)

One of the assumptions of the RD design is that the treatment effects should be more apparent right near the cut score. This If the redesign treatment had no effect on likelihood of passing, the line below 0 on the pretest should be a straight continuation of the line above the cut score.

Figure 4.2 illustrates the pretest score and the predicted probability of passing if there were no treatment effect present. Higher scores on the COMPASS Placement test would lead to a higher probability of passing the math course in which the student enrolls in the absence of a treatment effect. Therefore, in the use of the COMPASS Math

Placement test, students on either side of the cut score should have little difference in terms of their performance if there were no treatment effect.

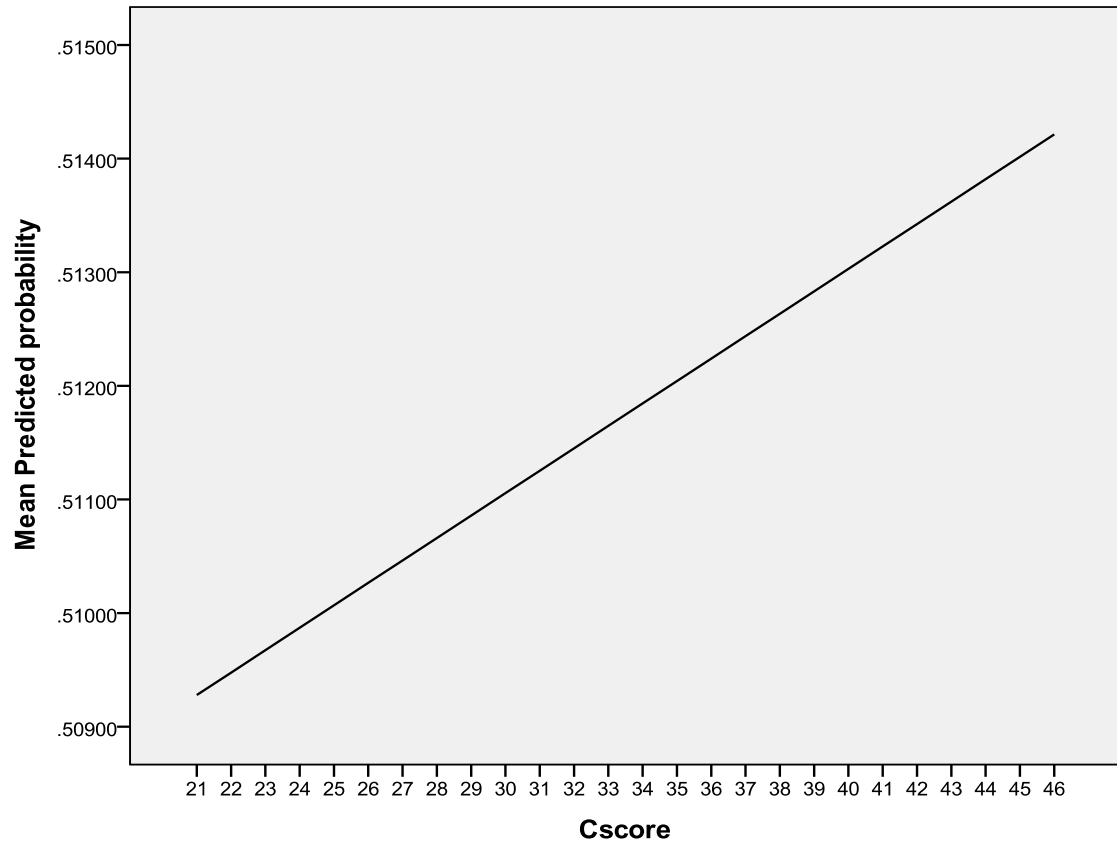


Figure 4.2. Predicted probability of passing based on pretest score.

Determining the Probability Someone Will Pass or Not Pass

We can use the odds ratio to determine the probability of passing a course or not if a student were enrolled in either the treatment or control group. For Spring 2010, to determine the probability passing for students in the treatment group versus control group (holding the other variables constant), the intercept odds ratio can be multiplied by the treatment odds ratio ($0.495 \times 3.232 = 1.60$). Next, using a form of Eq. 3.3 [(odds ratio / (1+ odds ratio))], the probability of passing would be estimated as 0.615 ($1.60/2.60$) for a

student in the treatment group. This means individuals in the treatment group had a probability of passing the course equal to 0.615, holding other variables constant. For Fall 2010 and Spring 2011, the probably of passing in the treatment group was even higher at 0.767 and 0.776, respectively. For all three semesters, the results suggest a high probability of passing the redesigned course.

For the control group, the odds of passing can be estimated from the intercept odds ratio. For Spring 2010, the odds of passing in the control group was 0.495 (since the intercept is the odds ratio when the other variables are 0). Using the same formula [(odds ratio)/(1+ odds ratio)], we obtain $0.495/1.495$, or a probability of passing of 0.331 for individuals in the control group, holding the other variables constant. For Spring 2010 and Fall 2011, the probably of passing would be 0.390 and 0.327, respectively, all coefficients considerably lower than if students were enrolled in the redesigned course.

Table 4.7 presents the results of the logistic regression models examining the redesigned course Math 82 versus traditional course Math 73. Only results from Fall 2010 and Spring 2011 are presented because there were too many misclassified cases for the initial implementation of the redesigned course in Spring 2010. This rendered the analysis with only correctly enrolled students unreliable. In the first column, the preliminary analysis is again presented for examining possible bias in treatment effects. Initially, there was a quadratic effect for the pretest, but as the other higher-order effects were removed sequentially, the quadratic effect became not significant. All higher order effects and interactions were therefore dropped from subsequent analyses presented.

The odds ratio for Fall 2010 was 0.329 (suggesting a small likelihood of passing if the student were in the control group holding other variables at 0). The odds ratio associated with the treatment course (Math 82) was 6.916 ($p < .05$), suggesting a considerable advantage favoring passing for students in the redesigned course versus their peers enrolled in the traditional Math 73 course. More specifically, being assigned to the redesigned course versus control course would increase one's likelihood to pass by a factor of about 6.9 times, other variables being held constant. Similarly, for Spring 2011, the intercept odds ratio was 0.453 and the odds ratio for the treatment was 5.721 ($p < .05$), again suggesting the odds of students passing in the treatment course (compared with the control group) were increased by a factor of 5.7, other variables being held constant. For percentage correctly classified, when higher pretest scoring students are in the treatment (unlike table 4.6), the percentage of correctly classified individuals in the models are much higher, averaging about 71%.

Table 4.7. Odds ratios explaining likelihood of passing Math 73(C) and 82(T).

Variables	Prelim	Fall10	Spring11
Intercept	0.358*	0.329*	0.453*
Pretest	1.207	0.960	1.018
Treatment	2.873	6.916*	5.721*
Treatment*Pretest	1.433	1.041	0.962
Pretest ²	1.074*		
Treatment*Pretest ²	0.845		
Pretest ³	1.005		
Treatment*Pretest ³	1.000		
Student N	191	191	151
Correctly Classified	71.2	71.2	70.2

Note: * $p < .05$; Treatment (redesign)

In terms of probably of passing the course, for Fall 2010 the probably would be 0.695 and for Spring 2011 it would be 0.722. In contrast, for the control group the probability would be 0.248 for Fall 2010 and 0.312 for Spring 2011. Again, these results suggest a considerable advantage for students enrolled in treatment versus control groups for the two developmental courses being examined.

Table 4.8 presents the results of the RD models examining the redesigned course Math 82 versus traditional course Math 83. Once again, only results from Fall 2010 and Spring 2011 are presented because there were too many misclassified cases for the initial implementation of the redesigned course in Spring 2010. In the first column, the preliminary analysis is again presented for examining possible bias in treatment effects. All higher order effects and interactions were not significant and, therefore, were dropped from subsequent analyses presented. In this case, students were assigned to the treatment (Math 82) based on lower pretest scores.

Table 4.8: Odds Ratios Explaining Likelihood of Passing Math 82(T) and Math 83(C).

Variables	Prelim	Fall10	Spring11
Intercept	0.367*	0.380*	0.878
Pretest	1.115	1.073*	0.951
Treatment	5.835	5.786*	2.376
Treatment*Pretest	1.048	0.918	1.029
Pretest ²	0.994		
Treatment*Pretest ²	1.083		
Pretest ³	1.000		
Treatment*Pretest ³	1.006		
Student N	195	195	107
Correctly Classified	67.2	65.6	67.3

Note: * $p < .05$; Treatment = redesign

The odds ratio for Fall 2010 was 0.380. The odds ratio associated with the treatment course (Math 82) was 5.786 ($p < .05$), suggesting a considerable advantage favoring passing for students in the redesigned course versus their peers enrolled in the traditional Math 83 course. More specifically, being assigned to the redesigned course versus control course would increase one's likelihood to pass by a factor of about 5.8 times, other variables being held constant. The pretest scores was also significant in explaining likelihood to pass, with higher scores providing an added advantage (OR = 1.073, $p < .05$), or about a 7.3% increase for each added point. Similarly, for Spring 2011, the intercept odds ratio was 0.878 and the odds ratio for the treatment was 2.376 ($p > .10$), which although it was in the right direction favoring students in the redesigned course, suggests there was no statistically significant difference in odds of passing between students in the redesigned course (Math 82) and traditional course (Math 83). It is likely, however, that the small number of students ($N = 107$) who were correctly classified contributed to the lack of statistically significant treatment effect, since the power to detect an effect, if one were present, was minimal with that small sample size.

Regression Discontinuity Analyses Including Misclassified Students

Because students had choice whether to enroll in the traditional or redesigned courses, follow-up analyses were also conducted that included who were misclassified into the treatment and controls; that is, they include students who chose to enroll in the appropriate redesigned or control course despite where they were placed. Importantly, the analyses in Tables 4.9, 4.10, and 4.11 illustrate in all cases that the treatment effects

worked even on students who were misclassified into the treatment or control groups according to their pretest scores.

Table 4.9: Odds ratios comparing likelihood of passing Math 18(T) and Math 22(C), including misclassified students.

Variables	Fall10	Spring11
Intercept	0.647*	0.561*
Pretest	1.037*	1.002
Treatment	3.567*	6.737*
Treatment*Pretest	1.106*	1.165**
Student N	435	195
Correctly Classified	60.7	64.1

Note: ** $p < .10$; * $p < .05$; Treatment (redesign)

The results (with considerably larger student Ns) suggest that including the misclassified students does not substantially diminish treatment effects. The odds ratio for Fall 2010 was 0.647 and the treatment odds ratio was 3.567, suggesting students who chose to enroll in, or were assigned to, the treatment math course had odds ratios of passing about 3.6 times greater than their peers who were assigned or choose to enroll in the traditional course, holding other variables constant. There was also a significant treatment-pretest interaction, suggesting that the treatment variable increased the likelihood of passing for students with higher pretest scores (OR = 1.106, $p < .05$).

Similarly, the odds ratio for Spring 2011 was 0.561 and the treatment odds ratio was 6.737, suggesting students who chose to enroll in, or were assigned to, the treatment

math course had odds ratios of passing about 6.7 times greater than their peers who were assigned or choose to enroll in the traditional course, holding other variables constant.

There was also a significant treatment x pretest interaction, suggesting that the treatment variable increased the likelihood of passing for students with higher pretest scores (OR = 1.165, $p < .05$).

Table 4.10 presents similar results for Math 73 (control) and Math 82 (treatment). For Fall 2010, the intercept odds ratio was 0.454, and the treatment odds ratio was 6.299 ($p < .05$). The odds of passing in the treatment were increased by a factor of 6.3 compared to the control group. For Spring 2011, the odds ratio was 0.471 and the treatment odds ratio was 6.170 ($p < .05$). The odds of passing were increased by a factor of 6.2 compared with the control group, holding other variables constant

Table 4.10: *Odds ratios explaining likelihood of passing Math 73(C) and Math 82(T), including misclassified students.*

Variable	Fall10	Spring11
Intercept	0.454*	0.471
Pretest	1.043	1.029
Treatment	6.299*	6.170*
Treatment*Pretest	0.957	0.933
Student N	272	155
Correctly Classified	70.6	70.3

Note: * $p < .05$; Treatment = redesign

Table 4.11 presents similar results comparing redesigned Math 82 versus traditional Math 83 including misclassified students in the analysis. For Fall 2010, the intercept odds ratio was 0.487 and the treatment odds ratio was 5.754 ($p < .05$). For

Spring 2011, the intercept odds ratio was 0.420, and the treatment odds ratio was 2.638 ($p < .05$). Because of the larger student N for Spring 2011 ($N = 384$), the result of the treatment was statistically significant (recall in Table 4.8 that the result for $N = 107$ was not significant). Both results indicate that students who enrolled or were placed in the redesigned course (Math 82) had greater odds of passing compared with students in Math 78, holding other variables constant. For Fall 2010, the odds of passing in the treatment were increased by a factor of 5.8 compared with the control group, and for Spring 2011 the odds of passing were increased by a factor of 2.6 compared with the control group, holding other variables constant.

Table 4.11: Odds Ratios Explaining Likelihood of Passing (Courses 82T and 83C)

Variables	Fall10	Spring 2011
Intercept	0.487*	0.420*
Pretest	1.045*	1.013
Treatment	5.754*	2.638*
Treatment*Pretest	0.972	0.859**
Student N	264	384
Correctly Classified	67.8	65.1

Note: ** $p < .10$; * $p < .05$; Treatment = redesign

Other Follow-Up Tests

It is also noted in the literature that it is useful to follow-up with individuals who are eligible to receive the treatment but who choose not to do so. This forms another type of control group, since in the absence of a treatment effect, we would expect these individuals to perform similarly to those students who were eligible to receive the

treatment and actually did. As Table 4.12 suggests, in each case students who were eligible to receive the treatment, but who chose the control group were not able to achieve the same benefit in terms of passing as their peers who enrolled in the treatment. In Fall 2010, for example, in Math 18T v. Math 22C, the results suggest that properly assigned students in the treatment were more likely to pass (OR = 3.431, $p < .001$) compared with the students who were eligible for the treatment but chose not to enroll in it (0.918, $p = .824$). The table also suggests the pretest was not significant ($p > .10$); however, there was an interaction between the treatment and pretest, suggesting students in the pretest with higher pretest scores were more likely to pass (OR = 1.110, $p < .05$). The results for students who were eligible to enroll in the treatment were similarly not significant for Fall 2010 (i.e., 73C v. 82T and 82T v. 83C) and Spring 2011, as shown in Table 4.12.

Table 4.12 Examining the impact of choosing not to enroll in the treatment course.

Variables	18(T) vs 22 Fall 1010	18(T) vs 22 Spring 11	73 vs 82(T) Fall 2010	82(T) vs 83 Fall 1010
Intercept	0.673*	0.444*	0.437*	0.256*
Pretest	1.110	1.028	1.037	1.055**
Treatment	3.431*	8.508*	6.550*	9.336*
Eligible, not enrolled	0.918	1.944	1.103	1.249
Treatment*Pretest	1.110*	1.136	0.962	0.963
Student N	435	195	272	264
Correctly Classified	61.7	64.1	70.6	68.6

Note: ** $p < .10$, * $p < .05$; T=treatment (redesign)

**RESEARCH QUESTION 2: DOES REDESIGN LEAD TO A
GREATER LIKELIHOOD TO ENROLL SUBSEQUENTLY?**

The next part of the analysis focuses on whether there are different likelihoods to enroll in subsequent courses in the sequence based on previous semester performance. Results will be presented by semester, the level of course. Table 4.13 presents results examining whether successfully passing either a treatment (redesigned) or control (traditional) course has any impact on likelihood to enroll in a subsequent course in the developmental sequence. In these analyses, the dependent variable examines students who completed the previous course (i.e., treatment or control) and chose to enroll in the next higher developmental course (coded 1) versus others (i.e., failed to pass, passed but did not enroll). The specific hypothesis investigated was that students who enrolled in the treatment versus control in the previous course would be more likely to pass and enroll subsequently in the higher course.

Table 4.13: Subsequent course enrollment (N =257), Spring2010 (22 v 97T)

Variables	97(T) vs. 22 Spring 10	18(T) vs. 22 Fall 10	73 vs. 82(T) Fall 10	82(T) vs. 83 Fall 10
Intercept	0.278*	0.457*	0.278*	0.330*
Pretest	1.068*	1.014	1.058*	1.024**
Treatment	0.763	1.528*	2.015*	1.033
Student N	257	435	272	341

Note: **p< .10, *p< .05; T = Treatment (redesign)

For Spring 2010, the treatment course (Math 97) did not provide completely clear results in differentiating subsequent enrollment ($OR = .763, p > .10$). There was, however, preliminary evidence that likelihood to enroll was contingent on students' pretest scores. More specifically, the interaction between pretest and treatment was significant ($OR = 1.068, p < .08$) and suggests students with lower pretest scores who were in the treatment were more likely to enroll subsequently. Other developmental courses offered in Spring 2010 were not significant in distinguishing between traditional (Math 73 or Math 83) versus redesigned (Math 98) courses using the Algebra pretest. Therefore, those comparisons are not tabled.

For Fall 2010, the effects of previous courses on subsequent enrollment were clearer. There was generally consistent evidence that passing the treatment versus control led to differences in subsequent course enrollment behavior. For example, for students in lower-level courses (Math 18T versus 22C), the results suggest students in the treatment group were more like to enroll in Spring 2011 ($OR = 1.528, p < .05$). More specifically, being in the treatment versus control group for the previous semester increases the odds of passing and enrolling in the subsequent semester by a factor of about 1.53 (or an increase of 53%), other variables held constant. The results suggest there was also a significant treatment by pretest interaction ($OR = 1.067, p < .10$), which suggests that students in the treatment received an additional advantage in likelihood to pass and enroll in the subsequent semester (compared to their peers in the control course) if they had higher pretest scores.

For Math 73 (control) versus Math 82 (treatment), the results also suggest students who enrolled in Math 82 were more likely to pass and to enroll subsequently in Spring 2011 (OR= 2.015, $p < .05$) compared with students in Math 73, other variables held constant.²

For Math 82 versus Math 83, once again the results suggest that students enrolled in the treatment (Math 82) were more likely to pass and enroll in a developmental course the next semester (OR= 2.976, $p < .05$), other variables held constant. This suggests the odds of passing and enrolling in the subsequent semester for students who previously enrolled in the treatment course were increased by a factor of about 3, compared with their peers who enrolled in the similar control course (other variables held constant). The pretest was also significant (OR = 1.024, $p < .10$), which suggests students with higher pretest scores were more likely to pass and enroll subsequently, other variables held constant.

RESEARCH QUESTION 3: DOES REDESIGN LEAD TO A GREATER LIKELIHOOD TO ENROLL IN COLLEGE-LEVEL MATH?

The final analyses examine whether participation in the treatment versus control developmental sequence enhances students' likelihood of enrolling in a 100 level math course. Readers should keep in mind a few limitations in evaluating the results presented. First, the results are not dependent on the RD design, since the results may take several semesters to fully observe. In this case, this particular question presupposes that students

² If the treatment x pretest interaction is removed, the treatment effect (OR = 2.012) is significant at $p < .05$.

passed the required courses from their initial entry into the developmental math sequence in order to be able to enroll in 100-level math courses within the time during which the study was conducted. As noted previously, successfully passing any particular course favors being in the treatment courses versus the control courses. Being in the treatment (versus control) group also enhanced likelihood to enroll in the next course in the developmental sequence. In addition, students had an easier time passing the control (passing = 80%) versus treatment (85%). For the treatment, students were only allowed to enroll in the course with the Credit/ No Credit grading option, and to pass, students had to complete their required work and earn an 85% on their tests. Students in the control group had the Letter Grade option available to them. Therefore for the purpose of this study, either an A or B was considered equivalent to Credit (for treatment group). Finally, the numbers of students who completed the developmental sequence within the three semesters of the study was a relatively-limited subset of the total number of enrolled students during the study.

Given these limitations, the examination was conducted several times using the algebra pretest and the pre-algebra pretests, as students had the option to take either of these two pretests for their initial placement into the developmental math sequence. Each semester was analyzed independently. The chi-square coefficient is used to determine whether there was a non-chance relationship between likelihood to enroll in a 100-level math course and whether or not students completed the last treatment or developmental course in which they enrolled.

Spring 2010 Algebra Pretest

Table 4.14 tests difference between treatment students and control students who passed their last developmental course and then subsequently enrolled in a Math 100 level course. The 100 level math course could have been taken in Fall 2010, Spring 2011, or early registered for Fall 2011.

Table 4.14. Spring 2010 students enrolling in 100 level math course (Algebra Pretest)

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	342.0	40.0	382.0
	Expected	337.2	44.8	382.0
Yes	Count	102.0	19.0	121.0
	Expected	106.8	14.2	121.0
Total	Count	444.0	59.0	503.0
	Expected	444.0	59.0	503.0

$$\chi^2 (1df) = 2.429, p < .12.$$

The results in Table 4.14 suggest that during the first iteration of the redesigned curriculum, there was not an observable significant difference in likelihood to enroll in a 100 level math course subsequently [$\chi^2 (1 \text{ df}) = 2.429, p < .12$].³ The required χ^2 coefficient would be 3.84 at $p = .05$. The contingency coefficient was 0.07.

³ For Spring 2010, there were 164 students who subsequently enrolled in 100-level math and received grades. A t-test of the difference in means for treatment versus control students was not significant ($t = 1.176, p = .24$).

Fall 2010 Algebra Pretest

Table 4.15 examined the Fall 2010 courses using the Algebra pretest. The students could have taken the 100 level math course either in spring 2011 or fall 2011. The results suggest there is a likely non-chance relationship [$\chi^2(1 \text{ df}) = 16.407, p < .001$]. The contingency coefficient was 0.17 (not tabled). The data suggest that students in the treatment sequence of courses who passed successfully were more likely to enroll in a 100 level math course than students who were in the control group and passed successfully.

Table 4.15. Fall 2010 Students enrolled in developmental math enrolling in 100 level math

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	335.0	49.0	384.0
	Expected	319.6	64.4	384.0
Yes	Count	102.0	39.0	141.0
	Expected	117.4	23.6	141.0
Total	Count	437.0	88.0	525.0
	Expected	437.0	88.0	525.0

$$\chi^2(1\text{df}) = 16.409, p < .001.$$

Spring 2011 Algebra Pretest

Table 4.16 is the examination of students who enrolled in a developmental course in Spring 11. These students who passed successfully could have enrolled in 100 level math course in Summer 2011 or Fall 2011.

Table 4.16: Spring 2011 Students enrolled in developmental math enrolling in 100 level math for Fall 2011

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	285.0	42.0	327.0
	Expected	270.8	56.2	327.0
Yes	Count	33.0	24.0	57.0
	Expected	47.2	9.8	57.0
Total	Count	318.0	66.0	384.0
	Expected	318.0	66.0	384.0

$$\chi^2(1df) = 29.199, p < .001.$$

Once again, the results in Table 4.16 suggest the redesigned course sequence was successful in leading to subsequent enrollment in a 100-level math course [$\chi^2(1 \text{ df}) = 29.199, p < .01$]. The contingency coefficient was 0.27 (not tabled). More students than expected in the treatment enrolled in 100 level math course than would be expected.

Spring 2010 Pre-Algebra Pretest

Turning to the pre-algebra pretest, for Spring 2010, in Table 4.17 we can see there was no significant difference between groups in terms of likelihood to enroll in a math 100 level course subsequently [$\chi^2(1 \text{ df}) = 7.809, p = .01$]. The contingency coefficient was 0.11 (not tabled).

Table 4.17: Spring 2010 (Pre-algebra pretest) Students enrolled in developmental math enrolling in 100 level math for Fall 2011

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	477.0	103.0	580.0
	Expected	466.7	113.3	580.0
Yes	Count	71.0	30.0	101.0
	Expected	81.3	19.7	101.0
Total	Count	548.0	133.0	681.0
	Expected	548.0	133.0	681.0

$$\chi^2 (1df) = 7.809, p < .001.$$

It should be noted that students who select the pre-algebra pretest at the placement exam self selected the level of the placement test and may recognize that they are not college level math ready. In addition, while the data collection point was after the Spring 2011 grades were entered in the student information system, students had not completed registration for the Fall 2011 semester. So the actual enrollment numbers may have changed.

Fall 2010 Pre-Algebra Pretest

Similarly, for Fall 2010, in Table 4.18, there was no significant difference between groups [$\chi^2 (1 \text{ df}) = 6.664, p = .01$] in likelihood to enroll in a 100 level math course, which could have been taken in either Spring 2011 or Fall 2011.

Table 4.18: Fall 2010 (prealgebra pretest) Students enrolled in developmental math enrolling in 100 level math Spring 2011 or Fall 2011

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	550.0	137.0	687.0
	Expected	539.4	147.6	687.0
Yes	Count	82.0	36.0	118.0
	Expected	92.6	25.4	118.0
Total	Count	632.0	173.0	805.0
	Expected	632.0	173.0	805.0

$$\chi^2 (1df) = 6.664, p < .001.$$

Spring 2011 Pre-Algebra Pretest

Finally, for Spring 2011, Table 4.19 indicates there was a significant difference between groups in likelihood to enroll in a 100 level math course in either Summer 2011 or Fall 2011 [$\chi^2 (1 df) = 48.839, p < .001$]. The contingency coefficient was 0.25 (not tabled). Once again, students who took the redesigned developmental course were more likely to enroll in a 100 level than their peers who enrolled in a control developmental math course.

Table 4.19: Spring 2011 (pre-algebra pretest) Students enrolled in developmental math enrolling in 100 level math Fall 2011 (N = 721)

Variables		Control	Treatment	Total
<i>Enroll</i>				
No	Count	490.0	40.0	530.0
	Expected	462.4	67.6	530.0
Yes	Count	139.0	52.0	191.0
	Expected	166.6	24.4	191.0
Total	Count	629.0	92.0	721.0
	Expected	629.0	92.0	721.0

$$\chi^2(1df) = 48.839, p < .001.$$

As Tables 4.14 through 4.19 indicate, in 5 of 6 cases tested, being in the redesigned curriculum led to statistically significant increased likelihood of enrolling in a 100 level math course. As Table 4.20 summarizes, in no case were students who passed the traditional developmental math sequence more likely to enroll in 100 level math classes.

Table 4.20: Enrolled in 100-Level Math Course

	Not Enrolled	Enrolled	Chi Square
<i>Algebra Pretest</i>			
<i>Spring 2010</i>			
Treatment = 0	342	102	
Treatment = 1	40	19	2.429
<i>Fall 2010</i>			
Treatment = 0	335	102	16.409*
Treatment = 1	49	39	
<i>Spring 2011</i>			
Treatment = 0	285	33	29.199*
Treatment = 1	42	24	
<i>Pre-Algebra Pretest</i>			
<i>Spring 2010</i>			
Treatment = 0	477	71	
Treatment = 1	103	30	7.809*
<i>Fall 2010</i>			
Treatment = 0	550	82	6.664*
Treatment = 1	137	36	
<i>Spring 2011</i>			
Treatment = 0	490	139	48.839*
Treatment = 1	40	52	

Note: * $p < .05$

SUMMARY OF RESULTS

First, the results from the analyses in Chapter 4 generally establish that students in the redesigned developmental courses had a greater probability of passing the course compared with their peers in the traditional courses. Importantly, this result was consistent whether only students who were correctly enrolled in the proper course based

on their pretest score were examined (correctly classified) or when student self-selection into courses was also considered (misclassified). Second, students who passed the redesigned developmental courses were also more likely to enroll in the subsequent developmental course the next semester, compared to their peers who passed the similar traditional developmental course. Third, the results also suggest preliminarily that students who participated in the redesigned developmental sequence (i.e., at least for their previous highest-level developmental course) were more likely to enroll in a Math 100 level course. These results are discussed in further detail in Chapter 5 and implications for practice and further research are also considered.

CHAPTER 5: DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

This final chapter provides a summary of the study's purposes, a discussion of the findings with respect to the research questions, draws several implications for research and practice, and presents its conclusions regarding developmental math redesign. Community colleges play an important role in remediation, with anywhere between 40-60 percent of first-year students at public two-year colleges enrolling in developmental courses (Rosksa, Jenkins, Jaggars, Zeidenberg & Cho, 2009; U.S. Department of Education, 2003). Unfortunately, in Hawai'i student success in these courses is approximately 54 percent (UHCC, 2007), which is consistent with the 58 percent reported nationally (Bailey & Cho, 2010).

PURPOSES AND OVERVIEW OF STUDY

Given the challenge of increasing student success in developmental math courses, the purpose of this study was to examine whether a course redesign model could be applied to the developmental math curriculum in a community college setting, in order to create a new curricular structure for teaching math that improves student performance as measured by passing each course. In addition, this study examined whether the redesigned sequence of developmental math courses led to higher subsequent student enrollments over successive semesters in developmental math courses and/or to increased likelihood to enroll in Math 100-level courses, which are required for obtaining either an associate's or a bachelor's degree.

There were five courses in this study, two at the Introductory Algebra level and three in the Algebraic Foundations series. The COMPASS Math Placement test, used by

the community college, was the instrument used to determine whether the students were placed in the redesigned/treatment group or traditional/control group. All courses in the introductory and foundational algebra developmental sequence were included.

Therefore, there was a redesigned or treatment sequence and a traditional or control sequence. The findings of this study point to the effectiveness of the redesigned model for developmental math.

Regression Discontinuity Design

In previous studies investigating the effectiveness of developmental programs, the lack of comparison groups developed through random assignment of subjects has been a consistent criticism (Cook & Campbell, 1979; Higbee et al., 2005; Moss & Yeaton, 2006). This design weakness hampers assessments of program effects, since rival explanations cannot be adequately controlled; therefore, institutions have not always been able to make valid programmatic decisions on their campus. As random assignment of students to the treatment or control groups is not generally possible in institutional settings, the regression discontinuity (RD) design was used for this study. As previously noted, the RD design (a type of quasi-experimental design), is a legitimate alternative to the randomized experiment when random assignment of subjects to treatment and control groups is not possible (Thislethwaite & Campbell (1960). The RD design represents a useful alternative, when a precise criterion for assignment of subjects to the treatment and control groups exists (Shadish et al., 2002).

In this study, the criterion used for placement into the various redesign/treatment or traditional/control groups for the math developmental sequence was student scores on

the COMPASS Math Placement test. The RD design alleviates the selection bias in initial math ability that can exist when groups are formed solely on naturally-occurring factors (e.g., student choice), since the previous math scores establish a precise criterion for course enrollment, and the effect of previous scores on current outcomes can be modeled separately from any treatment effects. The design also permits follow-up analyses on subgroups (e.g., students who were eligible to receive the treatment but chose not to enroll in the course).

DISCUSSION

This section includes a discussion of the findings organized around the three research questions:

1. Is there a difference in learning outcomes as measured by “passing” developmental courses between students in traditional face-to-face and redesigned courses?
2. Is there a difference in persistence rates as measured by enrollment in subsequent developmental courses or in college level math between students in traditional face-to-face and those in redesigned courses?
3. Is there a difference in persistence rates of students enrolling in college level math between traditional and redesigned courses?

Research Question 1: Did Redesign Affect Passing Rates?

At the introductory algebra level, Math 18 (a redesigned course) and Math 22 (the traditional course) are equivalent in content. Students were placed in one of these math courses based on the results of their COMPASS Math Placement Test. Students with the

lower scores were assigned to the redesigned course. To address possible treatment bias that can result from improperly modeling the assignment criterion and treatment effect, preliminary analyses were conducted to establish that the relationship between the assignment process and outcomes was linear (Moss & Yeaton, 2006). In each case, these analyses showed that there were no higher-order nonlinear effects or interactions that might bias treatment effects. Regarding treatment effects, students in the treatment course had odds ratios favoring passing ranging between 3.232 and 7.158; that is, students in the redesigned course had odds of passing that were 3.2 to 7.2 times greater than their peers in the traditional course. In terms of the probability of passing, this translated to about 62% to 78%, depending on the semester, compared against similar odds of passing of about 33% to 39% in the control group.

Math 82 (Algebraic Foundations I and II, a redesigned course) was examined twice, once as compared to Math 73 (Algebraic Foundations 1, a traditional course) and again as compared to Math 83 (Algebraic Foundations II, a traditional course), since Math 82 was a single, four-credit course, versus the two semester- long, three-credit courses (Math 73 and 83). The COMPASS Math Placement Test scores for Math 82 (30-39) were higher than those for Math 73 (scores of 0-29) and lower than those for Math 82 (scores of 30-39). Once again, in examining the results of students on either side of the cut score, students in the treatment group had odds ratios of passing ranging from a factor of almost 3 to 7 times greater than their peers in the Math 73 control course. In the Math 82 and Math 83 analysis, students in the treatment (Math 82) had odds ratios of passing ranging between about 2.4 to almost 6 times greater, and a probability of passing of about

68% compared to probability of passing of 25% to 31%, compared with their peers in control course.

Additional analyses were conducted including students who were misclassified into the control group. In the absence of a treatment effect, we would expect these students to perform similarly to those who were eligible to receive the treatment and did. In all cases analyzed, students in the redesigned courses did better, providing support for the view that it was the treatment that had the impact on students' odds of passing, versus alternative explanations focusing on their greater beginning math aptitude. Importantly, this result was consistent across both types of analyses (i.e., when only students who were correctly enrolled in the proper course based on their pretest score were examined and when student self-selection into courses was also considered). Moreover, when examining the subset of students who were eligible to receive the treatment but chose not to enroll in the redesigned course, the results indicated these students did not have the same higher probability of passing as their peers who were eligible to enroll in the redesigned course and actually did so. These results provide extra evidence to support the efficacy of the math redesign courses.

A variety of developmental education models exist (Higbee et al., 2005). Developmental programs have generally fallen into the prerequisite acquisition model (Clowes, 1982) or concurrent acquisition model (Dembo & Seli, 2004; Maxwell, 1997; McCabe & Day, 1998). Unfortunately, they have not been effective as measured by student success in these courses (Bailey & Cho 2009; Bettinger & Long, 2005). Unlike numerous previous studies, this one looked at the structure of the developmental course

using a redesigned model. As indicated in the premise of the redesign model, students who spend time “doing” math versus hearing or seeing math will have greater success in math. In addition, the redesign model uses technology for frequent assessment of student learning and provides students with immediate feedback. Both are essential components of developmental courses (Boylan & Bonham, 1998). This study clearly indicates that the redesigned model for developmental math provides greater chances of passing developmental math.

Research Question 2: Did Redesign Affect Subsequent Course Enrollment?

A previous study by Bailey et al. (2010) looked at progression data of students participating in the nationwide *Achieving the Dream* initiative. The researchers found that many students do not complete their sequence of developmental courses. Bailey and colleagues’ analysis of the data determined that only 31 percent of students successfully completed their sequence of math remediation. The entire developmental algebra series was included in this study, as passing the developmental requirements was found to be the first critical milestone toward degree attainment in under-prepared students (Adelman, 1999; Calcagno et al., 2006).

In contrast, the results of this study indicated that students who enrolled in the redesigned courses were more likely to then enroll in the subsequent course in the next semester. Although Spring 2010 did not provide clear results of a treatment effect in differentiating subsequent enrollment, this finding may have been because that semester was the beginning of the study, and the structure of the redesigned courses still needed some adjustment. It should be noted, however, that in this first semester there was a

significant interaction between the treatment and student pretest scores in determining subsequent enrollment behavior. More specifically, students with lower pretest scores who were in the treatment group were more likely than those in the treatment group to enroll in subsequent developmental courses. Importantly, in subsequent semesters, the results indicated that students enrolled in the treatment groups were more likely to pass and to enroll in the next developmental course.

This particular analysis did not include large numbers due to the temporal limitations associated with the study. The results, however, indicated that probabilities of passing and enrolling in a subsequent semester were much higher for students in the redesigned courses. These probabilities ranged from about 0.41 in the lowest level Math 18 course to about 0.50 in the Math 82 course compared with 0.31 and 0.25, respectively. What this might suggest is that as students in the redesigned courses were more successful at passing, this success encouraged students to continue in math developmental in the subsequent semester.

Research Question 3: Did Redesign Affect Enrollment in College Level Math?

The previously mentioned study by Bailey et al. (2010) also looked at those students who actually went onto college level courses. Their findings indicated that of the 31 percent who completed the developmental sequence, only about half (i.e., 16% overall) went on to college-level math within 3 years. This data is consistent with what was found within the University of Hawai'i community college system, where over the sequence of three developmental courses, only 54% of students were successful in each

course of the sequence (UHCC, 2007), and by the end of three semesters, only 16 of 100 students (16%) enrolled in college level math courses.

The results of this study, however, indicate that students who participated in the redesigned developmental sequence (i.e., at least for their previous highest-level developmental course) were more likely to enroll in a college-level math course during the three semesters data could be collected on 100-level college math enrollment. In considering these results, however, it is important to note that for the last semester of data collection (Spring 2011 students), only pre-registration data could be gathered, since Fall 2011 had not started by the time the data set was finalized.

For Spring 2010, for students who took the algebra placement test, there was no significant difference associated with group placement and likelihood to enroll in college-level math courses. For students taking the pre-algebra placement test in Spring 2010, however, those students who enrolled in the redesigned course sequence had a significantly greater likelihood of enrolling in a Math 100-level course in a subsequent semester. This is important to note, since students who take the pre-algebra placement test often consider themselves less math ready. Moreover, in Fall 2010 and Spring 2011, students in the redesigned courses were also more likely to pass their developmental courses and enroll in a Math 100-level course by Fall 2011.

Overall, the results showed that in 5 of 6 cases tested, being in the redesigned/treatment group sequence led to statistically significant difference in likelihood of enrolling in a 100-level math course. In no case were students who passed the traditional/control group sequence more likely to enroll in a 100-level math course

than their peers in the redesigned courses. Students are required to enroll and pass a 100 level math course if they seek to earn an Associate of Arts degree at a community college. For students who desire to transfer to a 4-year institution, they must complete their developmental math sequence at a community college prior to enrollment at a 4-year institution. The results of these analyses suggest that for either type of student, the redesigned/treatment provided the greatest opportunity for success.

IMPLICATIONS FOR RESEARCH AND PRACTICE

Limitations

From an educational policy perspective, intervention can only occur when students make themselves available to the intervention. Unfortunately, not all students who are identified as needing developmental education enroll due to a number of external factors impacting their enrollment decisions (Bailey & Cho 2012; Perna 2000; Tinto 1975). The reasons why these enrollment decisions occurred are not known from these data. More specifically, some students in this study did not enroll in the course in which they were supposed to enroll according to their math placement test results. This potential limitation was partially reduced, however, by also examining the results for students who were enrolled in the treatment or control group by choice.

In these latter cases, the results were consistent with the results that considered only those students who correctly enrolled in the course they were assigned to through their math pretest score; all students benefited from the redesign model. It should be noted, however, that it was not possible to examine the subset of students who, while needing a developmental math course, chose not to enroll in the sequence of either

redesigned or traditional developmental math courses. Therefore, although the findings from this research can help policy makers plan how to best serve developmental students, additional knowledge regarding students who do not enroll needs to be undertaken. In addition to student enrollment, concerns could be raised regarding possible instructor effects due to possible differences in skills among the faculty involved in teaching the treatment and control courses. This potential concern is reduced, however, in that students in the treatment group encountered various faculty members in addition to their own instructor of record during their lab and on-line sessions, reducing the likely interaction of instructor effects within that group. Moreover, nearly 20% of the involved faculty taught in both the treatment and control groups. The number of students taking courses each semester (as well as crossing over from treatment to control by choice) also lessens the likelihood of an instructor-treatment interaction.

Time was a second limitation in this study. During the first semester of the study (Spring 2010), the courses in the redesign sequence were still being modified. In addition, at the time the data were extracted from the student information system in early Summer 2011, although student grades had been posted, students had not finished registering for the Fall 2011 semester. Therefore, enrollment data regarding the “next” math course, whether in the developmental sequence or college level, was not complete.

Third, this study examined data within one large suburban community college with a fairly diverse ethnic student population. However, this initial analysis did not take into consideration, ethnicity, gender, age, or academic discipline, as this would have required further manipulation of the data and a higher level of approval from the

University's Institutional Research Board. These factors may have an impact on student choice and subsequent success in unknown ways; however, the RD design has generally been shown to reduce the potential effects of such covariates through direct modeling of the subject assignment process (Shadish et al., 2002).

Finally, the study produced considerable evidence that the redesigned math courses led to greater likelihoods for students to pass, enroll in subsequent developmental courses and, ultimately, enroll in 100-level math courses compared with students enrolled in the traditional courses. The reasons for this differential success, however, are not as apparent from these data. Preliminary follow-up interviews with some students and instructors suggest that the redesigned courses may change both the ways instructor work with students in the courses, as well as how students interact with course material and other peers. Further research might investigate this further by conducting interviews or surveys with participants.

Implications

In September 2006, the University of Hawai'i Community College formed the White Paper Group (UHCC, 2007) to examine the remedial and developmental programs of the seven campuses of the system. This was the result of concerns about the increasing number of students enrolling in developmental programs and the low numbers successfully completing the necessary developmental courses. While studies indicated that students who complete their developmental sequence subsequently perform as well as their peers who never needed developmental courses once they enrolled in college

level courses (Bahr, 2010; Roksa et al., 2009), there was increased concern regarding the percentage of students completing their needed sequence.

The present concerns surrounding graduation are not new, as evidenced by Tinto and his colleagues' work in the mid-1970s regarding students' likelihood of dropping out of higher education. Tinto's Student Integration Theory (1975, 1982) identified the need for student integration, both socially and academically, to increase student likelihood to persist. Qualitative studies showed that social integration through student activities and extracurricular activities resulted in a greater likelihood for students to continue at the institution (Astin, 1984, Pascarella, 1980, Terenzini et al., 1981). This was also true for academic integration, which focused on the learning experiences of the student in the classroom and lab (Tinto, 1998). Bean expanded on Tinto's research by examining conditions for student persistence that integrated organizational theory and student beliefs and asserting that if students had confidence in their academic abilities, they would be less likely to drop out (e.g., Bean & Metzner, 1985). Additional research in student engagement, retention, and attrition identified conditions for academic success for community college students, primarily around academic integration (Bers & Smith, 1991; Fox, 1986; Pascarella et al., 1986). This emphasis on academic integration could be due to the nature of community colleges, most often being commuter campuses with working students who may have less time for organized non-classroom activities, which promote social integration. These identified academic integration conditions included having clear and high expectations of students in the classroom, providing frequent assessment and

feedback, and utilizing a variety of teaching strategies (Bean, 1980; Bers & Smith, 1991; Shea et al., 2003; Tinto, 1998).

The concern regarding student retention and attrition increased as greater numbers of students were found to not be college ready. This was especially true at the community colleges, as evidenced by the National Center for Educational Statistics (1996) reporting that 99% of America's public community colleges offer remedial courses in one or more subject areas. Others have identified effective learning techniques for remedial and developmental education which supported the student integration theory proposed by Tinto's (1993) and Bean's (1980) student attrition models (Kulik & Kulik, 1991; Roueche, 1973). Mastery learning, utilizing computers for supplemental learning, and the use of a variety of teaching methods were among those effective learning techniques identified.

Despite the research that identified effective learning practices and techniques, questions are being raised as to the benefits of developmental education commensurate with the cost (U.S. DOE, 2012). This lack of success is detrimental to students, not only in terms of progress toward graduation, but also in terms of cost, as in many cases developmental courses do not count toward graduation requirements. There are also resource impacts for institutions when almost half the students in developmental courses are repeating the course. Not only are there fiscal costs associated with offering an increasingly growing number of developmental course sections, but there are physical resource needs associated with scheduling classrooms.

Advances in computer technology provide an ideal tool to pull together the findings of best practices in student engagement and developmental education to redesign math courses for student success. The course redesign framework is appropriate for developmental math due to the focus on individual students and their learning needs. As previously noted, the key elements of course redesign include encouraging active learning, providing students with individualized assistance, building in ongoing assessments and prompt feedback, and ensuring sufficient time on task. These are consistent with those strategies identified to be appropriate for developmental instruction (Boylan, 2002; Roueche, 1973; Twigg, 2003). The results of this study seem to support the centrality of Tinto's (1993) academic integration model. Students who are actively engaged in the learning process have a greater likelihood of success in the classroom and continue to remain at the institution.

In this study, students in the redesigned developmental math courses not only had a greater likelihood to pass, but they continued to register in subsequent developmental classes in higher numbers, as well as in registering for their first 100-level math course. Previously, the focus has been in academic integration for community colleges, due to the nature of community college students; commuters with additional responsibilities, limiting opportunities for social integration. However, the redesign model, in particular, the emporium model for developmental math, seems to create an environment conducive to social integration in the classroom—focused around the content being studied. Therefore, the academic integration and social integration found within the redesigned courses might have provided for greater engagement and persistence for the student. This

should be noted, as previously, social integration was primarily structured around extra-curricular activities or activities tangential to the classroom. The redesign developmental math courses bring the social integration component directly into the classroom, with direct faculty participation.

Further validating the need for course redesign are the results of a five-year evaluation of *Achieving the Dream*, due to the small-scale nature of many of the programs implemented, student outcomes did not change much (Rutschow et al., 2011). The positive results of this study suggest that community colleges consider offering their developmental math courses in the redesigned model for broader impact. Students would have the possibility of having greater success, as even misclassified students benefited from the redesign treatment. In addition, since the more semesters students spend in developmental courses, the less likely they are to complete college-level math (Hern, 2010), having a redesigned, technology-facilitated structure would allow students to complete their sequence in a shorter time, as courses do not need to be bound by terms. Of course, it is understood that this may require considerable negotiations with those who manage the campus registration system and financial aid officers, due to possible structural and federal regulations surrounding providing financial aid.

In this study, placement test results were mixed in influencing likelihood to pass and enroll in subsequent math courses. In various tests, previous learning, as measured by the placement was only significant in passing or enrolling in subsequent courses in approximately in half the scenarios. This is consistent with recent findings that have questioned the validity of placement tests to accurately place students in mathematics and

English. Analysis has shown that placement test scores are not good predictors of success (Bailey et al., 2010; Belfield & Costa, 2012; Scott-Clayton, 2012). However, since changes to student assignment may require policy changes, which traditionally take time in higher education, if community colleges redesigned college-level math courses, then even students who were misplaced based on their placement tests could quickly complete the redesigned developmental course and move into the college-level math course, possibly in one semester.

In addition to providing academic benefits for students to pass their developmental course sequence and register in college level math, there are also financial benefits. For students, greater success and fewer courses could mean tuition savings. In the emporium model used for this course redesign, students are required to attend one session in a lab with their faculty. Therefore, all students in this first session are students who signed up for the same course based on their placement test results. The second of their three sessions are in a math lab, with other students from various levels of the redesigned developmental courses and with a faculty, not necessarily their faculty. Therefore, the need for one course in one classroom with one particular faculty member no longer needs to exist. Finally, the student might participate in their required third session at a remote location, thereby possibly freeing up additional physical resources on campus. In addition, with more students passing developmental math, not having to repeat the course, fewer sections may be offered.

CONCLUSIONS

This study showed that in applying the redesign model to developmental math sequence, students in the redesigned curriculum passed their courses in greater numbers than their peers in the traditional curriculum. In addition, students in the redesigned curriculum also completed their developmental math sequence in greater numbers. Finally, students in the redesigned curriculum enrolled in college level math in higher numbers. Although the first semester, Spring 2010, did not yield strong indications of achievement differences between the treatment and control course sequences, with continued refinement of the course structure, positive results regarding differences were observed.

The recommendations from the Community College Virtual Symposium (2012) included tailoring the curriculum to teach students what they actually need to succeed in college and helping students move into college-level work as quickly as possible. This study of the redesign of the developmental math sequence reinforces these recommendations. This redesigned model began with conversations with college-level math faculty, to understand their requirements for knowledge and skills students need to have when entering their courses. Therefore, the curriculum was guided by what was required for success at the next level. The courses were backwards engineered, starting with what the final learning outcomes should be for entering college level math. Then working backwards from the highest level to the beginning developmental math course. Next, a strategy for structuring the curriculum to prepare students for these courses was implemented. The technology-facilitated nature of the redesign model allowed students to

concentrate on the material they did not know versus having instruction led by the faculty lectures. The positive results obtained in this preliminary study suggest further course modifications that increase student involvement and close monitoring of individual progress may pay dividends in helping students gain the skills necessary to succeed in required undergraduate courses.

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