PLACEMENT INTO FIRST COLLEGE MATHEMATICS COURSE: A COMPARISON OF THE RESULTS OF THE MICHIGAN STATE UNIVERSITY PROCTORED MATHEMATICS PLACEMENT EXAMINATION AND THE UNPROCTORED MATHEMATICS PLACEMENT EXAMINATION

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ABSTRACT

PLACEMENT INTO FIRST COLLEGE MATHEMATICS COURSE: A COMPARISON OF THE RESULTS OF THE MICHIGAN STATE UNIVERSITY PROCTORED MATHEMATICS PLACEMENT EXAMINATION AND THE UNPROCTORED MATHEMATICS PLACEMENT EXAMINATION

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The primary purpose of this study was to compare the results of the Michigan State University (MSU) unproctored examination to the results of the proctored examination. Both examinations are used to determine whether first time freshmen at MSU are ready for a standard mathematics course or if a remedial course is necessary. In addition to producing higher placement examination scores, the unproctored examination placed students into higher level courses and a larger proportion of student who was placed with the proctored examination enrolled in a course at a level lower than the course in which they were placed. Therefore, the first conclusion was that the unproctored examination produced more inappropriate placements than the proctored examination.

The second conclusion was that when the mathematics placement examination was considered alone, it was a significant predictor of the log odds of success in Intermediate Algebra (MTH1825), College Algebra (MTH103), and Calculus 1 (MTH132). When ACT Mathematics score, their high school GPA, the type of exam used for placement, whether a student enrolled in mathematics during his or her senior year of high school, and the last high school mathematics course taken were considered, the prediction of the log odds of success was improved for each of these courses. The additional variables improved the “hit rate” of the model containing only placement

examination score. In addition, the additional variables decreased the false positive rate of the model containing placement examination only. Therefore, the placement examination alone is not sufficient for placing students into their first college mathematics course.

Thirdly, students placed into remedial mathematics less often with the unproctored examination. In fact, the odds of placing into one of MSU's non-remedial mathematics courses with the proctored examination was approximately 1.5 times greater than the odds of placing into a non-remedial mathematics course with the unproctored examination. Therefore, placement into remedial mathematics was dependent on the type of examination used for placement.

Finally, there were students who enrolled in courses lower than the level in which they were placed. For example, approximately 30.8% of the students who enrolled in MTH103 and were placed with the proctored examination were eligible to enroll in a higher level course. Approximately 45.9% of the students who enrolled in MTH103 and were placed with the unproctored examination were eligible to enroll in a higher level course. This difference in percentages was significant.

It is important to the validity of the placement examination as well as the comparability of the proctored and unproctored placement examinations to determine why students enroll in courses lower than the level in which they were placed. Study limitations are discussed and suggestions for future research are given.

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CHAPTER 1

STATEMENT OF THE PROBLEM

Introduction

According to Jacobson (2006), a common requirement for obtaining a bachelor's degree is College Algebra, Statistics, or some other type of standard mathematics course. However, not all students have the mathematics background needed to be placed into a standard mathematics course during their first semester of college. Colleges and universities have taken on the responsibility of deciding on the type of mathematics course that is most appropriate for the first time college student.

To determine the type of course in which students should begin, some colleges and universities use information from students' academic background, others make decisions by using nationally standardized tests (ACT, SAT, COMPASS, etc,), yet others have developed their own mathematics placement examination. All of this is done in an effort to give students the best chance of succeeding in their first college mathematics course. In fact, Abraham (1992) conducted a study in which he found that 15 states have used a combination of 75 different examinations to determine placement in reading, writing, and mathematics. Also in a literature review, Sawyer and Schiel (2000) found that approximately 90% of postsecondary institutions offer some form of placement examination. Based on the scores on these examinations, students are labeled as either prepared or underprepared (Flores, 2007).

Additionally, according to Morante (1989), thousands of underprepared students enter American colleges not yet ready to handle college level coursework, and that between one-third and one-half of all entering college students do not possess the basic reading, writing and mathematics skills. In a study conducted by the American Council on Education (1996) it was found that approximately 17% of community college students and approximately 11% of students enrolled in four year public institutions were enrolled in remedial courses.

Lacking these fundamental skills may cause students to reconsider their choice of major. In fact, the Center for American Institutional Data Exchange and Analysis (as cited in Chang, 2002) found that almost 50% of the students entering college with the intention of majoring in science, mathematics, or engineering change from one of these 3 fields to another within the first 2 years. One of the reasons given for the change in major was the lack of science and mathematics skills needed to persist (Chang, 2002).

If students began in the appropriate college mathematics course, the attrition rate for majors in science, mathematics and engineering may be reduced. Requiring a mathematics placement criterion prior to students enrolling into their first college mathematics course could make it more likely that those students will begin in the most appropriate mathematics course.

Morante (1987) describes placement testing as merely a means for placing students into an appropriate first course. Therefore, institutions that use placement testing use it precisely for the reason of placing students into the most appropriate first college course. The most appropriate course is one that is neither too challenging nor too simple.

A course that is too challenging may have several repercussions, such as "dropping back" to a lower level course. If the student is fortunate enough to realize early that the course in which he or she is enrolled in not appropriate, then the student may be able to "drop back" to a lower, more appropriate course during the same semester and not have to spend a semester – possibly even two- away from mathematics.

On the other hand, the student may realize that the course is too challenging but persists in hope that he or she will be able to just pass the course. Perhaps the student passes but does not gain the skills necessary to do well in subsequent courses. The student may persist and be unsuccessful and may then be required to repeat the course. Either of the above scenarios could lead to the student developing a negative attitude or a more negative attitude toward mathematics. Nolting (2004) noted that students' attitude toward mathematics can play a major role in their success. Furthermore, students with poor attitudes stop attending class, procrastinate in doing homework, or avoid taking math altogether.

Failing or withdrawing from a course could increase the amount of time needed to graduate. In a study conducted by ACT (2008), it was found that less than one-half of students admitted to college graduate within five years. Furthermore, ACT (2002) reported that despite the many efforts to increase retention, graduation rates have been declining over the last 20 years. The National Center for Education Statistics (2010) determined that about 57% of first time students seeking a bachelor's degree and attending a 4-year institution full-time in 2001-2002, graduated within six years.

Research has also indicated how important success in mathematics can be to the length of time it takes to graduate from college. Seidman (2005) reported that students who failed College Algebra during their first term, and who were required to take the course at some time during their academic career, were less likely to graduate from college than those students who took and passed the course in their first semester. In contrast, Parker (2005) found that students who were more successful in mathematics were more likely to be retained and graduate in four years.

If a student does not graduate from college, his or her earning potential could be significantly affected. In 2002 the United States Census Bureau estimated that an average annual income of fulltime workers between the ages of 25 and 64, with a bachelor's degree, was approximately $22,000 more than the average annual income for fulltime workers in the same age group with a high school diploma but no bachelor's degree, and the gap was expected to widen (Cotter, 2007).

Incorrect placement could negatively affect what material is taught in the classroom or how that material is taught. If a classroom have many underprepared students, instructors may spend valuable class time working with the underprepared students. This may result in a neglect of the quality and rigor needed for subsequent mathematics classes.

Placing students into a course that is too easy can also have a negative effect. If students are placed into a course in which they feel the material has been presented in previous coursework, then the students may not put forth maximum effort. Although the student may pass the course, he or she may not have acquired the skills necessary for success in subsequent mathematics courses. Because of these consequences, placement into first college courses should be evaluated regularly.

Unproctored Placement Examinations

When examinations are proctored, the examinees are monitored, identities are confirmed, and the rules are followed. When examinations are unproctored, examinees are not monitored, and there is no way to be certain that rules are followed. When examinations are proctored, there is a reasonable assumption that distractions are minimized (or at least the testing environment is similar for each student). This may not be true of unproctored examinations. So besides administration differences, the proctored and unproctored examination could differ in environmental factors.

Institutions relying on mathematics placement examinations as tools for placing students into their first college mathematics course have the added responsibility of evaluating the effectiveness of these examinations. This becomes especially true when there are two examinations that purport to be a measure of a student's readiness for college mathematics, but are administered under different conditions. Schmitz and DelMas (1991) suggest that, once a placement system is employed, institutions have the responsibility of periodically evaluating the placement system.

If scores on an unproctored examination are going to be used in the same way as scores on a proctored examination, every effort should be made to verify that similar scores on either administration would result in similar placement as well as similar success in the course in which students are placed. In addition, students with similar skills and similar pre-college characteristics should be placed similarly regardless of the type of examination used for placement.

One concern of an examination should be its validity. Messick (1989) defines validity as "an integrated evaluative judgment of the degree to which empirical evidence and theoretical rationales support the adequacy and the appropriateness of inferences and actions based on test scores" (p. 13). When an examination is given in both a proctored and unproctored setting, the inference is that both perform equally well and it is the responsibility of the college or university to make sure that the two examinations are comparable.

Purpose of the Study

The primary purpose of this study was to compare the results of the Michigan State University Proctored Mathematics Placement Examination (hereafter known as the *proctored examination*) to the results of the Michigan State University Unproctored Examination (hereafter known as the *unproctored examination*). Comparing results mean not only comparing the scores across the two type of examinations but also the results of the decisions made as a result of the scores received on the two examinations. If significant differences exist across the examinations, this study will attempt to explain those differences by examining the pre-college characteristics of the students who are placed with the proctored examination and examining the pre-college characteristics of the students who are placed with the unproctored examination. Since placement decisions are made as a result of the scores on the placement examinations then examining the results of those decisions is an important aspect of evaluating the effectiveness of the placement examination.

Research Questions

This study was guided by the following research questions:

- *$Q_{1:}$ Are there significant differences in the pre-college characteristics of the students who were placed with the proctored examination and the pre-college* *characteristics of the students who were placed with the unproctored examination. If so, what are the differences? Furthermore, after controlling for these differences, are there significant differences in placement examination scores across the two groups?*

- Q_2*: Are the proctored and unproctored examination functioning similarly?*
- Q_3*: How well does the mathematics placement examination predict success in students' first college mathematics course? Furthermore, can the prediction of success in students' first college mathematics course be improved using the ACT Mathematics score, high school GPA, the type of mathematics courses taken in high school, and whether or not students took a mathematics course during their senior year of high school?*
- Q_4*: How do the grades in each course compare across different levels of placement examination scores?*

Placing students into the correct mathematics course is essential for the success of student. Furthermore "it affects the morale of the students and the workload of the instructors; and it ultimately affects the reputation of the university" (Rodgers & Wilding, 1998, p.203).

CHAPTER 2

LITERATURE REVIEW

Structure of the chapter

This chapter is organized into several parts. First, there is a discussion of the factors that should be considered when designing or choosing a placement examination. This includes choice of the assessment, the content of the assessment, test validity, test reliability, and the examination's ability to discriminate between examinees. Second, there is a review of students' pre-college variables that are related to mathematics placement. These variables include ACT Mathematics score, SAT Quantitative scores high school GPA, high school mathematics GPA, race, gender, type of classes taken during high school, and whether the student took mathematics during his or her senior year of high school. Third, there is a review of the factors that are related to students' success in their first college mathematics course. These factors include ACT Mathematics score, SAT Quantitative score, high school GPA, high school mathematics GPA, mathematics placement examination scores, race, and gender. Fourth, there is a discussion of the methods used to assess the validity of placement examinations. These methods range from placement validity to validating cut scores. Fifth, there is a review of some specific placement practices used by various colleges and universities to place students into their first college mathematics course. Finally, there is a discussion of proctored and unproctored examinations. This discussion includes situations in which an unproctored examination is appropriate and methods for comparing results of unproctored examinations to the results of proctored examinations to determine if the results are comparable.

Selecting a Mathematics Placement Test

When deciding on a mathematics placement examination, institutions have the option of using a nationally standardized assessment (i.e., COMPASS, ACCUPLACER, ACT scores, SAT scores, etc.,) or a locally designed assessment (i.e., a placement examination designed by the university). There are advantages and disadvantages of each. For example, one of the more obvious advantages to using a locally designed assessment is that its content may more closely resemble the course and the curriculum of the department (McDonald, 1989). Burton and Ramist (2001) believed that locally developed exams are customized to the institution's curriculum, student demographics, and the institution's standards.

One disadvantage to using a locally designed assessment is that mathematics faculty may not be trained in the design and validation of tests and, therefore, there is a greater temptation to ignore periodic reviews of the assessment (McDonald, 1989). This is important because alternate forms are an important part of testing and retesting and most faculty either do not have or do not use the level of psychometrics required to review these assessments in the appropriate manner (Morante, 1987). Ebel and Fisbie (1986) found that locally developed assessment tend to have low reliability.

One of the advantages of using standardized tests is that they tend to have high reliability; often 0.9 or higher (McDonald 1989). .

When deciding on whether to use a standardized examination or a locally designed examination for placement, Morante (1987) recommends that the following nine factors be considered:

- *Test content.* *With respect to a mathematics placement test, arithmetic and elementary algebra are essential components. Arithmetic exercises should be both problem solving and word problems and make use of fractions, decimals, and percents. While algebraic exercises should also include problem solving and word problems, they should also include linear equations involving numeral, fractional, and literal components.*

- *Criterion reference*. *Levels of difficulty and proficiency should be established by faculty judgments of what students should know.*

- *Discriminatory power*. *Discriminate accurately among students along a continuum of proficiencies.*

- *Speededness*. *Time limit should be such that 100 percent of the students can complete at least 75% of the items and 90% of the students can attempt all the items*

- *Reliability*. *Test-retest and split half are methods most often used. Reliability should be at least 0.90.*

- *Validity*. *Content, concurrent, and predictive.*

- *Guessing. Guessing can inflate scores. Provisions should be made to reduce the effects of guessing.*
- *Alternate forms. Every placement examination should have an alternate form for retesting or post-testing*
- *Cost. Includes cost of materials, cost to administer, and cost to score.*

When deciding on a placement examination it is clear that 1) faculty need training in test design, test validation, and psychometrics if they are going to design a local assessment and 2) whether local or standardized, there are important guidelines to consider.

Pre-college Variables Affecting Mathematics Placement

Pre-college variables are factors such as high school rank or high school grade point average, type of mathematics courses taken in high school, grades earned in high school mathematics courses, taking mathematics during senior year of high school, and standardized achievement tests such as the ACT or SAT. When placing students into their first college mathematics course, these pre-college variables can each have an isolated effect on placement or can be put together to have a combined effect on placement.   Either way determining how these pre-college variables effect placement may not be a simple task.

Hudson (1989), Matthew-Lopez (1989), Pugh and Lowther (2004), and Hill (2006) found strong correlations between ACT Mathematics scores and scores on locally developed mathematics placement examinations. Mathew-Lopez (1989) conducted a study using 200 students who took the Ohio University mathematics placement examination and found the correlation between ACT Mathematics score and scores on the mathematics placement examination is $r(198) = 0.767$ ($p < .01$). In their study of 920 students at Auburn University, Pugh and Lowther (2004) found a correlation of 0.682 and, in his study of 2386 students at Michigan State University, Hill (2006) found a correlation of 0.647. Even for "high risk" students, Pugh and Lowther (2004) found a significant correlation between ACT Mathematics scores and mathematics placement examination scores of 0.506. Pugh defined 'high risk" students as students who did not take mathematics during their senior year or go beyond algebra II.

Wattenbarger and McLeod (2008) conducted a study of 605 first time college students in which they correlated scores on the mathematics portion of the ACT and SAT with grades earned in first college mathematics courses and found that over half of the correlations were negative and only two of the positive correlations were above 0.5.

When Hill (2006) examined his data further, he found that students who earned a grade of B or better in AP Calculus improved their placement examination score (beyond what was predicted by their ACT Mathematics score); some of the improvements were statistically significant while others were not. Hill also found that students who received an A- or better in FST (functions, statistics, and trigonometry) received significantly higher placement examination scores than what was predicted by their ACT Mathematics scores. Overall, students who took challenging high school mathematics course were more likely to increase their placement score beyond what was predicted by ACT Mathematics score alone.

Pugh and Lowther (2004) also found significant correlations between high school GPA and scores on a mathematics placement examination ($r(2384) = 0.462$, $p < .001$) and students who had higher high school GPAs tend to receive higher placement examination scores. They also found that students who had high GPAs and no mathematics course during the senior year of high school resulted in lower placement scores than students who had high GPAs and were enrolled in mathematics during their senior year of high school.

Hill (2006) looked at students who placed into remedial mathematics and found that taking a mathematics course during senior year of high school was not enough to increase placement. He found that 18.4% of the students in the remedial mathematics course had taken a mathematics course during their senior year of high school. However these students either took a non-algebraically demanding course (below algebra II) or took an algebraically demanding course (above algebra II) and received a low grade (less than a C).

Matthew-Lopez (1998) developed a model to predict math placement examination score in an effort to circumvent the use of a placement test. She found that both high school percentile rank and ACT Mathematics score were correlated with math placement scores and together, they significantly predicted scores on the placement examination.

Prior research suggests that although universities are using placement examination scores, variables such as ACT Mathematics scores, high school GPA, type of mathematics course taken during high school, and taking mathematics during senior year of high school should also be considered when placing students.

Predictors of Success in First College Mathematics Course

Determining factors that predict success in mathematics can also be a very difficult process. First there are the factors that precede students' enrollment into their first college mathematics course. These factors include high school background, ACT Mathematics scores, and SAT Quantitative scores. These factors have been found to produce an isolated effect as well as a combined effect.

Pugh and Lowther (2004) examined the individual correlation of high school GPA, high school math GPA, ACT Mathematics scores, and SAT Quantitative scores on grades in first college mathematics courses. They found all of these pre-college factors to be significantly correlated with grades in first college mathematics courses with the highest correlation occurring between high school math GPA and grade in first college mathematics course. They then proceeded to construct a regression model and found that both high school mathematics GPA and math placement test accounted for 25% of the variation in first college mathematics course grade. Furthermore, the mathematics placement test significantly added to the prediction of course grade beyond the prediction using only high school mathematics GPA. However, when the "at risk" students were examined not only did the strength of the relationships with the dependent variables and first college math course grade decrease, but placement examination scores no longer added to the prediction of first college mathematics grade beyond high school mathematics GPA.

Nelson and Leganza (2006) looked at the relationship between several pre-college factors and grade in first college mathematics course for three different courses: liberal arts mathematics, applied calculus, and theoretical calculus. They found that high school GPA, gender, SAT Quantitative score, high school class rank, and SAT verbal score were significant predictors of grades in the liberal arts mathematics course. However, for the applied calculus course, only SAT Quantitative score, high school GPA, and gender were significant predictors of course grade. For theoretical calculus, the logistic regression model produced significant effect from high school GPA, SAT Quantitative score, and type of institution (public or private), but there was no gender effect. They also found that gender became less significant for higher level math courses. High school GPA was more significant for applied calculus and less significant for liberal arts mathematics.

Using information from 266 first time freshmen enrolled in a College Algebra course, Rodgers and Wilding (2006) developed a regression equation to predict final course grade. They found that the best model to predict grades in College Algebra used a combination of pre-college variables: algebra placement score, percentile rank, and SAT Quantitative score.

Hudson (1989) conducted a study involving 1854 students and found neither the ACT subscores nor the ACT composite score to be significantly correlated with final grades in students' first college mathematics course. However, when Hudson performed a multiple regression analysis, she found that ACT-M to be a significant predictor of final grade in only one of the three math courses included in the study.

Bridgeman and Wendler (1989) studied a total of nine different algebra and pre-calculus courses at several universities and found that SAT Quantitative scores significantly improved prediction of course grade. They also found that the gender of the student improved the prediction of course grade above SAT Quantitative scores alone, but gender had no increased effect in three of the courses where both SAT Quantitative and high school GPA were used as predictors of course grade. At one college, adding the experience score (the highest level mathematics course taken in high school) to SAT Quantitative and high school GPA significantly improved the prediction of course grade. At another college, when high school GPA and placement test were considered together, there was a greater effect on course grade than each of high school GPA and SAT mathematics considered alone.

Armstrong (2000) developed a model to predict course grade using mathematics placement score, student's situational variables (employment hours, support for attending school, financial aid, part-time ore full-time attendance, and family responsibilities), dispositional variables (cognitive, behavioral and affective traits), and instructor characteristics (instructor grading practices, full-time instructor, part-time instructor) and found that instructor characteristics accounted for the greatest variation in course grade. Armstrong also found that placement exam score was not a significant predictor of course grade for courses with full-time faculty members and believed that the interaction of instructor characteristics and student characteristics may explain the lack of the effect of the placement exam on course grade.

Gupta, Harris, Carrier, and Caron (2006) did not use placement scores to predict course grade. Instead, they used students' demographic information (sex, race, and college major), factors that could impact study time (number of hours employed per week, other coursework, number of children at home), academic background (number of high school math courses, number of year since last math course was taken),student learning behaviors (class absences and number of hours of tutoring), students' attitude toward mathematics, and students' course experience (type of technology used, instructor rank, number of times per week that course met). The final model indicated that older, male students, who are taught by lower ranked instructors, have positive attitudes, have taken a high number of high school mathematics courses, and have missed fewer classes are more likely to receive better course grades. All of this supports that no single measure should be used when placing students into their first college mathematics course.

Validating Placement Examinations

McDonald (1989) and Schmitz and Demas (1991) offered a set of guidelines for validating placement examinations. McDonald suggested that department faculty examine the items to make sure the items relate to the curriculum. Additionally, a sample of students should be tested, descriptive statistics computed, and the distribution of the scores from the sample should agree with what is expected. McDonald also suggested that the scores from the placement examinations should be correlated with one or more suitable criteria. McDonald says caution should be used when using end of course grades as a criterion because "grades are a composite measure of achievement that tend to vary greatly across instructors (pg 22)." The guidelines presented by Schmitz and DelMas (1991) focused on improving the criterion – related validity of the placement examination.

Schmitz and DelMas (1991) developed a set a guidelines for validating placement examinations. First evidence that the placement examination contributes to the prediction of course grades needs to be gathered before placement recommendations are put into effect. Otherwise, decisions made after students have been placed are confounded. Second, multiple regression, rather than correlation, is the preferred approach to judging the predictive validity of placement examination scores. Furthermore, it is suggested that the incremental validity of the examination be assessed. Incremental validity refers to the unique contribution an examination makes to a prediction equation and thus an examination is said to be valid if it produces a significant increment in the predictive accuracy over other entry level data (Schmitz and DelMas, 1991). Third, cutscores should be considered. Cutscores should be set so that the maximum number of correct decisions is made.

In 1969, Shevel and Whitney wanted to determine if the mathematics placement examination offered sufficient improvement in the prediction of college mathematics grades to warrant its addition to a college testing program. Additionally, they wanted to compare the predictive validity of the mathematics placement examination to that of ACT scores and high school mathematics grades for classes that differed in average math ability and classes that covered different types of material. They concluded that the addition of the mathematics placement examination improved college mathematics grades predictions over ACT scores and high school mathematic grades. Also, the improvement was greater for higher level courses.

Pugh and Lowther (2006) developed a regression equation and found that the placement test significantly added to the predictive power of the regression equation; beyond high school math GPA. However, when using students that were categorized as "at risk" the placement examination did not significantly add to the predictive power of the regression equation; beyond high school math GPA.

Other researchers have examined the cut scores as a way of supporting the validity of a placement test. Slark et al. (1991) examined the final grades of students scoring above and below the cut score across three different math courses: elementary algebra, elementary algebra review, and Intermediate Algebra. They found that of the students in elementary algebra, 48% of those scoring above the placement test cut score were successful compared with 41% of those scoring below the placement test cut score. Of the students in elementary algebra review, 62% of those scoring above the placement test cut score was successful compared with 47% of those scoring below the placement test cut score. Of the students in Intermediate Algebra, 65% of those scoring above the placement cut score were successful in the course compared with 58% of those scoring below the placement cut score. A successful student was defined as a student who received a grade of C or higher in the course.

Gabe (1989) examined the academic achievement of students who scored below or just above college level on a math placement examination and who did not enroll in a college preparatory (remedial) mathematics course at Broward Community College. A score of 12 or more resulted in placement into a college level mathematics course. Gabe defined just above college level placement as receiving a score of 12 or 13 on the placement test. Of the 1986 cohort who enrolled in college level mathematics (MAT1033), 60% were not successful. Furthermore, approximately 70% of the student who scored just above the cut score did not successfully complete MAT1033 within 7 terms.

Gabe also found that approximately 61% of the 1987 cohort who enrolled in MAT1033 with scores of 13 or below was not successful. Furthermore, approximately

85% of the students who scored just above the cut score did not successfully complete MAT1033 in 4 terms.

In his dissertation, Cotter (2007) examined the cut scores of a mathematics placement examination by computing the odds of success for different cut scores in three different courses at Georgia State University: Math Modeling for Non-Science Majors (Math1101), College Algebra (Math1111), and Pre-Calculus (Math1113). When defining success in first math course as receiving a course grade of D or better, Cotter found that of the students who met or exceeded the cut score for placement Math1101, Math1111, or Math1113 were approximately 2 times, 3.5 times, and 2 times more likely to be successful than those students who scored below the cut scores for placement into those courses. When defining success as receiving a grade of C or better, students who scored above the cut score for placement into the same courses were approximately 2 times, 3 times, and 1.5 times more likely to be successful than students who scored below the cut score. In both cases, those who scored above the cut score had a greater probability of being successful in the course than those students who scored below the cut score.

Sawyer (1989) developed placement validity indices based on logistic regression methods for determining course placement. Logistic regression can be used to estimate the conditional probability that a student would be successful in a course given the student's score on a given predictor variable. Using these conditional probabilities of success, the placement validity indices are computed. The validity indices are based on the following four possible estimated outcomes of a give cut off score

- *True positive: A student who is predicted to pass the course actually passes the course. (correct decision)*
- *False positive: A student who is predicted to pass the course actually fails the course. (incorrect decision)*
- *True negative: A student who is predicted to fail the course actually fails the course. (correct decision)*
- *False negative: A student who is predicted to fail the course actually passes the course. (incorrect decision)*

Ang & Nobel (1993) used these four decisions to compute the following two indices: accuracy rate (AR) and change in accuracy rate (ΔAR). AR is the proportion of students for whom the correct decision would be made using the cutoff score and the success criterion. The optimum cut off score will be the score for which the conditional probability of success is approximately 0.5. This cut off score is where the maximum AR will be attained. ΔAR is the difference between the maximum AR and the "base line" AR – the proportion of correct decisions associated with using the lowest possible cutoff score.

Matthews-Lopez (1998) used a cross validation technique to assess the validity of a mathematics placement examination. First a simple random sample of 200 students was drawn from a population of 3200 students who took the mathematics placement tests. Second, a multiple regression equation was developed using the scores from the placement examination as the dependent variable and ACT Mathematics exam and high school percentile rank as the independent variables. Third, an independent sample of 200 students was drawn from the same population and the multiple regression equation was used to predict scores on the placement test for this independent sample of students. The results of the comparison between predicted and actual placement level (for either data set) agreed in approximately 55% of the cases. Of the remaining 45%, recommended placement was lowered in 18% of the cases and in about 8% of the cases, the placement was raised.

The above research establishes that the validation of placement examinations should be an ongoing process and should consist of a combination of approaches. These approaches range from establishing the predictive validity of the examination to validating the cut scores to establishing the consistency of examination results for comparable groups to examining the decisions that are made as a result of the scores.

Unproctored and Proctored Examinations

There is extensive research on online unproctored examinations. Some of the advantages are the reduction in the number of computers and manpower needed to administer the test (McCloy, 2008; Sticha and Barber, 2003). Additionally, there is the reduction in travel costs for the test taker as well as the expansion of the applicant base (McCloy, 2008). One of the more serious disadvantages is the increase likelihood of cheating.

Proctored testing is most relevant when the examination is high stakes (Rovai, 2001). However, if the examination is not high-stakes then an unproctored examination may be appropriate because students may not be motivated to cheat. Kennedy, Nowak, Raghuraman, Thomas, and Davis (2000) reported that cheating was more likely to occur doing online tests than on tests that were administered face to face. However, another study, Charlesworth, Charlesworth, and Vlica (2006) reported that cheating was no more likely to occur in online examinations than on examinations administered in a face to face setting.

Harmon, Lambrinos, and Kennedy (2008) developed a model to predict the scores on an unproctored economics final examination. In order to detect cheating they used the model for the proctored examination to predict the final examination score for the unproctored examination. Harmon et al believed that if the class which took the unproctored examination had many students whose predicted score was far from their actual score, this would be an indication that cheating has occurred.

Davies, Norris, Turner, and Wadlington (2005) conducted an analysis of an unproctored administration of The Hogan Personality Inventory. They believed that if cheating was occurring then it would manifest itself as near perfect assessment scores. However, they did not find enough evidence to support cheating across administrations. If examinations are given online as an unproctored examination it should be assumed that the test items and scores may be compromised (Sticha and Barber, 2003). To minimize the negative consequences of the potential compromised information, procedures must be put in place.

Examples of such procedure would be to use items that have been retired from previous forms of an examination, administer the items in an adaptive format, have an extensive item pool, have ongoing item development and calibration, or verify the results with additional assessments under supervised conditions (McCloy, 2008).

Sticha and Barber (2003) describe a verification process associated with the administration of an unproctored online version of the Armed Services Vocational

Aptitude Battery (ASVAB). When an examinee takes the unproctored internet version of the ASVAB, they must have their scores verified by going to a Military Enlistment Processing Station (MEPS) and taking a short verification test; maybe less than 15 minutes. If the examinee does not pass this verification test, he or she would be forced to retake the complete test. If a verification process is used, this fact must be made clear to the examinees. Otherwise too many people will fail the verification process (Sticha and Barber 2003).

Rueda and Sokolowski (2004) compared the results of an unproctored placement examination to the results of previous monitored examination. They found no difference in the percentages of students who placed into the various mathematics courses.

Schumacher and Smith (2008) conducted a study in which they compared the scores of a proctored paper and pencil mathematics placement test (given in 2004) to the scores of an unproctored online test (given in 2005). They found that scores on the unproctored placement examination was significantly higher than scores on the proctored placement examination. However, they noted that students who took the unproctored placement examination had – on average – higher SAT Quantitative scores than students who took the proctored placement examination (576.81 unproctored vs. 568.58 proctored). Thus there is an implication that students who took the unproctored examination had higher mathematics ability than those who took the proctored examination the previous year and therefore the higher placement scores should be expected.

Finally, Schumacher and Smith (2008) develop a logistic regression model using placement into remedial math as the dependent variable and SAT verbal, SAT

Quantitative, placement test scores, and high school GPA as independent variables. The 2005 values were substituted into the model that used the 2004 data. This resulted in a prediction accuracy of approximately 94%.

Davies and Wadlington (2006) compared scores on The Hogan Personality Inventory (HPI) across proctored and unproctored settings. They compared the means, standard deviations, and coefficient alpha reliabilities of each personality scale across the two groups (proctored and unproctored). Although they found that the unproctored administration of the assessment resulted in significantly higher means on four of the scales, the effect sizes were small. Davies and Wadlington also conducted a DIF analysis and found that at least one item with significant DIF was found on each scale and four of the seven scales had more items with significant DIF across the two groups than would be expected by chance.

The above studies indicate that determining if an unproctored examination and a proctored examination are comparable, there mean scores can be compared and a DIF analysis can be conducted to see if items and functioning differently across examination types. To protect against cheating, a verification process can be implemented. This verification process can increase the validity of the unproctored examination. One vital piece of information that is missing is the examination of the course outcomes once students are placed by each type of examination.

Mathematics Placement Procedures

Colleges and Universities vary in the procedures used to place students into their first college mathematics course. These colleges and universities vary in the type of placement test used and how placement decisions are made. For example, Odell and

Schumacher (1995) developed a formula for placing students into their first college mathematics course: *2*placement test score + Math SAT score*. At the time this equation was developed, this particular university was using a test designed by the Mathematics Association of America.

At St. Olaf College, students choose one of three different placement exams. This choice depends on the student's academic plans. Using placement test scores and a large number of regression equations, students were placed into courses in which they would have a high probability of being successful (Flores, 2007).

A placement process described by Krawczyk and Toubassi placed students into their first mathematics course according to their score on one of two placement examinations and other factors such as high school GPA (as cited in Rueda and Sokolowski 2004).

To understand the similarities and differences of the current placement systems at various United State Colleges and Universities, a non scientific study was conducted in which information was gathered about the placement procedures at a sample of 50 colleges and universities. These institutions responded as follows:

- *17 schools indicated that they currently administered a placement examination developed by the Mathematics Department.*
- *5 schools indicated that they use ACT Mathematics scores or SAT Quantitative scores to determine initial placement. If the students would like to improve their placement, they must take a placement examination designed by the Mathematics Department.*

- *12 schools indicated that they offer the placement exam only in an unproctored setting.*
- *7 of the schools indicated that the results of the placement test were used as recommended placement and students were allowed to enroll in a course at a level higher or lower than what was indicated by their placement exam score.*
- *10 of the schools indicated that they use a combination of placement exam scores and high school information to place students into their initial mathematics course*

Procedures for placement vary across universities. Some universities place students using nationally standardized examinations, others use their own examination, and others use a combination of variables. Some universities use proctored examinations, others use unproctored examinations, and others use a combination of the two. Some allow multiple attempts and others allow only a single attempt. Whatever the case may be, these procedures need to be evaluated regularly and modified if necessary.

MSU Mathematics Placement Examination

Approximately 7000 first time college students enter Michigan State University (MSU) each fall with hopes of obtaining an undergraduate degree some years later. To graduate from MSU, each student must fulfill certain university requirements. These requirements consist of a series of courses which students must complete regardless of the major they have chosen. Among these courses are choices of several mathematics courses. In order to determine the most appropriate beginning math course, most students must take the MSU mathematics placement examination. The results of the examination are used to determine the most appropriate course mathematics course in which students must begin.

Description of the Michigan State University Mathematics Placement Examination

Figure 1 shows the structure of the MSU Mathematics Placement Examination. The placement examination was designed by the MSU Mathematics Department. The examination consists of a total of 28 multiple-choice items. There are about 14 different versions of each item thus allowing for multiple forms. An examinee begins with a group of 14 items (Group A). These initial 14 items are pre-calculus items. The examinee received 1 point for a correct answer and 0 points for an incorrect answer. If the examinee responds to 8 or fewer of these items correctly, the examinee is given another group of 14 algebra items (Group B). A correct response to a group B item is worth ½ point while an incorrect response is worth 0 points. The score from group B is added to the score from group A and this sum is rounded up to the next integer. This score is the examinee's total score on the placement examination and is used to determine the highest level course in which the student will be allowed to enroll. Examinees who go from group A to group B, can receive a maximum score of 15.

If an examinee responds to 9 or more of the initial 14 items correctly, the examinee is given another group of 14 items (Group C) that contains algebra, trigonometry, and precalculus items. A correct response is worth 1 point and an incorrect response is worth 0 points. The score from group A is added to the score from group C and this sum is the examinee's total placement examination score. Thus an examinee that goes from group A to group C will have a total placement examination score between 9 and 28.

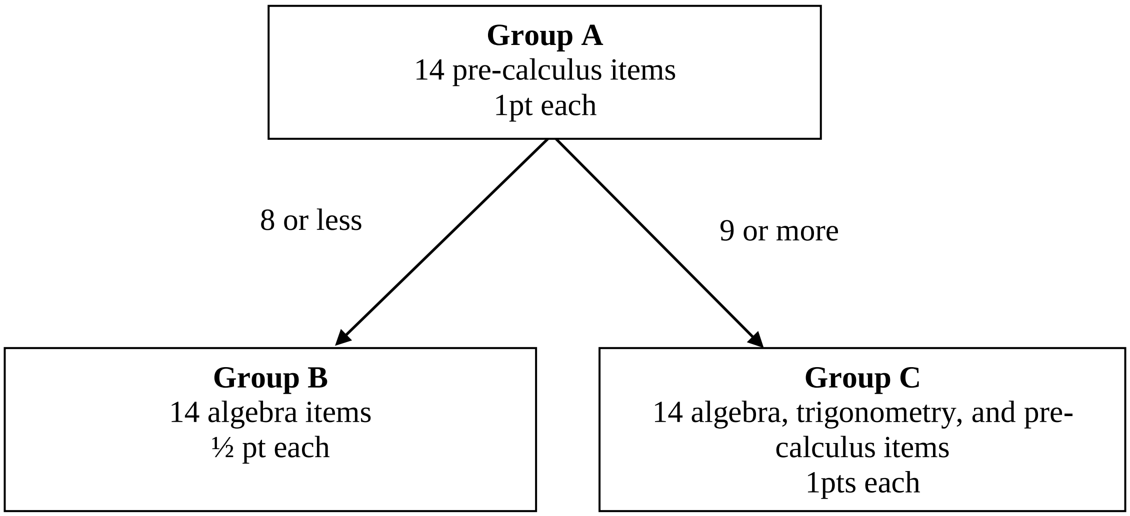

Figure 1. Structure of the MSU Mathematics Placement Examination

Placement

Based on the total score, students are placed into one of five levels of courses. These levels are described below. A description of the courses is given in appendix A. Each course is a one semester course. The levels are a modified version of the tiers used by Hill (2006).

Level 1*: Intermediate Algebra (MTH1825). This is the university's remedial mathematics course. The credits received in this course do not count toward a student's degree but it is included in the calculation of a student's GPA.*

Level 2*: College Algebra (MTH103) or Finite Mathematics and Elements of College Algebra. Students who enroll in MTH103 must take at least one additional math course above MTH103 to satisfy the university mathematics graduation requirement. MTH103 is worth 3 credits and MTH110 is worth 5 credits. The credits received in any of these courses count toward the minimum number of credits needed to obtain a degree. Placement at this level requires a minimum placement examination score of 10.*

Level 3*: College Algebra and Trigonometry (MTH116). This 5 credit course is intended to prepare students for technical calculus. The credits received in this course counts toward the minimum number of credits needed to obtain a degree. Placement at this level requires a minimum placement examination score of 12.*

***Level 4**: Finite Mathematics: Applications of College Algebra (MTH112), Survey of Calculus 1(MTH124), Elementary Mathematics for Teachers (MTH201) or Statistical Methods (STT200 or STT201). MTH112, MTH124, MTH201, and STT200 are each 3 credits and STT201 is 4 credits. The credits earned in any of these courses do count toward the minimum number of credits needed to obtain a degree. Placement at this level requires a minimum placement examination score of 15.*

***Level 5**: Calculus 1 (MTH132). This 3 credit course requires a minimum placement examination score of 19.*

The MSU mathematics placement examination is offered as a proctored examination or as an unproctored examination. Students are required to complete the examination before enrolling in classes at MSU or before their MSU Academic Orientation Program (AOP) session; whichever occurs first. Students who decide to take the proctored examination can do so at AOP or by making arrangements at one of several MSU extension offices. Students who decide to take the unproctored examination can do so from any location that has full internet access. Students can attempt the mathematics placement examination up to three times, but can only take the proctored examination once. Students must wait at least four weeks between each attempt. If students attempt the placement examination more than once, the highest score obtained will be used to determine placement. Any student receiving a minimum score of 19 – on the proctored examination - will be given credit for the university’s mathematics requirement.

Who Must Take the Mathematics Placement Examination?

While most first time college freshmen are required to take the mathematics placement examination, there are a few exceptions. According to the MSU Mathematics Placement Service any students falling into any of the following categories are not required to take the mathematics placement examination:

- *Students with credit in at least one of the following: MTH103, MTH116, MTH124, MTH132, MTH133*[1]*, MTH234*[2] *or any math course above MTH234.*
- *Students who have already been granted Advanced Placement (AP) Mathematics credits for calculus before their Academic Orientation Program (AOP).*
- *Students who have ACT Mathematics scores of at least 28 or SAT Quantitative scores of at least 640 and who will be taking math at MSU.*

Summary

This chapter points out several ideas. First, predicting mathematics placement as well as success in first college mathematics course is a very complex task. Using high school background information can be difficult because high school transcripts are difficult to interpret. In addition, predicting student's grades in their first college mathematics course using pre-course information can be difficult because of student's situational factors, dispositional factors, and even variability in instructors' grading pattern that take effect once students enroll in the course.

Second, because of the important decisions that are made as a result of the placement examination, it is important that the validity of the examination be assessed regularly.

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[1] Calculus II: Integral Calculus

[2] Calculus III: Multivariate Calculus

This includes assessing the predictive validity of the examination, examining cut scores, and investigating false positives.

Lastly, “how a test is administered can also significantly affect student’s scores and therefore test validity” (Akst and Hirsh, 1991, p4). Therefore, it is important that the scores across the different type of examinations be compared. If the scores are found to be different, then finding reasons for the difference is the only next logical step.

What is missing from the research on proctored and unproctored examination is the investigation of the course outcomes for each course in which students are placed into as a result of the each type of examination. This study will add to the body of research by investigating these course outcomes.

CHAPTER 3

METHOD

This chapter describes the study's design and research methodology. First there is a brief description of the design of the study, followed by a description of how the sample was determined. Second, there is an overview of the data collection process. This includes where the data was obtained, how the data was coded and a description of the variables created for this study. Finally, the methods of data analysis, for each research question, are introduced.

This study takes placed at Michigan State University (MSU); a public research university located in the northeastern part of the United States with a total student population of approximately 47,000. Each year, the university accepts approximately 7000 new freshmen. Many of these students are required to take a mathematics placement examination prior to enrolling in any mathematics course. Students have the option of taking a proctored examination or an unproctored examination. Hence the opportunity to evaluate the effectiveness of each type of examination presented itself.

Design

The study's general design is an ex post facto, quasi-experimental design with two non- randomized groups. The participants were divided into two groups according to the type of examination that was used as placement. The first group was the group of students who were placed with the proctored examination. This group consisted of 598 first time college freshmen who enrolled in mathematics during fall semester 2008. The second group was the group of examinees who were placed with the unproctored examination. This group consisted of 4382 first time college freshmen who enrolled in mathematics during fall semester 2008.

Sample

Because of the small number of students who were placed with the proctored examination, the entire group of 598 students was used in this study. To determine the minimum sample size needed for the group of students who were placed with the unproctored examination, the following formula was used

$$\boldsymbol{n = \frac{z^2 p(1-p)}{e^2}} \qquad (1)$$

Where

n is the minimum sample size

z-score is the standard normal score that cuts off the top (1 – desired confidence level) area of the normal curve

p is the estimated proportion of the attribute that exists in the population (for this study, the attribute was the proportion of students who were successful in their first college mathematics course)

e is the level of precision

For this study, a confidence level of 95% was used with a precision level of 3%. Since the variability was unknown, p =.5 allowed for maximum variability. Thus, the minimum sample size needed was computed as

$$\mathbf{n} = \frac{(\mathbf{1.96})^{\mathbf{2}}(\mathbf{0.5})(\mathbf{1} - \mathbf{0.5})}{(\mathbf{0.03})^{\mathbf{2}}} \approx \mathbf{1067}$$

The students in the unproctored group were placed in alphabetical order (by last name) and a systematic random sample was taken using every 4th student. This procedure produced a sample of 1098 students from the unproctored group. Table 1 gives the demographics for the sample of students used in this study.

Table 1

Distribution of Race and Gender for Proctored and Unproctored Data

	Group 1 (Proctored)	Group 2 (Unproctored)
Male	47.32%	44.08%
Female	52.68%	55.92%
White	66.56%	75.77%
Black	17.39%	8.11%
Asian	2.85%	5.10%
Hispanic	1.84%	3.01%
American Indian	0.50%	0.73%
Not indicated	10.87%	7.29%

Data Collection

Data was collected from students' college and high school transcripts obtained from the Michigan State University Registrar's Office. The registrar's office was asked to alphabetize the list of students in group 2 and take a systematic sample of every 4th student. The registrar's office then provided a file that contained information for all students in group 1 and the selected students from group 2. The file contained each student's mathematics placement examination score, ACT Mathematics score, type of examination used to place the student (proctored or unproctored), first college mathematics course, grade in first college mathematics course, gender and race.

The registrar's office then provided the high school transcripts of the students who were selected for this study. Taken from these transcripts were students' high school mathematics courses from ninth grade through twelfth grade and the grades received in each course. These grades were used to compute each student's mathematics GPA. This information was added to the file received from the registrar's office.

Letter Grade Conversion

The grading system varied across high schools. For example, some high schools graded students using only the traditional letter grades: A, B, C, D, and F. In addition to these traditional letter grades, other high schools used grades of A+, B+, C+, and D+. Additionally, some high schools gave grades of A-, B-, C-, and D-. Instead of letter grades, some schools awarded number grades. Some school awarded grades on a four point scale (4.0, 3.0, 2.0, 1.0, 0.0) while others included half grades (3.5, 2.5, 1.5) as well. Some school awarded grades that were not included in the calculation of students' GPA

(P = Pass, CR = Credit, NC = No Credit). These grades were not included in the calculation of students' mathematics GPA.

High schools also varied in the quality points awarded to each letter grade. For example, at one high school a B+ grade was awarded 3.5 points while at another high school a grade of B+ was awarded 3.33 points. Yet another high school awarded 3.30 points for a grade of B+.

Quality points also varied within high schools. Within schools, a grade of B received for an honors course was awarded more quality points than a B grade in a non-honors course. However, for this study, grades earned in an honors course were given the same quality points as similar grades earned in a non-honors course.

To develop a letter grade to number grade conversion table, each letter grade was converted to a range of quality points and the midpoint of the range was used as the point value for that letter grade. The range of quality points was determined from an analysis of the high school transcripts. The analysis of the transcripts revealed that the lowest quality points awarded to a grade of C- was 1.67 while the highest quality points awarded was 1.75. For the next highest grade, C, every high school awarded 2 points. So the quality point range for a C- was 1.67 to 2.00 (including 1.67 but not including 2.00). The midpoint of this range is 1.84 and this value was use as the point value for a grade of C-. The point value for the other letter grades was computed similarly. Table 2 lists the quality point range and the value used as the point value for each letter grade

Table 2

Letter Grade Conversion Chart Used to Compute Students' High School Mathematics GPA

GRADE	QUALITY POINT RANGE	VALUE	GRADE	QUALITY POINT RANGE	VALUE
A+	4.30 +	4.30	C	2.00 - 2.30	2.15
A	4.00 - 4.30	4.15	C-	1.67 - 2.00	1.84
A-	3.67 - 4.00	3.84	D+	1.30 - 1.67	1.49
B+	3.30 - 3.67	3.49	D	1.00- 1.30	1.15
B	3.00 - 3.30	3.15	D-	0.67 - 1.00	0.84
B-	2.67 - 3.00	2.84	F	0 - 0.67	0.34
C+	2.30 - 2.67	2.49			

Definition of Pre-college Characteristic Variables

For this study, there were several pre-college characteristic variables. One variable was students' high school grade point average (HSGPA). This continuous variable was included with the data file that was received from the MSU registrar's office. Because some schools award grades above 4.0, several students had high school GPAs greater than 4.0

Another pre-college characteristic variable was students' high school mathematics grade point average (HSMGPA). This continuous variable was constructed by converting the letter grade received in each mathematics course to its corresponding point value using table 2. These values were then averaged to produce a HSMGPA for each student. Some students were enrolled in one mathematics class for an entire school year while others were enrolled in one mathematics class during the first semester and a different mathematics class during the second semester. Students who were enrolled in one class for an entire school year usually had two grades recorded on their transcripts: one grade for semester 1 and another grade for semester 2. When this happened, both grades were used in the calculation of HSMGPA.

The course in which a student was enrolled at each grade level was used as a variable. The variable MATH9S1 and MATH9S2 represented students' 9th grade mathematics course for semesters 1 and 2 respectively. If a student was enrolled in the same course for the entire ninth grade, then that course was recorded for both MATH9S1 and MATH9S2. Similarly MATH10S1, MATH 10S2, MATH11S1, MATH11S2, MATH12S1, and MATH12S2 represented the courses in which students were enrolled during each semester of their tenth, eleventh, and twelfth grade years respectively.

GR9LS1 and GR9LS2 are the letter grades that students received in the ninth grade of semester 1 and semester 2 respectively. Similarly GR10LS, GR10LS2, GR11LS1, GR11LS2, GR12LS1, and GR12LS2 are the letter grades for each semester of students' tenth, eleventh, and twelfth grades respectively.

The last mathematics course taken in high school was also used as a pre-college characteristic variable. For this study, calculus, pre-calculus, and trigonometry were considered algebraically demanding courses and therefore, the most challenging courses in which a high school student could enroll. A course in algebra or Geometry was not considered algebraically demanding and not challenging enough for students who intended to pursue some type of postsecondary education. Therefore these courses were considered to be the lowest level of courses in which a high school student could enroll. Then, there were courses that were considered to be more challenging than algebra or geometry, but not as challenging as calculus, pre-calculus, or trigonometry. Courses in probability or statistics were considered to be one level below calculus, pre-calculus, or trigonometry. Courses in finite math, discrete math, math analysis, and FST (functions statistics, and trigonometry) were considered to be a level above algebra and geometry. The variable LAST was created and was given the value 1 if a student's last high school mathematics course was calculus (including AP calculus), pre-calculus, or trigonometry, the value 2 if a student's last high school math course was probability or statistics (including AP statistics), the value 3 if a student's last high school mathematics course was FST, discrete math, finite math, or math analysis, and the value 4 if a student's last math course was algebra or geometry.

For this study a passing grade in a high school course was considered to a grade of C or better. From this, the variable CABOVE was created. This variable had a value of 1 if a student received a grade of C or better in his or her last high school mathematics course and the value 0 if the student received a grade lower than C in his or her last mathematics course.

Whether or not a student took a mathematics course during his or her senior year was also included as a pre-college variable. This categorical variable was named SYM and was given the value 0 if the student was not enrolled in a mathematics course during his or her senior year of high school or the value 1 if the student was enrolled in a mathematics course during his or her senior year of high school.

ACT Mathematics score was used as a pre-college characteristic variable. This continuous variable was named ACTM. This variable was included in the data file that was received from the MSU registrar's office.

Definition of College Variables

Several college level variables were included in this study. One variable was the mathematics placement examination score. This continuous variable was named MPE and was included in the data file. This variable had a range of 0 to 28.

There were two type of mathematics placement examinations administered to students: proctored or unproctored. This dichotomous variable was named TYPE and was given the value 0 if the student was placed into their first mathematics course with the unproctored examination and the value 1 if the student was placed into their first mathematics course with the proctored examination.

First college mathematics course was another college variable. This categorical variable was called FMC. For this study, students' first mathematics course was one of the following: Intermediate Algebra (MTH1825), College Algebra (MTH103), Finite Mathematics (MTH110), College Algebra and Trigonometry (MTH116), Finite Mathematics: Application of College Algebra (MTH112), Survey of Calculus 1 (MTH124), Calculus 1 (MTH132), Math for Elementary Teachers 1 (MTH201), or Statistical Methods (STT200/STT201).

The variable GRADE was used to represent the grades given in the MSU mathematics course. MSU uses the following grading scale 4.0, 3.5, 3.0, 2.5, 2.0, 1.5, 1.0, 0.0, W (withdrawal), or I (incomplete). No student in this study received a grade of W or I.

Demographic Variables

There were two demographic variables used in this study. The first was Gender. This dichotomous variable was coded 0 if the student was a male and 1 if the student was female. The other demographic variable was RACE. This variable represented the race/ethnicity of the student and was coded 0 if the student was white, 1 if the student was black, 2 if the student was Hispanic, 3 if the student was American Indian, 4 if the student was Asian or a Pacific Islander, and 9 if a student's race was not indicated.

Analysis

The statistical analysis software package PASW Statistics 18 (formerly SPSS) was used to conduct the data analysis for this study. The research questions required the use of several statistical techniques. Among them were multiple linear regression (MLR), binary logistic regression (BLR), 2 independent sample t – tests, and Pearson chi-square test.

Multiple Linear Regression (MLR)

MLR expresses the linear relationship between a dependent variable (or outcome variable) and two or more independent variables (or predictor variables). The dependent variable must be continuous and the independent variables can be continuous or categorical. The prediction equation is given by:

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \qquad (2)$$

Where

$\hat{y}$ is the estimated value of the dependent variable

b_0 is the estimated value of the regression intercept

b_i is the estimated value of the regression slope for the i^{th} predictor

x_i is the value of the i^{th} predictor

Assumptions

MLR has several assumptions. When these assumptions are satisfied, the estimates of the regression coefficients are unbiased, efficient, and consistent (Ostrom, 1990). An estimator is unbiased if its expected value is equal to the true value of the parameter. An estimator is efficient if its variance is smaller than the variance of any other estimator. An estimator is consistent if it converges in probability to the true value of the parameter. MLR requires that the following assumptions be met:

- *Linearity*: MLR requires that a linear relationship exists between the outcome variable and each of the predictors. Visual inspection of a scatterplot can verify this assumption (Triola, 2010).
- *Multicollinearity*: Multicollinearity occurs when two or more predictor variables are highly correlated. This assumption can be checked by inspecting the correlation matrix of the predictors.

- *Normality*: The variables used in the model should be normally distributed. This assumption can be checked by visually inspecting the histogram associated with each variable used in the model.
- *Normally distributed errors with mean = 0*: The histograms of the error terms can be visually inspected for normality. Additionally, a normal probability plot can be used to assess the normality of the errors. If the points form a straight line, the normality assumption of errors is supported.
- *Homoscedasticity*: Homoscedasticity means that the variance of the errors is the same across all levels of each predictor and can be checked by visually inspecting the scatterplot of the standardized residuals and the standardized predicted values (Osborn and Waters, 2002).

Model Fit

In addition to checking the model assumptions, the model fit should also be checked. The fit of the MLR model can be checked in three ways.

- *Test of overall model fit*: PASW Statistics 18 produces an ANOVA table that is associated with the MLR model. This table has an F statistics that can be used to test the overall fit of the model. A significant finding indicates that at least one of the model coefficients is significantly different from zero.
- *Test of individual model coefficients*: The significance of each model coefficient can be tested using a t-test. A significant finding indicates the regression coefficient is significantly different from zero. The test of the individual model coefficients is given in PASW Statistics 18.

- *Coefficient of Determination (R^2):* This is a measure of the proportion of variation in the dependent variable accounted for by its linear relationship with the predictor variables. R^2 can also be used as a test of global model fit. R^2 ranges in value from 0 (no variation in the dependent variable is accounted for and therefore poor model fit) to 1 (all the variation is accounted for and therefore perfect model fit). R^2 can be requested in the multiple regression procedure in PASW statistics 18.

Binary Logistic Regression (BLR)

BLR is similar to MLR but is used when the dependent variable is dichotomous. The independent variables could be continuous or categorical. BLR models the log odds of belonging to a particular group. Usually the dependent variable takes on the value 1 when an observation belongs to the group and 0 when the observation does not belong to the group. The BLR model is given by:

$$Ln\left(\frac{P}{1-P}\right) = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \qquad (3)$$

Where

P is the probability that the dependent variable takes on the value 1

b_0 is the regression intercept

b_i is the estimated value of the regression slope for the i^{th} predictor

X_i is the i^{th} predictor

BLR can be used to calculate the conditional probability of achieving a score of 1. Manipulating equation (3), the conditional probability of achieving a score of 1 is given by

$$P(x = 1|X_1, X_2, \dots, X_n) = \frac{e^{b_0+b_1X_1+b_2X_2+\cdots+b_nX_n}}{1+e^{b_0+b_1X_1+b_2X_2+\cdots+b_nX_n}} \quad (4)$$

The following components are usually included when presenting BLR results; 1) overall goodness – of –fit statistics; 2) estimates of the model coefficients with test statistics, odds ratios, p –values, confidence intervals; and 3) classification tables (Cotter, 2007; Garson, 2010).

Model Fit

- *The Hosmer Lemeshow Test:* The Hosmer and Lemeshow test is usually preferred as the test of overall fit of the BLR model (Hosmer and Lemeshow, 2000). A non-significant finding indicates that the BLR model fits the data well. The Hosmer and Lemeshow test can be requested as part of the logistic regression procedure in PASW Statistics 18.
- *Omnibus Test of Model Coefficient*: This test is similar to the F test of overall model fit in MLR and tests the null hypothesis that that the model with additional predictors does not fit the data better than the intercept only model.

- *<u>Wald χ^2 statistic:</u>* This statistic is similar to the t-test used to test the significance of the individual coefficients in MLR. A significant finding indicates that the coefficient is different from zero. The Wald χ^2 statistic is a standard output of the logistic regression procedure in PASW Statistics 18.
- <u>Classification Table:</u> The classification table can be used to determine the percentage of correct decisions made by the model. When the model predicts that a student will be successful and the student is actually successful, then the model has produced a correct decision. Also, when the model predicts that a student will be unsuccessful and the student is actually unsuccessful, the model has also produced a correct decision. The percentage of correct decisions made will be called the "hit rate". The classification table can also be used to compute the percentage of false positives and false negatives produced by the BLR model

When variables are added to a BLR model, one is concerned about whether the additional variables improve the prediction of the model. The deviance statistic can be used to determine if additional variables improve the prediction of the model. In PASW Statistics 18, the deviance statistic is given by the -2log likelihood statistic. To determine if the additional variables improve the fit of the overall model, the deviance of the model that was constructed with the additional variables is subtracted from the deviance of the model without the additional variables. This difference has a chi-square distribution with the degrees of freedom equal to the number of variables added to the model. A significant finding indicates that the additional variables improve the prediction.

Two Independent Sample T-Test

A 2 independent sample t-test is used to determine if there is a statistically significant difference in the means of two independently sampled groups. A significant finding indicates that the two group means are different.

Assumptions

- *Groups are sampled from two different populations*: This assumption is part of the research design.
- *Normality of independent variables*: This can be checked by visually inspecting the histogram of the independent variables
- *Homogeneity of variances*: Levene's test can be used to test this assumption. Levene's test is part of the PASW Statistics 18 output. A non-significant finding indicates that the group variances are equal.

Pearson Chi-Square Test of Independence

When two variables are not associated they are considered to be statistically independent (Frankfort-Nachmias & Leon-Guerrero, 2009). This study looks for dependence in course success across various groups by using Pearson's chi-square test of independence. This is done by computing the cell frequencies that are expected under the null hypothesis that there is no association between the two variables. If these expected cell frequencies are statistically different from the observed cell frequencies, then the variables are said to be statistically dependent (Frankfort-Nachmias & Leon-Guerrero, 2009).

Assumptions

The chi-square test of independence has two important assumptions:

- The sample size is large
- Each expected cell count is at least 5

If either of these assumptions is not satisfied, then Fisher's exact test can be used as an alternative to Pearson's chi-square test. Fisher's exact test computes the conditional probability of getting the observed contingency table. Pearson chi-square test and Fisher's exact test can be requested as output in PASW statistics 18.

Effect Size Measures

Neill (2008) noted that statistical significance is not a direct indicator of effect size and that statistical significance is a function of sample size. Also, in the case of large samples, significant testing can give misleading results because even small or trivial effects can be statistically significant. Thus a measure of effect size can be used in these situations. The effect size measures used in this study is R^2, odds ratio, and Cohen's standardized difference (Cohen's d).

An effect size measure that is often used with MLR is the proportion of variance in the dependent variable that is due to its relationship with the independent variables.

This is known as R^2. The value of R^2 ranges from 0 to 1 with proportions close to one indicating perfect model fit. The value of the adjusted R^2 is also reported when there are a large number of independent variables. If there are a small number of independent variables, R^2 and adjusted R^2 will be close but if there are a large number of independent variables, the adjusted R^2 may be lower than R^2. This effect size is reported with all MLR models used in this study. Frankfort-Nachmias & Leon-Guerrero, 2009, Gravetter & Wallnau, 1985 and Triola, 2010 should be consulted for more information on R^2.

For binary logistic regression, the odds ratio is used as a measure of effect size. If the independent is dichotomous, the odds ratio can be interpreted as the odds of success of one group relative to the odds of success for the other group. If the independent variable is continuous, then the odds ratio can be interpreted as the factor by which the independent variable changes (increases or decreases) the odds of the dependent variables. The odds ratio was used as an effect size measure for all BLR models used in this study.

The odds ratio can also be used as an effect size when performing a 2 x 2 contingency table analysis. In this situation, the odds ratio can be used to determine whether two dichotomous variables are associated. Below is an example of a 2 x 2 contingency table. To calculate the odds ratio, one can simply divide the product of A and D by the product of B and C (e.g. (A*D)/(B*C)) . Of course, the computation of the odds ratio will depend on the odds of interest. For this study, the odds ratio was computed for each analysis involving a 2 x 2 contingency table.

Table 3

Example of a 2 x 2 Contingency Table

	Variable 1		**Total**
Variable 2	A	B	A+B
	C	D	C+D
	A+C	B+D	

Cohen's standardized difference (Cohen's d) is the effect size measure most used with 2 independent sample t-tests. Cohen's d is given by:

$$d = \frac{|\bar{x}_p - \bar{x}_u|}{\sqrt{\frac{(n_p - 1)s_p^2 + (n_u - 1)s_u^2}{n_p + n_u}}} \qquad (5)$$

Where

$\bar{x}_p$ = mean score of the independent variable on the proctored examination

$\bar{x}_u$ = mean score of the independent variable on the unproctored examination

s_p^2= variance of the independent variable on the proctored examination

s_u^2 = variance of the independent variable on the unproctored examination

n_p = sample size of the independent variable on the proctored examination

n_u = sample size of the independent variable on the unproctored examination

This value gives the mean difference of two variables expressed in standard deviation units (Neill, 2008). For Cohen's d, an effect size below 0.2 is a small; an effect size between 0.2 and 0.5 is a moderate, and an effect size greater than 0.5 is a large (Cohen, 1989). For this study, Cohen's d was reported for each test involving the comparison of two means.

Question 1

Are there significant differences in the pre-college characteristics of students who were placed with the proctored examination and the pre-college characteristics of those students who were placed with the unproctored examination? If so, what are the differences? Furthermore, after controlling for these differences, do significant differences exist in the placement examination scores across the two groups?

One important aspect of comparing group performance is to determine whether the groups are equivalent. This could be of particular importance when the researcher was not involved in the group assignment process. If the two groups are not similar then difference in performance on the placement examination or in the grade received in their first college mathematics course, may not be attributed to differences the type of test used for placement. Therefore the following null hypotheses were tested:

H_{01}: There is no significant difference in the mean ACT Mathematics scores of the students who were placed with the proctored examination and the mean ACT Mathematics scores of the students who were placed with the unproctored examination.

H_{02}: There is no significant difference in the mean high school GPA of the students who were placed with the proctored examination and the mean high school GPA scores of the students who were placed with the unproctored examination.

H_{03}: There is no significant difference in the mean high school mathematics GPA of the students who were placed with the proctored examination and the mean high school mathematics GPA of the students who were placed with the unproctored examination.

If there are significant differences in the mathematics ability of each group, then it should come as no surprise to see differences in placement examination scores across the groups. If similar students are considered, then there should be no difference in placement examination scores. To address this question a multiple linear regression model was constructed. This model used mathematics placement examination score (MPE) as the criterion and ACT Mathematics score, high school GPA, high school mathematics GPA, and type of exam used for placement as predictors (TYPE). If the variable TYPE was significant then students with similar combinations of ACT Mathematics scores, high school GPA, and high school mathematics GPA, received higher placement examination scores on one type of examination. The MLR model was run using PASW Statistics 18. The model assumptions were checked and the value of R^2 was reported.

Question 2

Are the proctored and unproctored examinations functioning similarly?

This question is an important one because it can determine if a particular exam type is more (or less) advantageous for a particular group of students. If the exams are used in the same way, then similar students should see similar results.

First of all, the reliability of the placement examination was computed using the Kuder-Richardson 21 (KR21) reliability index as an estimate. KR21 was computed using the following formula:

$$\boldsymbol{r_{xx} = \frac{n}{n-1}\left(1 - \frac{\bar{x}(n-\bar{x})}{n s_x^2}\right)} \qquad (6)$$

where

r_{xx} is the estimate of the test reliability

n is the number of items on the examination

$\bar{x}$ is the mean examination score

s_x^2 is the variance of the examination scores

The data for this study consisted of total examination scores; not the item responses. Thus, KR21 reliability was the most appropriate reliability index to compute because the formula uses the total number of test items as well as the mean and variance of the examination scores. These values could be easily computed from the data. KR21 assumes that all items are of equal difficulty. When this is not the case KR21 will underestimate the exam's true reliability (Allen and Yen, 1979). Thus, KR21 is a conservative estimate of the reliability of the exam and the exam's true reliability would be higher.

Second, a separate correlation matrix was constructed for the entire data set, for the proctored data, and for the unproctored data. The following variables were included in each of the correlation matrices:

- ACT Mathematics score
- High school GPA
- High school mathematics GPA
- Math placement examination score
- Grade in college mathematics course
- Gender (1 if female, 0 if male)
- Senior year math (1 if the student took math during their senior year of high school, 0 other wise)
- CPT (1 if student took calculus, pre-calculus, or trigonometry; 0 otherwise)
- RACE/ETHNICITY (1 if the student was white, 0 otherwise)

If the proctored and unproctored examinations are functioning similarly, the correlation matrix for the unproctored data should be similar to the correlation matrix for the proctored data. For example, variables that are highly correlated in the unproctored matrix should be highly correlated in the proctored matrix. So the correlations of the variables in the unproctored correlation matrix were compared to the correlations of the variables in the proctored correlation matrix.

To test the equality of the correlation matrix each correlation was normalized using Fisher's Z transformation (Thorndike and Dinnel, 2001). This formula is given by

$$Z_r = 1.1513 log\left(\frac{1+r}{1-r}\right) \quad (7)$$

where r is the value of the correlation coefficient.

After each correlation is transformed, a statistical test is conducted to determine if the corresponding entries in the proctored and unproctored correlation matrices are statistically equivalent. The test statistic can be found in Thorndike and Dinnel (2001) and is given by:

$$Z = \frac{Z_{rP} - Z_{rU}}{\sqrt{\frac{1}{N_P - 3} + \frac{1}{N_U - 3}}} \quad (8)$$

where

Z_{rP} is the Fisher's Z transformation of the proctored correlation

Z_{rU} is the Fisher's Z transformation of the unproctored correlation

N_P is the sample size used to compute the proctored correlation

N_U is the sample size used to computed the unproctored correlation

Multiple Hypothesis Testing

When a hypothesis test is conducted, the decision is either to reject the null hypothesis or retain the null hypothesis. If the null hypothesis is actually true and the decision is to reject it, then a Type I error has been committed. This Type I error (usually referred to as alpha (α) is usually assigned at the beginning of the study. One of the problems with conducting multiple hypothesis tests is that the Type I error becomes inflated and it becomes more likely that the null hypothesis will be rejected when it is true (Abdi, 2010).

There are several methods of correcting for the inflation in the Type 1 error rate and the reader is encouraged to consult Shaffer (1995). One way of controlling this inflation in Type 1 error is by testing each of the n significance tests at a significant level of $\frac{\propto}{n}$. The procedure is known as the Bonferroni Correction Method. Any hypothesis test with a p –value ≤ $\frac{\propto}{n}$ is rejected. The Bonferroni Correction Method was chosen because it is easy to calculate.

Another method used to determine if the two examinations are functioning similarly was to create a model to predict placement examination scores using the proctored data and fitting that model to the unproctored data. This would give an estimate of the placement exam scores in which a student who was placed with the unproctored examination would have received had he or she been placed with the proctored examination. Predicted placement should agree with actual placement. Similarly, a model to predict placement examination scores using the unproctored data was created. This model was fitted to the proctored data to determine the unproctored placement of the students who were placed with the proctored examination.

Without concern for their significance, the MLR model used to predict placement examination scores used MPE as the dependent variable and ACTM, HSGPA, HSMGPA, SYM, GENDER, RACE, LAST, C_ABOVE and TYPE as the independent variable and PASS as the dependent variable. Dummy variables were created for the variables LAST and RACE. LAST was a categorical variable with 4 levels and RACE was a categorical variable with 5 levels.

For LAST, students whose last mathematics course was calculus (including AP), pre calculus, or trigonometry were used as the reference group. The variables PSTT, ALG, and OTHER were created as dummy variables for LAST. PSTT took on the value 1 if a student's last class was probability or statistics (including AP statistics) and 0 otherwise. ALG took on the value 1 if a student's last high school math class was algebra 1, algebra 2, algebra 3, algebra 4, or geometry and the value 0 otherwise. OTHER took on the value 1 if a student's last high school mathematic course FST (functions, statistics, and trigonometry), discrete math, math analysis, or finite math. The reference group was represented in each of PSTT, ALG, and OTHER have a value of 0.

White was used as the reference group for RACE. Thus, the dummy variables for RACE were BLACK (1 if the student was black and 0 otherwise), HISPANIC (1 if the student was Hispanic and 0 otherwise), INDIAN (1 if the student was American Indian and 0 otherwise), and ASIAN (1 if the students was ASIAN and 0 otherwise).

Three groups were created. The first group, AGREE, consisted of the subjects whose predicted placement agreed with their actual placement. For example, if a student's predicted placement with the proctored regression model was MTH103 and the student's actual placement using the unproctored examination was MTH103, then this student would belong to the AGREE group.

The second group, LOWER, consisted of students whose predicted placement with the proctored regression model was lower than their actual placement with the unproctored examination. For example, if a student's predicted placement using the proctored model was MTH103 but the student was actually placed into MTH132 with the unproctored examination, then this student would belong to the LOWER group.

The HIGHER group consisted of students whose predicted proctored placement was higher than their actual placement. For example, if a student's predicted placement using the proctored regression model was MTH132 but the student was actually placed in MTH132 with the unproctored examination, then this student would belong to the HIGHER group. If the unproctored examination and proctored examination are functioning similarly, there should be a high level of agreement between the placement predicted by the proctored model and the actual placement by the unproctored examination.

Also, to help support the idea that both examinations are functioning similarly, the success rates in each course across both exams were considered. To determine if the success rates differ across examinations, a series of contingency table analyses were performed. The Pearson chi–square test was used to determine if the success rates were different. If there were significant differences in success rates across the two types of examinations, then the success rates among different groups of examinees across examination types were examined.

Question 3

How well does the mathematics placement examination predict success in students' first college mathematics course? Furthermore, can the prediction of success in students' first college mathematics course be improved using ACT Mathematics score,

high school GPA, the type of mathematics courses taken in high school, and whether or not students took a mathematics course during their senior year of high school?

At the time of this study, MSU used only the placement examination to place students into their first college mathematics course. Thus the obvious concern is whether the placement examination significantly predicts success in first college mathematics course. A binary logistic regression model was developed to predict the log odds of success in Intermediate Algebra (MTH1825), College Algebra (MTH103), College Algebra and Trigonometry (MTH116), Survey of Calculus 1 (MTH124) and Calculus 1 (MTH132) was constructed using placement examination scores as the predictor and the variable PASS (1 if the student received a 2.0 or better and 0 otherwise) as the outcome.

The next task was to determine if the prediction of success in first college mathematics course can be improved by using student background information in addition to placement examination scores. To do this, ACT Mathematics scores (ACTM), high school GPA (HSGPA), whether a student took a math course during senior year of high school (SYM), type of examination used for placement (TYPE) and the dummy variables PSTT, ALG, and Other were added to the model containing MPE of each of the courses.

To determine if the new model added to the prediction of success in first college mathematics course, the change in the deviance was tested. The deviance is also known as the -2 log likelihood in PASW Statistics 18. The change in the deviance has a chi-squared distribution with degree of freedom equal to the number of predictors added to the model. A significant finding indicates that the model with the predictors added improved the prediction of success beyond MPE. If the model containing the additional variables provides a better prediction of success, then the additional variables should improve the “hit rate” and decrease the false positives.

Question 4

How do the grades in each course compare across different levels of placement examination scores?

When a placement examination places a student into a mathematics course, the exam is predicting that the student will be successful in the course in which he or she is placed. Furthermore, it is assumed that the student will be successful in any course lower than the one in which he or she was placed. When students are predicted to be successful and are actually unsuccessful, we say that the exam has given a false positive.

A crosstabulation of course grades by placement examination score was done to examine the distribution of grades at each placement exam score for MTH1825, MTH103, MTH110, MTH116, MTH124, and MTH132. As the placement examination scores become higher, more students should receive high course grades than low course grades. This crosstabulation also shows the number of false positives. Crosstabulations of course grade by placement examination score by type of examination was also examined to determine which examination, if any, produces the greater number of false positives.

Some of the students in this study enrolled in a course lower than that which was recommended by their placement examination score. Some of these students received placement scores just above the minimum score while others received placement scores well above the minimum score. For this study, a student is said to have received a score just above the minimum score needed for placement into a course if the student was eligible for a course one level higher than the course in which he or she enrolled. Additionally, a student is said to have received a score well above the minimum score needed for placement if the student was eligible to enroll in a course two or more levels above the course in which he or she enrolled.

It is important to the validity of the placement examination that 1) explanations be sought as to why a student would enroll in a course lower than the level at which he or she was placed and 2) students who scored well above the minimum cut score needed for placement into a course would be unsuccessful in the course. If these reasons are associated with the examination, then it is the researchers recommendation that the examination be revised (e.g. revision or deletion of items, change in administration procedures).

This section demonstrates that validating placement examination requires a variety of evidence from different sources. The process becomes even more tedious when there are two types of examinations that are administered differently. Not only is there a concern about the validity of the placement examination as a whole, but the comparability of the results from the two types of examinations.

CHAPTER 4

RESULTS

Introduction

The primary purpose of this study was to determine if the proctored and unproctored examinations are functioning similarly. This means that no group should be advantaged (or disadvantages) by the type of examination used for placement. This means that placement is independent of examination used for placement. This means that the type of examination used for placement should not have an effect on course outcomes. This section is divided according to the research questions.

Question 1

Are there significant differences in the pre-college characteristics of students who were placed with the proctored examination and the pre-college characteristics of those students who were placed with the unproctored examination? If so, what are the differences? Furthermore, after controlling for these differences, are there significant differences in placement examination scores across the two groups?

Table 4 shows that the mean ACT Mathematics score, mean high school GPA, mean high school mathematics GPA, and mean placement examination score were all higher for the students in the unproctored group than for students in the proctored group. It came as no surprise that the mean placement examination score for the unproctored examination was higher than the mean placement examination score for the proctored examination. A larger proportion of the students who were placed with the proctored examination may have been given the secondary group of items that are scores ½ point each (Group B). In contrast, a larger proportion of the students who were placed with the unproctored examination may have been given the secondary group of items that are scored 1 point each (group C). This difference alone could account for the large difference in the mean placement examination scores. Nonetheless, if math achievement and skill is determined by ACT Mathematics score and high school math GPA, it appears that the students who were placed with the proctored examination were less talented, mathematically, than the students who were placed with the proctored examination. The differences in the mean of the proctored examination and the mean of the unproctored examination (P – U) were each tested using the independent sample t-test in PASW Statistics 18.

Table 4

Descriptive Statistics for ACT Math Scores, High School GPA, High school Mathematics GPA, and Mathematics Placement Examination for Proctored and Unproctored Group

	Proctored (P)			Unproctored (U)			P - U
Category	N	M	SD	N	M	SD	M
ACTM	521	22.87	4.16	1006	23.58	3.83	-0.72
HSGPA	544	3.52	0.35	1032	3.57	0.31	-0.05
HSMGPA	576	3.32	0.58	1090	3.39	0.49	-0.07
MPE	598	12.06	5.05	1098	14.18	5.65	-2.12

Figures 2 thru 9 show the histograms and the normal probability plots for ACTM, HSGPA, HSMGPA, and MPE. The assumption of normality does not appear to hold for HSMGPA (Figures 6 and 7). The histogram is negatively skewed and the points on the normal probability plot stray from the straight line at the low and high ends. The normal probability plot (Figure 8) for MPE show the existence of few outliers, how not enough to effect the normality of the distribution. Otherwise the assumption of normality does not appear to be violated for HSGPA and ACTM.

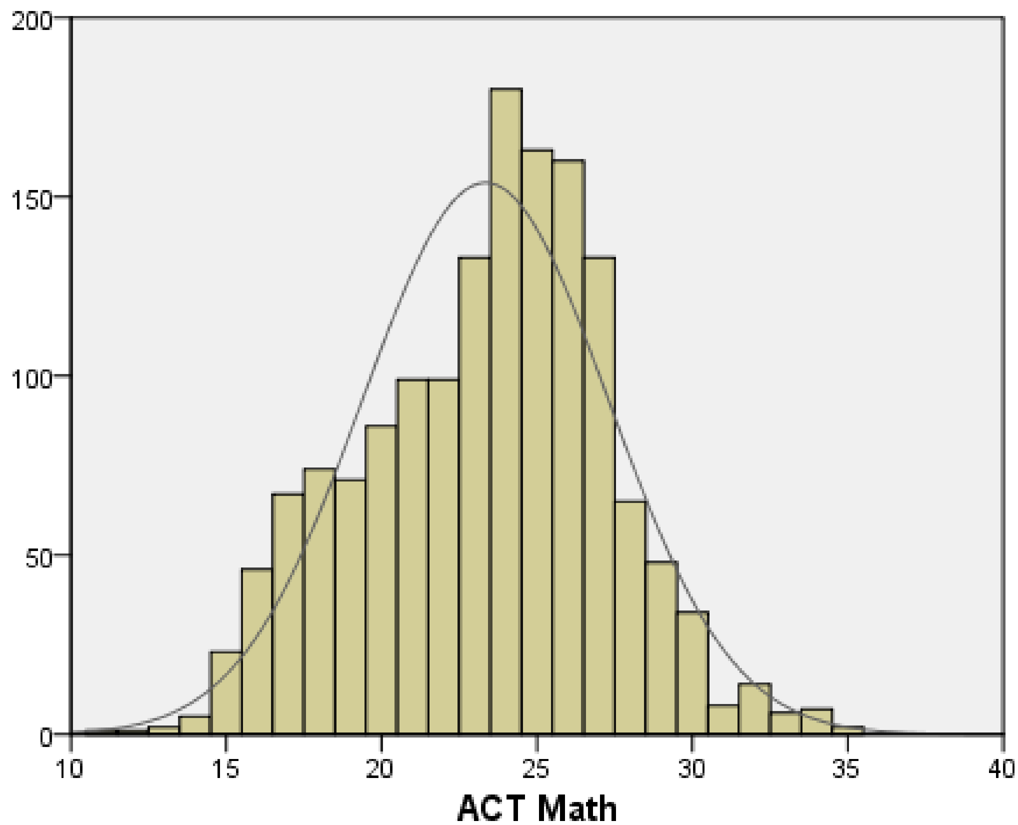

Figure 2 Histogram of ACT Mathematics Scores

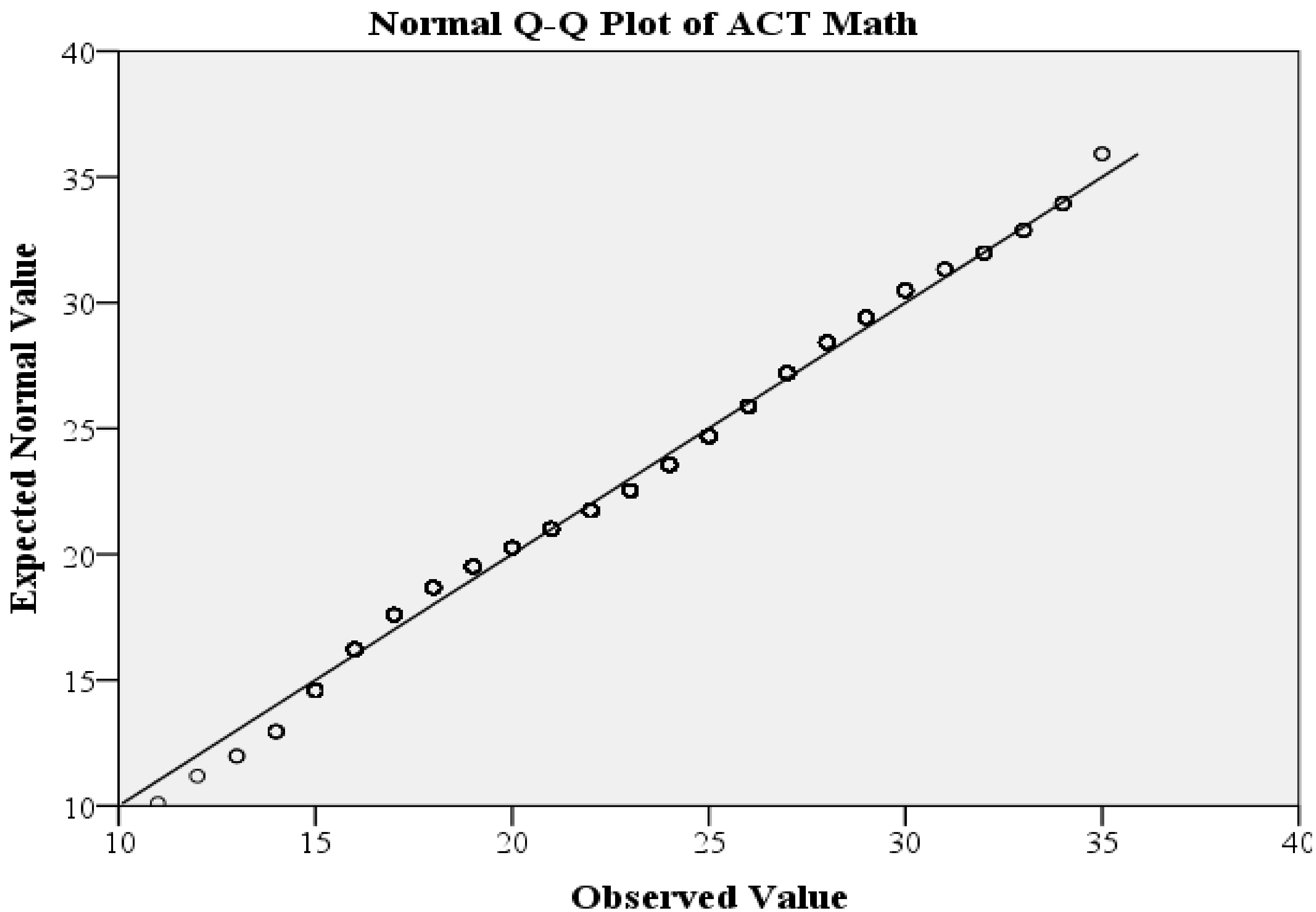

Figure 3. Normal Probability Plot of ACT Mathematics Scores

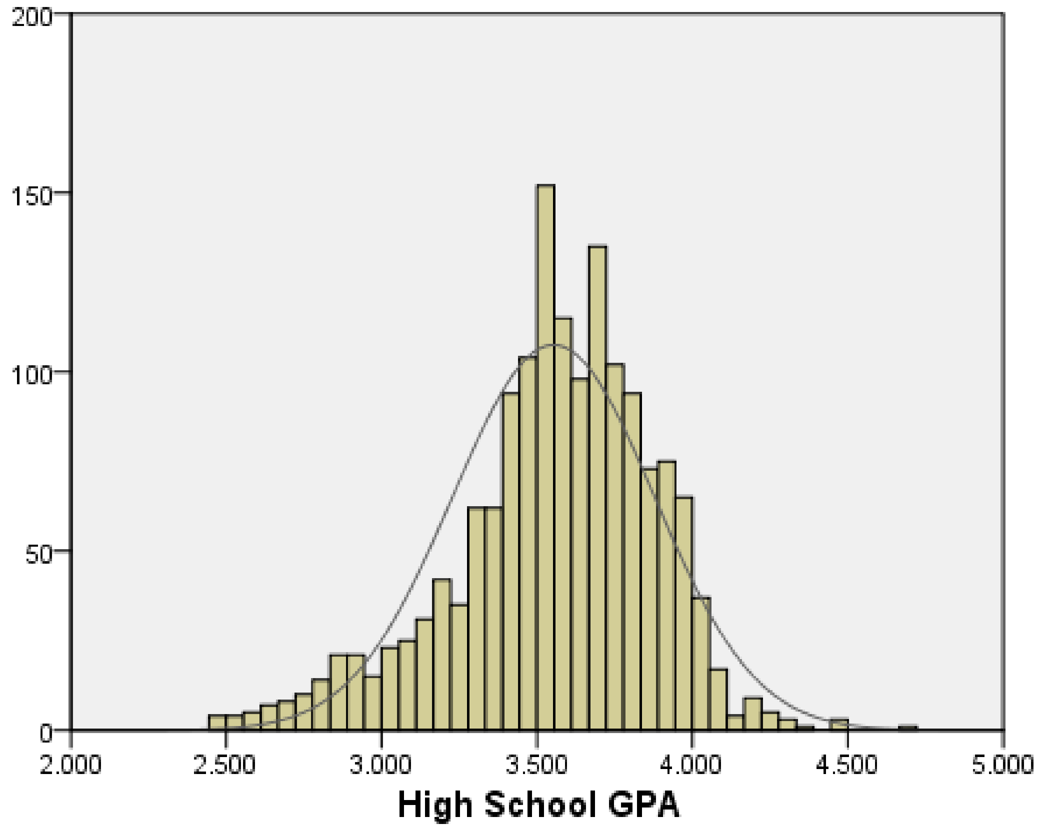

Figure 4. Histogram of High School GPA

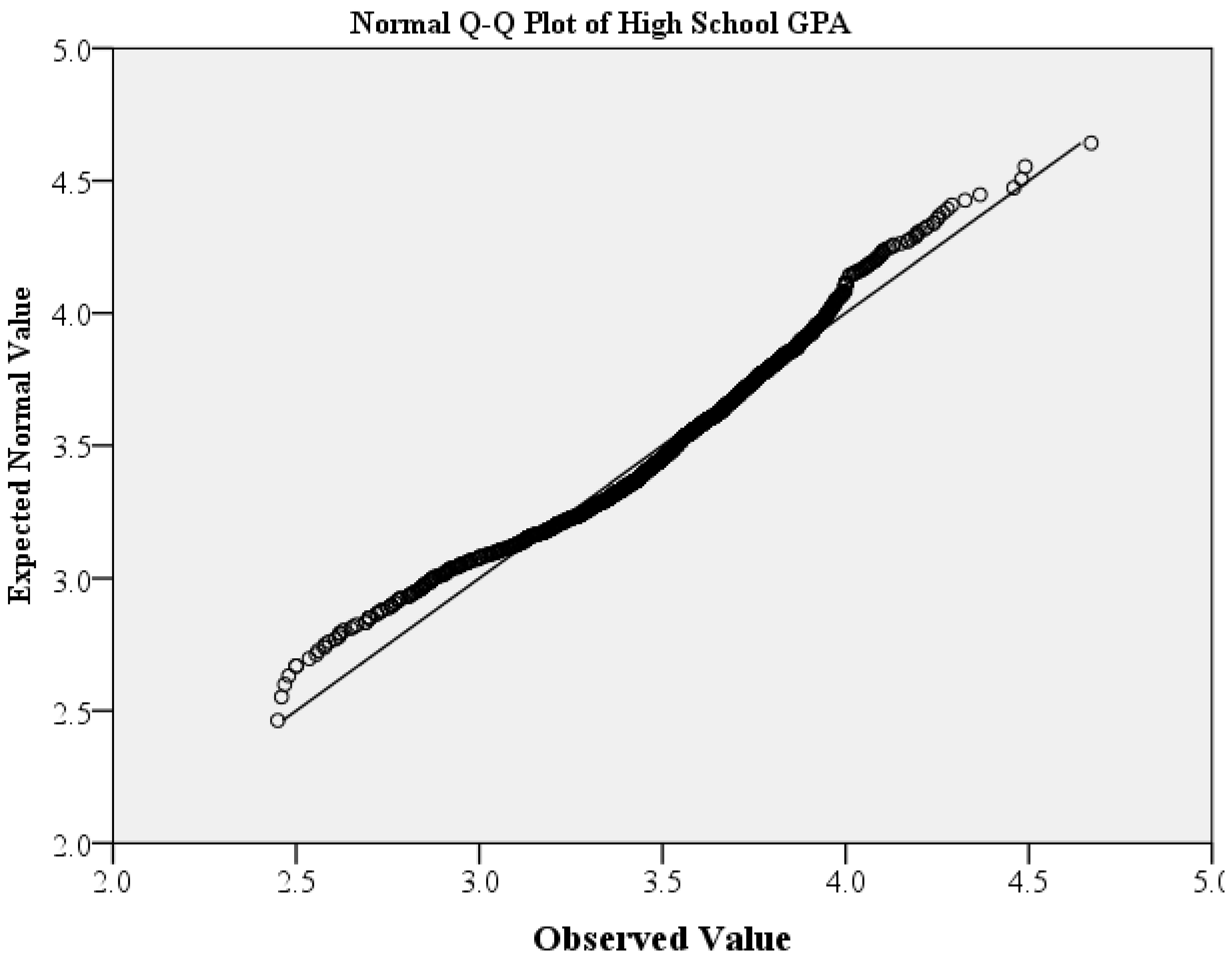

Figure 5. Normal Probability Plot of High School GPA

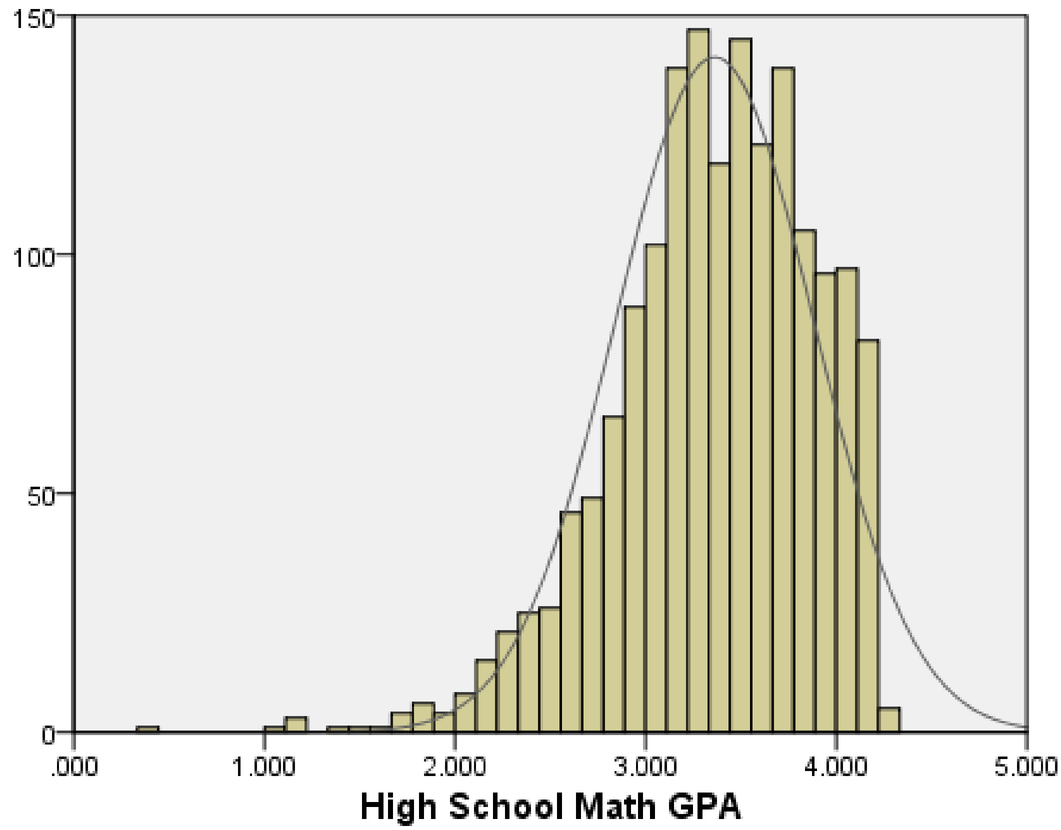

Figure 6. Histogram of High School Math GPA

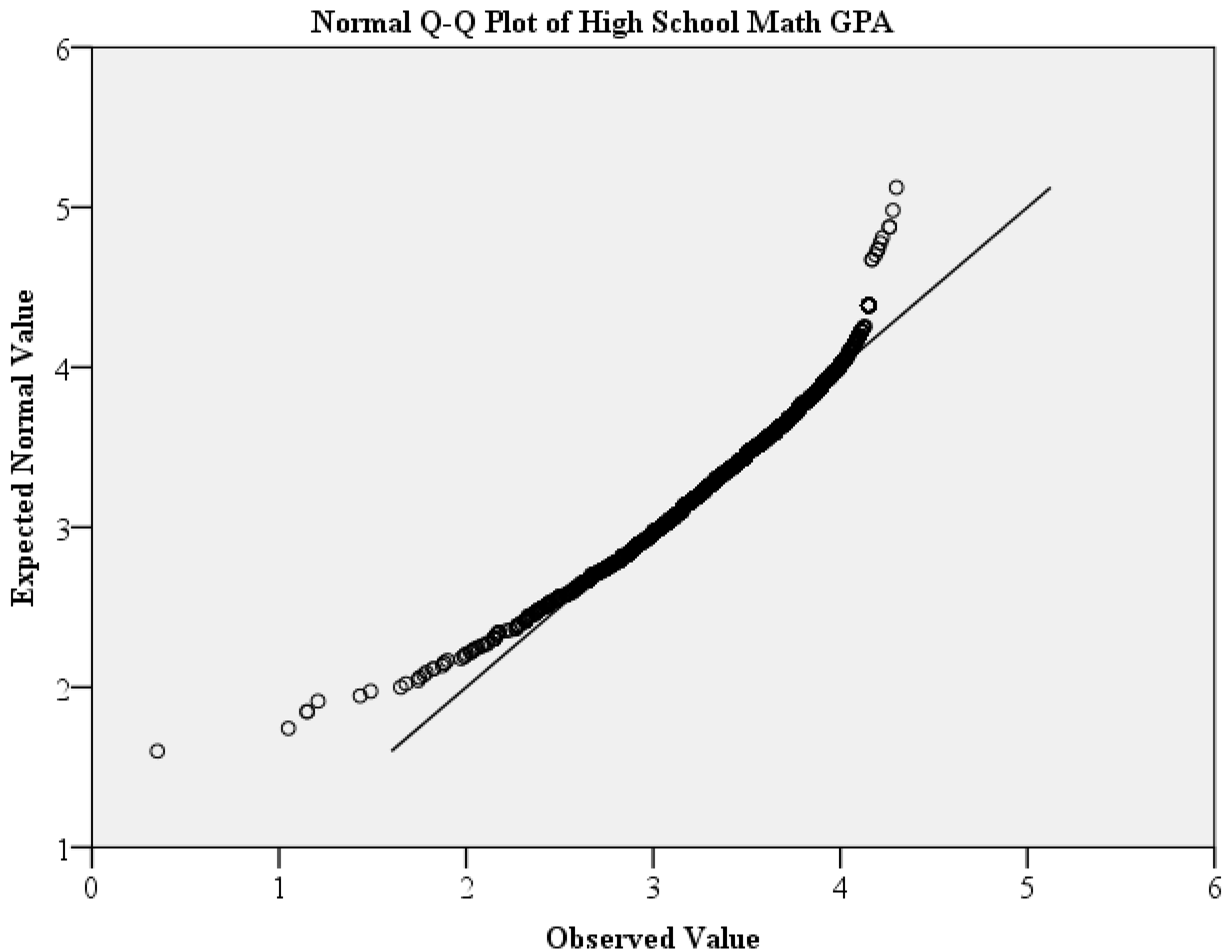

Figure 7. Normal Probability Plot of High School Mathematics GPA

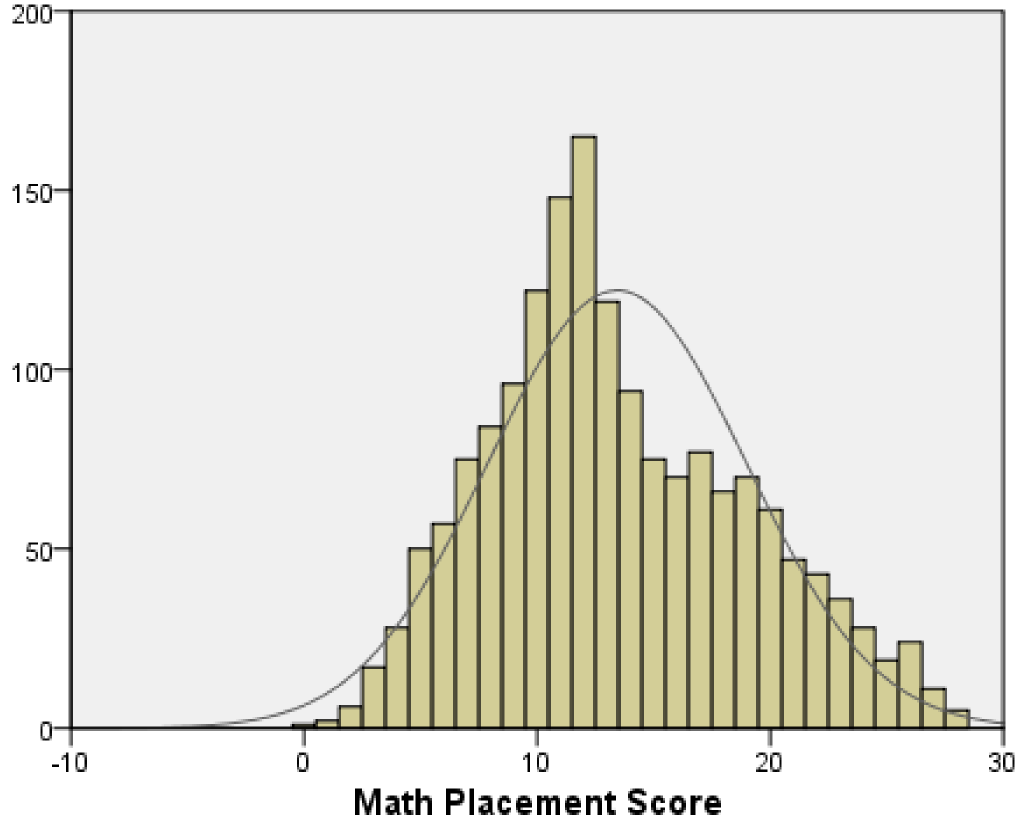

Figure 8. Histogram of Mathematics Placement Examination Scores

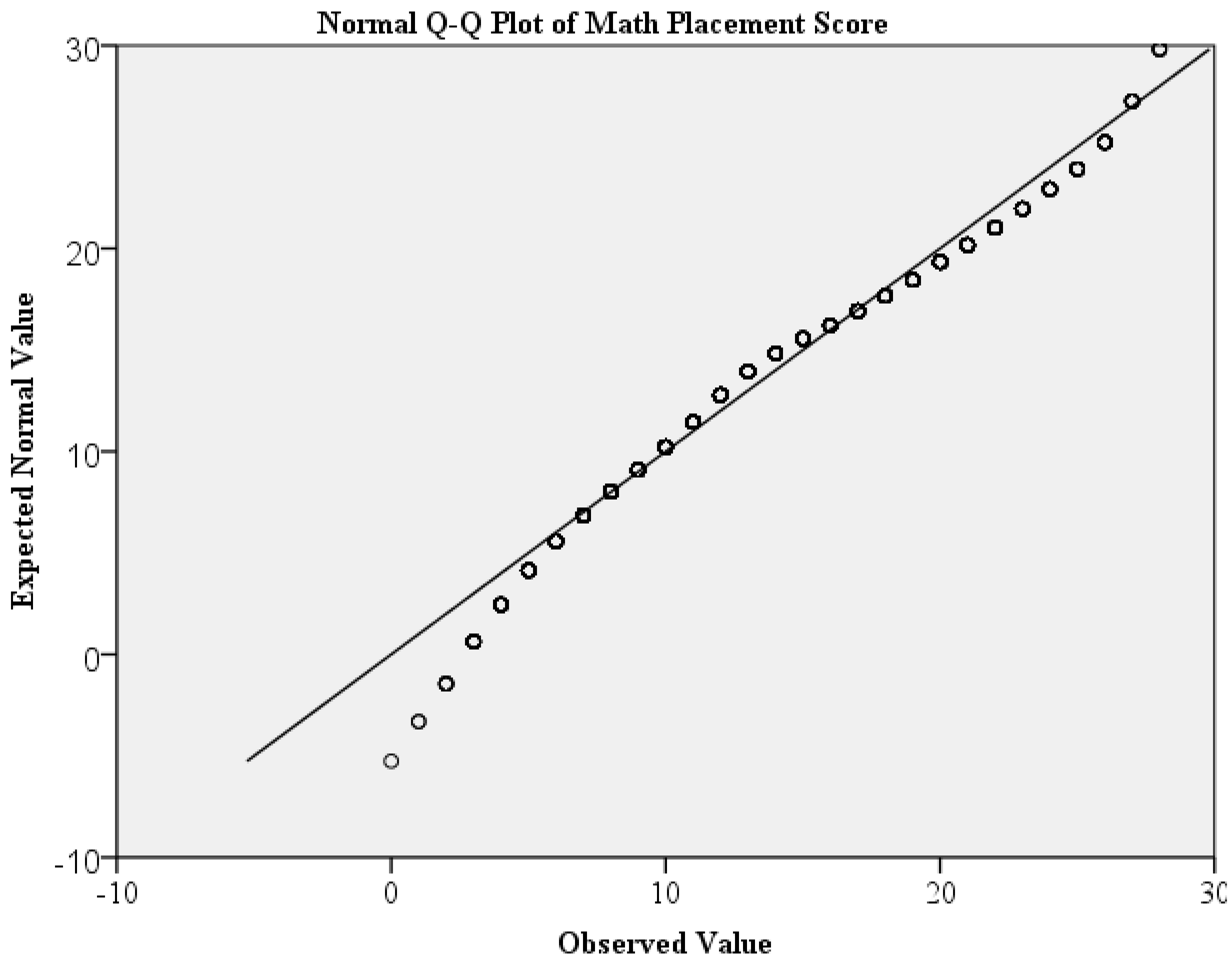

Figure 9. Normal Probability Plot of Math Placement Exam Score

Homoscedasticity Assumption: Levene's test was used to check the homoscedasticity (equal variance) assumption. PASW Statistics 18 conducts Levene's test as part of its 2 independent sample t-test. Table 5 gives the results of Levene's test for each dependent variable, the results of the t-test, and the value of Cohen's mean difference effect size. For Levene's test, the *F* statistic is significant for ACTM, HSGPA, and MPE. Thus equal variances cannot be assumed and the corresponding test statistics are significant.

The students who were placed with the proctored examination appear to have lower mean ACT Mathematics scores, lower mean HSGPA, and lower mean placement examination scores. Cohen's d indicates that the difference in the mean ACT Mathematics scores was small (d = 0.117) and the difference in the mean high school GPA was small (d = 0.151), however the difference in mean placement examination scores is somewhat more substantial (d = 0.584).

Table 5

Test of the Equality of Variances and Equality of Means

		Levene's Test for Equality of Variance		T-test for Equality of Means			
		F	p	t	df	p	d
ACTM	Equal variances assumed	10.41	.001	-3.498	1504	.000	.177
	Equal variances not assumed			-3.399	957.477	.001	
HSGPA	Equal variances assumed	9.454	.002	-2.681	1504	.007	.151
	Equal variances not assumed			-2.595	947.412	.010	
HSMGPA	Equal variances assumed	1.214	.271	-1.014	1504	.311	.055
	Equal variances not assumed			-0.994	980.123	.320	
MPE	Equal variances assumed	11.261	.001	-6.879	1504	.000	.584
	Equal variances not assumed			-7.109	1133.37	.000	

To determine if there were group differences in the proportion of students who took math during their senior year or group differences in the proportion of students who were enrolled in algebraically demanding courses (calculus, pre-calculus, or trigonometry), a Pearson's chi-square test was used. Table 6 shows the contingency table .of senior year math by examination type. Approximately 78.5% of the students who were placed with the proctored examination were enrolled in a math course during their senior year of high school compared to approximately 82% of the students who were placed with the unproctored examination. The chi-square test statistics was not significant

$\chi^2(1, N =1147) = 29.75$, $p =.085$. Therefore, the proportion of students who took a math class during senior year of high school and were placed with the proctored examination was not different from the proportion of students who took mathematics during their senior year and was placed with the proctored examination.

Table 6

2 x 2 Contingency Table for Senior Year Math by Type of Examination

	Type of Exam	
Senior Year Math	Proctored	Unproctored
No	21.55%	17.93%
Yes	78.45%	82.07%
Total	100.00%	100.00%

It is also possible that the two groups could have differed on the type of mathematics classes in which they were enrolled in high school. Therefore, a chi-square test was conducted to determine if there was a difference in the type of high school math courses in which students were enrolled. Table 7 show a 4 x 2 contingency table with the type of high school math course by type of examination. From the table, approximately 57% of the students who were placed with the proctored examination had calculus, pre-calculus, or trigonometry as their last high school math course compared to approximately 61%. The chi-square statistic was not significant $\chi^2(3, 1669) = 3.838$, $p =.281$. Therefore there was no difference in the distribution of last high school math courses taken by the students in each group.

Table 7

4 x 2 Contingency Table of Last High School Mathematics Course by Type of Examination

Last High School Math Course	Type of Exam: Proctored	Unproctored
CPT[a]	57.34%	61.01%
PSTT[b]	9.84%	7.98%
ALG[c]	15.20%	12.94%
OTHER[d]	17.62%	18.07%
Total	100.00%	100.00%

[a]CPT = calculus, pre-calculus, or trigonometry, [b]PSTT = probability or statistics, [c]ALG = algebra I, algebra II, or geometry, [d]OTHER = FST (function, statistics, and trigonometry), business math, consumer math, or math analysis

The students who were placed with the proctored examination were different from the students who were placed with the unproctored examination due to their lower average ACT Mathematics score; lower highs school GPA, and lower placement examination scores. However, both groups appear to have taken similar type of courses and enrolled in mathematics during their senior year of high school.

. It was already determined that the students who were placed with the unproctored examination received higher placement examination scores (M = 14.18, SD =5.65) than the students who were placed with the unproctored examination (M =12.06, SD =5.05). This should come as no surprise because the mean ACT Mathematics score of the students who were placed with the unproctored examination (M =23.58, SD = 3.83) was higher than the mean ACT Mathematics score of the student who were placed with the proctored examination (M = 22.87, SD = 4.16) and the mean high school GPA of the students who were placed with the unproctored examination (M = 3.57, S = 0.31) was higher than the mean high school GPA of the students who were placed with the proctored examination (M = 3.52, S = 0.35). However, if ACT Mathematics scores and high school GPA were controlled, is there still a significant difference between the mean placement examination score of the students who were placed with the proctored examination and the mean placement examination score of the students who were placed with the unproctored examination?

To determine if controlling for ACT Mathematics score and high school GPA would still produce an examination effect, a multiple linear regression (MLR) equation was developed using PASW Statistics 18. MPE was used as the dependent variable and ACTM, HSGPA, and TYPE were used as predictors.

Multiple Linear Regression (MLR)

Normality Assumption. The normality of ACTM, HSGPA, and MPE was illustrated in Figures 2 thru 9 above.

Linearity Assumption: Figures 10, 11, and 12 shows a scatterplot of ACTM, HSGPA, and MPE. The scatterplot shows that both ACTM and HSGPA are linearly related to MPE. Also, ACT Mathematics scores appear to have a stronger linear relationship with placement examination score.

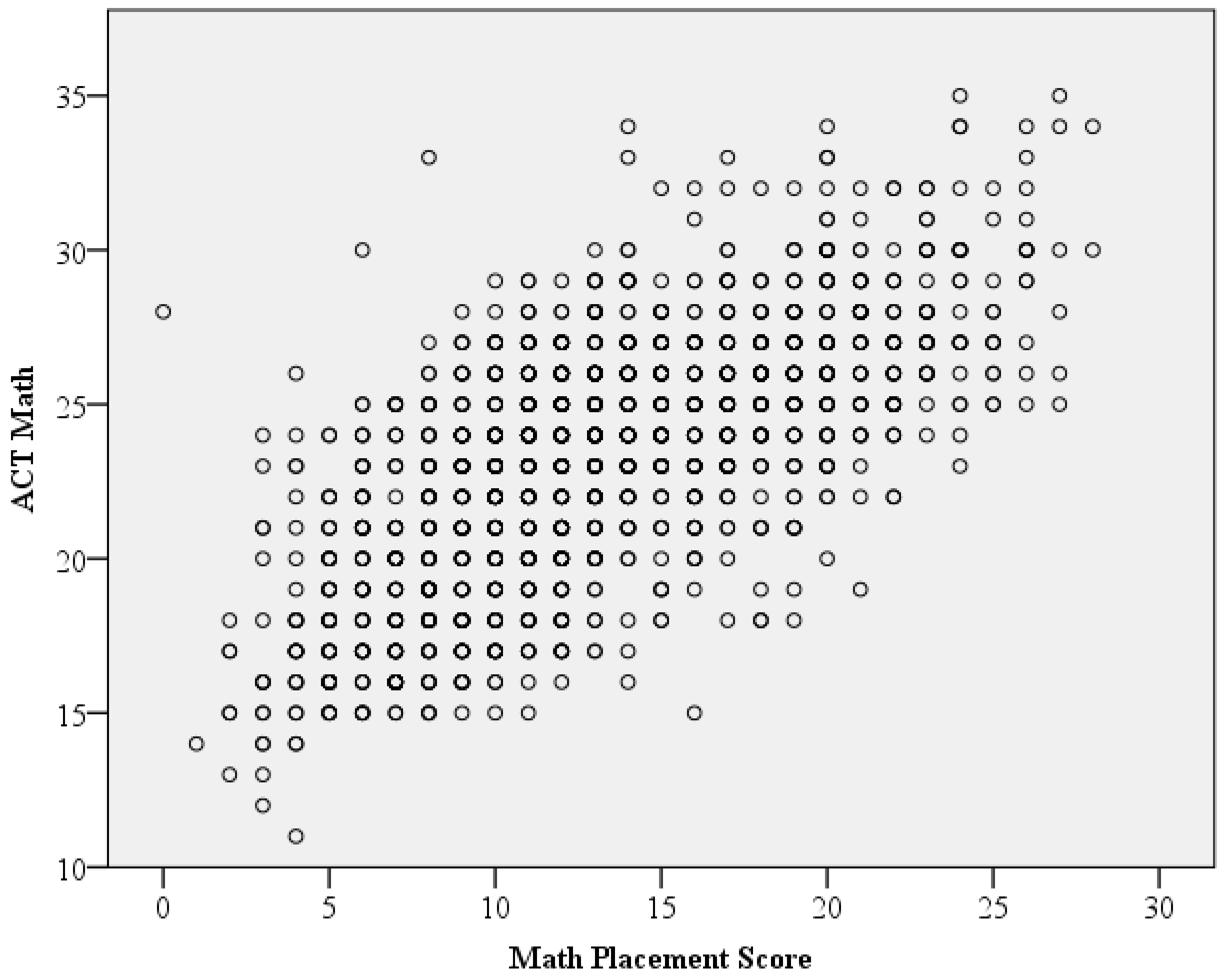

Figure 10. Scatterplot of Math Placement Scores and ACT Math Scores

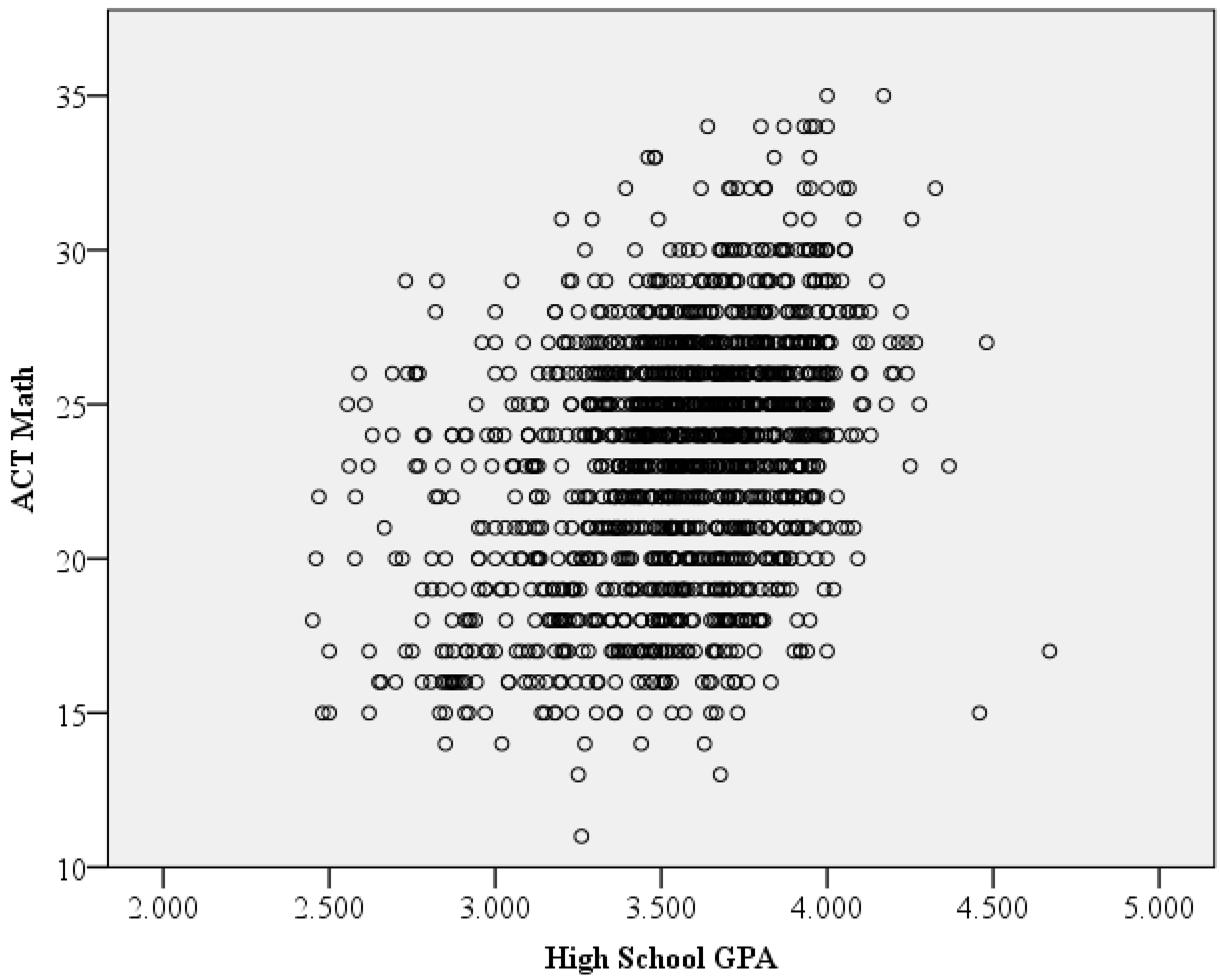

Figure 11. Scatterplot of ACT Math Scores and High School GPA

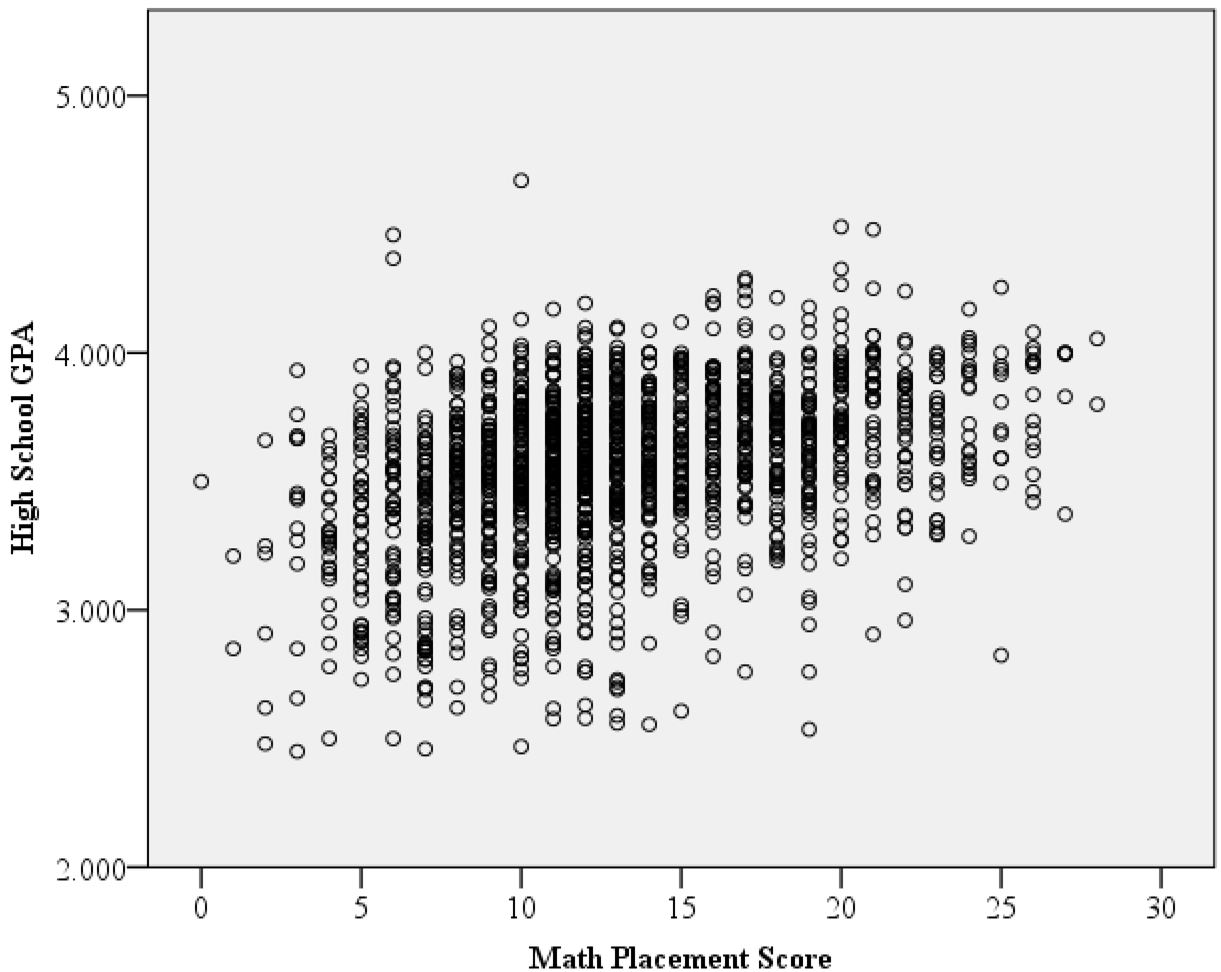

Figure 12. Scatterplot of High School GPA and Math Placement Scores

Multicollinearity Assumption: Table 8 gives the correlation matrix for the independent variables used in the MLR model. The predictors are not highly correlated with one another and, therefore, multicollinearity is not a problem.

Table 8

Correlation Matrix for ACTM, HSGPA, and TYPE

	HSGPA	TYPE
ACTM	0.366*	-0.086*
HSGPA	1.000	-0.079*
TYPE		1.000

* p < 0.01

Multiple Linear Regression Model

A multiple linear regression model was constructed to determine if, after controlling for ACTM and HSGPA, the students who were placed with the unproctored examination received higher placement examination scores than the students who were placed with the proctored examination. The regression equation was given by:

$$\mathbf{MPE = -13.858 + -0.807*ACTM + 2.415*HSGPA - 1.230*TYPE}$$

The test of overall fit was significant $F(3,1509) = 459.619$, p = .000, indicating that at least one of the regression coefficients is significantly different from zero.

Table 9 lists the regression coefficients, standard error, t value, and p-value. The table shows that each of the regression coefficients are a significant predictor of placement examination score.

The multiple linear regression equation also indicates that keeping ACTM and HSGPA constant, students who were placed with the proctored examination scored, on average, just over 1 point less on the placement examination score than the students who are placed with the unproctored examination.

Table 9

Multiple Linear Regression Results

Predictor	b	Std. Error	t	p
Intercept	-13.858	1.126	-12.304	0.000
ACTM	0.807	0.027	30.157	0.000
HSGPA	2.415	0.330	7.307	0.000
TYPE	-1.230	0.207	-5.927	0.000

Residual Analysis of the Multiple Linear Regression Model

Figure 13 below shows the histogram of the residuals generated by PASW Statistics 18. The figure clearly shows that the distribution of the error terms is normal with a mean of 0. Additionally, the normal probability plot in figure 14 shows that the points form a straight line and the figure supports the assumption of the normality of the error terms.

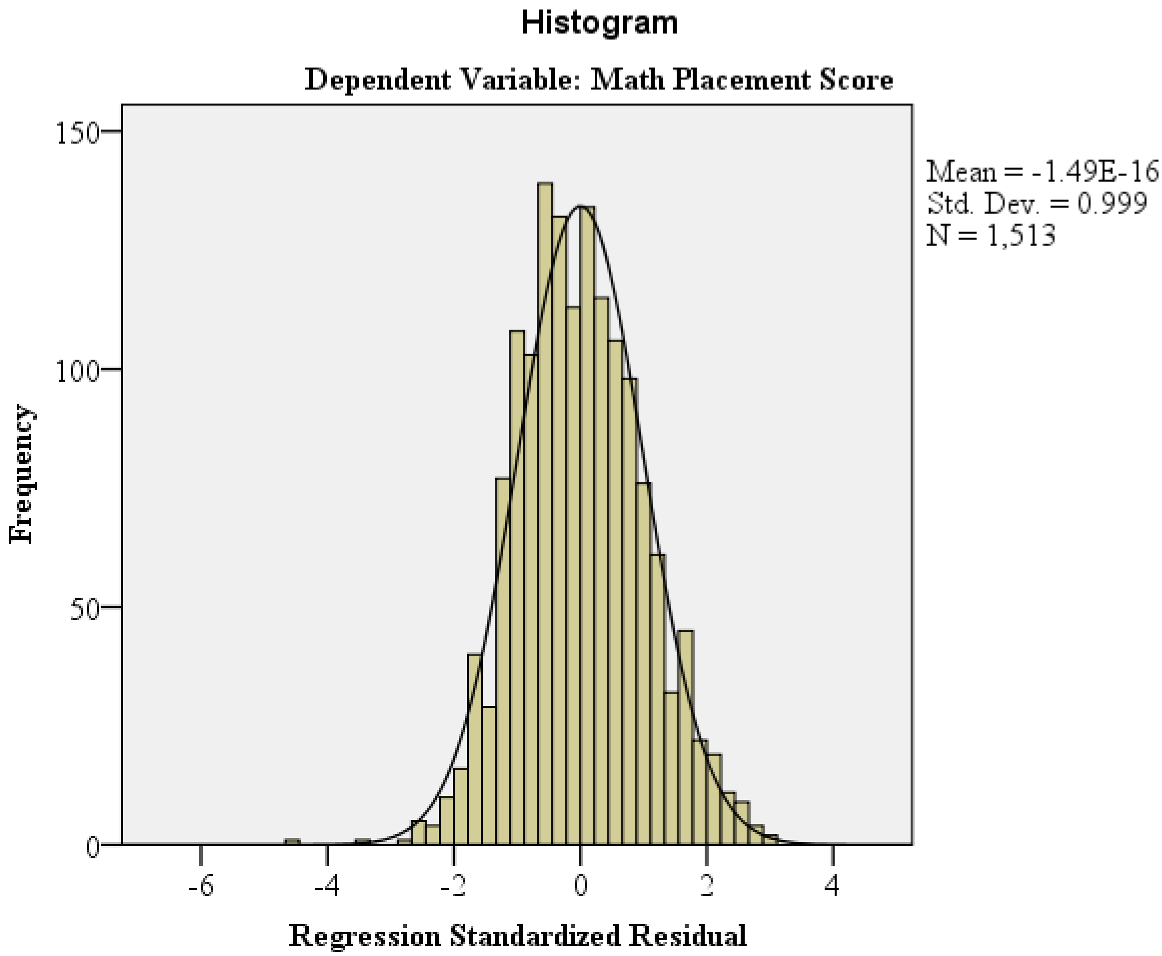

Figure 13. Histogram of the Residuals Associated with the Linear Regression Model Described in Table 9

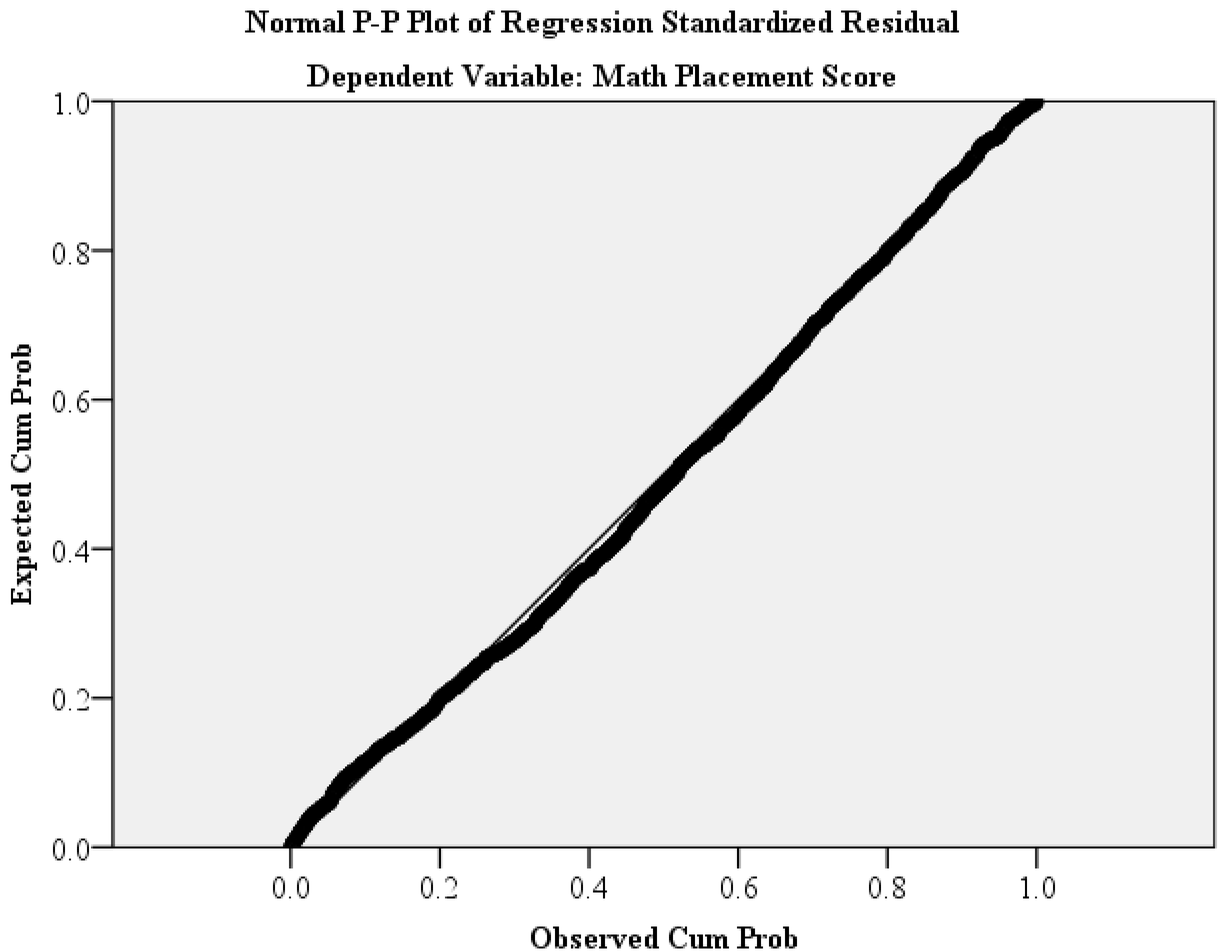

Figure 14. Normal Probability Plot of the Residuals Associated with the Regression Model in Table 9

Question 2

Are the proctored and unproctored examinations functioning similarly?

Reliability

Determining whether the two types of examinations are functioning similarly required several analyses. Table 10 shows the estimated reliabilities of the combined placement examination, the proctored examination, and the unproctored examination using equation (6). As indicated, the reliability estimate of the unproctored examination is higher than the reliability estimate of the proctored examination. All the reliability estimates are greater than 0.70 so the reliabilities are high enough for the examinations to be used. The formula for KR21 uses mean score and variance. Since the proctored examination produced higher mean examination scores and higher variance, it was no surprise that the reliability estimate for the unproctored examination was higher than the reliability estimate for the proctored examination. Additionally, students were able to take the proctored examination more than once. This could have accounted for the higher reliability estimate of the unproctored examination.

Table 10

Reliability Estimates of the Overall Examination, the Proctored Examination, and the Unproctored Examination

Overall	Proctored	Unproctored
0.80	0.76	0.81

The next step was to compare the correlation matrix of the variable using the proctored data to the correlation matrix of the variables using the unproctored examination. Second was to determine if placement was dependent on the type of examination used for placement. Third, a multiple linear regression equation was created using the proctored data. This equation was then fitted to the unproctored data to determine if the students who were placed with the unproctored examination would have received the same placement if they had been placed with the proctored examination. Also, a multiple linear regression equation was created using the unproctored data. This equation was fitted to the proctored data to determine if the students who were placed with the proctored examination would have received the same placement if they would have been placed with the unproctored examination.

Finally, the success rates of the different courses were examined to determine if success rates were dependent on type of examination used for placement.

Correlation for Combined Data (Proctored data and Unproctored Data)

Table 11 is the correlation matrix for all the variables that will be used in the overall (proctored data and unproctored data combined) MLR model. As indicated, all the variables are significantly correlated with the scores on the mathematics placement examination. The table shows that the variable that is most highly correlated with placement examination scores is ACTM. Thus, student with high ACT Mathematics scores tend to receive higher placement examination scores. ACTM is also the variable that is correlated most highly with grades in first college mathematics course. HSGPA, HSMGPA and MPE are moderately correlated with the scores on the mathematics placement examination as well as grades in first college mathematics course.

The correlations between the dichotomous variables (C_ABOVE, GENDER, SYM, WHITE, and CALC) and MPE or GRADE are point biserial correlations. A point biserial correlation is used as a measure of association between a dichotomous variable and a continuous variable (Allen & Yen, 1979). Positive values are an indication that moving from a value of 0 to a value of 1, for example, tends to result in higher scores on the continuous variables. Similarly negative values of the point biserial correlation indicates that moving from a value of 0 to 1 tend to result in a decrease on the continuous variable. Thus, the correlation between CPT and MPE indicates that students, who took calculus, pre-calculus, or trigonometry as their final high school math course; tend to have higher placement examination scores than the students who took a course other than calculus, pre-calculus, or trigonometry as their final high school math course. Also, females tend to receive lower placement examination scores than males, non-whites tend to receive lower placement examination scores than whites, students who received a grade of C or better in their last high school mathematics course tend to received higher placement scores than students who received a grade lower than a C in their final high school math course. The reader should ignore the perfect correlation between the variable G and W. Both variables are dichotomous and therefore the Pearson's correlation coefficient is not an appropriate measure of association for the two variables. Also, the correlations between these two variables have no substantive interpretation.

Table 11

Correlation Matrix for the Combined Data (Proctored and Unproctored)

	A	GR	H	HM	C	S	W	CPT	MPE
G	-.275	.035	.064*	-.012	-.005	.019	1.000**	-.099**	-.154**
A	1.000	.383**	.366**	.376**	.156**	.059*	-.275**	.294**	.666**
GR		1.000	.353**	.392**	.137**	.064*	.035	.150**	.364**
H			1.000	.670**	.197**	.017	.064*	.186**	.379**
HM				1.000	.411**	.028	-.012	.116**	.379**
C					1.000	-.038	-.005	-.048	.122**
S						1.000	.019	.279**	.121**
W							1.000	-.099**	-.154**
CPT								1.000	.341**
MPE									1.000

Note: G = Gender, A = ACTM, GR = GRADE, H = HSGPA, HM = HSMGPA, C = CABOVE, S = SYM, W = WHITE, CPT = Calculus, pre-calculus, or trigonometry

**p < .05. **p < .01*

Correlations for Proctored Data

Table 12 gives the correlation of variables using the proctored data. Of particular interest are the variables that are correlated with placement examination score and grade in first college mathematics course. As indicated in the matrix, all variables are significantly correlated with scores on the mathematics placement examination with ACT mathematic score being the variable that is most highly correlated with mathematics placement examination score.

The matrix also indicates that all the variables are significantly correlated with grades in first college mathematics course except taking a math course during senior year of high school (S) and race/ethnicity (W). Therefore, those students who took a mathematics course during their senior year of high school was did not tend to received better grades in their first college mathematics course. Additionally, white students who were placed with the proctored examination did not tend to do better in their mathematics course than non-whites who were placed with the proctored examination.

Table 12

Correlation Matrix for the Proctored Data

	A	GR	H	HM	C	S	W	CPT	MPE
G	-.289**	.006	.016	-.042	-.060	.034	1.000**	-.047	-.214**
A	1.000	.493**	.429**	.450**	.188**	.027	-.289**	.222**	.722**
GR		1.000	.421**	.413**	.139**	.071	.006	.174**	.448**
H			1.000	.697**	.221**	.000	.016	.197**	.394**
HM				1.000	.476**	-.009	-.042	.104*	.393**
C					1.000	-.042	-.060	-.055	.152**
S						1.000	.034	.298**	.084*
W							1.000	-.047	-.214**
CPT								1.000	.334**
MPE									1.000

Note: G = Gender, A = ACTM, GR = GRADE, H = HSGPA, HM = HSMGPA,

C = CABOVE, S = SYM, W = WHITE, CPT = Calculus, Pre-calculus, or Trigonometry

$*p < .05$; $**p < .01$

Correlations for Unproctored Data

Table 13 shows the correlation matrix for the unproctored data. Just as with the proctored data, the interest in these correlations is in the variables that are correlated with placement examination scores and grades in first college mathematics course. As shown in the table, all the variables are significantly correlated with the unproctored placement examination with ACT Mathematics score being the variable that is most highly correlated with scores in placement examination score.

The correlation matrix also shows that all the variables are significantly correlated with grades in first college mathematics course except S and W (similar to the correlation matrix for the proctored data). However, unlike the proctored correlation matrix, high school mathematics GPA is the variable that is most highly correlated with grades in first college mathematics course.

Table 13

Correlation Matrix for Unproctored Data

	A	GR	H	HM	C	S	W	CPT	MPE
G	-.289**	.006	.016	-.042	-.060	.034	1.000**	-.047	-.214**
A	1.000	.493**	.429**	.450**	.188**	.027	-.289**	.222**	.722**
GR		1.000	.421**	.413**	.139**	.071	.006	.174**	.448**
H			1.000	.697**	.221**	.000	.016	.197**	.394**
HM				1.000	.476**	-.009	-.042	.104*	.393**
C					1.000	-.042	-.060	-.055	.152**
S						1.000	.034	.298**	.084*
W							1.000	-.047	-.214**
CPT								1.000	.334**
MPE									1.000

Note: G = Gender, A = ACTM, GR = GRADE, H = HSGPA, HM = HSMGPA,

C = CABOVE, S = SYM, W = WHITE, CPT = Calculus, Pre-calculus, or Trigonometry

$*p < .05$; $**p < .01$

Table 14 shows the matrix of p-values associated with the test of equality of correlations. There were a total of 44 tests. Thus, each test was conducted using the Bonferroni Correction Method with a significance level of $\frac{0.05}{44} = 0.001$. Table 13 shows that correlation between ACT Mathematics score and grades in first college mathematics course could not be assumed equal across examination types. Also, the correlation between grades in first college mathematics course and placement examination scores was marginally significant.

Table 14

P-values for the Test of Equality of Correlations

	A	GR	H	HM	C	S	W	CPT	MPE
G	.718	.410	.156	.373	.088	.639	-	.131	.119
A		.000	.019	.010	.278	.396	.718	.029	.003
GR			.010	.372	.800	.735	.410	.478	.001
H				.137	.354	.653	.156	.751	.509
HM					.006	.282	.373	.707	.571
C						.942	.088	.840	.214
S							.639	.541	.373
W								.131	.119
CPT									.671

Note: G = Gender, A = ACTM, GR = GRADE, H = HSGPA, HM = HSMGPA, C = CABOVE, S = SYM, W = WHITE, CPT = Calculus, Pre-calculus, or Trigonometry

Placement into Intermediate Algebra (MTH1825)

Table 15 shows the crosstabulation for placement into remedial mathematics by type of examination. The table shows that approximately 25% (147/598) of the students who were placed with the proctored examination were placed into MTH1825 and approximately 17% (188/1098) of the students who were placed with the unproctored examination were placed into remedial mathematics. The Pearson chi-square statistic was significant, $\chi^2(1, n = 1698) = 14.772$, $p = .000$, indicating that the percentage of students placing into remedial mathematics was higher for those students placed with the proctored examination. The odds ratio associated with table 13 was computed to be approximately 1.6 ((24.92*82.87)/(75.08*17.13)) indicating that the odds of being placed into a remedial mathematics course with the proctored examination was about 60% more than the odds of being placed into a remedial mathematics course with the unproctored examination.

Table 15

Crosstabulation of Type of Course by Type of Exam

	Type of Exam		
Course Type	Proctored	Unproctored	Total
Non-Remedial	75.08%	82.87%	78.95%
Remedial	24.92%	17.13%	21.05%
Total	100%	100%	

Multiple Linear Regression Model for the Combined Data

Table 16 gives the results of the regression coefficients of the overall MLR model used to predict placement examination scores. The type of examination used to place students was a significant predictor of placement examination scores. The coefficient of TYPE indicates that when holding all other predictors constant, students who were placed with the proctored examination scored, on average, about 1 point lower on the placement examination than the students who were placed with the unproctored examination. The multiple linear regression equation has $R^2 = 0.523$ so that the predictors explain 52.3% of the variation in mathematics placement examination scores. The overall model is significant, $F(14, 1289) = 100.947$ $p = .000$.

Table 16

Results of Multiple Linear Regression Coefficients Use to Predict Mathematics Placement Examination Scores (N=1304)

Predictor	b	SE(b)	t	p
Intercept	-11.819	1.422	-8.312	0.000
GENDER	-0.239	0.216	-1.108	0.268
ACTM	0.739	0.032	23.080	0.000
HSGPA	1.245	0.459	2.710	0.007
HSMGPA	1.109	0.304	3.645	0.000
SYM	1.393	0.295	4.714	0.000
CABOVE	-0.520	0.451	-1.153	0.249
BLACK	-0.129	0.363	-0.357	0.721
HISPANIC	-0.356	0.593	-0.601	0.548
INDIAN	-0.564	1.110	-0.508	0.612
ASIAN	0.257	0.495	0.520	0.603
TYPE	-1.186	0.216	-5.496	0.000
PSTT	-2.448	0.352	-6.957	0.000
ALG	-1.151	0.360	-3.196	0.001
OTHER	-1.474	0.300	-4.922	0.000

Note. R^2 = 0.523 and adjusted R^2 = 0.517

Residual Analysis of Overall Regression Model

Figure 15 below shows the histogram of the residuals generated by PASW Statistics 18. The figure clearly shows that the distribution of the error terms is normal with a mean of 0.

Also, the normal probability plot in figure 16 also supports the assumption of the normality of the error terms. Although there are a few point that stray from the straight line,

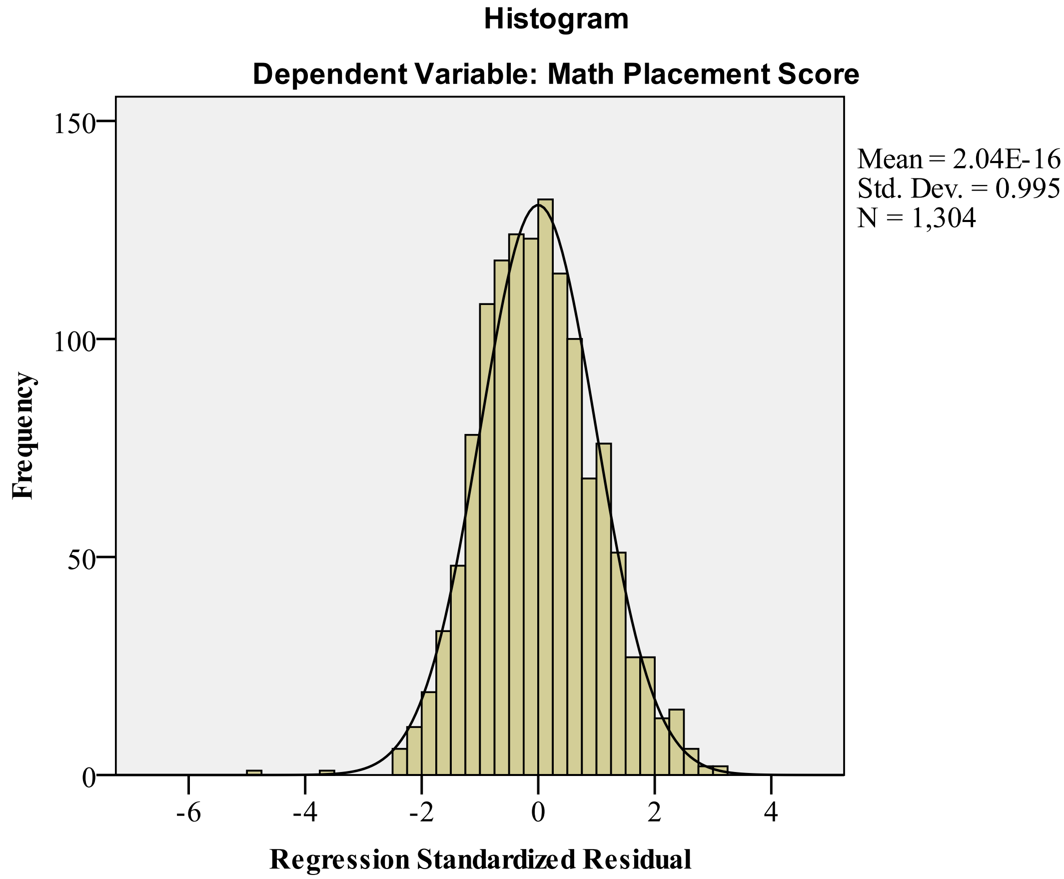

Figure 15. Histogram of the Residuals of the Regression Model for the Combined Data

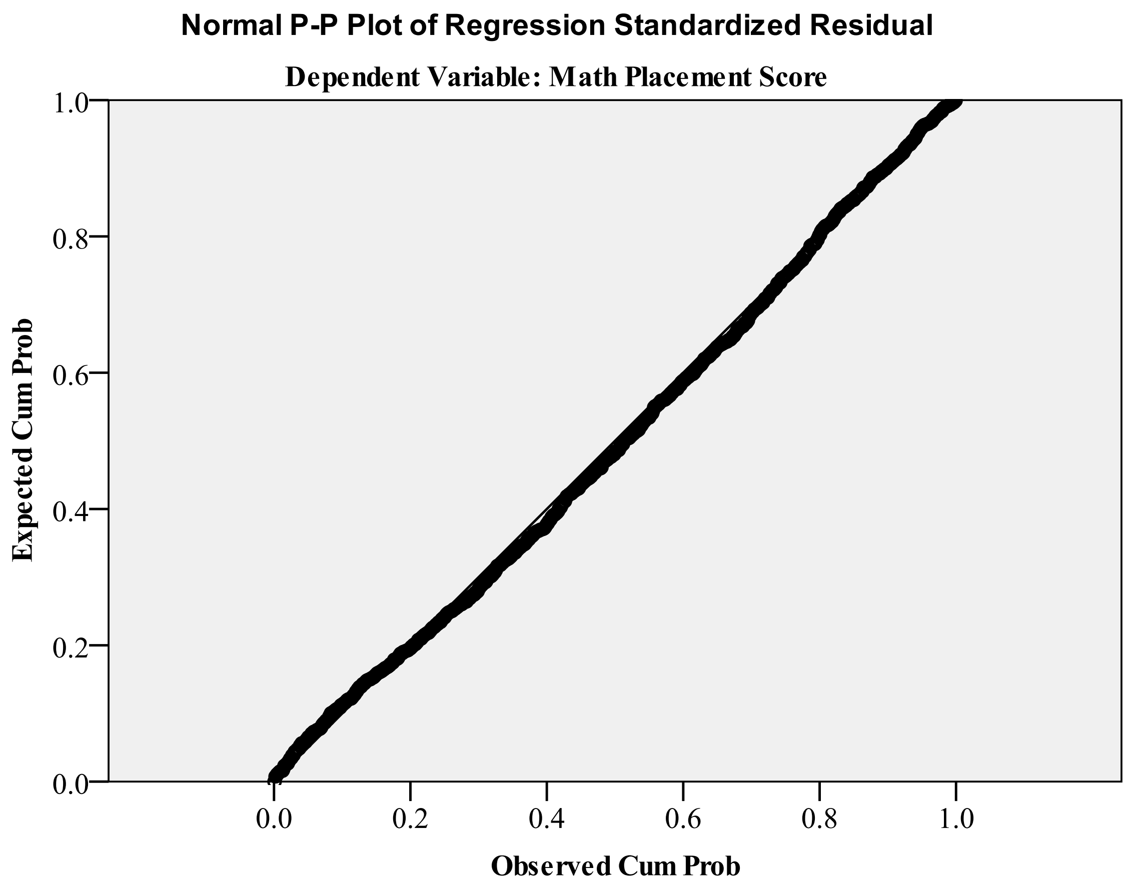

Figure 16. Normal Probability Plot of Residuals for the Overall Data

Figure 17 checks the homoscedastiscity assumption. Clearly the errors are randomly distributed about zero and therefore the assumption of homoscedastiscity is verified.

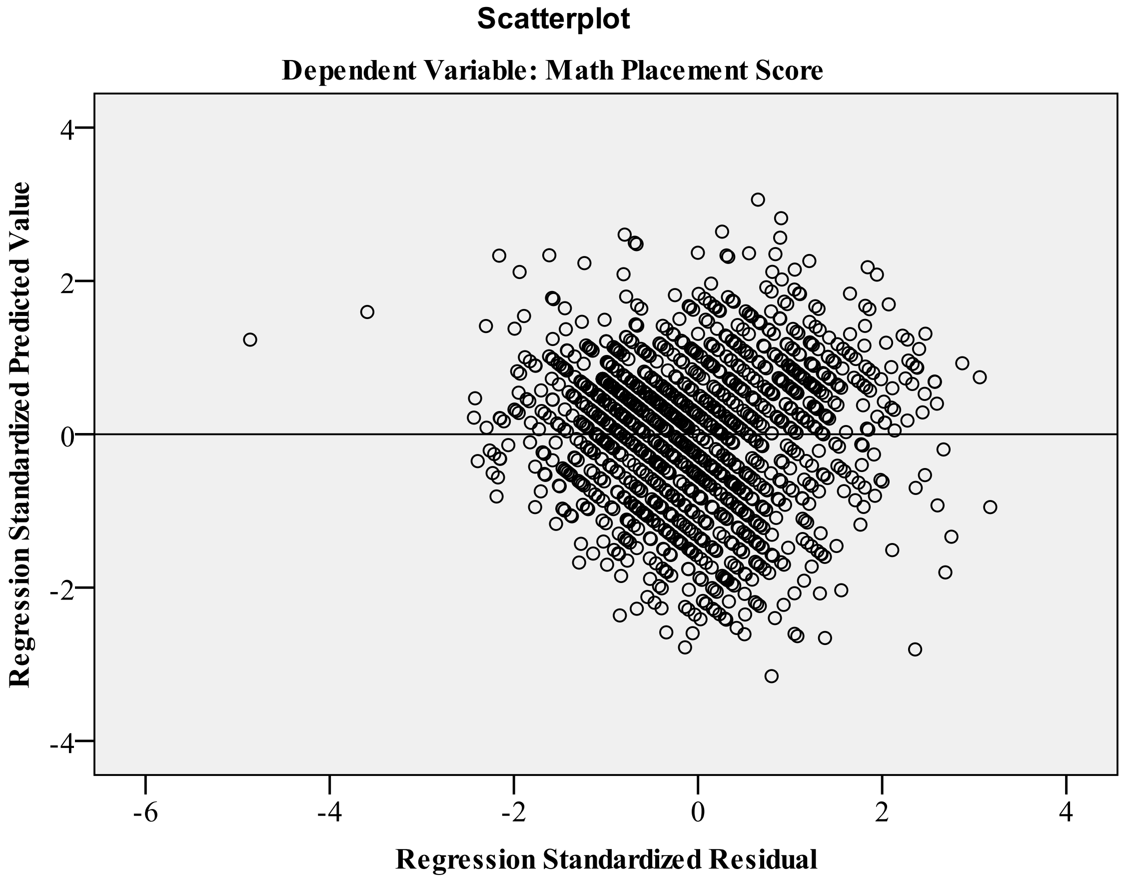

Figure 17. Scatterplot of Standardized Residuals vs. Standardized Predicted Value

The assumptions of the multiple linear regression model are satisfied and therefore, the model fits the data well.

Multiple Linear Regression Model for the Proctored Data

Table 17 gives the results of the regression coefficients used to predict mathematics placement examination scores using the proctored data. The predictors in this model explained 58.6% of the variation in the proctored mathematics placement examination. The overall model fit was significant (*F*(13,436) = 47.524, p = .000). Unlike the overall model, HSGPA and HSMGPA were not significant predictors of scores on the proctored examination.

Table 17

Summary of Multiple Linear Regression Coefficients used to Predict Placement using the Proctored Examination (N=450)

Predictor	b	SE(b)	t	p
Intercept	-11.080	2.152	-5.149	0.000
GENDER	-0.471	0.319	-1.474	0.141
ACTM	0.752	0.049	15.371	0.000
HSGPA	0.866	0.697	1.243	0.215
HSMGPA	0.789	0.469	1.680	0.094
SYM	1.380	0.428	3.223	0.001
CABOVE	-0.396	0.627	-0.632	0.528
BLACK	0.496	0.497	0.999	0.319
HISPANIC	-1.068	0.988	-1.081	0.280
INDIAN	1.705	1.847	0.923	0.357
ASIAN	0.507	0.899	0.564	0.573
PSTT	-2.375	0.498	-4.772	0.000
ALG	-1.107	0.531	-2.084	0.038
OTHER	-1.026	0.439	-2.339	0.020

Note. R^2 = 0.586 and adjusted R^2 = 0.574

Residual Analysis of Proctored Multiple Linear Regression Model

Just as with the overall multiple regression model, the errors were checked for normality and the equal variance assumption was checked. Figure 18 shows a histogram of the error terms. The histogram shows that the error terms are normally distributed with a mean of zero. The Q-Q plot (figure 19) also supports the normality of the errors assumption.

Figure 20 is a plot of the standardized residuals against the standardized predicted values. The errors appear to be randomly distributed about zero, so the homoscedastiscity assumption is verified.

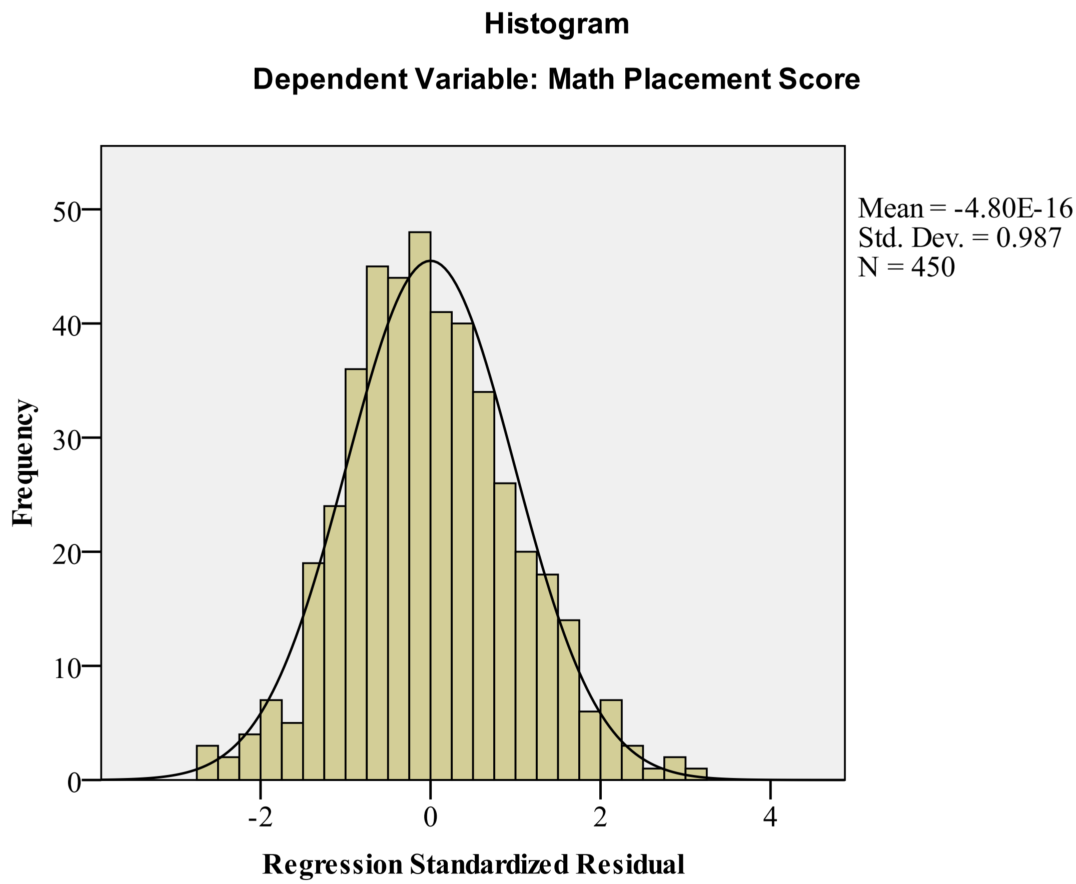

Figure 18. Histogram of the Residuals of the Regression Model for the Proctored Regression Model

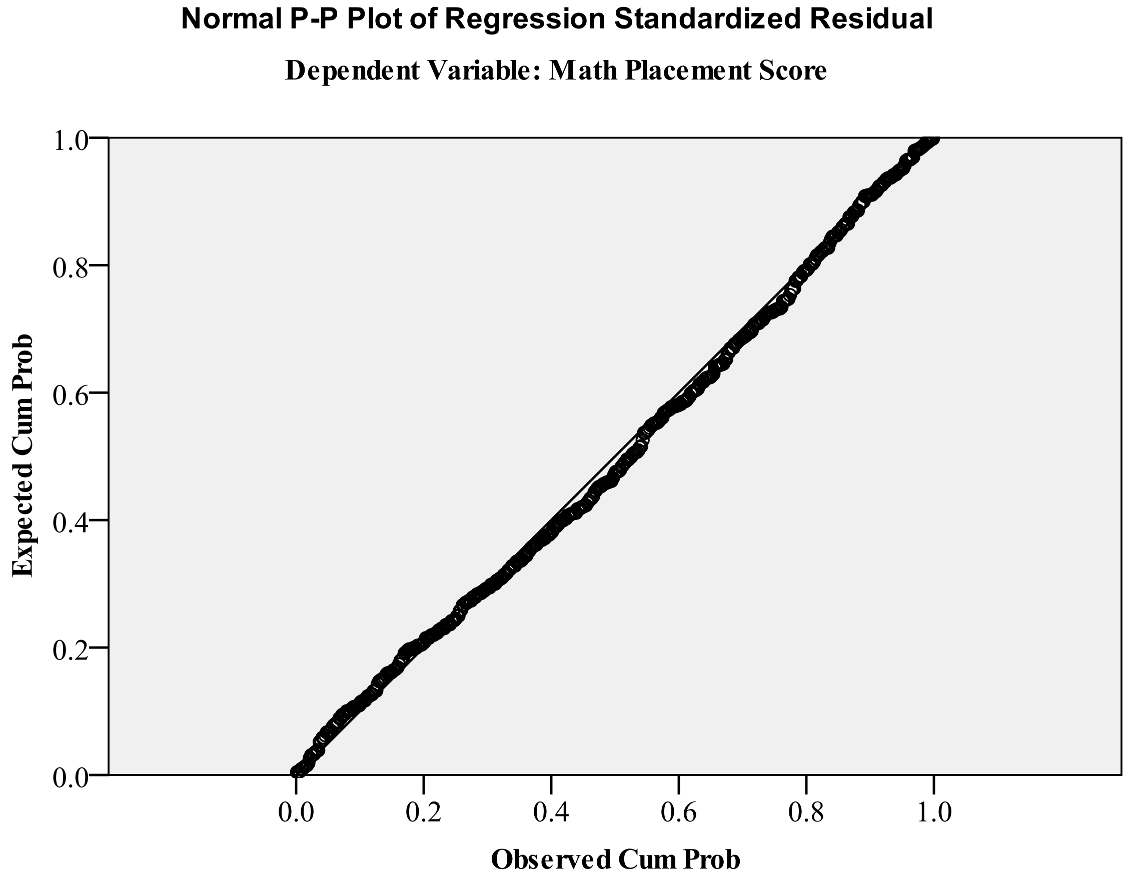

Figure 19. Normal Probability Plot of the Residuals for the Proctored Regression Model

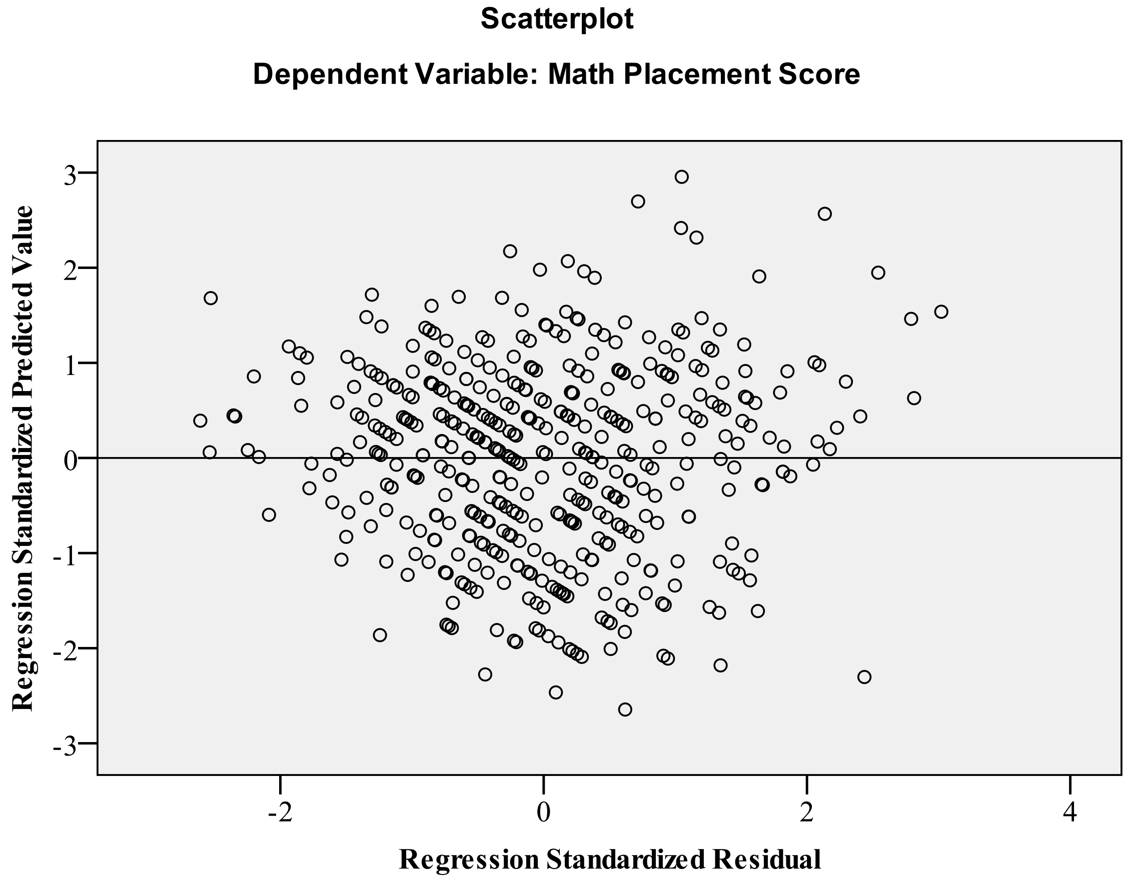

Figure 20. Scatterplot of Standardized Residuals of the Proctored Regression Model

When the unproctored data was substituted into the above proctored model the resulting scores were an estimate of the scores in which the students who were placed with the proctored examination would have received if they had been placed with the proctored examination. The correlation between these predicted scores and the actual unproctored placement scores was significant, r(909) = 0.682, p = .000, indicating the presence of a linear correlation between the predicted unproctored examination scores and the actual unproctored examination scores.

Despite the high correlation coefficient, only about 35% of the students who were placed with the unproctored examination would have received the same placement if they would have been placed with the proctored examination. Additionally, approximately 21.5% and 43.5% of the students would have received higher and lower placements respectively. Therefore, the unproctored examination does not place students in the same way as the proctored examination. In fact, the unproctored examination appears to be more likely to place students into higher level mathematics courses than the proctored examination.

Multiple Linear Regression Model for the Unproctored Data

Table 18 gives the results of the regression coefficients used to predict mathematics placement examination scores using the unproctored data. The predictors in this model explained 48.2% of the variation in the unproctored mathematics placement examination. The overall model fit was significant $F(13,840) = 60.149$, p = .000, indicating that at least one of the predictors significantly predict the scores on the unproctored placement examination. In this model, both HSGPA and HSMGPA are significant predictors of the unproctored mathematics placement examination scores whereas HSGPA and HSMGPA were not significant predictors of proctored placement examination scores.

Table 18

Summary of Multiple Linear Regression Coefficients used to Predict Placement using the Unproctored Examination (N=909)

Predictor	b	SE(b)	t	p
Intercept	-13.103	1.854	-7.068	0.000
GENDER	-0.100	0.284	-0.354	0.723
ACTM	0.737	0.042	17.724	0.000
HSGPA	1.454	0.598	2.431	0.015
HSMGPA	1.323	0.393	3.369	0.001
SYM	1.344	0.394	3.410	0.001
CABOVE	-0.600	0.620	-0.968	0.333
BLACK	-0.940	0.521	-1.804	0.072
HISPANIC	-0.102	0.739	-0.139	0.890
INDIAN	-1.263	1.391	-0.908	0.364
ASIAN	0.188	0.600	0.313	0.754
PSTT	-2.458	0.475	-5.170	0.000
ALG	-1.117	0.477	-2.343	0.019
OTHER	-1.700	0.396	-4.295	0.000

Note. R^2 = 0.482 and adjusted R^2 = 0.474.

Residual Analysis of the Unproctored Regression Model

Just as with the overall multiple regression model, the errors were checked for normality and the equal variance assumption was checked. Figure 21 shows a histogram of the error terms. The histogram shows that the error terms are normally distributed with a mean of zero. The Q-Q plot (figure 122) also supports the normality of the errors assumption.

Figure 23 is a plot of the standardized residuals against the standardized predicted values. The errors appear to be randomly distributed about zero, so the homoscedastiscity assumption is verified.

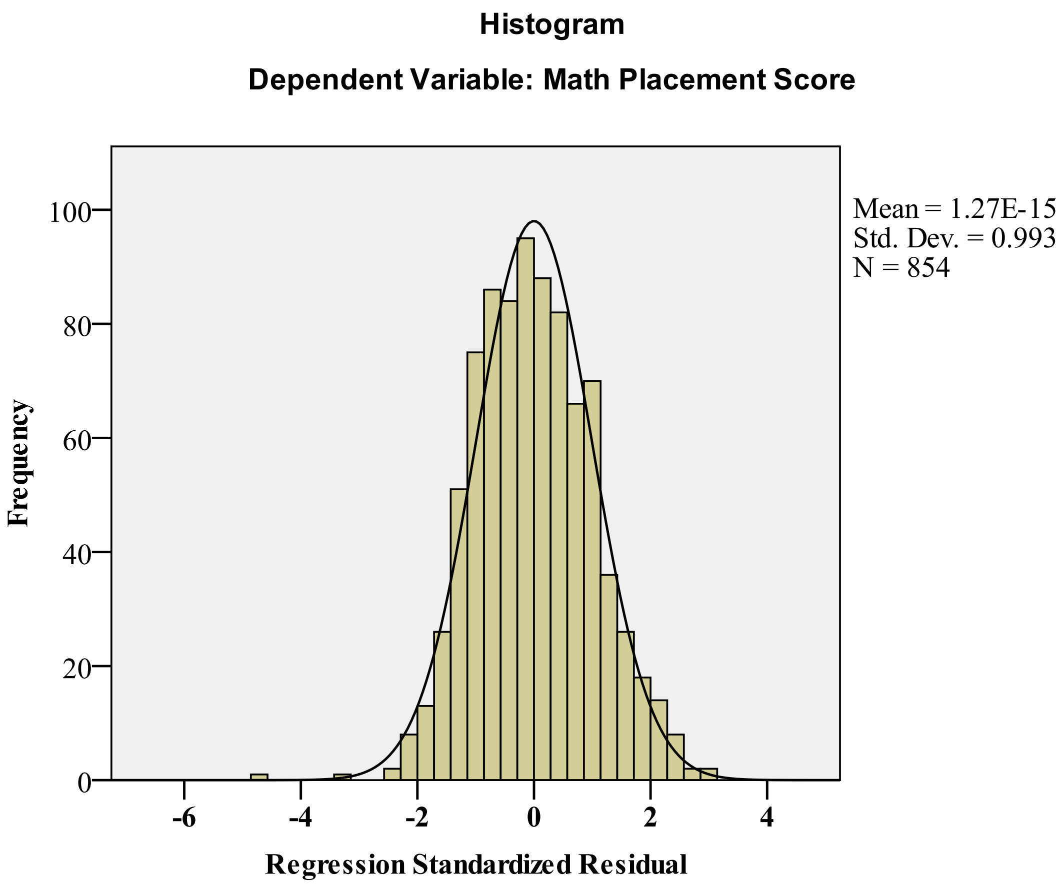

Figure 21. Histogram of Residuals of the Regression Model of the Unproctored Regression Model

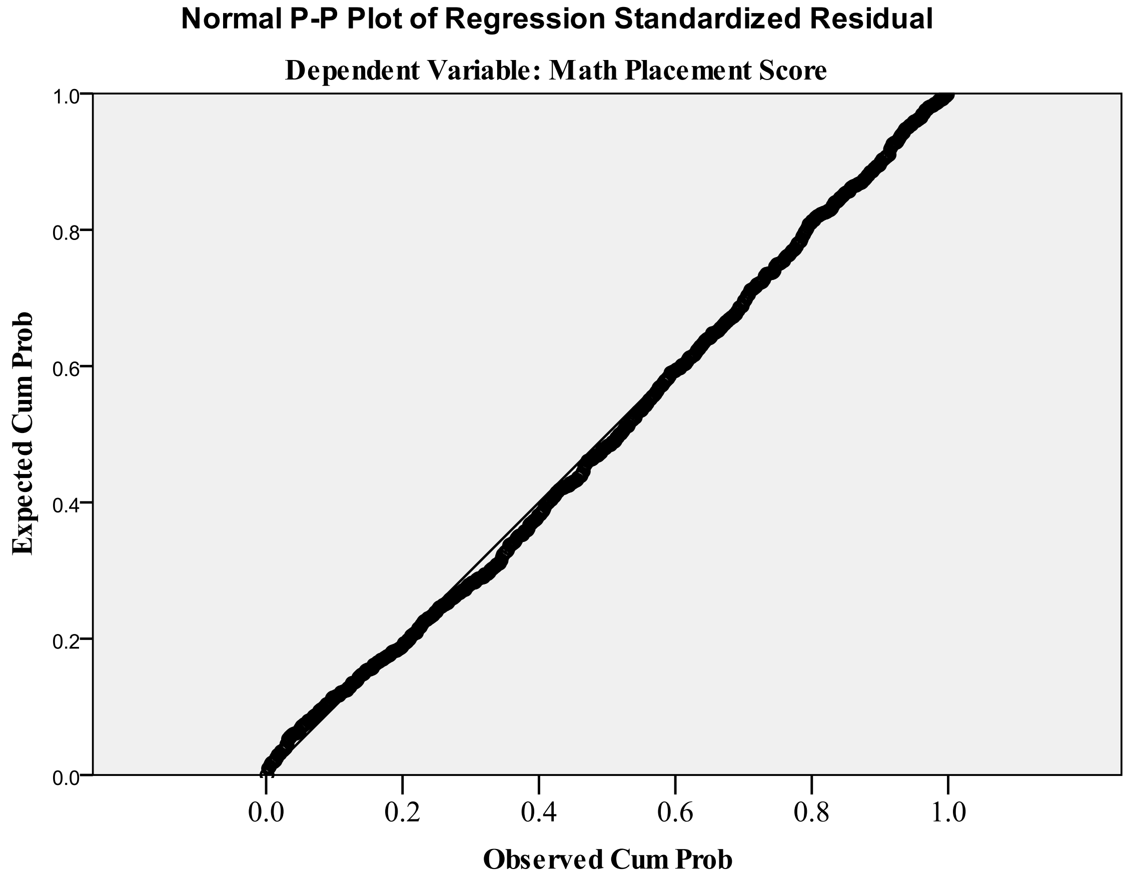

Figure 22. Normal Probability Plot of Residuals of the Unproctored Regression Model

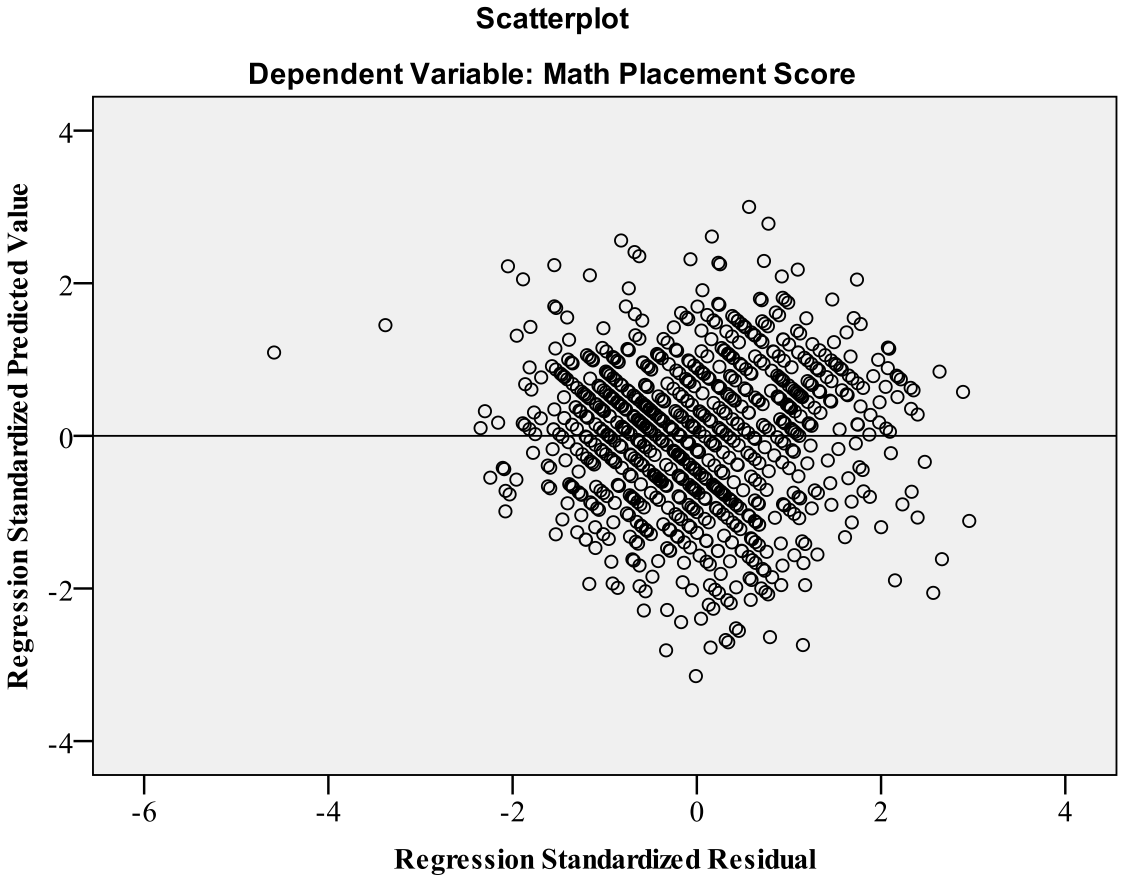

Figure 23. Scatterplot of the Standardized Residuals vs. Standardized Predicted Values for the Unproctored Regression Model

When the proctored data was substituted into the unproctored model the resulting scores were an estimate of the scores in which the students who were placed with the proctored examination would have received if they had been placed with the unproctored examination. The correlation between these predicted proctored scores and the actual proctored placement scores was significant, $r(450) = .749$, $p = .000$, indicating the presences of a linear relationship between predicted proctored examination scores and actual proctored examination scores.

Despite the high correlation coefficient, approximately 41% of the students who were placed with the proctored examination would have received the same placement if they would have been placed with the unproctored examination. Additionally, approximately 39% and 20% of the students would have received higher and lower placements respectively. Although there is indication that more of the students who were placed with proctored examination would have received the same placement if they would have been placed with the proctored examination than vice versa, this agreement rate was less than ½.

Another technique that was used to determine if the unproctored examination is functioning in the same way as the proctored examination was to determine if a particular group of students received an advantage as a result of being placed with a particular examination. So the success rates of several groups of students, under each type of exam were determined using a contingency table analysis.

Success Rate for Combined Data

Table 19 shows the 2 x 2 contingency table of course success by type of examination. As indicated almost 79% of the students who were placed with the proctored examination were successful in their first college mathematics course compared to approximately 86% of the students who were placed with the unproctored examination. This difference in percentage of students who were successful was significant $\chi^2(1, n=1698) = 5.883$, $p = .015$, indicating that course success was dependent on the type of examination used for placement with the students who were placed with the unproctored examination being more successful in their first college mathematics course. Also, the ratio associated with table 17 is approximately 1.36 ((83.2*21.6)/(78.4*16.8)) indicating that odds of a student being successful in their first college mathematics course when placed with the unproctored examination is about 36% more than the odds of a student being successful when placed with the proctored examination. This was a surprising outcome.

Table 19

2 x 2 Contingency Table of Math Course Outcome by Type of Examination

	Type of Examination	
Course Outcome	Proctored (n = 598)	Unproctored (n = 1098)
Unsuccessful	21.6%	16.8%
Successful	78.4%	83.2%
Total	100.00%	100.00%

Success in Intermediate Algebra (MTH1825)

Table 20 shows a 2 x 2 contingency table of MTH1825 course outcome by the type of examination. According to the table, approximately 73.3% of the students who were placed with the unproctored examination were successful in MTH1825. Also, approximately 53.1% of the students who were placed with the proctored examination were successful in MTH1825. This difference in percentage of students who were successful was significant $\chi^2(1, n = 335) = 14.328$, $p = .000$, indicating that the students who were placed into MTH1825 with the unproctored examination were more likely to be successful in MTH1825 than the students who were placed with the proctored examination. The odds ratio associated with table 18 is 2.42 ((73.30*46.90)/(53.10*26.70). So the odds of being successful in MTH1825 under the unproctored examination was over 140% more than the odds of being successful in MTH1825 under the proctored examination.

Table 20

2 x 2 Contingency Table of MTH1825 Course Outcome by Type of Examination

	Type of Examination	
Course Outcome	Proctored (n = 147)	Unproctored (n = 188)
Unsuccessful	46.90%	26.70%
Successful	53.10%	73.30%
Total	100.00%	100.00%

White students: Table 21 shows a 2 x 2 contingency table of MTH1825 course outcome by the type of examination for the white students who were placed into MTH1825. According to the table, approximately 78.2% of the white students who were placed with the unproctored examination were successful in MTH1825 compared to approximately 77.4% of the white students who were placed with the proctored examination. The value of the test statistic to test the null hypothesis that the proportion of white students in MTH1825 students who were successful when placed with the unproctored examination is the same as the proportion of white students in MTH1825 students who were successful when placed with the unproctored examination was not significant $\chi^2(1, n = 262) = 0.013, p = .908$. Therefore there were no significant difference in the percentage of white students who were successful in MTH1825 with the proctored examination and the percentage of white students who were successful in MTH1824 who were placed with the unproctored examination.

Table 21

2 x 2 Contingency Table of Course Outcome by Type of Examination for the White Students Enrolled in MTH1825

	Type of Examination	
Course Outcome	Proctored (n = 53)	Unproctored (n = 119)
Unsuccessful	22.60%	21.80%
Successful	77.40%	78.20%
Total	100.00%	100.00%

Black Students: Table 22 shows a 2 x 2 contingency table of MTH1825 success rate by type of examination for the black students who were placed in MTH1825. As indicated, approximately 38% of the black students who were placed into MTH1825 with the proctored examination were successful compared to approximately 60.4% who were placed with the unproctored examination. The value of the test statistic to test the null hypothesis that the proportion of black students in MTH1825 students who were successful when placed with the unproctored examination is the same as the proportion of black students in MTH1825 students who were successful when placed with the unproctored examination was significant $\chi^2(1, n = 119) = 5.762$, $p = .016$. Thus, there was a significant difference in the success rate for the black students who were placed into MTH1825 with the proctored examination and the success rate of the black students who were placed into MTH1825 with the unproctored examination.

The odds ratio of 2.49 ((60.40*62)/(38*39.6)) indicates that the odds of being successful for black students who took the unproctored examination and enrolled in MTH1825 were 149% more than the odds of being successful for black students who took the proctored placement examination and enrolled in MTH1825.

Table 22

2 x 2 Contingency Table of Course Outcome by Type of Examination for the Black Students Enrolled in MTH1825

	Type of Examination	
Course Outcome	Proctored (n = 71)	Unproctored (n = 48)
Unsuccessful	62.00%	39.60%
Successful	38.00%	60.40%
Total	100.00%	100.00%

Gender: Table 23 shows a 2 x 2 contingency table of MTH1825 course outcome by type of examination for the male students who were placed in MTH1825. As indicated, approximately 55% of the male students who were placed into MTH1825 with the proctored examination were successful compared to approximately 73.3% who were placed with the unproctored examination. The value of the test statistic to test the null hypothesis that the proportion of male students in MTH1825 students who were successful when placed with the unproctored examination is the same as the proportion of male students in MTH1825 students who were successful when placed with the unproctored examination was significant $\chi^2(1, n = 111) = 4.109, p = .043$. Thus, for the male students who placed into MTH1825, success was dependent on the type of examination used for placement. Furthermore, the odds ratio of 2.26 (73.30*45.10)/(54.9*26.70) indicates that the odds of being successful for the male students who enrolled into MTH1825 with the unproctored examination was 126% more than the odds for the males who enrolled with the proctored examination.

Table 23

2 x 2 Contingency Table of Course Outcome by Type of Examination for the Male Students Enrolled in MTH1825

	Type Of Examination	
Course Outcome	Proctored (n = 51)	Unproctored (n = 60)
Unsuccessful	45.10%	26.70%
Successful	54.90%	73.30%
Total	100.00%	100.00%

Table 24 shows a 2 x 2 contingency table of MTH1825 course outcome by type of examination for the female students. As indicated, approximately 54.2% of the female students who were placed into MTH1825 with the proctored examination were successful compared to approximately 73.4% who were placed with the unproctored examination. The value of the test statistic to test the null hypothesis that the proportion of female students in MTH1825 students who were successful when placed with the unproctored examination is the same as the proportion of female students in MTH1825 students who were successful when placed with the unproctored examination was significant $\chi^2(1, n = 124) = 8.976$, $p = .003$. Furthermore, the odds ratio of 2.33 ((73.40*45.80)/(54.20*26.60) indicates that the odds of being successful for the female students who were placed into MTH1825 with the unproctored examination was 133% more than the odds for females who were placed with the proctored examination.

Table 24

2 x 2 Contingency Table of Course Outcome by Type of Examination for the Female Students Enrolled in MTH1825

	Type of Examination	
Course Outcome	Proctored (n = 96)	Unproctored (n = 128)
Unsuccessful	45.80%	26.60%
Successful	54.20%	73.40%
Total	100.00%	100.00%

Senior Year Math: Table 25 shows a 2 x 2 contingency table of MTH1825 course outcome by type of examination for the students who were not enrolled in mathematics during their senior year of high school. As indicated, approximately 51.6% of the students who were placed into MTH1825 with the proctored examination were successful compared to approximately 71.7% who were placed with the unproctored examination. The value of the test statistic to test the null hypothesis the proportion of students in the proctored group who were successful is the same as the proportion of students in the unproctored group who were successful was not significant $\chi^2(1, n = 84) = 3.437$, $p = .064$.

Table 25

2 x 2 Contingency Table of Course Outcome by Type of Examination for Students Who Were Not Enrolled in Math during Senior Year of High School and Enrolled in MTH1825

	Type Of Examination	
Course Outcome	Proctored (n = 31)	Unproctored (n = 53)
Unsuccessful	48.40%	28.30%
Successful	51.60%	71.70%
Total	100.00%	100.00%

Table 26 shows a 2 x 2 contingency table of MTH1825 course outcome by type of examination for the students who were enrolled in a mathematics course during their senior year of high school. As indicated, approximately 56.0% of the white students who were placed into MTH1825 with the proctored examination were successful compared to approximately 73.8% who were placed with the unproctored examination. The difference in the percentages was significant $\chi^2(1, n = 321) = 80.63$, $p = .005$. The odds ratio 2.21 ((73.8*44.00)/(56.00*26.20)). So the students who were enrolled in a mathematics course during their senior year of high school were more likely to be successful in MTH1825 if placed with the unproctored examination.

Table 26

2 x 2 Contingency Table of MTH1825 Course Outcome by Type of Examination for Students Who Were Enrolled in Math during Senior Year of High School

	Type Of Examination	
Course Outcome	Proctored (n = 109)	Unproctored (n = 122)
Unsuccessful	44.00%	26.20%
Successful	56.00%	73.80%
Total	100.00%	100.00%

Last high school mathematics course: Table 27 is a 2 x 2 contingency table of the MTH1825 course outcome by type of examination for students whose last high school math course was either calculus, pre-calculus, or trigonometry. As indicated, approximately 60% of the students who were placed into MTH1825 with the proctored examination were unsuccessful compared to approximately 76.5% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of these students who were successful in the proctored group is the same as the proportion of these students who were successful in the unproctored group was significant $\chi^2(1,151) = 4.794$, $p = .029$. The odds ratio was 2.17 ((76.50*40.00)/(60.00*76.50)) indicating that the students who were placed with the unproctored examination and took calculus, pre-calculus, or trigonometry during their senior year of high school were more likely to be successful in MTH1825 than the students who were placed with the proctored examination.

Table 27

2 x 2 Contingency Table of the MTH1825 Course Outcome by Type of Examination for Students Whose Last High School Math Course was Calculus, Pre-Calculus, or Trigonometry in High School

	Type Of Examination	
Course Outcome	Proctored (n = 70)	Unproctored (n = 81)
Unsuccessful	40.00%	23.50%
Successful	60.00%	76.50%
Total	100.00%	100.00%

Table 28 shows the 2 x 2 contingency table of the MTH1825 course outcome by type of examination for students whose last high school mathematics class was either algebra I, algebra II, or geometry. As indicated, approximately 37.5% of these students who were placed with the proctored examination were successful compared to approximately 71.4% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of male students who were successful in the proctored group is the same as the proportion of students who were successful in the unproctored group was significant $\chi^2(1, n = 81) = 9.149, p = .002$. The odds ratio was 2.17 ((76.5*40)/(60*23.5)). So the of being successful for students who enrolled in MTH1825, who were placed with the unproctored examination and took either algebra I, algebra II, or geometry as their last high school math course was over 2 times the odds of being successful for students who enrolled in MTH1825, who were placed with the proctored examination, and took either algebra I, algebra II, or geometry as their last high school math course.

Table 28

2 x 2 Contingency Table of MTH1825 Course Outcome by Type of Examination For The Students Whose Last High School Math Course Was Algebra I, Algebra II, or Geometry

	Type Of Examination	
Course Outcome	Proctored (n = 32)	Unproctored (n = 49)
Unsuccessful	62.50%	28.60%
Successful	37.50%	71.40%
Total	100.00%	100.00%

Table 29 shows the 2 x 2 contingency table of the MTH1825 course outcome by type of examination for students whose last high school mathematics course was statistics or probability. As indicated, approximately 57.1% of these students that were placed with the proctored examination were successful in MTH1825 compared to 66.7% of those who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of male students who were successful in the proctored group is the same as the proportion of students who were successful in the unproctored group was significant $\chi^2(1, n = 67) = 0.632$, $p = .427$.

Table 29

2 x 2 Contingency Table of MTH1825 Course Outcome by Type of Examination for the Students Whose Last High School Math Course Was Statistics or Probability

	Type Of Examination	
Course Outcome	Proctored (n = 28)	Unproctored (n = 39)
Unsuccessful	42.90%	33.30%
Successful	57.10%	66.70%
Total	100.00%	100.00%

Success in College Algebra (MTH103)

Table 30 shows a 2 x 2 contingency table for MTH103 course outcome by type of examination. As indicated, approximately 85.1% of the students who were placed in MTH103 with the proctored examination were successful compared to approximately 77.1% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of MTH103 students who were successful in the proctored group is the same as the proportion of MTH103 students who were successful in the unproctored group was not significant $\chi^2(1, n = 270) = 2.016, p = .156$.

Table 30

2 x 2 Contingency Table of MTH103 Course Outcome by Type of Examination

	Type Of Examination	
Course Outcome	Proctored (n = 101)	Unproctored (n = 169)
Unsuccessful	14.90%	21.90%
Successful	85.10%	77.10%
Total	100.00%	100.00%

Success in College Algebra and Trigonometry (MTH116)

Table 31 shows the 2 x 2 contingency table of the math 116 course outcome by type of examination. As indicated, approximately 81.1% of the students who were placed in math 116 with the proctored examination were successful compared to approximately 81.1% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is the proportion of students who were successful in the proctored group is the same as the proportion of students who were successful in the unproctored group was not significant $\chi^2(1, n = 127) = 0.000$, $p = .994$.

Table 31

2 x 2 Contingency Table of Math 116 Course Outcome by Type of Examination

	Type of Examination	
Course Outcome	Proctored (n = 53)	Unproctored (n = 74)
Unsuccessful	18.9%	18.9%
Successful	81.1%	81.1%
Total	100.0%	100.0%

Success in Survey of Calculus 1 (MTH124)

Table 32 shows the percentage of students who were unsuccessful in MTH124 by the type of examination used to place the students. As indicated, approximately 94.1% of the students who were placed in MTH124 with the proctored examination were successful compared to approximately 90.8% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of students who were successful in the proctored group is the same as the proportion of students who were unsuccessful in the unproctored group was not significant $\chi^2(1, n = 121) = 0.354$, $p = .552$.

Table 32

2 x 2 Contingency Table of MTH124 Course Outcome by Type of Examination

Course Outcome	Proctored (n = 34)	
Unsuccessful	5.9%	9.2%
Successful	94.1%	90.8%
Total	100.0%	100.0%

Success in Calculus I (MTH132)

Table 33 shows the percentage of students who were unsuccessful in MTH132 by the type of examination used to place the students. As indicated, approximately 93.7% of the students who were placed in MTH132 with the proctored examination were successful compared to approximately 86.1% who were placed with the unproctored examination. The value of the test statistics used to test the null hypothesis that there is no difference between the proportion of students who were successful in the proctored group is the same as the proportion of students who were unsuccessful in the unproctored group was not significant $\chi^2(1, n = 147) = 1.368, p = .242$.

Table 33

2 x 2 Contingency Table of MTH132 Course Outcome by Type of Examination

Course Outcome	Proctored (n = 32)	Unproctored (n = 115)
Unsuccessful	6.3%	13.9%
Successful	93.8%	86.1%
Total	100.0%	100.0%

The contingency table analysis of the overall data set revealed that the students who were placed with the unproctored examination were more likely to be successful in the course in which they were placed. Upon further analysis, it was revealed that this phenomenon was only true of the university's remedial mathematics course (MTH1825) and not the non-remedial mathematics courses.

Question 3

How well does the mathematics placement examination predict success in students' first college mathematics course? Furthermore, can the prediction of success in students' first college mathematics course be improved using ACT Mathematics score, high school GPA, the type of mathematics courses taken in high school, and whether or not students took a mathematics course during their senior year of high school?

Michigan State University currently uses the results of the mathematics placement examination to place students into their first college mathematics course.

Predicting Success in Intermediate Algebra (MTH1825)

Since Michigan State University uses the scores on the placement examination to place students into their first college math course, the first logistic regression model (Model 1) uses mathematics placement examination score (MPE) as the predictor and PASS as the criterion. Table 34 shows the logistic regression results. As indicated in the table, the odds ratio for MPE is 1.386. Thus, for a 1 point increase in placement examination score, the odds of passing MTH1825 increase by about 39%. The Hosmer and Lemeshow Test is not significant ($\chi^2(5, N = 335) = 9.877, p = .079$) indicating that there is a linear relationship between MPE and the log odds of being successful in Intermediate Algebra and therefore Model 1 fits the data well. The binary logistic regression equation is given by

$$\mathbf{Ln(odds(success)) = -1.470 + 0.326*MPE}$$

Table 34

Summary of Logistic Regression Results of Model 1

Predictor	b	S.E.	Wald	df	Sig.	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.326	0.065	25.617	1	0.000	1.386	(1.221, 1.573)
Constant	-1.470	0.423	12.097	1	0.001	0.230	

Student #218 was unsuccessful in MTH1825. This student had a placement examination score of 5. Using the logistic regression equation above and equation 4, the predicted probability of success in MTH1825 for student #216 was 0.539. Thus the above model predicted this student to be successful although the student was not successful.

Table 35 is the classification table that corresponds to the logistic regression model above. The model correctly predicted 87.6% (191/218) of the successes but only 21.4% (25/117) of the non-success. Overall, the correct decision was made 64.4% of the time. Also, a total of 283 students were predicted to be successful in MTH1825 based on their scores on the placement examination but 92 of them were not successful. Hence this model has a false positive rate of 32.5% (92/283). Similarly, the model has a false negative rate of 52% (27/52).

Table 35

Classification Table Corresponding to Model 1

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	25	92
	Successful	27	191
		Hit Rate =64.4%	

In an attempt to improve the prediction of success in Intermediate Algebra, ACTM, HSGPA, SYM, last math course taken in high school, and the type of mathematics used for placement was added to Model 1. The resulting model will be referred to as Model 2. The logistic regression results are given in table 36.

The table shows that SYM, TYPE, and the last math course taken in high school. SYM and the last high school math course taken in high school were kept in the model because researchers (Hill, 2006; Adelman 1999, Berry 2003) concluded that taking a challenging math course in high school (beyond algebra 2) and taking mathematics during senior year is important to success in college level mathematics as well as college success overall. Additionally, TYPE remained in the model because of the *a priori* interest in the effect of type of examination on success in first college math course.

Table 36

Summary of Logistic Regression Coefficients for Model 2

Predictor	b	SE(b)	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.231	0.085	7.487	1	0.006	1.260	(1.068 , 1.487)
ACTM	0.235	0.060	15.476	1	0.000	1.264	(1.125 , 1.421)
HSGPA	1.337	0.436	9.400	1	0.002	3.806	(1.620 , 8.943)
TYPE	-0.406	0.292	1.932	1	0.164	0.667	(0.376 , 1.181)
SYM	0.227	0.356	0.407	1	0.523	1.255	(0.625 , 2.520)
PSTT	0.380	0.528	0.519	1	0.471	1.462	(0.520 , 4.112)
ALG	0.072	0.395	0.033	1	0.856	1.074	(0.495 , 2.332)
Other[a]	-0.261	0.388	0.453	1	0.501	0.770	(0.360 , 1.649)
Constant	-9.584	1.878	26.036	1	0.000	0.000	

[a] Includes FST (functions, statistics, and trigonometry), Business math, Consumer math, Math Analysis, Discrete Math

MPE, ACTM, and HSGPA were all significant predictors of success in Intermediate Algebra. According to the table, a 1 point increase in the placement examination score increases the odds of being successful in MTH1825 by about 26%. A 1 point increase in ACT Mathematics score also increases the odds of success in Intermediate Algebra of about 26%. The odds ratio for HSGPA is 3.806 and therefore, a 1 point increase in HSGPA increases the odds of being successful in MTH1825 by about

280%. However, if an increase of 0.1 points in HSGPA is considered, then the odds ratio would be $3.806^{0.1} = 1.14$. Thus an increase of 0.1 points in the HSGPA results in an increase in the odds of being successful in Intermediate Algebra of about 14%.   The odds ratio for TYPE indicated that the students who were placed into MTH1825 with the proctored examination had odds of success that were 0.667 times the odds of success of the students who were placed into MTH1825 with the unproctored examination. This odds ratio was not statistically significant.

The reader should be reminded that the variables PSTT, ALG, and Other are dummy variables created from variable LAST (last high school mathematics course taken) where a calculus, pre-calculus, or trigonometry was used as the reference group. Thus the odds ratio for ALG indicates that an Intermediate Algebra student, whose last high school math course was algebra I, algebra II, or geometry had odds of passing Intermediate Algebra that were 1.074 times greater than the odds of an Intermediate Algebra student who took calculus, pre-calculus, or trigonometry as their last high school math course. However, this odds ratio was not significant.

The values of the deviance for Model 1 and Model 2 were 403.989 and 298.639 respectively. This difference was significant $\chi^2(7, n = 332) = 105.35$, $p = .000$.   Thus, Model 2 improves the prediction of success in Intermediate Algebra beyond Model 1. The logistic regression equation is given by

Ln(odds(success)) = -9.584 + 0.231*MPE + 0.235*ACTM + 1.337*HSGPA – 0.406*TYPE – 0.227*SYM + 0.380*PSTT +0.072*ALG – 0.261*Other

Students #218 had MPE = 5, ACTM = 17, HSGPA = 2.78 , was placed with the proctored examination, and was enrolled in probability and statistics during his senior year of high school Using the logistic regression model and equation 4, this student's predicted probability of passing MTH1825 of 0.374. If this student was placed with the unproctored examination, the probability of being successful would increase to 0.472. Using only the placement examination score, this student was predicted to pass. Using information in the student's background, in addition to placement examination score, this student was predicted to be unsuccessful; and he was unsuccessful. With the low ACT Mathematics score, low mathematics placement examination scores, and high school GPA below 3.0, this student could be singled out and referred to academic resources within the university (e.g. tutoring).

Table 37 gives the classification table associated with Model 2. The model correctly predicted 89.5% (170/190) of the successes and 54.2% (52/96) of the non-successes. Overall, the correct decision was made 77.6% of the time. Also, using this model, a total of 214 students were predicted to be successful in MTH1825, but 44 of them were not successful. Hence this model has a false positive rate of 20.6% (44/214). Similarly, the model has a false negative rate of 27.7% (20/72).

Table 37

Classification Table for Model 2

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	52	44
	Successful	20	170
		Hit Rate =77.6%	

As indicated, Model 2 fits the MTH1825 data better than Model 1. Furthermore, Model 2 has a smaller false positive rate than Model 1.

Predicting Success in College Algebra (MTH103)

Table 38 gives the logistic regression results for the logistic regression model used to predict success in MTH103 with placement examination scores (Model 3). As indicated by the model, placement examination score is a significant predictor of the log odds of being successful in College Algebra. The odds ratio for MPE indicates that a 1 point increase in the placement examination score increases the odds of being successful in college algebra by about 25%. The Hosmer and Lemeshow Test produced a significant chi-square value, $\chi^2(5, N = 477) = 4.014$, $p = .547$. Therefore, Model 3 fits the data well. Furthermore the Omnibus Test of Model Coefficients produces a significant chi-square value, $\chi^2(1, N = 477) = 15.502$, $p = .000$ so that Model 3 fits the data better than the intercept only model. The binary logistic regression equation is given by

$$\mathbf{Ln(odds(success)) = -0.854 + 0.224*MPE}$$

Table 38

Summary of Logistic Regression Results for Model 3

Predictor	b	SE(b)	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.224	0.060	14.096	1	0.000	1.251	(1.113, 1.407)
Constant	-0.854	0.647	1.742	1	0.187	0.426	

Student #1681 received a placement examination score of 10. Using Model 3 and equation 4 the predicted probability of success in college algebra for a student who scores 10 on the placement examination is 0.80. Student #1681 was not successful.

The classification table corresponding to Model 3 is given in table 39. The model correctly predicted 100% of the successes and 1.3% of the failures for an overall "hit rate" of 83.4% (388/477). Model 3 predicted that 476 of the students would be successful in College Algebra. However, 79 of these students were unsuccessful. Thus, Model 3 has a false positive rate of 16.6% (79/476).

Table 39

Classification Table Corresponding to Model 3

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	1	79
	Successful	0	397
		Hit Rate =83.4%	

Attempting to improve on the prediction of success in MTH103, Model 4 was created by adding the variables ACTM, HSGPA, SYM, TYPE, PSTT, ALG, and Other to Model 3. The logistic regression results of Model 4 are given in Table 40. MPE, ACTM, and HSGPA are all significant predictors of the log odds of being successful in college algebra. The odds ratio for ACTM indicates that when all the other predictors are held constant, the odds of being successful in college algebra increases by about 11% for a 1 point increase in ACT Mathematics score. The odds ratio for HSGPA indicates that, when all the other predictors are held constant, the odds of being successful in college algebra increases by over 270% when the for a 1 point increase in the high school GPA. However, if an increase of 0.1 points in HSGPA is considered, then the odds ratio would be $3.794^{0.1} = 1.14$ and an increase of 0.1 points in high school GPA increases the odds of being successful in college algebra by about 11%.

The odds ratio for TYPE indicated that, when all the other predictors are held constant, the odds of being successful in college algebra when placed with the proctored examination is about 87% more than the odds of being successful in college algebra when placed with the unproctored examination. However, the variable TYPE was not significant.

The Hosmer Lemeshow chi-square produced a non significant chi-square value, $\chi^2(8, n = 405) = 37.15, p = .882$. Thus, Model 4 fits the data well. Also, the omnibus test of model coefficients produced a significant chi–square, $\chi^2(7, n = 405) = 38.455, p = .000$ indicating that Model 4 fits better than the intercept only model. The value of the deviance for Model 3 and Model 4 were 215.125 and 165.239 respectively. The difference was significant $\chi^2(7, n = 405) = 46.886, p = .000$. Therefore the Model 4 significantly adds to the prediction of success in college algebra beyond placement examination score. The logistic regression model is given by

$$Ln(odds(PASS)) = -8.117 + 0.293*MPE + 0.105*ACTM + 1.333*HSGPA +$$

$$0.626*TYPE + 0.243*SYM + 0.015*PSTT - 0.628*ALG + 0.240*Other$$

Table 40

Summary of Logistic Regression Results for Model 4

Predictor	b	SE(b).	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.243	0.078	9.780	1	0.002	1.274	(1.095, 1.481)
ACTM	0.105	0.050	4.449	1	0.035	1.111	(1.007, 1.224)
HSGPA	1.333	0.441	9.141	1	0.002	3.794	(1.598, 9.006)
TYPE	0.626	0.330	3.600	1	0.058	1.870	(0.980, 3.569)
SYM	0.243	0.078	9.780	1	0.002	1.274	(0.480, 2.141)
PSTT	0.015	0.493	0.001	1	0.976	1.015	(0.386, 2.667)
ALG	-0.628	0.402	2.434	1	0.119	0.534	(0.243, 1.174)
Other[a]	0.240	0.426	0.318	1	0.573	1.271	(0.552, 2.930)
Constant	-8.117	2.027	16.039	1	0.000	0.000	

[a] Includes FST (functions, statistics, and trigonometry), Business math, Consumer math, Math Analysis, Discrete Math

Student #1016 was placed into college algebra with the unproctored examination with a score of 11. This student had ACTM = 21, HSGPA = 3.722, and his last mathematics course was Pre-calculus during his junior year of high school. Using Model 4 and equation 4, his predicted probability of success was given as 0.848. A similar student placed with the proctored examination would have a predicted probability of success of 0.913. This student was not successful in college algebra.

The classification table is given in table 41. The table shows Model 4 correctly predicted almost 84.2% of correct course outcomes. Model 4 predicted 398 successes but 62 of the students were actually unsuccessful corresponding to a false positive of 15.6% (62/398). The model also gives a false negative rate of 28.6% (2/7). Model 4 improved the "hit rate" of Model 3 and have lower false positive and false negative rates.

Table 41

Classification Table Corresponding to Model 4

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	5	62
	Successful	2	336
		Hit Rate = 84.2%	

Predicting Success in College Algebra and Trigonometry (MTH116)

Table 42 shows the binary logistic regression results for the model used to predict the log odds of success in MTH116 using MPE as the only predictor (Model 5). The odds ratio for MPE is 1.020 indicating that the odds of being successful in MTH116 increases by about 2% for a 1 point increase in placement examination score. This ratio is not significant. Also the Hosmer and Lemeshow Test is significant (χ^2(5 , N = 249) = 4.774, p =.573) indicating that Model 5 fits the data well. However, the omnibus test of model coefficients produced a non-significant chi-square (χ^2(1, N = 249) = 0.095, p

=.758) indicating that Model 5 does not fit the data better than the intercept only model. The binary logistic regression equation is given by

Ln(odds(success))= 1.324 + 0.019*MPE

Table 42

Summary of Logistic Regression Results for Model 5

Predictor	b	SE(b).	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.019	0.063	0.094	1	0.759	1.020	(0.901, 1.154)
Constant	1.314	0.927	2.009	1	0.156	3.722	

Student #1510 scored 12 on the placement examination. Using Model 5 and equation 4, the predicted probability of being successful in MTH116 was 0.824.

Table 43 is the classification table for Model 5. Model 5 gives a hit rate of 83.1%. Also, 249 of the students were predicted to be successful but 42 of them were not successful corresponding to a false positive rate of 16.9%.

Table 43

Classification Table Corresponding to the Model 5

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	0	42
	Successful	0	207
		Hit Rate = 83.1%	

Attempting to improve on the prediction of the log odds of success in MTH116, the variables ACTM, HSGPA, SYM, TYPE, PSTT, ALG, and Other were added to Model 5. The logistic regression results of the new model (Model 6) are given in table 44. ACTM and HSGPA are both significant predictors of the log odds of being successful in MTH116. The odds ratio for ACTM indicates that the odds of being successful in MTH116 increases by almost 17% for each 1 point increase in ACT Mathematics score. The odds ratio for HSGPA indicates that the odds of being successful in MTH116 increases by over 17% for a 1 point increase in high school GPA. If we consider an increase of 0.1 points, then the odds ratio would be $18.461^{0.1} = 1.34$. Thus, for every 0.1 point increase in high school GPA, the odds of being successful in MTH116 increased by about 34%. The odds ratio for TYPE is 0.614 indicating that the odds of being successful in MTH116 when placed with the proctored examination is about 0.614 times the odds of being successful in MTH116 when placed with the unproctored examination. This odds ratio is not significant. Although the only significant predictors were ACTM and HSMGPA, the other variables remained in the model because either prior research indicated their effect on success in mathematics or the *a priori* interest in their effect on course success. The value of the deviance for Model 5 and Model 6 were 225.887 and 147.282 respectively. The difference was significant $\chi^2(7, n = 209) = 78.605$, $p =.000$. Therefore the predictors that were added to Model 5 significantly adds to the prediction of success in MTH116 beyond placement examination score. Model 5 is given by:

Ln(odd(success)) = - 12.652 + 0.052*MPE + 0.155*ACTM +2.916*HSGPA – 0.495*SYM + 0.243*TYPE- 0.530*PSTT – 0.142*ALG + 0.071*Other

Table 44

Logistic Regression Results for Model 6

Predictor	b	SE(b).	Wald	df	P	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.052	0.092	0.317	1	0.573	1.053	(0.875 , 1.262)
ACTM	0.155	0.075	4.275	1	0.039	1.168	(1.008 , 1.362)
HSGPA	2.916	0.876	11.085	1	0.001	18.461	(3.318 , 102.725)
SYM	-0.495	0.788	0.395	1	0.530	0.610	(0.130 , 2.854)
TYPE	0.243	0.481	0.255	1	0.614	1.275	(0.496 , 3.274)
PSTT	-0.530	0.755	0.493	1	0.483	0.589	(0.134 , 2.585)
ALG	0.142	1.004	0.020	1	0.888	1.152	(0.161 , 8.240)
Other[a]	0.071	0.637	0.013	1	0.911	1.074	(0.308 , 3.740)
Constant	-12.652	3.780	11.203	1	0.001	0.000	

[a] Includes FST (functions, statistics, and trigonometry), Business math, Consumer math, Math Analysis, Discrete Math

Table 45 shows the classification table associated with Model 6. Model 6 improved the "hit rate" of Model 5 to 86.9%. Also, Model 6 predicted that 202 students would be successful in MTH116, but 26 were unsuccessful. This resulted in a false positive rate of 12.9% (26/202). Similarly, Model 6 resulted in a false negative rate of 25%.

Table 45

Classification Table Corresponding to Model 6

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	3	26
	Successful	1	176
		Hit Rate = 86.9%	

Predicting Success in Survey of Calculus I (MTH124)

Table 46 shows the logistic regression results for predicting the log odds success in MTH124 using MPE as the only predictor (Model 7). The odds ratio for MPE indicate that a 1 point increase in placement examination score results in an increase in the odds of being successful in MTH124 of about 11%. The Hosmer and Lemeshow chi-square statistic was not significant $\chi^2(8, n = 256) = 8.873$, $p = .353$ indicating that Model 7 fits the data well. However the omnibus test of model coefficients was not significant $\chi^2(1, n = 256) = 2.355$, $p = .125$ indicating that Model 7 does not fit the data better than the intercept only model. Model 7 is given by

$$Ln(odds(success)) = 0.758 + 0.104 * MPE$$

Table 46

Summary of Logistic Regression Results for Model 7

Predictor	b	SE(b).	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.104	0.067	2.396	1	0.122	1.110	(0.973,1.267)
Constant	0.758	1.206	0.395	1	0.530	2.133	

Using Model 7 and equation 4, the probability that a person with a score of 15 on the placement examination will be successful in MTH124 is 0.913

The classification table for Model 7 is given in table 47. Model 7 has predicted that 256 of the students enrolled in MTH124 would be successful. However, 17 of the students were not successful resulting in a false positive rate of 6.6%. The model has a "hit rate" of 93.4%.

Table 47

Classification Table Corresponding to Model 7

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	0	17
	Successful	0	239
		Hit Rate = 93.4%	

Just as with previous models, Model 8 was constructed by adding ACTM, HSGPA, SYM, TYPE, PSTT, ALG, and Other to Model 7. The logistic regression results are given in Table 48. HSGPA was the only significant predictor of success in MTH124. The odds ratio for HSGPA indicates that the odds of being successful in MTH124 is almost 26 times the odds of being unsuccessful when high school GPA increases by 1 point. However, if an increase in HSGPA of 0.1 point is considered then the odds of being successful in MTH124 is $25.876^{0.1} = 1.38$ times the odds of being unsuccessful in MTH124. Also, when considering an increase in HSGPA of 0.1 point, the 95% confidence interval is reduced to (1.09, 1.73). The Hosmer and Lemeshow test produced a non significant chi-square $\chi^2(8, n=183) = 3.833$, $p = .872$. Therefore, Model 7 fits the data well. Although the other variables were not significant, they remained in the model because of the interest in their effect on success. The deviance statistics for Model 7 and 8 were 122.697 and 71.286.respectively. This difference was significant ($\chi^2(7, n=183) = 51.411$, $p = .000$). Therefore, the predictors that were added to Model 7 added to the prediction of the log odds of success in MTH124.

Table 48

Logistic Regression Results for Model 8

Predictor	b	SE(b).	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
ACTM	-0.017	0.122	0.020	1	0.887	0.983	(0.773,1.249)
HSGPA	3.253	1.144	8.089	1	0.004	25.876	(2.749 ,243.522)
SYM	-0.305	1.216	0.063	1	0.802	0.737	(0.058,7.994)
TYPE	-0.092	0.758	0.015	1	0.904	0.912	(0.207,4.031)
PSTT	18.731	8317.058	0.000	1	0.998	1.38E+08	
ALG	-0.533	1.245	0.183	1	0.669	0.587	(0.051,6.739)
Other[a]	-0.265	0.913	0.084	1	0.771	0.767	(0.128,4.583)
Constant	-8.045	4.836	2.768	1	0.096	0.000	

[a] Includes FST (functions, statistics, and trigonometry), Business math, Consumer math, Math Analysis, Discrete Math

Table 49 shows the classification table for Model 8. Model 8 improved the “hit rate” to 94%. Model 8 has a false positive of 6% (11/182).

Table 49

Classification Table Corresponding to Model 8

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	0	11
	Successful	1	171
		Hit Rate = 94.0%	

Predicting Success in Calculus 1(MTH132)

Table 50 shows the logistic regression results for predicting success in MTH132 with math placement examination scores only (Model 9). Model 9 indicates that the odds of being successful in MTH132 is 1.298 times the odds of being unsuccessful in MTH132 for a 1 point increase in the placement examination score. The Hosmer and Lemeshow test produced a non significant chi-square value χ^2 (7, N = 177) = 6.415, 0.492. This indicates that the model containing MPE fits the data well. The logistic regression equation is given by

$$\textbf{Ln (odds(success)) = -1.929+ 0.181*MPE}$$

Table 23

Summary of Logistic Regression Results for Model 9

Predictor	b	SE(b)	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.181	0.057	9.953	1	0.002	1.298	(1.071 , 1.340)
Constant	-1.929	1.123	2.949	1	0.060	0.145	

Using Model 9 and equation 4, a person who scores a 19 on the placement examination has a predicted probability of being successful in MTH132 of 0.819.

The classification table for Model 9 is given in table 51. Model 9 has a hit rate of 84.2%. Furthermore, the model predicted that 175 students would be successful but 27 students were not successful. Thus, the model had a false positive of 15.4 % (27/175).

Table 51

Classification Table for Model 9

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	1	27
	Successful	1	148
		Hit Rate = 84.2%	

Model 10 was created by adding ACTM, HSGPA, SYM, TYPE, PSTT, ALG, and Other. MPE and HSGPA are the only significant predictors in Model 10. However, just as in the previous models all the predictors were retained in the model. The logistic regression results are given in table 52. The odds ratio for ACTM indicates that the odds of being successful in MTH132 are 1.142 times the odds of being unsuccessful.

However, the odds ratio is not significant. The odds ratio for HSGPA indicates that the odds of being successful in MTH132 are 18.355 times the odds of being unsuccessful. If an increase of 0.1 in the GPA is considered then the odds of being successful in MTH132 is 1.34 ($18.355^{0.1}$) times the odds of being unsuccessful. The confidence interval is then reduced to (1.065, 1.679). The model also shows that the odds ratio for TYPE is 5.132 indicating that the odds of being successful in MTH132 when placed with the proctored examination is over 5 times the odds of being successful in MTH132 when placed with the unproctored examination. This odds ratio is not significant. The table also shows that students whose last high school mathematics course was either calculus, pre-calculus, or trigonometry had higher odds of being successful in MTH132, than the students whose last high school mathematics course was of course other than calculus, pre-calculus, or trigonometry. The Hosmer and Lemeshow test produced a significant chi-square ($\chi^2(8, n=177) = 18.567, p = .017$). The omnibus test of model coefficient, however, produces a significant chi-square statistic $\chi^2(7, n=177) = 25.61, p = .001$ indicating the Model 10 fits better than the intercept only model. The deviance statistics for Model 9 and Model 10 were 144.200 and 84.94 respectively. The difference was significant $\chi^2(6, n=121) = 59.506, p = .000$. Thus, Model 10 fits the MTH132 data better than Model 9. Model 10 is given by

$$Ln(odds(success)) = -16.357 + 0.241*MPE + 0.133*ACTM + 2.910*HSGPA + 1.636*TYPE - 0.809*SYM - 0.455*PSTT - 3.775*Other$$

Table 52

Logistic Regression Results for Model 10

Predictor	b	SE(b)	Wald	df	p	Odds Ratio	95% C.I. for the Odds Ratio
MPE	0.241	0.096	6.248	1	0.012	1.273	(1.053 , 1.538)
ACTM	0.133	0.101	1.731	1	0.188	1.142	(0.937, 1.393)
HSGPA	2.910	1.160	6.292	1	0.012	18.355	(1.889, 178.315)
SYM	-0.809	1.162	0.485	1	0.486	0.445	(0.046, 4.343)
TYPE	1.636	0.963	2.884	1	0.089	5.132	(0.777, 33.892)
PSTT	-0.455	1.276	0.127	1	0.722	0.635	(0.052, 7.748)
Other[a]	-3.775	1.561	5.852	1	0.016	0.023	(0.001, 0.488)
Constant	-16.357	5.509	8.817	1	0.003	0.000	

[a] Includes FST (functions, statistics, and trigonometry), Business math, Consumer math, Math Analysis, Discrete Math

Student #1666 was placed into MTH132 with a score of 22 on the unproctored examination, had an ACT Mathematics score of 27, had a high school GPA of 3.369, and his last course was pre-calculus during his senior year of high school. Model 10 and equation 4 predicted that the student would be successful in MTH132 with probability 0.822.

The classification table for Model 10 is given in table 53. Model 10 improves the "hit rate" of Model 9 to 89.1%. Model 10 also decreased the false positive rate to 11.5%.

Table 53

Classification Table for Model 10

		Predicted	
		Unsuccessful	Successful
observed	Unsuccessful	5	14
	Successful	1	117
		Hit Rate = 89.1%	

Question 4

How do the grades in each course compare across different levels of placement examination scores?

When students enroll in a course in which they received a placement examination score that was higher than the minimum score needed for placement into that course, then that student should be more likely to be successful in that course than someone who scored at the cut score. This phenomenon should not be dependent on the type of examination used for placement.

Intermediate Algebra (MTH1825)

Table 54 shows the crosstabulation of grades in Intermediate Algebra by mathematics placement examination scores. The placement examination scores for students who enrolled in Intermediate Algebra ranged from 1 to 11. As the placement examination scores get higher, more students received high course grades than lower course grades. This phenomenon would be expected. However, a student who scores 1 point on the placement examination would not be expected to receive a 4.0 in Intermediate Algebra.

Student #1671 was the student who received the grade of 4.0. This student was placed with the unproctored examination, had a high school GPA of 3.21, had a high school math GPA of 3.15, enrolled in a pre-calculus course during her senior year of high school and received a B in the pre-calculus course. Given her high school record, it is no surprise that the student received a 4.0 in Intermediate Algebra. However, it is surprising that the student would score so low on the placement examination that she would be placed into Intermediate Algebra.

Student #295 was the student who scored 1 on the placement examination and received a grade of 0.0 in Intermediate Algebra. This student scored 14 on the mathematics section of the ACT, had a high school GPA of 2.8, had a high school mathematics GPA of 2.37, did not take a mathematics course during his senior year of high school, but took trigonometry in 11^{th} grade and received a B. Although scoring 1 point on the placement examination is surprising for any student, it is not surprising that the student received a 0.0 in Intermediate Algebra.

The crosstabulation shows that 117 students were not successful in MTH1825 resulting in a false positive rate of 34.9% (117/335). Recall that Model 1 (the model used to predict success in MTH1825 using MPE as the only predictor) produced a false positive rate that was slightly lower than the actual false positive rate (32.5%) while Model 2 had a false positive rate of 20.6%. MTH1825 is the lowest level mathematics course at MSU so if a student is predicted to be unsuccessful in MTH1825 it can be recommended that they take a lower level course at a community college or these students can be given access to academic resources within the university.

Table 54

Crosstabulation of Grades in Intermediate Algebra by Placement Examination Score

	Grade in Intermediate Algebra (MTH1825)								
MPE	0.0	1.0	1.5	2.0	2.5	3.0	3.5	4.0	Total
1	1	0	0	0	0	0	0	1	2
2	4	0	0	0	0	0	1	0	5
3	9	1	1	4	1	1	0	0	17
4	7	2	0	3	8	6	0	2	28
5	14	2	9	8	10	4	0	0	47
6	9	6	7	7	8	4	5	4	50
7	9	7	6	15	9	7	10	4	67
8	7	2	7	6	11	11	9	4	57
9	3	2	2	17	9	12	8	4	57
10	0	0	0	2	0	1	1	0	4
11	0	0	0	0	0	0	0	1	1
Total	63	22	32	63	56	46	34	20	335

Students who received a placement examination score of 10 or 11 can enroll in College Algebra (MTH103). Table 52 shows that 4 of the students in Intermediate Algebra received a score of 10 on the placement examination and 1 student received a score of 11 on the placement examination. All 5 of these students were successful in Intermediate Algebra.

Table 55 shows the characteristics of the five students who were eligible to enroll in MTH103 but enrolled in MTH1825. Although student #549 scored 17 on the mathematics section of the ACT there is nothing else in his record that would explain why the student would not enroll in MTH103. Similarly, there is nothing in the other students' background that would explain why the others would not enroll in MTH103

Table 55

Students Who Placed into College Algebra but Enrolled in Intermediate Algebra

ID	MPE	ACTM	HSGPA	HSMGPA	LAST (Grade)	MTH1825 Grade	P[a]
4	10(P)	22	3.96	3.96	FST (A)	3.5	0.93
46	10(P)	22	3.90	3.84	Calc (A-)	2.0	0.92
277	11(P)	27	3.85	3.96	Calc (B)	4.0	0.95
549	10(P)	17	3.47	3.60	Precalc (B+)	3.0	0.79
1489	11(U)	24	3.00	3.51	Math Studies (A-)	2.0	0.80

[a]Probability of passing College Algebra

Table 56 is a crosstabulation of grades in MTH1825 by placement examination score by type of examination. The distribution of MTH1825 course grades appears to be exhibiting the pattern that is expected. That is, students with low placement examination scores have low grades. However, as the placement examination scores increase, the grades began to shift to the right and until most, if not all, of the students with high placement examination scores have grades above 2.0. This pattern does not appear to be happening with the unproctored data. In fact, the grades do not appear to be shifting to the right as the placement examination scores become larger.

Table 56

Crosstabulation of Grades in Intermediate Algebra by Placement Examination Score by Type of Examination

		Grades in Intermediate Algebra (MTH1825)								
	MPE	0.0	1.0	1.5	2.0	2.5	3.0	3.5	4.0	Total
Proctored	1	1	0	0	0	0	0	0	0	1
	2	2	0	0	0	0	0	0	0	2
	3	6	1	0	1	0	0	0	0	8
	4	4	1	0	0	2	4	0	0	11
	5	10	1	6	4	5	1	0	0	27
	6	5	1	4	4	1	0	1	1	17
	7	5	6	5	10	5	4	1	0	36
	8	4	0	3	2	4	4	5	1	23
	9	2	0	0	7	5	2	0	2	18
	10	0	0	0	1	0	1	1	0	3
	11	0	0	0	0	0	0	0	1	1
	Total	39	10	18	29	22	16	8	5	147
Unproctored	1	0	0	0	0	0	0	0	1	1
	2	2	0	0	0	0	0	1	0	3
	3	3	0	1	3	1	1	0	0	9
	4	3	1	0	3	6	2	0	2	17
	5	4	1	3	4	5	3	0	0	20
	6	4	5	3	3	7	4	4	3	33
	7	4	1	1	5	4	3	9	4	31
	8	3	2	4	4	7	7	4	3	34
	9	1	2	2	10	4	10	8	2	39
	10	0	0	0	1	0	0	0	0	1
	Total	24	12	14	33	34	30	26	15	188

College Algebra (MTH103)

Table 57 shows the crosstabulation of grades in College Algebra by placement examination scores. The table shows the pattern of the shift in grades as the placement examination scores become higher. There were 195 students who enrolled in MTH103 but were eligible to enroll in a course whose level was higher than MTH103   Eighteen of these students were not successful in MTH103.   Also, there were 5 students who enrolled in college algebra but were eligible to enroll in Calculus 1. One of these students was not successful. Overall, the placement examination produced a total of 80 false positives for MTH103 resulting in a false positive rate of 16.8% (80/477).   Model 5 above had a slightly lower false positive rate (15.6%). Again, the distribution of grades appears to be exhibiting the expected pattern. There appears to be a shift to the right in grades as the MPE scores become larger.

Table 57

Crosstabulation of Grades in College Algebra by Placement Examination Score

	Grade in College Algebra (MTH103)								
MPE	0.0	1.0	1.5	2.0	2.5	3.0	3.5	4.0	Total
10 - 11	25	10	27	52	48	66	40	14	282
12 - 14	5	5	7	31	24	44	27	23	166
15 - 18	0	0	0	2	2	7	11	2	24
19 +	0	0	1	0	0	0	1	3	5
Total	30	15	35	85	74	117	79	42	477

Table 58 also shows that of the 17 students who were eligible to enroll in MTH116 but enrolled in MTH103, 15 of them were placed with the unproctored examination. Of these 15 students

- One had an ACT Mathematics score of 17, was enrolled in algebra during his senior year of high school and received a D+, and had a high school mathematics GPA of 2.443.
- Five enrolled in trigonometry, pre-calculus, or calculus during their senior year of high school.
- Five had high school mathematics GPA's below 3.0.
- One took FST (functions, statistics, and trigonometry) during his senior year of high school and received a C+

The unproctored placement examination indicated that there were 15 students who were prepared for MTH116 but they were not even successful in MTH103. Chances are that these 15 students would not have been successful in MTH116.

Table 58

Crosstabulation of Grades in College Algebra by Placement Examination Score by Type of Examination

		Grades in College Algebra (MTH103)								
	MPE	0	1	1.5	2	2.5	3	3.5	4	Total
Proctored	10 - 11	14	3	5	19	21	30	16	2	110
	12 - 14	0	1	1	11	5	14	9	4	45
	15 - 18	0	0	0	0	0	1	2	0	3
	19 +	0	0	0	0	0	0	1	0	1
	Total	14	4	6	30	26	45	28	6	159
Unproctored	10 - 11	11	7	22	33	27	36	24	12	172
	12 - 14	5	4	6	20	19	30	18	19	121
	15 - 18	0	0	0	2	2	6	9	2	21
	19 +	0	0	1	0	0	0	0	3	4
	Total	16	11	29	55	48	72	51	36	318

Table 58 also appears to be exhibiting the expected pattern for both the proctored and unproctored data. As the placement examination scores increase, the grades appear to be shifting to the right. This pattern is what should be expected.

Table 58 shows that 49 of the 159 students (30.8%) who were placed with the proctored examination enrolled in math 103, but were eligible to enroll in a higher level course. Also, 146 of the 318 students (45.9%) who were placed with the unproctored examination were eligible to enroll in a higher level course. The difference in the percentages was significant ($z = -3.16$, $p = .001$) indicating that the percentage of students who enrolled MTH103, but were eligible to enroll in a higher level course was higher under the unproctored examination.

Table 59 shows the characteristics of the students who were eligible to enroll in MTH132, but enrolled in MTH103 instead. Four of these five students were placed with the unproctored examination. Student #677 scored 21 on the unproctored placement examination and received a grade of 1.5 in college algebra. This student scored 22 on the mathematics section of the ACT, had a high school GPA of 3.42, had a high school mathematics GPA of 3.75, took pre-calculus during her senior year of high school and received a grade of A-. With such a background, it is surprising that this student received a 1.5 in college algebra. If this student received such a low grade in college algebra, one can only conclude that the student would not have been successful in calculus.

Student #340 took AP Calculus in her senior year of high school and received a D-. This student may not have felt comfortable with taking a college calculus course given her poor performance in AP Calculus. The remaining 3 students had pre-college characteristics that would suggest that they would be prepared for a college calculus course, but these students enrolled in College Algebra.

Table 59

Students Who Were Eligible to Enroll in Calculus I, but Enrolled in College Algebra

ID	MPE	ACTM	HSGPA	HSMGPA	LAST (Grade)	MTH103 Grade	P[a]
340	19(P)	26	3.80	3.16	AP Calc(D-)	3.5	0.99
677	21(U)	22	3.42	3.76	Pre-calculus(A-)	1.5	0.99
1151	21(U)	27	4.48	4.15	Trigonometry(A)	4.0	0.99
1189	19(U)	26	4.00	4.15	Pre-calculus(A)	4.0	0.99
1472	19(U)	25	3.83	4.04	Discrete math(A)	4.0	0.99

[a]Probability of passing Calculus 1

Finite Mathematics (MTH110)

Table 60 shows the distribution of grades in finite mathematics by scores on mathematics placement examination. A minimum score of 10 is needed for placement into finite mathematics. As the placement examination scores get higher fewer students receives course grades below 2.0. There were 2 students who received were eligible to enroll into calculus but enrolled in finite mathematics. One of the students received a grade of 2.0 and the other received a grade of 3.5. It is this researcher's belief that a student will enroll in finite mathematics instead of calculus because their choice of major does not require a course in calculus. Overall, the placement examination produced 15 false positives for MATH110 for a false positive rate of 14% (15/104).

Table 60

Crosstabulation of Grades in Finite Mathematics by Placement

	Grade in Finite Math (Math110)								
MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
10 - 11	4	0	3	9	9	11	5	3	44
12 - 14	2	4	2	8	12	11	5	11	55
15 - 18	0	0	0	0	0	2	0	1	3
19+	0	0	0	1	0	0	1	0	2
Total	6	4	5	18	21	24	11	15	104

Table 61 shows the crosstabulation of grades in finite mathematics by placement examination scores by type of examination. The table shows that 26 of the 49 students (53.1%) who were placed with the proctored examination enrolled in math 110, but were eligible to enroll in a higher level course. Also, 34 of the 55 students (63%) who were placed with the unproctored examination were eligible to enroll in a higher level course.

The difference in the percentages was not significant (z = -0.9, p =.367) indicating that there was no evidence that the percentage of students who enrolled in MTH110, but were eligible to enroll in a higher level course, was difference across examination types

Table 61

Crosstabulation of Grades in Finite Mathematics by Placement Examination Scores by Type of Placement Examination

		Grades in Finite Mathematics (MATH110)								
	MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
Proctored	10 - 11	2	0	1	5	5	6	3	1	23
	12 - 14	0	4	1	1	5	3	3	7	24
	15 - 18	0	0	0	0	0	2	0	0	2
	Total	2	4	2	6	10	11	6	8	49
Unproctored	10 - 11	2	0	2	4	4	5	2	2	21
	12 - 14	2	0	1	7	7	8	2	4	31
	15 - 18	0	0	0	0	0	0	0	1	1
	19 +	0	0	0	1	0	0	1	0	2
	Total	4	0	3	12	11	13	5	7	55

College Algebra and Trigonometry (MTH116)

Table 62 shows the distribution of grades in college algebra and trigonometry by placement examination scores. The minimum placement exam score needed for placement into this course is 12. As the placement examination scores get higher, more students earn higher course grades. Of the 249 students who enrolled in MTH116, 42 of them were not successful. The placement examination produced a false positive rate of approximately 16.9% (42/249) form MTH116. Model 6 above produced a false positive rate of 12.9%

Table 62

Crosstabulation of Grades in College Algebra and Trigonometry by Placement Scores

	Grade in College Algebra and Trigonometry (MTH116)								
MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
12 - 14	12	4	10	26	26	29	18	17	142
15 - 18	4	2	4	8	14	19	17	21	89
19 +	3	2	1	2	0	2	4	4	18
	19	8	15	36	40	50	39	42	249

Table 63 shows the crosstabulation of grades in MTH116 by placement examination score by type of examination. Of the students who enrolled in MTH116 and were placed with the proctored examination, approximately 34.7% (34/98) of them were eligible to enroll in a higher level math course. Of the students who were enrolled in MTH116 and were placed with the unproctored examination, approximately 48.3% (73/151) of them were eligible to enroll in a higher level math course. The difference in percentages was significant ($z = -2.13$, $p = 0.03$).

Table 63

Crosstabulation of Grades in College Algebra and Trigonometry by Placement Examination Scores by Type of Examination

		Grades in College Algebra and Trigonometry (MTH116)								
	MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
Proctored	12 - 14	5	2	4	11	14	10	8	10	64
	15 - 18	1	0	2	3	6	5	6	9	32
	19 +	0	0	1	0	0	1	0	0	2
	Total	6	2	7	14	20	16	14	19	98
Unproctored	12 - 14	7	2	6	15	12	19	10	7	78
	15 - 18	3	2	2	5	8	14	11	12	57
	19 +	3	2	0	2	0	1	4	4	16
	Total	13	6	8	22	20	34	25	23	151

Table 64 shows the characteristics of the 5 students who were eligible for Calculus 1, but were unsuccessful in MTH116. Although student #1272 scored a 22 on the placement examination and received a 22 on the mathematics section of the ACT, both her high school GPA and high school mathematics GPA are below 3.0. This student also took a pre-calculus course during her senior year of high school and received a grade of C. Student #1250 scored 19 on the placement examination, 18 on the mathematics section of the ACT, and took a geometry course during his senior year of high school and received a grade of C-. There appears to be something in all 5 students' background that may explain their enrollment into MTH116 instead of Calculus 1.

Table 64

Characteristics of the Students Who Were Eligible for MTH132, but Enrolled in MTH116 and Were Unsuccessful

ID	MPE	ACTM	HSGPA	HSMGPA	LAST (Grade)	MTH116 Grade
1250	19	18	3.475	3.288	Geometry (C-)	1.0
1273	22	22	3.361	3.669	Statistics (A)	1.0
1606	21	24	2.906	2.375	Pre-calculus (C)	0.0
1655	20	-[a]	-[a]	-[a]	None	0.0
1668	20	26	-[a]	3.483	Pre-calculus[b]	0.0

[a] missing value [b] no grade recorded

Survey of Calculus 1 (MTH124)

Table 65 shows the crosstabulation of grades by placement examination score for the students who were enrolled in survey of Calculus I (MTH124). The placement examination gave a total of 19 false positives for MTH124 resulting in a false positive rate of 7.4%. Model 8 above produced a false positive of 6% for MTH124.

Table 65

Crosstabulation of Grades in Survey of Calculus by Placement Scores

	Grade in Survey of Calculus 1 (MTH124)								
MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
15 – 18	4	3	6	10	25	34	29	27	138
19 +	1	0	5	4	13	17	26	54	120
Total	5	3	11	14	38	51	55	81	258

Table 66 shows the distribution of grades by placement examination scores by type of examination. Of the 67 students who enrolled in MTH124 under the proctored examination, approximately 32.8% (22/67) of them could have enrolled in Calculus 1 (MTH132) Of the 191 students who enrolled in MTH124 under the unproctored examination, approximately 51.3% of them could have enrolled in Calculus 1. There was no significant difference in the percentage of students who were unsuccessful in MTH124 across examination types ($z = -2.61$, $p = .009$). Therefore, there was a difference in the percentage of students who enrolled in MTH124 but could have enrolled in MTH132.

It should be noted, however, that MTH124 is a course that is taken mostly by students who intend to major in business related courses whereas MTH132 is a course that is taken mostly by students who intend to major in science, mathematics, or engineering. Thus, the significant difference that is observed here could be the result of the differences in intended major and not differences in examination type.

Table 66

Crosstabulation of Grades in MTH124 by Placement Scores by Type of Exam

		Grades in Survey of Calculus 1 (MTH124)								
	MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**Total**
Proctored	15 - 18	3	1	1	4	6	9	12	9	45
	19 +	1	0	1	1	3	3	4	9	22
	Total	4	1	2	5	9	12	16	18	67
Unproctored	15 - 18	1	2	5	6	19	25	17	18	93
	19 +	0	0	4	3	10	14	22	45	98
	Total	1	2	9	9	29	39	39	63	191

Calculus 1 (MTH132)

Table 67 shows the crosstabulation of grades by placement examination scores for the students who enrolled in Calculus 1. As the placement examination scores get higher, the number of students who receive high course grades increase. The placement examination produced a total of 28 false positives for MTH132 resulting in a false positive rate of 14.7% (28/191). Model 10 above produced a false positive of 11.5% for MTH132.

Table 67

Crosstabulation of Grades in Calculus 1 by Placement Examination Scores

	Grade in Calculus 1 (MTH132)								
MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**total**
19	7	6	4	4	11	12	5	6	55
20	0	1	1	8	2	5	8	4	29
21	0	1	1	3	2	3	3	8	21
22	2	0	2	1	3	1	6	6	21
23	0	0	0	2	3	3	5	1	14
24	2	0	0	0	1	0	2	6	11
25	0	0	0	2	0	0	4	4	10
26	0	1	0	2	0	0	2	5	10
27	0	0	0	0	0	1	1	2	4
28	0	0	0	0	1	0	0	1	2
total	11	9	8	22	23	25	36	43	177

Table 68 shows the crosstabulation of grades in MTH132 by placement exam score by exam type. A score of 19 is the minimum score needed to place into MTH132. Overall, there were a total of 55 students who received a score of 19 on the placement examination. Thirty percent (17/55) of these students were not successful in MTH132. Of the 122 students who placed into MTH132 with a placement exam score of more than 19, 9% of them were unsuccessful in MTH132. This could suggest an increase in the minimum score needed to place into calculus is needed.

Table 68

Crosstabulation of Grades in Calculus 1 by Placement Exam Score by Type of Examination

	Grades in Calculus 1 (MTH132)									
	MPE	**0.0**	**1.0**	**1.5**	**2.0**	**2.5**	**3.0**	**3.5**	**4.0**	**total**
Proctored	19	3	2	0	1	5	4	2	1	18
	20	0	0	0	2	1	3	1	2	9
	21	0	0	0	1	0	0	1	3	5
	22	0	0	0	0	1	0	0	0	1
	24	1	0	0	0	0	0	0	2	3
	25	0	0	0	0	0	0	1	0	1
	26	0	0	0	1	0	0	0	2	3
	27	0	0	0	0	0	0	1	0	1
	28	0	0	0	0	1	0	0	1	2
	Total	4	2	0	5	8	7	6	11	43
Unproctored	19	4	4	4	3	6	8	3	5	37
	20	0	1	1	6	1	2	7	2	20
	21	0	1	1	2	2	3	2	5	16
	22	2	0	2	1	2	1	6	6	20
	23	0	0	0	2	3	3	5	1	14
	24	1	0	0	0	1	0	2	4	8
	25	0	0	0	2	0	0	3	4	9
	26	0	1	0	1	0	0	2	3	7
	27	0	0	0	0	0	1	0	2	3
	Total	7	7	8	17	15	18	30	32	134

Overall, 21% of the students enrolled in a course lower than the level indicated by their placement examination score. In addition, there were 598 students placed with the proctored examination. Of these approximately 19% (113/598) enrolled in a course at a level lower indicated by their placement examination score. There were 1098 students in this study who were placed with the unproctored examination. Of these students, approximately 23% (253/1098) of them enrolled in a course lower than the level indicated by their placement examination score. It is important to the validity of the placement examination to understand the reasons in which students enroll in a course lower than that in which they were placed.

CHAPTER 5

DISCUSSION

The primary purpose of this study was to compare the results of the proctored mathematics placement examination to the results of the unproctored mathematics placement examination. Of particular interest was whether the students tend to score higher on the unproctored examination than on the proctored examination. Also of interest was whether the type of examination used for placement produced an effect on grades in students' first college mathematics course or on course performance.

This section begins with a discussion of the conclusions reached as a result of this study. Then there is a discussion of the threats to the validity of this study. Finally, there are some recommendations for future research.

Conclusion 1

The unproctored examination has more inappropriate placements than the proctored examination.

This study concluded that students who were placed with the unproctored examination received higher average placement examination scores than the students who were placed with the proctored examination. As a result, students are placed into higher level mathematics courses with the unproctored examination.

Moreover, of the 598 students who were placed with the proctored examination, approximately 19% (113/598) enrolled in a lower course. Of the 1098 students who were placed with the unproctored examination, approximately 23% (253/1098) of them enrolled in a lower level course. Although a higher proportion of students are placing into higher level math courses with the unproctored examination, a larger proportion of those students are enrolling in courses that are lower than the level in which they are placed.

Conclusion 2

The proctored examination and the unproctored examination are not functioning similarly.

When the unproctored examination is used in the same manner as the proctored examination, it is important to make sure that the two exams are comparable. In other words, similar students should receive similar placements regardless of the exam used to place them. In addition to course placement, the effect on the course outcomes (i.e. grades) should be similar for similar students. Clearly, this is not happening.

First of all, students are not being placed similarly. The multiple linear regression model that was constructed with the proctored data predicted that about 35% of the students who were placed with the unproctored examination would have received similar placement had they been placed with the proctored examination. Additionally, about 21.5% would have received higher placement and about 43.5% would have received lower placement.

The multiple linear regression model that was constructed using the unproctored data predicted that about 41% of the students who were placed with the proctored exam would have received the similar placement if they would have been placed with the unproctored examination. Additionally, about 39% would have received higher placement and about 21% would have received lower placement. Either model indicates that students are placed higher with the unproctored examination.

Second the test of equality of the correlations revealed that the correlation matrices were not equal. Specifically, the correlation of ACT Mathematics score with grades in first college mathematics course was not equal across examination types. Also, the correlation between ACT Mathematics scores and placement examination scores was marginally significant across examination types. Additionally, ACT Mathematics score was the variable that was most highly correlated with the grades first college mathematics course for the proctored data. However, for the unproctored data, high school mathematics GPA was the variable that was most highly correlated with grades in first college mathematics course.

Additionally, the unproctored placement examination has a higher reliability than the proctored examination (r_{xx} = 0.81 for the unproctored examination, r_{xx} = 0.76 for the proctored examination).

Conclusion 3

The mathematics placement examination alone is not sufficient for deciding placement.

Currently, students are placed into their first college mathematics course as a result of the scores on the placement examination. Binary logistic regression models were constructed to predict the conditional probability that a student would be successful in their first college mathematics course. When the placement examination score was considered alone, it was found to be a significant predictor of the success in Intermediate

Algebra (MTH1825), College Algebra (MTH103) and Calculus 1 (MTH132). However, when ACT Mathematics scores, high school GPA, type of exam used for placement, whether a mathematics course was taken during senior year of high school, and the type of high school mathematics course taken last was considered in addition to placement examination score, the prediction of the success in each course was improved. The classification tables showed an increase in the percentage of correct decisions as well as a decrease in the false positive rate for each course when the additional variables are considered. Therefore ACT Mathematics scores, high school GPA, type of exam used for placement, whether a mathematics course was taken during senior year of high school, and the type of high school mathematics course taken last should all be considered when placing students into their first college mathematics course.

Limitations

This study has several limitations. First, the results of this study cannot be generalized to all college students. The students in this study chose to take mathematics during their first semester at MSU. However some students do not enroll in their first mathematics course until their second semester or their second year at MSU.

Random group assignment was not possible. Students chose the type of examination to take and, therefore, the groups used in this study were predetermined. The groups however were found to be non-equivalent.

Some of the students at MSU participate in summer “bridge” programs prior to their enrollment in mathematics. Some of these programs are designed to help improve students reading, writing, and/or mathematics skills. These students may have had exposure to the type of mathematics that they would be studying the following fall. Students in this study may have participated in these programs.

Some of the courses in this study may have been special courses designed for either exceptional students or for “at risk” students. These courses may provide more (less) rigor to the students enrolled than what a regular course would provide. Thus, there may be an effect on course grade due to class type. Students in these courses may have been included in this study.

The students in this study were allowed 3 attempts at the placement examination but only one attempt at the proctored examination. Students with multiple attempts may have attempt the proctored examination as one of their attempts or they have not attempted the proctored examination at all. The placement scores used in this study are the highest scores received by students on any attempt of the placement examination. Students who took the examination more than once may have matured between attempts. The multiple attempts may have better prepared students for their first mathematics course. Additionally, differences that were found could be due to the fact that the students may have attempted the unproctored examination more than once.

Grades in first college mathematics course were used as a criterion variable in this study. There are multiple sections of the same course. Sometimes the assessments are uniform across these multiple sections while other times the assessments are not uniform.

Future Research

This study has found that students who are placed with the unproctored examination received higher placement exam scores than students who are placed with the proctored examination; even after controlling for ability. To help explain this phenomenon, an investigation of the items may be necessary. Differential item functioning (DIF) occurs when "examinees from each group with equal knowledge exhibit different probabilities of success on an item" (Schumacher, 2005, p. 1). Although guessing is not encouraged it is this researcher's belief that students do guess. Therefore, the three parameter logistic item response theory model could be fitted to both the proctored and unproctored data and the item difficulty and item discrimination parameters could be estimated. Item characteristic curves can be constructed for each item and differences in the parameters can be tested by estimating the area between the item characteristic curves (Clauser & Mazor, 1998). Items are then flagged for DIF if the item characteristics curves for each group are different. Items flagged for DIF can be scrutinized to determine if they require modification or removal from the examination.

Once a student enrolls in a course, there are other variables that could affect their course performance. As a follow up to this study, consideration should be given to classroom variables as well as student variables. Classroom variables include but are not limited to instructor classification (full-time, part-time, graduate student) and class size. Student variables include, but are not limited to, number of other courses in which the students are enrolled, whether or not students receive tutoring, students' study skills, students' motivation, and choice of major. Understanding how these variables influence students' success in mathematics can help university advisors recommend appropriate courses as well as appropriate academic services for the struggling student.

This study contained students who enrolled in a course at a level lower than the level in which they were placed. For example, 30.8% of the students who were placed with the proctored examination and enrolled in MTH103 were eligible to enroll in a higher level course while 45.9% of the students who were placed with the unproctored examination and enrolled in MTH103 were eligible to enroll in a higher level course. It is however, unclear whether students began in the lower level course or "dropped back" to the lower level course. In either case, it is important to the validity of the placement examination, as well as the comparability of the proctored and unproctored examination, to further investigate why students are in course that are lower than the level in which they were placed.

Summary

This study was motivated by the interest in determining if the MSU unproctored mathematics placement examination can and should be used to place students into their first college mathematics course. The short answer is no. Placement into remedial mathematics was shown to be dependent on the type of test used for placement with the unproctored examination placing students into remedial mathematics less often than the proctored examination. Scores on the unproctored examination are significantly higher, on average, than the scores on the proctored examination and students are placing at a higher level with the unproctored examination.

Although students are being placed at a higher level with the unproctored examination, there is a greater proportion of students enrolling into courses lower than the level at which they were placed. It is, however, unclear as to whether students are "dropping back" to the lower level courses or beginning in the lower level courses. Whatever the case may be, users of the mathematics placement examination must consider the unproctored examination differently when using it to place students into their first college mathematics course.

This study also shows that pre-college variables (e.g. ACT Mathematics scores, high school grade point average) can be used to help increase the prediction of success in students' first college mathematics course. The models developed in this study increased the "hit rate" beyond that predicted by placement examination score alone and decrease the false positive rate. While there are no courses at a level lower than MTH1825, these pre-college characteristics can be used to help identify students who may benefit from some of the academic support services offered by Michigan State University.

Mathematics has influenced college graduation rates, choice of college major, and even earning potential. It can be the difference between receiving a bachelor's degree in 4 years or in 7 years (or not at all). It can be the difference between completing a bachelor's degree in a mathematics based field or completing a bachelor's degree in a non-mathematics based field. Whatever the case may be, mathematics is not going away and it is everyone's responsibility to help students overcome their difficulties with mathematics. One way colleges and universities can help is by examining their mathematics placement procedures so that it is very likely that a first time college student begins in the appropriate mathematics course.

Appendix

Appendix

Description of Mathematics Courses[3]

- MTH1825 (Intermediate Algebra)[4]
  Description: Properties of real numbers. Factoring. Roots and radicals. First and second degree equations. Linear inequalities. Polynomials. Systems of equations.

- MTH103 (College Algebra)
  Description: Number systems; functions and relations; exponents and logarithms; elementary theory of equations; inequalities; and systems of equations.

- MTH110 (Finite Mathematics and Elements of College Algebra)
  Description: Functions and graphs. Equations and inequalities. Systems of equations. Matrices. Linear programming. Simplex algorithm. Probability and statistics.

- Math 112 (Finite Mathematics: Applications of College Algebra)
  Description: Combinatorics, probability and statistics, mathematics of finance, geometry, transition matrices, and linear programming. The course emphasizes applications and includes work using spreadsheets.

- Math 116 (College Algebra and Trigonometry)
  Description: Functions and graphs. Equations and inequalities. Exponential and logarithmic functions. Trigonometric functions. Systems of equations. Binomial theorem.

- MTH124 (Survey of Calculus I)
  Description: Study of limits, continuous functions, derivatives, integrals and their applications.

- MTH132 (Calculus I)
  Description: Limits, continuous functions, derivatives and their applications. Integrals and the fundamental theorem of calculus.

- STT200 (Statistical Methods)
  Description: Data analysis, probability models, random variables, estimation, tests of hypotheses, confidence intervals, and simple linear regression.

- STT201 (Statistical Methods)
  Description: Probability and statistics with computer applications. Data analysis, probability models, random variables, tests of hypotheses, confidence intervals, simple linear regression. Weekly lab using statistical software.

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[3] http://www.reg.msu.edu/Courses/Request.asp

[4] This course does not count toward a student's degree

Bibliography

Bibliography

Abraham, Ashley. (1992). *College remedial studies: Institutional practices in the SREB states.* Southern Regional Education Board, Atlanta, GA. (ERIC Document Reproduction Services No. ED 345 617).

ACT. (2008). *College retention and graduation rates.* Retrieved April 27, 2009 from http://www.act.org/research/policymakers/reports/graduation.html

ACT. (2002). *College Graduation Rates Steady Despite Increase In Enrollment.* Retrieved April 27, 2010 from http://www.act.org/news/releases/2002/11-15-02.html

Akst, G & Hirsch, L. (1991). *Selected studies on math placement.* National Center for Developmental Education, Reich College of Education, Appalachian State University, Boone, NC (ERIC Document Reproduction Service No ED 354m 964).

Allen, M.J., & Yen, W. M. (2002). *Introduction to Measurement Theory*. Long Grove, IL: Waveland Press.

American Council on Education. (1996). *Remedial Education: An undergraduate student profile.* Washington, D.C: Author

American Educational Research Association, American Psychological Association, National Council on Measurement in Education. (1999). *Standards for educational and psychological testing*. Washington DC: American Psychological Association.

Ang, C. H., & Noble, J. (1993). Incremental validity of ACT assessment scores and high school course information for freshmen course placement. (Report No. ACT- RR-93-5). ACT, Iowa City, IA.

Arifin, M. Z. (2009, May 24). *Sample Logic Probit: Session 6: Logistic Regression*, Retrieved from http://www.docstoc.com/docs/docs/6382581/Sample-logit-probit

Armstrong, W, B. (2001). Explaining student course outcomes by analyzing placement test scores, student background data, and instructor effects. (ERIC Document Reproduction Service No. ED 454 907).

Bridgeman, B., & Lewis, C. (1995*)* Gender Differences in College Mathematics Grades and SAT-M Scores: A Reanalysis of Wainer and Steinberg.(Report No. ETS-RR-95-17) Educational Testing Service, Princeton, New Jersey (ERIC Document Reproduction Services No. ED397074).

Bridgeman, B., & Wendler, C. (1991). Gender differences in predictors of college mathematics performance and in college mathematics course grades. *Journal of Educational Psychology*. *83*(2), 275-84.

Bridgeman, B., & Wendler, C. (1989) Prediction of grades in college mathematics courses as a component of the placement validity if SAT mathematics scores. (Report No. RR 89-9) College Entrance Examination Board, New York, NY. (ERIC Document Reproduction Services No. ED 395-019).

Beaty, J. C, Fallon, J.B, & Shepard W, J. (2002, April). Unproctored Web-Based Administration of a Cognitive Ability Test. Paper Presented at the Annual Conference of the Society of Industrial/Organizational Psychology, Toronto, Canada.

Chang, J. C. (2002). "*Women and Minorities in the Science, Mathematics and Engineering Pipeline*. ERIC Digest. Retrieved from http://www.ericdigests.org/2003-2/women.html

Center for Institutional Data Exchange and Analysis. (2000). *1999-2000 SMET retention report.* Norman, OK: University of Oklahoma.

Charlesworth, P., Charlesworth, D. & Vician, C. (2006). Students' perspectives of the influence of Web-enhance coursework on incidences of cheating. *Journal of Chemical Education 83(9), 1368 – 1385.*

Cohen, Jacob. (1988). *Statistical power analysis for the behavioral sciences*. New York, NY: Academic Press, Inc.

Cotter, J. W. (2007). *Comparison of three methods of placement and advisement into freshmen mathematics courses and the effects on eventual degree completion.* Unpublished doctoral dissertation, Georgia State University, Atlanta, Georgia.

Davies, S. A, & Wadlington, P, L. (2006, May). *Factor & Parameter Invariance of a Five Factor Personality Test across Proctored/Unproctored Computerized Administration*. Paper presented at the Annual Conference of the Society of Industrial and Organizational Psychology, Dallas, Texas.

Davies, S. A, Norris, D, Turner, J, & Waldington P. (2005, April). *Cheating, Guessing, Faking, and Self Presentation in Assessment Responses.* Paper presented at the 20th Annual Conference of the Society for Industrial and Organizational Psychology, Los Angeles, California.

Ebel, R. L. (1986). Essentials of educational measurement (4th Ed.). Englewood Cliffs, NJ; Princeton-Hall.

Frankfort-Nachmia, C., & Leon-Guerrero, A. (2009). *Social statistics for a diverse society* (5th ed.). Thousand Oaks, CA: Pine Forge Press.

Flores, R. (2007). *Psychometric analysis of a mathematics placement examination*. Unpublished master's thesis, Texas Tech University, Lubbock, Texas.

Gabe, L. C. (1989). *Relating college – level performance to ASSET placement scores* (Report No. RR 89-22). Fort Lauderdale, FL. Broward Community College. (ERIC Document Reproduction Service No ED 309 823).

Garson, G. David. (2010). Logistic Regression, from *Statnotes: Topics in Multivariate Analysis.* Retrieved from http://faculty.chass.ncsu.edu/garson/PA765/logistic.htm

Gupta, S., Harris, D. E., Carrier, N. M., & Caron, P. (2006). Predictors of Student Success in Entry-Level Undergraduate Mathematics Courses. *College Student Journal*. *40*(1), 97-108.

Harmon, O. R., Lambrinos, J., & Kennedy, P., Ed. (2008). Are Online Exams an Invitation to Cheat? *Journal of Economic Education*. *39*(2), 116-125.

Hill, R. O. (2006). *On the transition in mathematics from high school to Michigan State University*, Retrieved from http://www.math.msu.edu/~hill/Transition.pdf

Hudson, J. B. (1989). *An analysis of ACT scores, placement tests and academic performance in reading, English, and mathematics courses*. Louisville University. Ky. Preparatory Division. (ERIC Document Reproduction Service No ED 334 916).

Hunsley, J., & Meyer, G. (2003). The incremental validity of psychological testing and assessment :conceptual, methodological, and statistical issues. *Psychological Development, 15(4), 446-455*

Jacobson, E. (2006). Higher placement standard increase course success but reduce program completion*s. The Journal of General Education,* 55(2), 139-159.

Kennedy , K., Nowak, S.; Raghuraman, R., Thomas, J.,& Davis, S. F. (2000). Academic dishonesty and distance learning: Student and faculty views. *College Student Journal 34(2), 309 -314.*

Matthews-Lopez, J. L. (1998). Mathematics Placement Testing: Is it really necessary? (ERIC Document Reproduction Services No. ED 457 165).

McCloy, R. (2008). *Unproctored Internet Testing* [PowerPoint slides]. Retrieved from http://www.mppaw.org/slidesarchive.php

McDonald, A. D. (1989). Issues in Assessment and Placement for Mathematics. *Journal of Developmental Education*. *13*(2), 20-23.

Messick, S. (1989). Validity. In R. L. Linn (Ed.). *Educational Measurement* (pp.13 – 103). New York: Macmillan.

Morante, E. A. (1989). Selecting tests and placing students. *Journal of Developmental Education*. *13*(2), 2-4,6.

National Center for Education Statistics. (2010). *The Condition of Education 2010* (NCES 2010-028), Indicator 21. Retrieved from http://nces.ed.gov/FastFacts/display.asp?id=40.

Nelson, C. V., & Leganza, K. K. (2006). Is gender a predictor of success in college mathematics courses? *College and University*. *81*(4), 11-18.

Neill, J. (2008). *Why use effect size instead of significance testing in program evaluation?* Retrieved from http://wilderdom.com/research/effectsizes.html

Nolting, P. (2004). *Math study skills workbook (3rd ed.).* Chicago, Illinois: Houghton Mifflin.

Osborne, Jason & Elaine Waters (2002). Four assumptions of multiple regression that researchers should always test. *Practical Assessment, Research & Evaluation*, 8(2). Retrieved from http://PAREonline.net/getvn.asp?v=8&n=2

Ostrum, C. W. (1990). *Time series analysis: Regression techniques. Quantitative applications in the social sciences* (2nd ed., Vols. 07-009). Newbury Park: Sage Publications.

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

Peck, J. D. (1997). *Statistics: The Exploration and Analysis of Data* (3 ed.). New York, NY Duxbury Press.

Peng, C.Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *Journal of Educational Research*. *96*(1), 3-14.

Pugh, C., & Lowther, S. (2004). *College math performance and last high school math course.* Paper presented at the annual conference of the Southern Association for Institutional Research, Biloxi, Mississippi.

Rodgers, K. V., & Wilding, W. G. (1998). Studying the Placement of Students in the Entry-Level College Mathematics Courses. *Primus*. *8*(3), 203-08.

Rovai, A. P. (2001). Online and traditional assessments: What is the difference? *Internet and Higher Education 3(3), 141-151.*

Rubin, L. & Nora, A. (2002, April). *Factors impacting the Academic Status of Undergraduate Students at Four-Year Institutions* Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA.

Sawyer, R., & Schiel, J. (2000). Posttesting Students to Assess the Effectiveness of Remedial Instruction in College. ACT Research Report. Retrieved from http://www.act.org/research/reports/pdf/ACT_RR2000-7.pdf

Sawyer, R. (1996). Decision theory models for validating course placement tests. *Journal of Educational Measurement*. *33*(3), 271-90.

Schmitz, C. C., & DelMas, R. C. (1990). Determining the validity of placement exams for developmental college curricula. *Applied Measurement in Education*. *4*(1), 37-52.

Schumacher, P. A. & Smith, R. M. (2008). A comparison of placement in first – year university mathematics course using paper and pencil and online administration of a placement test. *International Electronic Journal of Mathematics Education.* 4(3), 193 – 202.

Schumacker, R. (2005). *Test bias and differential item functioning*. Retrieved from http://www.appliedmeasurementassociates.com/White%20Papers/TEST%20BIAS%20AND%20DIFFERENTIAL%20ITEM%20FUNCTIONING.pdf

Seidman, A. (2005) Where do we go from here: A retention formula for student success. In A. Seidman (Ed.), College student retention (pp. 295 – 316). Westport: Praeger Publishers.

Shaffer, J. P. (1995). *Multiple hypothesis testing.* Annual Review of Psychology. 46, 591 – 584.

Shepard, W. J., Do, B. R., Drasgow F. L. (2002, April). Assessing Equivalence of Online Non-Cognitive Measures. Paper Presented at the Annual Conference of the Society of Industrial/Organizational Psychology, Orlando, FL

Shevel, L. R., & Whitney, D. R. (1969). Predictive validity of the mathematics placement examination. *Educational and Psychological Measurement*. *29*(4), 895-901.

Slark, J., et al. (1991). *RSC validation of mathematics placement tests.* Rancho Santiago Community College. Santa Ana, Ca. (ERIC Document Reproduction Service No ED 341 418).

Sticha, P. J., & Barber, G. (2003). *CAT-ASVAB prototype internet delivery system: final report (*Report #FS-03-46). Retrieved from http://www.psych.umn.edu/psylabs/catcentral/pdf%20files/st03-01.pdf

Thorndike, R. M., & Dinnel, D. L. (2001). *Basic Statistics for the Behavioral Sciences.* Upper Saddle River, NJ: Prentice-Hall.

Tippen, N et al. (2006). Unproctored internet testing in employment settings. *Personnel Psychology*, 59(1), 189-225.

Triola, M. F. (2010). *Elementary statitics* (11th ed.). Boston, MA: Addison Wesley

Wattenbarger, J. L., & McLeod, N. (1989). Placement in the mathematics curriculum: what are the keys? *Community College Review*. *16*(4), 17-21.

Wheland, E., Konet, R.,& Butler, K. (2003). Perceived inhibitors to mathematics success. *Journal of Developmental Education, 26(3) 19-27.*