A SYSTEM FOR MATHEMATICS STUDENT PLACEMENT IN COLLEGE ALGEBRA

By

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CHAPTER I

INTRODUCTION

Introduction

Dana Doright has just graduated from a small high school in rural Oklahoma. Dana finished high school with a grade point average of 3.25 and a math ACT score of 22. Dana plans to attend Oklahoma State University after the summer and major in business. Dana has never been fond of math and is unsure about taking College Algebra in the fall semester. Before enrolling, Dana meets with an advisor, Dr. In A. Quandary. Dr. Quandary looks at Dana's information and is faced with the question, "Is Dana ready for College Algebra at OSU?".

Every Fall semester students and advisors alike are faced with the above predicament. The question of whether a student is ready for college level mathematics or needs remediation is not a new one. Conflict over whether colleges should offer remediation began as early as 1828 in the *Yale Report* and has continued to this day (Abraham, 1991). The idea of placement is closely tied to remediation in that students must be evaluated in terms of whether they are prepared for college level courses. Placement schemes vary greatly from school to school, but a large percentage of institutions have placement procedures set up to identify and place students needing remedial work. Over eighty percent of the institutions in a Southern Regional Education Board (SREB) survey have written policies concerning placement and forty five percent or more of the public institutions are guided by state or system level policies (Abraham, 1992).

Purpose of the Study

The purpose of this study is to develop a placement system for College Algebra. This will be accomplished by identifying, correlating, and evaluating predictors of grades in College Algebra for first-time freshmen at Oklahoma State University. This is a prediction study that involves the use of multiple regression. The independent variables studied include: High school grade point average, high school class rank, high school code average in College Algebra, gender, math ACT score, composite ACT score, math SAT score, and total SAT score. The dependent variable for this study is the final grade in College Algebra.

After a review of the literature, these variables will be correlated with final grades in College Algebra using multiple regression techniques. The research questions addressed in this study are:

1. Is there a linear relationship between the independent variables and the dependent variable?
2. Are the coefficients in the multiple regression models nonzero?
3. For those equations that are statistically viable (i.e. nonzero coefficients and linear relationship), which variables contribute the most to the equation?
4. What are the predictive abilities for the statistically viable models?
5. Which equations are influenced by gender?

Definition of Terms

What follows is a list of terms that will be used throughout this paper.

General Terms

College Algebra: This is the lowest college level mathematics course taught at OSU. It is a general education requirement for many of the majors offered. The content of this course includes quadratic equations, functions and graphs, inequalities, systems of equations, exponential and logarithmic functions, theory of equations, and conic sections (Choike & Jobe, 1991). For the years studied, College Algebra was a standardized course. Almost all instructors lectured from the same lecture guide (Choike & Jobe, 1991), had common grading schemes, and all exams were common. College Algebra is taught in 17 week semesters.

First-time freshmen: Those students that became freshmen at OSU within six months of graduating high school, their first college mathematics course was College Algebra taken within their first two semesters at OSU, and they made a grade of A, B, C, D, F, or W in College Algebra. A grade of W means that the student withdrew from the course before the end of the semester.

Intermediate Algebra: This is the remedial mathematics course designed to prepare students for College Algebra at OSU. The content of this course includes: Review of fundamental operations of algebra, rational expressions, exponents and radicals, linear and quadratic equations, inequalities, introduction to analytic geometry (OSU Catalog, 1994). This course does not count for college credit.

Oklahoma State University (OSU): Oklahoma State University is a large comprehensive university located in Stillwater, Oklahoma. The main campus serves about 18,000 students per year. About eighty-six percent of the undergraduate enrollment is from Oklahoma; eight percent from other states; and six percent from more than 90 foreign countries. Of the undergraduate population, 54 percent are men and 46 percent are women. Minorities make up about 12 percent of the undergraduate student body. (OSU catalog 1994)

Placement System: This term is used to describe an overall placement scheme. It is composed of several multiple regression models, as well as cutoffs and placement recommendations for each model.

Success Percent and Misplaced Percent: These will be used in reference to the predictive abilities of the models generated. The formulas for their calculation are listed below.

Let **CAC** (College Algebra Correct) be the number of students that are given a College Algebra placement and make a grade of A, B, or C in College Algebra . Let **CAI** (College Algebra incorrect) be the number of students given a College Algebra placement that make a grade of D, F, or W in College Algebra. Let **IAC** (Intermediate Algebra correct) be the number of students that are given an Intermediate Algebra placement and make a grade of D, F, or W in College Algebra. Let **IAI** (Intermediate Algebra incorrect) be the number of students given an Intermediate Algebra placement and who make a grade of A, B, or C in College Algebra. Let **N** be the number of students in the sample. In this study, students that made a grade of A, B, or C in College Algebra are considered successful and all others unsuccessful. The formulas for Success percent and Misplaced percent are listed below.

$$\textbf{Success Percent} = \left(\frac{\text{CAC} + \text{IAC}}{\text{N}}\right) * 100 \qquad \textbf{Misplaced Percent} = \left(\frac{\text{CAI} + \text{IAI}}{\text{N}}\right) * 100$$

Variables

CACT: This is the comprehensive score on the American College Test.

CODE: Each high school in Oklahoma is assigned a six digit code by ACT. Each high school code was assigned a number between zero and four which represents the average of all its first-time freshmen in College Algebra. For example, suppose 30 students from Excellent High School (EHS) were first-time freshmen in the years studied here. Their grades in College

Algebra would be averaged and this average would be assigned to the high school code for EHS. More simply, this is a way to quantify how each high school's first-time freshmen perform in College Algebra at OSU. It is important to note however, that this says ***nothing*** about the quality of the high school. Even if most students from a particular high school take Calculus their first semester, the school may still have a low code average.

All in-state schools that had less than five first-time freshmen were pooled and given a common average. All out of state schools were pooled and given a common average. In-state schools with more than four first-time freshmen were given their own average.

GENDER: This refers to the gender of the student.

GRD: This represents a student's grade in College Algebra where A=4, B=3, C=2, D=1, and F=0. Grades of W will not be used in the calculation of the regression models or high school code averages, but will be used in the calculation of Success and Misplaced Percent.

HSGPA: This refers to high school grade point average on a four point scale.

MACT: This is the mathematics subscore on the American College Test.

MSAT: This is the mathematics subscore on the Scholastic Aptitude Test.

RANK: This is a student's rank percentage upon graduating from high school. It is computed by dividing the student's class rank by his or her graduating class size and converting to a percent (rounded to one decimal place).

TSAT: This is the total of the verbal and mathematics scores on the Scholastic Aptitude Test.

Significance of the Study

The literature concerning placement, using the independent variables above, is not extensive. Part of the reason for this may be that many departments use tests created by the department and do not publish the results. Abraham (1992) found that institutionally developed tests were used more than twice as often as the next highest ranking test, the ACT-combined. In addition, there is some controversy over whether high school records or standardized tests are the best predictors of performance in college level mathematics (Thornell & Jones, 1986; Crouse & Trusheim, 1988; Gougeon, D., 1984). This study will add to the literature that exists and assist in refining the theories of placement.

In addition to adding to the present knowledge base on placement, the results can be used to help OSU advisors place students correctly. The findings in this study can be used as an additional tool in advising students to take the course that they are most prepared for.

Lastly this study can be used as a recipe to perform similar research at other institutions. The results of this study only generalize to the population of first-time freshmen at OSU. Institutions wishing to develop placement tools can use this study as a guide to conduct similar research.

Assumptions and Limitations

The following is a list of limitations and assumptions of this study:

1. The study is restricted to first-time freshmen in the academic semesters Fall 1991 to Fall 1994. Transfer students and returning students are not considered.

2. High School GPA scores from schools that do not have a four point scale are converted to a four point scale by computing the percent and multiplying by four, then rounding to two decimal places.

3. Some of the students in the sample do not have all of the independent variables being studied. In generating the multiple regression models, all students with the required information were included. All information was collected from high school transcripts, ACT reports, and SAT reports.

4. One possible limitation to the generalization of the results of this study is that College Algebra or a higher level course is required for almost all students at OSU. Furthermore, College Algebra is the lowest level math course for which the students get college credit.

5. Placement at OSU during the 10 semesters studied was voluntary except for the Fall 1994 semester. In 1993, the State Regents of Oklahoma passed a three point plan to better prepare students for college (Oklahoma State Regents for Higher Education, 1993b). In particular the plan requires students who score below a 19 on the ACT Mathematics subtest to take Intermediate Algebra or undergo additional testing to determine their readiness for college level work. Comparing the Fall 1994 semester to other Fall semesters in the study, there were about 30 fewer students in the Fall 1994 semester that scored lower than 19 and took College Algebra. In the semesters where placement was voluntary, students still met with advisors and received placement recommendations.

6. Students that withdrew from College Algebra were not used in the calculation of the regression models. Since students have varied reasons for withdrawing from a course, any number chosen to represent a grade of W would be conceptually meaningless. However, since these students did not complete the course, they were combined with the D's and F's in the calculation of Success Percent. This has the effect of lowering the Success and Misplaced Percents of the models. Note that 3.7 percent of the students in the sample had a grade of W.

7. The assumptions for regression analysis are listed in Appendix B.

To give the reader a feel for the situation in which this research is conducted, the OSU placement system in mathematics is described in the next few sentences. At OSU, professional advisors talk with the first-time freshmen, examine their high school records, and make placement recommendations. Placement is voluntary except for the Regent's three-point plan discussed in Chapter 2 under the heading of Placement. Traditionally, students have been given the Mathematical Association of America's test in algebra to assist advisors in placing students.

Organization

The rest of this report is broken into five sections:

Review of the Literature: This section contains a review of the literature that exists and includes information on remediation, general placement considerations, and placement using the independent variables listed previously.

Method: This includes a description of the population being considered as well as the sample selected. Information on SAT and ACT, as well as a description of the research design used, can be found in this section.

Analysis of Data: This section is broken into two parts. The first part is devoted to the correlations between the independent variables and the dependent variable. Next the models generated will be tested for linear relationships and nonzero coefficients. All models that fail the linear relationship test or nonzero coefficient test, will be scrapped. The equations that are left will be examined to determine which independent variables contribute the most to each model, what the Success and Misplaced percents of each model are, and whether the equation is affected by gender.

Conclusions: This section summarizes the results of the study.

Bibliography: This section contains 70 references used throughout this thesis.

CHAPTER II

REVIEW OF THE LITERATURE

Introduction

The purpose of this review is to provide the reader with information on the topics of placement and remediation and to acquaint the reader with some of the findings in this field of research. The review will begin with some information on remediation and conclude with some findings on using the independent variables for this study in placing students into basic level mathematics courses.

Remediation

Remediation, in the context of this report, is the process of preparing students for college level courses. The question of whether colleges should be responsible for remediation has been around for a long time. In the *Yale Report* of 1828, the faculty condemned the practice of enrolling students that were not properly prepared for college level courses (Abraham, 1991). In 1849, the University of Wisconsin established a Department of Preparatory Studies to combat the problem of remediation, and by 1900, 84 percent of the colleges and universities in the United States had similar preparatory schools (Boylan, 1987). In the 1920s and 1930s, there was an explosive growth of junior colleges. This is illustrated by the fact that in 1918 there were 85 junior colleges serving 4,500 students and by 1940, there were 456 junior colleges serving 149,854 students (Levine, 1986). The arrival of the junior colleges helped the universities shoulder the burden of remediation. In 1947, the President's Commission on Higher Education recommended that the junior colleges take over the task of remediation (Ostar, 1991). In the 1980s, the issue of remediation again became an important issue. This began with the report *A Nation At Risk*, by the National Commission on Excellence in Education. The report called for high schools to provide a solid foundation in english, math, science, and social studies (Goldberg & Harvey, 1983). In addition, the commission recommended that all institutions of higher education raise their entry requirements.

Remediation is not a silent issue in the 1990s, nor are the southern states free from these concerns. A 1991 report by the Southern Regional Education Board (SREB), shows that over 90 percent of the colleges and universities surveyed in the SREB region (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia) have remedial/developmental programs and that more than a third of the first-time freshmen were enrolled in at least one remedial course (Abraham, 1991). About 85 percent of the responding institutions had at least one remedial course in reading, writing, or mathematics (Abraham, 1992). In a survey of two and four year colleges, Schonberger (1985) found an average of two remedial mathematics courses per institution. In Oklahoma, the level of remediation for first-time freshmen in the Fall 1992 semester was 29 percent (Oklahoma State Regents for Higher Education, 1993a), and mathematics accounts for 65 percent of the remedial enrollments.

Placement

The question most closely associated with remediation is, "Who needs to take remedial classes?". The study of placement is the quest to find the answer to this question. It is important to note that this is different from who should be admitted to the institution, even though many times prospective students are given the same exams for admissions as they are for placement.

Typically, however, placement exams are more narrow in focus and cutoffs are usually more stringent for placement. Abraham (1987) defines placement as "... the process of deciding whether students admitted to college have the skills and knowledge necessary to begin courses that count toward an undergraduate degree" (p. 3). For the purpose of this study, Abraham's description of placement will be used as the definition. Placement essentially boils down to trying to predict grades of students in particular courses. One of the major tools for predicting grades is statistical regression, which is used in this study.

After defining placement, one might ask, "Who uses placement and what do they use it for?". The quick and simple answer to this question is that most institutions of higher learning have some sort of placement policy. Furthermore, these policies are used for a wide variety of disciplines. For example, there are studies pertaining to placement in engineering and computer science (Nordstrom, 1989), political science and history (Georgakakos, 1990), english (Digby, 1986; Bauer, 1987), and statistics (Ware & Chastain, 1989). English and mathematics are the disciplines that most often have placement policies. Part of the reason for this is that many institutions of higher education require english and mathematics for completion of the degrees they offer. Another reason is that many students need remedial help in these areas. Abraham (1991) found that 38.5 percent of the entering freshmen in the SREB states needed remedial assistance in mathematics.

The next question is, "Who has placement policies?". In a survey of 99 California community colleges, Rounds and Anderson (1982) found that assessment for english placement was required by 56 percent of the institutions and 25 percent of the schools had required placement procedures in mathematics. In a survey of 14 junior and community colleges in Mississippi, Young (1993) found that 77.5 percent of the students were assessed in mathematics. In a survey of 683 community and junior colleges, Woods (1985) found that over 90 percent used tests to place first-time freshmen into proper courses. In addition, Woods indicated that placement in mathematics and language arts was expected to increase. In a survey of 606 SREB colleges and universities, Abraham (1992) found that over 80 percent had written policies to govern the placement of students into remedial courses. Moreover, at least 45 percent of the public institutions in the survey indicated that they were guided by state or system level policies. These studies indicate that a large portion of higher education institutions have policies regarding placement. With this in mind, the next question to answer is, "What do institutions use to place students?".

Most likely, the simplest placement system involves the use of a placement test. This system involves giving students that have been admitted to the institution a placement exam, and determining whether the students got enough of the questions correct to be placed into college-level courses. There is a great deal of variety in placement tests, ranging from institutionally developed tests to the Mathematical Association of America's math placement test (Melanacon & Thompson,1990) to computerized placement tests (CPTs). No matter which test is used, however, the strategy is still the same: The student takes the exam, scores above or below the cutoff score, and is placed into the appropriate course.

Many institutions develop their own placement tests. In an SREB survey of 606 institutions of higher education, Abraham (1992) found that institutionally developed tests were the most frequently used tests in placement, while the composite ACT score came in a distant second. In a survey of California community colleges, Rounds and Andersen (1984) found that the most frequently used placement scheme involved locally developed tests. Some studies that look at these locally developed tests in terms of how well they place students include: Johnson (1983), Clark (1982), Akst and Hirsch (1991), Grulick (1986), Mills (1993), Hudson (1989), and Spahr (1983). For the most part, the results of such studies are mixed. Some institutions find that the locally developed test lacks the precision necessary for placing students, and some find that their own in-house exams are better for placing students than either the ACT or SAT. One advantage to using a locally developed placement test is that the test can be tailored to fit a specific course. One disadvantage is that the test can cost the institution time and money for development and grading.

Two exams commonly used for single variable placement into mathematics courses are the ACT and the SAT. Studies that discuss using these variables include: College Entrance Examination Board (1984a), Dwinell (1985), Noble and Sawyer (1987), ERIC Clearinghouse for Junior Colleges (1982). In 1993, the State Regents of Oklahoma passed a three-point plan to better prepare students for college (Oklahoma State Regents for Higher Education, 1993b). In particular, the plan requires students who score below a 19 on an ACT subtest to take the specified remedial course, or undergo additional testing to determine their readiness for college level work. For example, first-time freshmen coming to Oklahoma State University (OSU) that have an 18 on the ACT mathematics subtest will be given the option of taking Intermediate Algebra or taking a computerized mathematics test to determine their readiness for college level mathematics. Failure to pass the computerized mathematics test will force the student into Intermediate Algebra. If the student passes the test, he or she may take College Algebra. The major advantage to using either the ACT or the SAT for placement is the low cost to the institution. Most high school students take one of these tests before graduating high school, and so there is no cost to the institution for grading or development. A disadvantage is that the exams may not test the topics of the course placement is being used for. If this is the case, these tests would not be appropriate to use for placement.

If locally developed tests are not used for placement, many times a combination of variables will be used. This will often take the form of a multiple regression equation. Much of the research devoted to mathematics placement using multiple regression techniques involves the ACT, SAT, and high school grade point average. In *Validating the use of ACT Assessment scores and high school grades for remedial course placement in college*, Sawyer (1989) not only validates the use of multiple regression in course placement, but outlines the steps necessary to do so. Other studies which report on multiple regression in course placement include: Sue and Abe (1988), Baron and Norman (1992), Myers and Pyles (1992), Lemay (1994), and Shoemaker (1986).

Findings for these studies are mixed. Some schools find that the ACT is a good predictor of college course grades while others find that it does not work at their institution. Some suggest that the best predictor variables are standardized tests, while others claim that high school records are better predictors. Although there are several proponents of using the ACT and SAT as predictors of college grades, there are some that suggest that the use of high school grades alone are enough to place students. Furthermore, these authors claim that the additional stress placed on high school students is not worth the small predictive ability added by either of these tests. In *The College Admissions Equation: ACT scores versus Secondary Grade Performance*, Thornell and Jones (1986) found that high school performance was a better predictor than the ACT composite score in predicting freshmen GPA. In *The Case against the SAT*, Crouse and Trusheim (1988) found that high school performance was a better predictor than the SAT in predicting college grades. These authors believe that too much emphasis is placed on the ACT and the SAT, and that more emphasis should be placed on previous work.

One way in which both the American College Testing Program (ACT) and the College Entrance Examination Board (SAT) have answered these challenges, is to provide statistical services to institutions all around the country. For those institutions wishing to evaluate their local placement tests and compare it to either the SAT or ACT, these services are free.

Essentially, these companies will generate the multiple regression equations and evaluate any variables the institution wishes to examine. Another way in which these two companies answer these challenges, is to fund many validity studies as well as running their own studies. One such project funded by the College Board is *Predicting College Grades: An Analysis of Institutional Trends over Two Decades,* edited by Willingham, Lewis, Morgan, and Ramist (1990).

Placement using the independent variables

The literature concerning mathematics placement is far from complete. This may be due to the fact that many mathematics placement procedures use institutionally developed tests to place students, and that research concerning these tests is specific to the institution and is not published. Another problem may be that there is little external funding for research (Schonberger, 1985).

This section of the review is broken down by the variables used in this study. To assist the reader in his or her own research, each section is preceded by a list of references that discuss the use of that variable in placement.

HSGPA (High School Grade Point Average)

TABLE 2.1

Thornell & Jones	1986	Crouse & Trusheim	1988
Moline	1987	Gougeon	1984
College Entrance Examination Board	1984a,b 1988	Sawyer	1989
Dwinell	1985	Sue & Abe	1988
Myers & Pyles	1992	Clark	1982

Of all the variables used for mathematics placement, three are the most prevalent: MACT, MSAT, and HSGPA. Some authors believe that the ACT and SAT are good predictors of grades and some do not. However, very few authors dispute the predictive value of HSGPA. In fact, most studies involving multiple regression and placement involve the use of HSGPA as one of the predictors.

Many validity studies look at HSGPA when considering predictive validity. Most of these studies have been compiled by the College Board and ACT. The College Entrance Examination Board (1984b) found an average correlation of .32 between HSGPA or RANK (combined) and mathematics course grades. ACT (1988) reports a median correlation of .415 between HSGPA and mathematics course grades. The ACT statistic is based on a sample of 188 colleges, while the College Board statistic is based on a sample of 23 colleges.

Based on the literature, HSGPA is expected to be positively correlated with GRD in this study.

RANK (Percentile Rank in High School Graduating Class)

TABLE 2.2

Butler & McCauley	1987	College Entrance Examination Board	1984b 1988
Moline	1987		

The use of RANK in predicting grades was more prevalent in the 1970s and early 1980s. The College Entrance Examination Board (1984b) reports that for validity studies of entering classes before 1977, 65 percent used RANK and 35 percent used HSGPA. For studies of entering classes from 1977 to 1981, only 51 percent used RANK and 49 percent used HSGPA. The ACT technical manuals do not list RANK in their validity studies. Most of the literature found for this study used HSGPA.

One possible advantage to using RANK is that it is somewhat independent of particular high schools. For example, it would not be uncommon to have several students from one high school with HSGPAs better than 3.8. It would be uncommon to find several students from the same high school with a rank of three or better. The point being that high schools could have inflated HSGPAs while it is not as common for high schools to have inflated RANKs.

The only direct reference to using RANK in predicting college mathematics grades was found in a paper by the College Entrance Examination Board (1988). This study combines RANK and HSGPA to give an average correlation of .32 with college mathematics grades.

The literature regarding RANK is not comprehensive enough to draw any conclusions about what the correlation between RANK and GRD might be.

CODE (Average Grade in College Algebra for each High School)

TABLE 2.3

Clark	1994

One of the first things that the reader notices when getting to this section is that Table 2.3 is very short! The CODE variable represents the grade average for first-time freshmen in college algebra from each high school. This variable is very scarce in the literature on placement, and yet most professional advisors will say that they use the high school a student is from when making a placement decision. Interviews with professional advisors from four colleges on the OSU campus were conducted in the Spring 1994 semester. In every case, advisors indicated that the student's high school played an important role in placing the student. The CODE variable is simply a way to quantify what advisors have been using all along.

Clark's study (1994) is an indirect reference to this variable. Clark used scores on a placement test as the criterion variable and high schools as the unit of analysis. The only major conclusion that Clark makes is that high schools can use the placement test to help improve their curriculums. This study makes direct use of the CODE variable.

The literature regarding CODE is not comprehensive enough to draw any conclusions about what the correlation between CODE and GRD might be.

ACT (Composite and Math ACT Scores)

TABLE 2.4

American College Testing Program	1989 1991a,b	National Council of Teachers of Mathematics	1995
Gibson	1989	Thornell & Jones	1986
Gougeon	1985	Sawyer	1989
Lovell & Fletcher	1989	Rounds & Andersen	1984
Hudson	1989	Myers & Pyles	1992

The use of the ACT Mathematics subtest is well documented in the studies above. The American College Testing Program (1991a) lists correlations ranging from .34 to .56 between ACT Mathematics subscores and grades in College Algebra at state universities. The technical manuals for the Enhanced ACT Assessment do not list correlations between the ACT combined score and mathematics grades. Myers and Pyles (1992) report a correlation of .35 between CACT and grades in a required mathematics course at a public regional university in Mississippi.

Based on the literature, MACT scores are expected to be positively correlated with GRD in this study. Based on Myers and Pyles (1992) report, CACT scores are expected to be positively correlated with GRD.

SAT (Total and Math SAT Scores)

TABLE 2.5

Gougeon	1984 1985	Crouse & Trusheim	1988
College Entrance Examination Board	1984a,b 1988	Dwinell	1985
Butler & McCauley	1987	Rounds & Andersen	1984
Grulick	1986	Baron and Norman	1992

The most comprehensive information concerning placement using the SAT has been collected by the College Entrance Examination Board (1984a, 1984b, 1988). The College Board reports an average correlation of .35 between the MSAT score and mathematics course grades. This is based on information from 29 colleges. None of the literature found for this study discussed the use of TSAT in predicting grades in mathematics.

Based on the literature that exists, MSAT is expected to be positively correlated with GRD. The literature regarding TSAT is not comprehensive enough to draw any conclusions about what the correlation between TSAT and GRD might be.

GRD (Final Grade in College Algebra)

TABLE 2.6

College Entrance Examination Board	1988	American College Testing Program	1987 1988 1991a
Sawyer	1989		

GRD is the criterion variable used in this study and it represents students' final grade in College Algebra. The College Entrance Examination Board (1988) discusses the use of final grades in a particular course as the criterion variable in predictive research. The College Board suggests that a common departmental examination would be a better criterion than final grades in a course. Part of the reason for this suggestion relies on the fact that grades from different instructors may not be comparable. In other words, two students of the same ability may be assigned different grades by different instructors. In this study, however, GRD is based on common exams and similar grading schemes. With this in mind, GRD is an appropriate choice of a criterion variable. In addition to this argument, it should be noted that most of the validity studies for course placement used by ACT and the College Board rely on final course grades as the criterion.

GENDER (Gender of the Student)

TABLE 2.7

Lovell & Fletcher	1989	National Council of Teachers of Mathematics	1995
Cooper & Robinson	1989	Powers	1985
Lips	1988	Reeves	1992
McConeghy	1987		

Gender is being considered so as to provide an opportunity to further gender research in mathematics. Results from the literature are mixed. In a study involving gender and mathematics, Reeves (1992) determined that there were gender differences associated with mathematics, while McConeghy (1987) and Cooper and Robinson (1989) found that there were no differences. It is expected that gender will affect some of the models generated here.

Summary

The research questions that will be addressed in this study are:

1. Is there a linear relationship between the independent variables and the dependent variable?
2. Are the coefficients in the multiple regression models nonzero?
3. For those equations that are statistically viable (i.e., nonzero coefficients and linear relationship), which variables contribute the most to the equation?
4. What are the predictive abilities for the statistically viable models?
5. Which equations are influenced by gender?

As pointed out in the last few sections there are several variables that require more research in regard to placement in mathematics. Specifically information on CACT, MSAT, RANK, and CODE is scarce in the literature regarding mathematics placement. Information on GENDER, MACT, and MSAT shows mixed results. The answers to the first three questions will help to expand the knowledge of these variables in relation to mathematics placement. The answer to Question 4 will assist researchers in understanding the value of these variables in mathematics placement. Question 5 will provide researchers working in the field of gender differences in mathematics with an avenue for additional research. The methods used to answer the research questions will be addressed in Chapter 3.

CHAPTER III

METHODS

Introduction

This section contains information about the subjects used in the study, the instruments used, and the research design. In the subjects section there is a description of the population and the methods used to select the sample. The instruments sections contains information about the ACT and the SAT. In the research design section, the methods for answering the research questions listed in Chapter 1 are discussed.

Subjects

The target population in this study includes all first-time freshmen beginning in the Fall 1991 semester and extending into the future (see the definition of first-time freshmen in the definition of terms section in the introduction). A major purpose for the models generated in this study is to predict grades in College Algebra. Consequently, the population under consideration includes first-time freshmen that will eventually come to OSU. The models should be valid until major changes take place in the course or other unseen factors change the setup being studied here. Thus, it is impossible to predict how far into the future the population will extend.

The sample used for this study is composed of all first-time freshmen from the Fall 1991 semester to the Fall 1994 semester. This sample was not randomly selected, yet this shortcoming is offset by the fact that the sample does contain all of the existing population. Since the results of this study could be used to predict performance in College Algebra, it is best to generate results based on all the information that exists rather than taking a chance that a random sample will not be representative of the population. In addition, this sample is the best possible representation of the unknown population. The original source of the data was obtained from the Freshman Admissions Office at Oklahoma State University. All data collected by the Admissions Office was obtained from high school transcripts and ACT/SAT reports. The characteristics of the sample are listed below. Note that data for some students is incomplete. For example, most students have either ACT scores or SAT scores, but not both.

Sample Size: The overall sample size for this study was 2593 students.

Gender Distribution: The sample was composed of 1134 males (43.7 percent) and 1459 females (56.3 percent).

Race Distribution: The descriptions for race come from the Freshmen Admissions Office. The sample consisted of 48 Hispanic students (1.9 percent), 61 nonresidents alien students (2.4 percent), 41 Asian students (1.6 percent), 89 African American students (3.4 percent), 179 Native American students (6.9 percent), and 2175 others (83.9 percent).

Breakdown by Beginning Semester: What follows is a breakdown of the students based on when they took College Algebra.

TABLE 3.1

Semester	Number of Students
Fall 1991	574
Fall 1992	589
Fall 1993	583
Fall 1994	589
Spring 1992	69
Spring 1993	74
Spring 1994	79
Summer 1992	20
Summer 1993	3
Summer 1994	13

The next table describes the students by each of the variables used in the study. Again note that not all students have all of the information being studied.

TABLE 3.2

Variable	Total Number of Students	Mean	Median	Standard Deviation
HSGPA	2324	3.42	3.49	0.45
RANK	2412	23	19.4	17.37
CODE	2593	2.24	2.25	0.31
MACT	2435	22.1	22	2.98
CACT	2435	23.19	23	3.17
MSAT	582	511.82	510	77.48
TSAT	582	976.05	970	138.21
GRD	2593	2.24	2	1.35
AGE	2593	17.98	18	0.41

Instruments

The only two tests used in this study are the ACT and the SAT. What follows is a discussion of the validities and reliabilities of the two tests.

ACT

The ACT Assessment is composed of four separate tests: English, mathematics, reading, and natural sciences. Each of these is designed to measure academic achievement in a major area of high school study (ACT, 1990). The raw scores for each subtest are converted to a scale score ranging from 1 to 36. The composite score (CACT) is the average of the four subtest scores.

The Mathematics subtest is composed of 60 multiple-choice questions to be answered within 60 minutes. The content of the test is composed of five areas: pre-algebra (20 percent), intermediate algebra and coordinate geometry (30 percent), plane geometry (23 percent), and trigonometry (7 percent) (American College Testing Program , 1990). The target population of the test is composed of all college bound high school juniors and seniors (Rudner, 1991).

The Enhanced ACT Assessment was first introduced in October 1989. Studies concerning the reliability and validity of the overall test and the subtests are not complete at this time. The information that does exist can be found in the *Technical Manual for the ACT Assessment Program* (1987), the *Preliminary Technical Manual* (1989), and the *Supplement to the Preliminary Technical Manual* (1991a), all published by ACT. The information that follows comes from those three manuals.

Reliability

Test-Retest Reliability: The technical manuals for the Enhanced ACT do not list test-retest reliabilities. According to Gay (1992), test-retest reliability is appropriate when alternate forms of a test are not available (p. 163). This is not the case with the ACT tests. Multiple forms for each subtest are administered on each test date. Consequently this form of reliability does not apply.

Equivalent-Forms Reliability: ACT is very thorough in constructing the exams. Tests are constructed based on item difficulties and then the individual tests are given an overall difficulty rating. Although the different forms of the test may not have the same difficulty rating, scaled scores from the test are generated based on the difficulty rating so that scaled scores are equivalent. This process eliminates the need for equivalent-forms reliability. The process is described in detail in chapter 3 of the *Preliminary Technical Manual* (1989).

Internal Consistency: Studies by ACT indicate that the ACT mathematics subtest has a KR-20 reliability of .86 to .91 with a median KR-20 of .89. The composite score has a minimum KR-20 of .94 to .95 with a median of .95.

Scorer/Rater Reliability: The ACT mathematics subtest is a 60 item multiple choice test that is scored by machine. Consequently this type of reliability does not apply to the subtest. In fact all of the subtests are multiple choice and scored by machine. Thus, this type of reliability does not apply to the composite score either.

Validity

Content Validity: Test items for the ACT test are reviewed by content consultants, measurement consultants, and minority consultants. A complete description of the process can be found in chapter 2 of the *Preliminary Technical Manual* (1989).

Construct Validity: Since the test is not designed to measure a defined construct, this type of validity is not addressed.

Concurrent Validity: Although ACT does not address concurrent validity specifically, new forms of the test are equated to existing forms so that scale scores are comparable from year to year.

Predictive Validity: This study uses the ACT mathematics subtest and the ACT composite score to predict freshman grades in College Algebra. Studies conducted by ACT show that the correlation between MACT scores and grades in College Algebra range from .34 to .56 in state universities. The technical manuals do not list correlations between the composite score on the Enhanced ACT and grades in College Algebra.

SAT

The SAT is a multiple choice test that is composed of two main subtests: Verbal and mathematics. It tests verbal ability, mathematical ability, and the ability to recognize standard written english (Brownstein, Weiner, Green, 1989). The scale scores for each half of the test range from 200 to 800. The variable TSAT used in this study is the sum of the verbal and mathematics sections of the test.

The mathematics section of the test has a total of 60 questions that require knowledge of arithmetic, elementary algebra, and geometry. The questions are all multiple choice which have five answer choices. The variable MSAT represent the score on this half of the test.

At the time of this writing, the technical manual for the SAT was out of print. However information concerning the predictive validity of the test was available. Since this is a predictive study, predictive validity is the most relevant to this research. The College Board reports an average correlation of .35 between SAT Mathematics score and mathematics course grade (Ramist, 1984). Another reference for the predictive validity of the SAT is Willingham, Lewis, Morgan, & Ramist (1990). This reference addresses predictive validity in relation to gender and in predicting freshmen GPA.

Research Design and Procedure

This research is a prediction study. In the first step of the analysis, correlations between the independent variables (HSGPA, RANK, CODE, MACT, CACT, MSAT, and TSAT) and the dependent variable (GRD) will be established. Information on multiple correlation can be found in Ott (1988), Neter, Wasserman, and Kutner (1989), and Pedhazur (1982). The multiple regression models will be generated using the statistical software package SAS.

After the models are generated, the research questions will be addressed. What follows is a description of how each research question will be answered.

Question 1: Is there a linear relationship between the independent variables and the dependent variable?

Question 2: Are the coefficients in the multiple regression models nonzero?

When SAS generates the regression models, it also generates the p-values to test both of these questions. The answer to both of these questions will use an α-level of .05. After answering the above two questions for each model generated, there will be two sets of models: A "good" set and a "bad" set. The good set will consist of all the models that demonstrated both a linear relationship and whose coefficients were statistically different from zero. The bad set will consist of all the rest. Appendix A contains a sample SAS program and a sample SAS output.

Question 3: For those equations that are statistically viable (i.e. nonzero coefficients and linear relationship), which variables contribute the most to the equation?

There are two methods for answering this question. The first is to convert all of the variables to standardized scores and rerun the regressions. An equivalent way of converting the coefficients to standardized coefficients is described Chapter 8 of Pedhazur (1982). In short, the formula for converting unstandardized coefficients into standardized ones is: $\beta_j = b_j\left(\frac{s_j}{s_y}\right)$ where β_j is the standardized coefficient, b_j is the unstandardized coefficient, s_j is the standard deviation of the jth variable, and s_y is the standard deviation of the dependent variable. The standardized coefficients can be compared across variables, unlike the original regression coefficients. After the conversion, the coefficients can be used to determine which variables have the most effect on the model. Pedhazur (1982) warns that the standardized coefficients are sample specific and cannot be used for the purpose of generalizations across settings and populations. In another study, with a different sample, the size of the standardized coefficients would most likely be different.

Question 4: What are the predictive abilities for the statistically viable models?

The answer to this question involves Success and Misplaced percents as defined in Chapter 1. Since these models may be used for placement purposes, they should be practical. Statistical tests do not always show that a model is useful. Sawyer (1989) suggests using a decision theory model to evaluate the overall effectiveness of the predictions in terms of the number of correct placement decisions versus the number of incorrect decisions. The calculation of the Success and Misplaced percents will allow for this type of evaluation.

Several multiple regression equations will be generated in this study. These equations are designed to predict grades in College Algebra. The output for such functions is between zero and four, where zero represents an F and four represents an A. The calculations for Success and Misplaced percent require a cutoff. This is a number between zero and four where students scoring above that cutoff are expected to pass College Algebra and those scoring below are expected to be unsuccessful. The logical cutoff to use in this study is 2.0 since that represents a C in College Algebra. However, study of this cutoff score reveals a gray area in the range of 1.6 to 2.0, where some of the students pass College Algebra and some of them fail the course. To provide a more accurate picture, three types of placement recommendations will be given: Yes, Maybe, and No. A recommendation of Yes means that the student is expected to pass College Algebra. A recommendation of Maybe means that the student may or may not pass the course. A recommendation of No means that the student is expected to fail College Algebra. No placement system should replace the human element. Students should still talk with professional advisors about what course they should take and those advisors can get a more accurate picture of the student's situation with the scheme described above. Success and Misplaced percents for each of the above recommendations will be addressed in Chapter 4. When computing the overall Success and Misplaced percent of the system, Maybes will count as Yes recommendations.

Question 5: Which equations are influenced by gender?

This is an area which may provide an avenue for further research. In this study, the viable regression models will be checked to see if they are unaffected by gender. In other words, is the regression equation the same for both males and females. This will be accomplished through the use of dummy variables. Information on regression using dummy variables can be found in Hardy (1993) and Pedhazur (1982). Gender will be encoded by assigning a 1 to females and 0 to males. Then for those regression models that proved viable, the variable GENDER will be added. To see if GENDER had an effect, the coefficient will be tested to see if it is nonzero. If the coefficient is nonzero, then the predicted value for females would be different than that for males. If the coefficient tests to be zero then the predicted grades in College Algebra for males and females would be the same.

CHAPTER IV

DATA ANALYSIS

Introduction

This chapter begins by looking at the correlations between the independent variables. The following section will examine models generated in this study, followed by a listing of the 35 models that survived the statistical tests listed in research questions one through three. The next section will discuss the success and misplaced percentages of the surviving models and the last section will examine what happens when gender is added to each of the surviving models.

Correlations Between the Independent Variables

The following table lists the correlations between the independent variables in this study.

TABLE 4.1

	GPA	RANK	MACT	CACT	MSAT	TSAT	CODE
GPA	1	-0.892	0.2332	0.2597	0.0769	0.1188	0.098
RANK		1	-0.2144	-0.2574	-0.0633	-0.1137	-0.01
MACT			1	0.6343	0.6543	0.5451	0.0825
CACT				1	0.5866	0.7816	0.0557
MSAT					1	0.831	0.1093
TSAT						1	0.0816
CODE							1

There are some very strong correlations between the independent variables. In particular, RANK correlates strongly with GPA, CACT correlates strongly with TSAT, and MSAT correlates strongly with TSAT. Strong correlations between independent variables in the same model typically cause the failure of one or more of the coefficients to be significantly different from zero. Consequently, models involving any of the pairs listed above are expected to fail coefficient tests.

Models

Appendix C lists all 127 models and their p-values. Of the 127 models considered, only 35 survived the coefficient tests and the test for a linear relationship. Those 35 models are listed in Table 4.2 below. Each model has two lines devoted to it: One giving the coefficient estimates, R^2 value, and mean square error (MSE), the next giving the standardized coefficients. Each line is preceded by a model name with each variable represented by one letter: G=GPA, M=MACT, A=CACT, R=RANK, C=CODE, S=MSAT, T=TSAT (INTER=INTERCEPT). The number in each model represents the number of independent variables in the model. Each model name ends with an E or a Z. The E represents the coefficient estimates and the Z represents the standardized coefficient estimates. Here is an example of how to read the table. The first two lines in the table are M1AE and M1AZ. The line M1AE contains the coefficient estimates for the one variable model involving CACT. The model equation is $GRD = .164 + .0890\,(CACT)$. The R^2 for this model is .0433 and the MSE is 1.7521. The standardized equation is $GRD = .2082\,(\text{standardized CACT})$. Note that when the equations are standardized, the intercept is always zero.

TABLE 4.2

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2	MSE
M1AE	0.1640			0.0890					0.0433	1.7521
M1AZ				0.2082						
M1CE	0.0065					0.9984			0.0539	1.7287
M1CZ						0.2322				
M1GE	-2.1919	1.2814							0.1868	1.4645
M1GZ		0.4322								
M1ME	-1.0710		0.1493						0.1083	1.6331
M1MZ			0.3291							
M1RE	2.9348				-0.0307				0.1575	1.5271
M1RZ					-0.3968					

TABLE 4.2 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2	MSE
M1SE	0.5682						0.0035		0.0441	1.6182
M1SZ							0.2100			
M1TE	0.8748							0.0015	0.0266	1.6479
M1TZ								0.1630		
M2ACE	-1.8263			0.0836		0.9497			0.0941	1.6598
M2ACZ				0.1956		0.2257				
M2ARE	1.8217			0.0462	-0.0292				0.1715	1.5109
M2ARZ				0.1082	-0.3729					
M2CSE	-1.0373					0.7626	0.0033		0.0647	1.586
M2CSZ						0.1444	0.1942			
M2CTE	-0.8592					0.8098		0.0014	0.0499	1.6111
M2CTZ						0.1534		0.1504		
M2GAE	-2.9063	1.2408		0.0364					0.1971	1.4531
M2GAZ		0.4138		0.0858						
M2GCE	-3.7642	1.2262				0.7908			0.2225	1.4008
M2GCZ		0.4136				0.1899				
M2GME	-4.0559	1.1467	0.1051						0.2403	1.3749
M2GMZ		0.3825	0.2301							
M2GSE	-2.9742	1.1670					0.0028		0.2323	1.2982
M2GSZ		0.4388					0.1686			
M2GTE	-2.4752	1.1692						0.0010	0.2143	1.3286
M2GTZ		0.4396						0.1019		
M2MCE	-2.8726		0.1414			0.8873			0.1525	1.5529
M2MCZ			0.3117			0.2108				
M2MRE	0.3029		0.1151		-0.0271				0.2217	1.4195
M2MRZ			0.2530		-0.3465					
M2RCE	0.7415				-0.0306	0.9797			0.2105	1.4315
M2RCZ					-0.3945	0.2304				
M2RSE	1.3240				-0.0254		0.0034		0.1925	1.3677
M2RSZ					-0.3786		0.1991			
M2RTE	1.7141				-0.0251			0.0014	0.1731	1.4006
M2RTZ					-0.3750			0.1425		
M3ARCE	-0.1910			0.0413	-0.0291	0.9535			0.2226	1.4184
M3ARCZ				0.0966	-0.3715	0.2263				
M3GACE	-4.3729	1.1823		0.0346		0.7692			0.2313	1.3919
M3GACZ		0.3943		0.0815		0.1861				

TABLE 4.2 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2	MSE
M3GASE	-2.5663	1.2704		-0.0463			0.0036		0.2397	1.3051
M3GASZ		0.4678		-0.1141			0.2112			
M3GCSE	-4.9206	1.1932				0.8886	0.0025		0.2618	1.2507
M3GCSZ		0.4480				0.2528	0.1497			
M3GCTE	-4.5616	1.1976				0.9349		0.0008	0.2472	1.2756
M3GCTZ		0.4503				0.1821		0.0869		
M3GMAE	-3.8347	1.1780	0.1293	-0.0374					0.2448	1.3673
M3GMAZ		0.3929	0.2833	-0.0879						
M3GMCE	-5.4019	1.0947	0.1007			0.7292			0.2709	1.32
M3GMCZ		0.3651	0.2206			0.1765				
M3MARE	0.6133		0.1362	-0.0328	-0.0279				0.2251	1.4138
M3MARZ			0.2994	-0.0768	-0.3564					
M3MRCE	-1.5393		0.1076		-0.0271	0.9000			0.2670	1.3374
M3MRCZ			0.2366		-0.3459	0.2136				
M3RCSE	-0.9004				-0.0270	1.0689	0.0030		0.2304	1.306
M3RCSZ					-0.4032	0.1972	0.1780			
M3RCTE	-0.6008				-0.0269	1.1095		0.0012	0.2140	1.3338
M3RCTZ					-0.4014	0.2046		0.1230		
M4GACSE	-4.5531	1.2879		-0.0457		0.9147	0.0033		0.2740	1.2492
M4GACSZ		0.4743		-0.1125		0.1859	0.1931			
M4GMACE	-5.1816	1.1252	0.1242	-0.0361		0.7257			0.2752	1.3129
M4GMACZ		0.3753	0.2720	-0.0850		0.1756				
M4MARCE	-1.2259		0.1291	-0.0334	-0.0279	0.9012			0.2706	1.3314
M4MARCZ			0.2838	-0.0781	-0.3558	0.2139				

As expected, models involving any of the pairs RANK and GPA, CACT and TSAT, or MSAT and TSAT failed coefficient tests. The next section lists the predictive values for these 35 models.

Predictive Values.

In this section the predictive values of the 35 models will be examined. Recall that Success Percent is the number of students receiving a Yes or Maybe placement and who made a grade of A, B, or C in College Algebra plus the number of students who received a No placement and make a grade of D, F, or W divided by the total number of students placed by the model converted to a percent. Misplaced percent is 100 minus Success Percent. Another type of predictive value that will be listed is Regents Success Percent. In the early 1990s, the State Regents for Higher Education in Oklahoma mandated that any placement system used by colleges and universities in the state must be at least 70 percent successful. Furthermore, a successful placement was defined as one in which the student was placed into College Algebra and made a grade of A, B, or C in the course. At first this does not look that different than Success Percent defined in this study. However, it differs in that students given a No placement are not considered in its calculation. For this research, Regents Success Percent is the number of students that were given a Yes or Maybe placement and made a grade of A, B, or C in College Algebra divided by the number of Yes and Maybe placements made by the model. This type of success is most relevant to colleges and universities in Oklahoma.

Table 4.3 lists the success and misplaced percents for each of the surviving models. Again the one letter convention is used for each model name: G=GPA, M=MACT, A=CACT, R=RANK, C=CODE, S=MSAT, T=TSAT. Total Placed refers to the number of students placed by each model. Recall that some students do not have all the required data and that is why different models place a different number of students. Students in Oklahoma are not required to take the SAT and that is why models with an S or a T in them placed so few students. The first model in the table is the one involving CACT. This model placed 2527 of the students in the sample with a Success Percent of 68.26, Misplaced Percent of 31.74, and a Regents Success Percent of 68.27.

TABLE 4.3

Model	Total Placed	Success Percent	Misplaced Percent	Regents Success Percent
M1A	2527	68.26%	31.74%	68.27%
M1C	2593	71.27%	28.73%	71.86%
M1G	2415	70.06%	29.94%	71.90%
M1M	2527	68.62%	31.38%	69.31%
M1R	2503	70.20%	29.80%	71.87%
M1S	598	72.07%	27.93%	72.03%
M1T	598	71.91%	28.09%	71.91%
M2AC	2435	70.97%	29.03%	72.09%
M2AR	2412	69.73%	30.27%	71.70%
M2CS	582	74.05%	25.95%	74.09%
M2CT	582	74.05%	25.95%	74.09%
M2GA	2341	70.14%	29.86%	72.10%
M2GC	2324	73.58%	26.42%	76.03%
M2GM	2341	71.21%	28.79%	73.30%
M2GS	510	74.12%	25.88%	75.83%
M2GT	510	72.75%	27.25%	75.00%
M2MC	2435	70.88%	29.12%	73.05%
M2MR	2412	71.35%	28.65%	73.40%
M2RC	2412	73.30%	26.70%	75.83%
M2RS	548	73.54%	26.46%	75.56%
M2RT	548	72.81%	27.19%	74.95%
M3ARC	2326	73.00%	27.00%	75.94%
M3GAC	2254	73.11%	26.89%	75.94%
M3GAS	436	73.85%	26.15%	76.24%
M3GCS	499	75.75%	24.25%	78.11%
M3GCT	499	75.55%	24.45%	77.80%
M3GMA	2341	71.38%	28.62%	73.57%
M3GMC	2254	73.25%	26.75%	76.52%
M3MAR	2412	71.68%	28.32%	73.57%
M3MRC	2326	73.30%	26.70%	76.51%
M3RCS	534	75.47%	24.53%	77.64%
M3RCT	534	76.22%	23.78%	78.05%
M4GACS	429	75.76%	24.24%	78.28%
M4GMAC	2254	74.22%	25.78%	77.26%
M4MARC	2326	73.43%	26.57%	76.68%

The above table lists the Success and Regents Success Percents for the entire sample. However, many times it is more useful to know these percents in the Fall semesters since that is when most new freshmen enter OSU. The table on the next page lists the Success and Regents Success percents in each of the Fall semesters included in this study. The total number of students used in each calculation of Success Percent is also listed.

TABLE 4.4

	Fall 91 Total	Fall 91 Success	Fall 91 Regents Success	Fall 92 Total	Fall 92 Success	Fall 92 Regents Success	Fall 93 Total	Fall 93 Success	Fall 93 Regents Success	Fall 94 Total	Fall 94 Success	Fall 94 Regents Success
M4MARC	529	69.38%	70.48%	524	71.56%	72.91%	518	77.80%	84.51%	557	75.04%	77.73%
M4GMAC	524	71.56%	72.96%	503	71.77%	73.63%	510	80.00%	84.62%	527	75.14%	77.19%
M4GACS	92	68.48%	72.22%	93	82.80%	83.33%	112	87.50%	87.85%	95	68.42%	69.66%
M3RCT	104	71.15%	72.22%	123	78.86%	80.91%	144	82.64%	85.19%	117	70.09%	70.37%
M3RCS	104	70.19%	71.43%	123	78.86%	80.91%	144	82.64%	85.19%	117	68.38%	69.44%
M3MRC	529	69.38%	70.48%	524	72.14%	73.30%	518	77.61%	84.01%	557	74.87%	77.57%
M3MAR	545	69.36%	68.60%	541	69.87%	70.24%	532	76.50%	82.06%	575	73.39%	75.10%
M3GMC	524	70.80%	72.22%	503	71.37%	73.15%	510	78.82%	83.63%	527	73.62%	76.43%
M3GMA	540	70.00%	70.02%	520	70.77%	71.33%	526	76.05%	81.06%	545	71.93%	73.35%
M3GCT	102	67.65%	71.60%	112	81.25%	80.61%	140	86.43%	87.02%	104	66.35%	68.75%
M3GCS	102	69.61%	72.84%	112	82.14%	82.11%	140	85.71%	86.36%	104	66.35%	68.75%
M3GAS	93	64.52%	67.95%	94	80.85%	81.25%	114	83.33%	85.19%	96	70.83%	70.79%
M3GAC	524	69.47%	70.86%	503	72.37%	73.37%	510	79.41%	83.59%	527	72.30%	75.16%
M3ARC	529	69.19%	70.02%	524	72.33%	73.05%	518	78.57%	83.89%	557	73.07%	76.41%
M2RT	106	66.04%	67.71%	124	77.42%	78.95%	147	78.91%	82.96%	122	67.21%	67.57%
M2RS	106	67.92%	69.15%	124	79.84%	81.08%	147	79.59%	83.09%	122	66.39%	66.96%
M2RC	541	69.13%	69.98%	548	72.63%	73.05%	550	79.27%	83.88%	570	72.81%	75.65%
M2MR	545	68.62%	68.23%	541	69.87%	70.24%	532	76.50%	82.06%	575	73.04%	74.80%
M2MC	557	66.61%	66.87%	550	67.09%	68.92%	541	78.37%	81.55%	565	70.44%	73.00%
M2GT	103	63.11%	67.44%	113	77.88%	77.45%	143	83.22%	84.85%	108	65.74%	67.00%
M2GS	103	65.05%	68.18%	113	81.42%	80.61%	143	83.92%	84.96%	108	65.74%	67.00%
M2GM	540	69.44%	69.71%	520	70.00%	70.47%	526	77.19%	81.30%	545	72.29%	73.55%

TABLE 4.4 cont.

	Fall 91 Total	Fall 91 Success	Fall 91 Regents Success	Fall 92 Total	Fall 92 Success	Fall 92 Regents Success	Fall 93 Total	Fall 93 Success	Fall 93 Regents Success	Fall 94 Total	Fall 94 Success	Fall 94 Regents Success
M2GC	534	68.91%	70.14%	522	72.22%	73.15%	538	80.67%	84.07%	536	72.95%	75.42%
M2GA	540	67.04%	67.52%	520	69.81%	70.02%	526	76.81%	80.56%	545	69.36%	71.46%
M2CT	113	68.14%	67.86%	136	74.26%	74.26%	153	81.70%	82.24%	126	68.25%	68.25%
M2CS	113	68.14%	67.86%	136	74.26%	74.26%	153	81.70%	82.24%	126	68.25%	68.25%
M2AR	545	64.95%	65.25%	541	68.39%	68.81%	532	76.69%	81.41%	575	71.30%	73.15%
M2AC	557	63.20%	64.24%	550	67.64%	68.15%	541	80.22%	81.42%	565	71.33%	72.83%
M1T	116	65.52%	65.52%	137	73.72%	73.72%	156	80.77%	80.77%	131	65.65%	65.65%
M1S	116	66.38%	66.09%	137	73.72%	73.72%	156	80.77%	80.77%	131	65.65%	65.65%
M1R	558	66.67%	66.19%	565	69.03%	69.32%	565	75.93%	80.85%	591	70.73%	72.23%
M1M	573	64.22%	63.40%	568	64.96%	65.49%	557	77.38%	78.99%	584	69.01%	69.93%
M1G	550	66.55%	67.04%	539	69.20%	69.58%	555	76.58%	80.32%	557	69.66%	71.26%
M1C	574	64.11%	64.63%	589	66.38%	67.08%	583	80.45%	80.91%	589	72.16%	72.85%
M1A	573	61.08%	61.08%	568	64.79%	64.66%	557	78.10%	78.20%	584	63.36%	69.62%

Models with GENDER Added

This section looks at what happens when the GENDER variable is added to the 35 models that survived the statistical tests in this study. Appendix D lists all of the models with GENDER added as well as the p-values of the coefficients. Table 4.5 below lists the models where GENDER proved to be significantly different from zero. In addition, the standardized coefficients are listed below the normal coefficient estimates. The format for Table 4.4 is exactly like Table 4.2: E represents the coefficient estimates and Z represents the standardized coefficients. The first line in the table is M1AE. This is the model involving the independent variables CACT and GENDER. The coefficient for CACT is .088 and the coefficient for GENDER is .3179. The next line is M1AZ and this gives the standardized coefficients for CACT and GENDER. The standardized coefficient for CACT is .2059 and the standardized coefficient for GENDER is .1161. Males were assigned a value of 0 and females a value of 1.

TABLE 4.5

MODEL	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	GENDER
M1AE	0.0025			0.0880					0.3179
M1AZ				0.2059					0.1161
M1CE	-0.2023					1.0085			0.3313
M1CZ						0.2345			0.1216
M1ME	-1.4834		0.1568						0.4284
M1MZ			0.3456						0.1565
M1SE	-0.1846						0.0043		0.6146
M1SZ							0.2584		0.2355
M1TE	0.4105							0.0017	0.5221
M1TZ								0.1824	0.2001
M2ACE	-1.9958			0.0826		0.9526			0.3216
M2ACZ				0.1933		0.2264			0.1174
M2CSE	-1.8181					0.7738	0.0041		0.6182
M2CSZ						0.1466	0.2427		0.2369
M2CTE	-1.3866					0.8352		0.0016	0.5319
M2CTZ						0.1582		0.1699	0.2038

TABLE 4.5 cont.

MODEL	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	GENDER
M2GME	-4.0991	1.0997	0.1100						0.1693
M2GMZ		0.3668	0.2409						0.0624
M2GSE	-3.0709	1.0933					0.0032		0.2717
M2GSZ		0.4111					0.1909		0.1042
M2MCE	-3.2777		0.1488			0.8847			0.4261
M2MCZ			0.3281			0.2102			0.1556
M2MRE	0.0418		0.1203		-0.0257				0.1954
M2MRZ			0.2645		-0.3278				0.0716
M2RSE	0.7823				-0.0227		0.0039		0.3776
M2RSZ					-0.3386		0.2295		0.1447
M2RTE	1.3773				-0.0230			0.0015	0.2929
M2RTZ					-0.3440			0.1556	0.1122
M3GASE	-2.6393	1.1849		-0.0486			0.0040		0.2936
M3GASZ		0.4363		-0.1197			0.2399		0.1109
M3GCSE	-5.0092	1.1208				0.8833	0.0029		0.2666
M3GCSZ		0.4214				0.1721	0.1720		0.1022
M3GMAE	-3.8653	1.1289	0.1365	-0.0402					0.1851
M3GMAZ		0.3765	0.2990	-0.0945					0.0682
M3GMCE	-5.4577	1.0445	0.1059			0.7346			0.1794
M3GMCZ		0.3484	0.2319			0.1778			0.0661
M3MARE	0.3642		0.1440	-0.0362	-0.0264				0.2104
M3MARZ			0.3166	-0.0846	-0.3372				0.0771
M3MRCE	-1.7955		0.1128		-0.0256	0.8990			0.1933
M3MRCZ			0.2480		-0.3273	0.2134			0.0709
M3RCSE	-1.3484				-0.0244	1.0391	0.0035		0.3555
M3RCSZ					-0.3648	0.1917	0.2072		0.1362
M3RCTE	-0.8851				-0.0249	1.0931		0.0013	0.2769
M3RCTZ					-0.3716	0.2016		0.1357	0.1061
M4GACSE	-4.5795	1.2080		-0.0478		0.8957	0.0037		0.2732
M4GACSZ		0.4448		-0.1178		0.1820	0.2201		0.1032
M4GMACE	-5.2242	1.0732	0.1317	-0.0391		0.7313			0.1947
M4GMACZ		0.3579	0.2885	-0.0919		0.1770			0.0717
M4MARCE	-1.4709		0.1368	-0.0367	-0.0264	0.9002			0.2085
M4MARCZ			0.3008	-0.0859	-0.3369	0.2137			0.0764

Note that all of the coefficients for GENDER are positive in every model. The significance of this and other interesting facts can be found in Chapter V in the section that contains the answer to Question 5.

CHAPTER V

SUMMARY

Introduction

This chapter begins by discussing the answers to the research questions posed earlier. Afterwards, there will be a discussion of which model was best overall and what the best single predictor was. The chapter ends with some ideas of how to expand this research. The models discussed in this chapter are named using the one letter convention mentioned in Chapter IV. The abbreviations are listed in the table below.

TABLE 5.1

Variable	One Letter Abbreviation
GPA	G
RANK	R
MACT	M
CACT	A
MSAT	S
TSAT	T
CODE	C

M4GMAC represents the model involving the variables GPA, MACT, CACT, and CODE.

Answer to Question 1 and Question 2

The first two research questions posed were: "Is there a linear relationship between the independent variables and the dependent variable?" and "Are the coefficients in the multiple regression models nonzero?". There were 127 models considered in this study (see Appendix C, Table C.1). In every case, there proved to be a linear relationship between the independent variables and the dependent variable. However, only 35 models had nonzero coefficients for every independent variable (listed in Table 4.2). As stated earlier in Chapter IV, this was expected. There were some strong correlations between GPA and RANK, CACT and TSAT, and MSAT and TSAT. Hence, these coefficients were expected to fail when a pair of these were included in the same model. There is one interesting twist in the data. MACT and CACT had a correlation of .6343, while MACT and MSAT had a correlation of .6543. Eight statistically viable models contain both MACT and CACT, while none of the statistically viable models contain both MACT and MSAT. Considering how close the correlations are, this is indeed strange. One might expect the correlation between MACT and MSAT to be stronger than .6543, but this correlation may be due to the sample. This number was calculated from those students that took both the ACT and the SAT and attended OSU as first-time freshmen.

Answer to Question 3

The third research question in this study was: "For those equations that are statistically viable (i.e. nonzero coefficients and a linear relationship), which variables contribute the most to the equation?". The answer to this question can be found by analyzing the rows that end in a Z in Table 4.2. The two largest contributors to the models were GPA and RANK. Since these two variables were highly correlated, they never appeared in the same model. However, these two variables dominated other variables in any model in which they appeared. GPA appeared in 14 of the 35 statistically viable models and RANK appeared in 12 of the statistically viable models. The third largest contributor was MACT since the standardized coefficient for MACT ranked next highest in all models behind RANK and GPA. MACT appeared in 10 of the 35 models. MSAT appeared in 8 of the models and CODE appeared in 18 of the models. MSAT and CODE make similar contributions to each model and consequently are the fourth and fifth largest contributors. The two least significant contributors are TSAT and CACT. TSAT appeared in 6 of the 35 models and CACT appeared in 10 of the models. Both of these variables have the smallest standardized coefficient in every model in which they appear.

Answer to Question 4

Research question 4 was: "What are the predictive abilities for the statistically viable models?". There are two types of success to be considered in answering this question: Success Percent and Regents Success Percent. Success Percent is calculated by taking the number of students given a Yes or Maybe placement who made an A, B, or C in College Algebra plus the number given a No placement who made a D, F, or W in College Algebra and dividing by the total number placed. Regents Success Percent is calculated by taking the number of students given a Yes or Maybe placement who made an A, B, or C in College Algebra divided by the number of students given a Yes or Maybe placement. Regents Success Percent is most relevant to colleges and universities in Oklahoma. The predictive abilities can be considered as overall success and as success per Fall semester. Success per Fall semester is the more practical of the two since it is desirable for the models to be stable from one freshman class to the next. All of this information can be found in Tables 4.3 and 4.4.

The top five models in overall Success Percents are the same as the top five models in Regents Success Percents: M4GACS, M3RCT, M3GCS, M3GCT, M3RCS. All of these models include one of the SAT variables. Recall that students that took the SAT comprise a small percent of the total number of students in the sample: about 23%. The SAT models above each apply to less than 600 students in the sample. Of the models that applied to at least 2200 students in the sample, M4GMAC, M4MARC, M3GMC, M3MRC, M2GC, and M2RC have the highest Success and Regents Success Percents.

There is no strong evidence that suggests which model's predictions are the best from one Fall semester to another. Examining the top five models in each Fall semester for Success Percent, models without either SAT variable dominate the Fall 1991 and 1994 semesters, while models with the SAT variable dominate the Fall 1992 and 1993 semesters. No model makes it into the top five for Success Percent more than two semesters. Considering the top five models in each Fall semester for Regents Success Percent, M3GCS and M4GACS appear in three different semesters. Again, it is important to note that the number of students having an SAT score is small compared to the total sample size. Models involving the SAT placed less than 175 students per Fall semester. Models without either SAT variable placed over 500 students per Fall semester. Considering only models without the SAT variable, M4GMAC and M3GAC appear in the top five three different semesters for Success Percent and M4GMAC appears in the top five in all four Fall semesters for Regents Success Percent. Excluding models that include the SAT variables, M4GMAC has the best record of success. This model has the highest Success Percent in the Fall 1991 and 1994 semesters and it appears in the top five in three different semesters. It clearly has the best record for Regents Success Percent since it has the highest Regents Success Percent in the Fall 1991, 1992, and 1993 semesters. It also rates in the top five in the Fall 1994 semester. This is the only model to rate in the top five for all four Fall semesters. M4GMAC also has the highest overall Success and Regents Success Percent.

Answer to Question 5

The final research question in this work was: "Which equations are influenced by gender?". Recall that the sample consisted of 1134 males and 1459 females. There are some important facts to remember when answering this question. These are summarized in the following table. It contains the average scores for each independent variable in this study broken down by gender. For example, the first line of the table indicates that the average GPA for females in the sample is 3.51, while the average GPA for males in the sample is 3.32.

TABLE 5.2

Independent Variable	Average for Females	Average for Males
GPA	3.51	3.32
MACT	21.83	22.46
CACT	23.25	23.12
RANK	19.46	27.58
CODE	2.23	2.24
MSAT	497.37	529.35
TSAT	963.89	990.8
GRD	2.38	2.06

The most important average to note is that of GRD. This average shows that females in the sample make better grades in College Algebra than males do. This explains why the coefficients for GENDER in Table 4.5 are positive. Females in the sample make better grades in College Algebra, and consequently the GENDER variable is trying to compensate by adding to the model instead of subtracting. Note that when GENDER was added to the single variable models involving RANK and the one involving GPA, the GENDER coefficient failed to be significant. The reason that this occurs comes from the fact that females have higher GPA and RANK averages and thus do not need the assistance of the GENDER variable in adding to their predicted values for College Algebra. Male averages for MACT, MSAT, CODE, and TSAT are all higher than female averages for these variables. Consequently, the GENDER variables proves to be significantly different from zero in the single variable models involving these variables. Again the reason for this comes from the fact that females in the sample made better grades in College Algebra and the GENDER variable attempts to compensate the predicted GPA for females. Females have a higher CACT average, however this average is not much higher than the male CACT average. Thus, GENDER again compensates in the single variable model involving CACT. The GENDER variable survives in all models with more than one variable that do not include RANK or GPA and this is expected for the reasons discussed above.

So far the discussion has been very general. To fully understand why GENDER survives in some models and not in others, specific grade differences and predicted grade differences need to be considered. Table 5.3 below lists the average predicted grades and real grades in College Algebra for males and females in each of the surviving 35 models (*without* GENDER added). Average Predicted Grade for Females indicates the average predicted grade for females for each particular model. Real Grade Average for Females indicates the actual grade average for females including only those placed by the particular model. Recall that some students were missing data; consequently, the number of students placed differs from model to model. Predicted Grade Difference is the difference between the Average Predicted Grade for Females and the Average Predicted Grade for Males. Real Grade Difference is the difference between Real Grade Average for Females and Real Grade Average for Males. The rows with models in which GENDER failed to be significantly different from zero are highlighted. For example, the first line of the table indicates that the average predicted grade for females using the model M4MARC is 2.28 and the average predicted grade for males is 2.15. The difference of these two numbers is .13. This line also shows that the actual grade average for females is 2.37 while the males that the model placed had an actual grade average of 2.04. The difference in the actual grade averages is .33

TABLE 5.3

Model	Average Predicted Grade for Females	Average Predicted Grade for Males	Predicted Grade Difference	Real Grade Average for Females	Real Grade Average for Males	Real Grade Difference
M4MARC	2.28	2.15	0.13	2.37	2.04	0.33
M4GMAC	2.25	2.13	0.13	2.33	2.02	0.31
M4GACS	2.47	2.22	0.24	2.57	2.08	0.49
M3RCT	2.50	2.26	0.24	2.62	2.12	0.50
M3RCS	2.47	2.29	0.18	2.62	2.12	0.50
M3MRC	2.29	2.15	0.14	2.37	2.04	0.33
M3MAR	2.28	2.15	0.13	2.37	2.04	0.33
M3GMC	2.26	2.12	0.14	2.33	2.02	0.31
M3GMA	2.26	2.12	0.13	2.33	2.02	0.31
M3GCT	2.46	2.20	0.26	2.54	2.10	0.44
M3GCS	2.44	2.24	0.20	2.54	2.10	0.44
M3GAS	2.46	2.24	0.22	2.57	2.08	0.49
M3GAC	2.30	2.07	0.23	2.33	2.02	0.31
M3ARC	2.33	2.09	0.23	2.37	2.04	0.33
M2RT	2.49	2.27	0.23	2.62	2.12	0.50
M2RS	2.47	2.31	0.16	2.62	2.12	0.50
M2RC	2.33	2.09	0.24	2.37	2.05	0.32
M2MR	2.29	2.15	0.14	2.37	2.04	0.33
M2MC	2.19	2.28	-0.09	2.37	2.04	0.33
M2GT	2.46	2.20	0.26	2.54	2.10	0.44
M2GS	2.43	2.23	0.20	2.54	2.10	0.44
M2GM	2.26	2.11	0.15	2.33	2.02	0.31
M2GC	2.30	2.07	0.23	2.33	2.03	0.30
M2GA	2.30	2.06	0.24	2.33	2.02	0.31
M2CT	2.35	2.40	-0.05	2.59	2.11	0.48
M2CS	2.32	2.43	-0.12	2.59	2.11	0.48
M2AR	2.33	2.09	0.24	2.37	2.04	0.33
M2AC	2.23	2.22	0.01	2.37	2.04	0.33
M1T	2.35	2.39	-0.04	2.59	2.11	0.48
M1S	2.32	2.43	-0.11	2.59	2.11	0.48
M1R	2.34	2.09	0.25	2.37	2.05	0.32
M1M	2.19	2.28	-0.09	2.37	2.04	0.33
M1G	2.31	2.06	0.25	2.33	2.03	0.30
M1C	2.23	2.25	-0.01	2.38	2.06	0.32
M1A	2.23	2.22	0.01	2.37	2.04	0.33

If the difference between the Average Predicted Grade for Females and the Average Predicted Grade for Males is large and the difference between the Average Real Grade for Females and the Average Real Grade for Males is small, then GENDER is expected to fail. In fact this is the case. Table 5.3 indicates that if the absolute value of the Predicted Grade difference is less than half the Real Grade difference then GENDER proves to be significant.

The above results show that the predicted grade for females is underestimated in some models. The fact that GENDER proved significant in 25 models suggests that the GENDER variable may need to be included in the overall placement system. Aside from the political consideration of using GENDER in placement, the next major concern would be how GENDER affects success percents of the models. Table 5.4 below lists the success percent of the 25 models in which GENDER proved significantly different from zero. The columns are as follows:

- Model - Each model name represents two models one with GENDER and one without GENDER. M/G1A represents the one variable model with CACT and the two variable model using CACT and GENDER
- Success Without Gender - This is the Success Percent of the model without the GENDER variable added.
- Success With Gender - This is the Success Percent of the model with the GENDER variable added.
- Gender-Nongender - This is the difference of the Success Percents in the previous two columns.
- Regents Success Without Gender - This is the Regents Success Percent of the model without GENDER.
- Regents Success With Gender - This is the Regents Success Percent with GENDER added.
- Regents Gender-Nongender- This is the difference of the Regents Success Percents in the previous two columns.

The end of the table contains the maximum, minimum, and average of each column.

TABLE 5.4

Model	Success Without Gender	Success With Gender	Gender - Nongender	Regents Success Without Gender	Regents Success With Gender	Regents Gender - Nongender
M/G1A	68.26%	70.92%	2.66%	68.27%	71.07%	2.80%
M/G1C	71.27%	71.38%	0.12%	71.86%	72.19%	0.33%
M/G1M	68.62%	70.88%	2.26%	69.31%	72.59%	3.28%
M/G1S	72.07%	74.40%	2.33%	72.03%	74.61%	2.58%
M/G1T	71.91%	73.88%	1.98%	71.91%	73.97%	2.06%
M/G2AC	70.97%	71.46%	0.49%	72.09%	72.48%	0.40%
M/G2CS	74.05%	74.40%	0.34%	74.09%	74.78%	0.69%
M/G2CT	74.05%	74.23%	0.17%	74.09%	74.39%	0.30%
M/G2GM	71.21%	72.63%	1.42%	73.30%	75.66%	2.37%
M/G2GS	74.12%	74.15%	0.03%	75.83%	76.94%	1.11%
M/G2MC	70.88%	71.46%	0.57%	73.05%	74.04%	1.00%
M/G2MR	71.35%	73.47%	2.12%	73.40%	76.13%	2.72%
M/G2RS	73.54%	75.84%	2.30%	75.56%	77.96%	2.41%
M/G2RT	72.81%	74.72%	1.91%	74.95%	76.89%	1.94%
M/G3GAS	73.85%	74.13%	0.27%	76.24%	77.27%	1.03%
M/G3GCS	75.75%	74.75%	-1.00%	78.11%	77.60%	-0.51%
M/G3GMA	71.38%	73.16%	1.78%	73.57%	76.18%	2.61%
M/G3GMC	73.25%	73.87%	0.62%	76.52%	76.95%	0.44%
M/G3MAR	71.68%	73.65%	1.96%	73.57%	76.02%	2.44%
M/G3MRC	73.30%	73.47%	0.17%	76.51%	76.69%	0.19%
M/G3RCS	75.47%	76.03%	0.56%	77.64%	78.13%	0.49%
M/G3RCT	76.22%	75.66%	-0.56%	78.05%	77.80%	-0.25%
M/G4GACS	75.76%	75.06%	-0.70%	78.28%	78.11%	-0.18%
M/G4GMAC	74.22%	73.96%	-0.27%	77.26%	77.04%	-0.22%
M/G4MARC	73.43%	74.03%	0.60%	76.68%	77.01%	0.33%
Max	76.22%	76.03%	2.66%	78.28%	78.13%	3.28%
Min	68.26%	70.88%	-1.00%	68.27%	71.07%	-0.51%
Avg	72.78%	73.66%	0.89%	74.49%	75.70%	1.21%

Table 5.4 shows that the GENDER variable improves the Success Percents of some models and not others. The models that show the greatest improvement from the addition of the GENDER variable are the single variable models involving MACT and CACT. As discussed earlier, the MACT variable underestimates female grades in College Algebra. Consequently, the

addition of the GENDER variable to this model compensates for the lower estimate. The averages in the difference columns show that GENDER does not add a great deal to the Success Percents of the models. When this system of models is put into use, very few students would be placed by the single variable models involving MACT and CACT. This is because most students would enter the university with more information than MACT and CACT. At OSU, most first-time freshmen would be placed using one of the four variable models. Considering the fact that GENDER does not make a large contribution to the Success Percents of the models and the political dilemma involved in using GENDER in placement, it should not be used in the placement system.

Trying to Choose a Best Overall Model

In trying to choose the best overall model, two types of evaluation must be performed: Statistical and practical. Models with the same number of variables can be compared using the R^2 value of each model. Since adding a variable to a model cannot decrease the R^2 value, models with a different number of variables cannot be compared using the R^2. Another statistic commonly used to compare models with a different number of variable is the Mean Square Error (MSE). That is the statistic that will be used for comparison here. The lower the MSE of a model, the more sound it is statistically. Practical evaluation involves the use of Success Percents and Regents Success Percents discussed earlier.

The top five models with the lowest MSE are: M4GACS (1.2492), M3GCS (1.2507), M3GCT (1.2756), M2GS (1.2982), M3GAS (1.3051). Note that all of these models involve the SAT variables. The top five models without SAT are: M4GMAC (1.3129), M3GMC (1.32), M4MARC (1.3314), M3MRC (1.3374), M3GMA (1.3673).

The top five models with the highest Success Percents are: M3RCT (76.22%), M4GACS (75.76%), M3GCS (75.75%), M3GCT (75.55%), M3RCS (75.47%). The top five models with the highest Regents Success Percents are: M4GACS (78.28%), M3GCS (78.11%), M3RCT (78.05%), M3GCT (77.8%), M3RCS (77.64%). Note that all of these involve the SAT variables. Excluding the SAT variables, the top five models with the highest Success Percents are: M4GMAC (74.43%), M2GC (73.58%), M4MARC (73.43%), M3MRC (73.3%), M2RC (73.3%). The top five variables with the highest Regents Success Percents are: M4GMAC (77.26%), M4MARC (76.68%), M3GMC (76.52%), M3MRC (76.51), M2GC (76.03%).

There is one definitive answer here: When the SAT variables are excluded, the best overall model is M4GMAC. Due to the small number of students in the sample that have the SAT variable, this may be the best answer to the question. If, however, the SAT variables are included, M4GACS is the best model overall since it has the lowest MSE and one of the highest Success and Regents Success Percents.

Picking the Best Single Predictor

When looking for the best single predictor it is important to consider both the statistical and practical aspects of the variables. Since only one variable models are considered here, the R^2 values can be used to compare across models. The practical evaluation involves the Success and Regents Success Percents.

The single variable models with the highest R^2 values are the ones involving GPA (.1868) and RANK (.1575). The single variable models that have the highest success percents involve MSAT and TSAT. This conflicting information does not give conclusive evidence of which variable is the best predictor. If, however, the SAT variables are excluded then GPA and RANK are the best predictors of grades in College Algebra.

A Practical Example

This section discusses how to set up a placement system within a university setting. Following that, a discussion of how the models in this study would have done had they been put into practice in the Fall 1994 semester.

The steps listed below give an example of how to set up a placement system similar to the one discussed in this research. It is listed in step by step format.

Step 1: The first step is decide what years should be considered in the data. If grade in College Algebra (GRD) is to be the dependent variable, it is important to consider the consistency of the course from term to term. Changing books, for example, may have an effect on GRD. Changing from large sections to small ones can also have an effect. Try to choose terms in which College Algebra is as consistent with the current course as possible.

Step 2: The second step is gain permission for the study and to collect the data on each first-time freshman in the terms being studied. Gaining permission to collect the data is very important here. Many institutions have review boards that grant permission for studies of this type. After gaining permission, find out what information the institution collects from the students. It is cheaper and easier to use information that the university collects anyway. Try to get all information that may be relevant to grades in College Algebra.

Step 3: Review the literature on placement to see what variables have been used before. Any variable used in placement must have some theoretical relation to grades in College Algebra. Other sources for finding variables are professional advisors on campus.

Step 4: Using a statistical package, like SAS, generate and evaluate the models. Models which contain variables whose coefficient is not significantly different from zero should not be included in the placement system. Models in which there fails to be a linear relationship between the independent variables and the dependent variable should be eliminated also. This should leave a set of statistically viable models.

Step 5: The next step is to evaluate the models practically. To use Success Percent discussed in this research, cutoff scores must be established. This can take some time. It is easier to start with what should constitute a College Algebra placement. This is the same as the Yes placement discussed in this study. One way is to set a cutoff and then calculate the Success Percent, then set another and calculate the percent again. Some students close to the cutoff that is set will probably pass College Algebra and some will fail. This will generate a gray area in the cutoff scheme where the placement system will not be efficient. If placement at the institution is voluntary, advisors are going to have to be a part of the system. In this study, advisors were asked to work with students in the gray area. The gray area in this paper involves the Maybe placements.

Step 6: At this point the statistically viable models have cutoffs. There are some details that need to be ironed out however. Here are some of the questions that need to be answered at this point.

If a student has enough information to be placed with two different models, which one should be used?

It is best to place students with the most information possible. Consequently, students should be placed with the model that has the most variables in it. For example, if a student can be placed with a four variable model and a three variable model, then he or she should be placed with the four variable model. Another way to handle this question is to always place students with the model that has the highest success percent. The method used in the example below is to place students with the model that has the largest number of variables. If he or she can be placed with two models with the same number of variables, the maximum placement is taken. For example, if the student can be placed with two of the four variable models and one model gives a No placement and the other gives a Maybe placement, then the student is given the Maybe placement.

How does the placement information get to the advisors?

Here is an example of how the system could work: The student applies to the university listing some or all of the placement variables. The university admissions office collects this information and passes it on to the placement agency (Math department, university assessment, etc.). The placement agency calculates the placement of the student and generates a College Algebra placement letter (Yes, Maybe, or No). This letter then travels back to the admissions office to be placed in the student's folder. The student then takes the folder to his or her advisor when enrolling for classes. Maybe letters let the advisor know that he or she needs to pay special attention to the student as far as placement in College Algebra.

The success percents discussed so far have been for each model when the model was applied to everyone in the sample with the correct variables. In practice a student would only be placed with one model rather than five. This example looks at what would have happened in the Fall 1994 semester if the models in this study had been put into practice. The Fall 1994 students were examined to determine which models would apply to them. Students were placed with the model with the largest number of variables which applied to them individually. There were 611 first-time freshmen that took College Algebra in the Fall 1994 semester. Of these students, 561 were placed with one of the four variable models, 33 placed with one of the three variable models, 10 placed with one of the two variable models, and 7 placed with one of the one variable models. If students could be placed with more than one of the models with the same number of variables, they were given the highest placement of those models. For example, if the student can be placed with two of the four variable models and one model gives a No placement and the other gives a Maybe placement, then the student is given the Maybe placement. The Success Percent of this system was 71.03% and the Regents Success Percent of this system was 72.38%.

These results could change once the advisors were incorporated into the system. In this example, only 42.67% of the Maybe placements were successful.

Ideas for Further Research

The following is a list of ideas for further research.

1. The methods could be expanded to other universities. It is doubtful that these methods could be applied to an entire state with high success percents at each university. There is too much variation in courses from institution to institution.

2. The methods could be expanded to include other courses: Calculus, Precalculus, etc.

3. Placement for transfer and non-traditional students needs a great deal of work. A variation of the CODE variable in this study may work for junior and community colleges.

Concluding Remarks

It is unlikely that a perfect placement system will ever be developed. Human beings are far too complex to ever be explained by a simple mathematical model. Furthermore, it is impossible to predict all the situations students will find themselves in when they go to college, nor can their reactions to these situations be predicted. However, a step which could bring a placement system closer to perfection would be to include a measure of long term motivation. It is the author's belief that GPA measures, at least in part, a student's long term motivation. A more accurate measure could improve a placement system dramatically. Until variables like long term motivation can be measured, researchers will have to strive for perfection as best they can.

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APPENDIX A

EXAMPLE OF SAS PROGRAM AND OUTPUT

Example of SAS Program

```
1 Data Math;
2 Infile 'math.txt';
3 Input GRD 1 MACT 3-4 HSGPA 6-9 CODE 11-14;
4 run;
5 PROC REG Data=Math;
6   MODEL GRD=MACT HSGPA CODE ;
7 RUN;
8 PROC REG Data=Math;
9   MODEL GRD=MACT HSGPA;
10 RUN;
```

Lines one through four of the program input the data set Math into SAS from an external text file math.txt. Lines five through seven calculate the regression equation with GRD as the dependent variable and MACT, HSGPA, and CODE as the independent variables. Lines eight through ten calculate the regression equation with GRD as the dependent variable and MACT and HSGPA as independent variables. A sample output of this program is listed below.

Example of SAS Output

Model: MODEL1
Dependent Variable: GRD

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	350.61628	116.87209	115.650	0.0001(I)
Error	472	476.98666	1.01056(II)		
C Total	475	827.60294			

Root MSE	1.00527	R-square	0.4237(III)
Dep Mean	2.30882	Adj R-sq	0.4200
C.V.	43.54030		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-3.900297	0.39907889	-9.773	0.0001
MACT	1	0.002259	0.00057790	3.910	0.0001(IV)
HSGPA	1	1.040455	0.09728700	10.695	0.0001
CODE	1	0.764966	0.06932110	11.035	0.8567

(I) This is the p-value associated with the test of a linear relationship. If this value is less than .05 then there is a linear relationship between the independent variables and the dependent variable. There are two equivalent statistical interpretations of this statistic. The first involves the null hypothesis that all of the coefficients are zero versus at least one of the coefficients being nonzero (i.e. $H_0 : \beta_1 = \beta_2 = ... = \beta_k = 0$, $H_1 :$ Some $\beta_i \neq 0$). This is equivalent to testing whether or not $R^2 = 0$. If R^2 is statistically different from zero then a significant portion of the variance in the dependent variable is explained by a linear relationship with the independent variables.

(II) This value is the mean square error (MSE) associated with the equation. This is the statistic commonly used to compare models with different numbers of variables. The smaller the MSE, the less error associated with the model. The above model has a smaller MSE (1.01) than the model below (1.34). Consequently, the above model contains less error and hence is a better model statistically.

(III) This is the R^2 value associated with the equation. It explains how much of the variance in the dependent variable is explained by a linear relationship with the independent variable. In this example about 42 percent of the variance of GRD is explained by a linear relationship with MACT, HSGPA and CODE.

(IV) This is the p-value associated with the test of coefficients being zero. If this value is less than .05, then the coefficient is statistically different from zero. In this example, the only coefficient which fails to be significantly different from zero is the CODE coefficient.

Note: These examples do not represent real data used in this study.

Model: MODEL1
Dependent Variable: GRD

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	1412.16980	706.08490	512.314	0.1051
Error	2560	3528.26017	1.37823		
C Total	2562	4940.42996			

Root MSE	1.17398	R-square	0.2858
Dep Mean	2.09988	Adj R-sq	0.2853
C.V.	55.90688		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-2.420605	0.16829212	-14.383	0.0001
MACT	1	0.125003	0.00766948	16.299	0.0001
HSGPA	1	0.854233	0.03751078	22.773	0.0001

This model fails the linear relationship test with a p-value of .1051. This means that there is not a linear relationship between the dependent variable and the independent variables at the $\alpha = .05$ level. Consequently, the model would not be considered for the research questions three through five.

APPENDIX B

ASSUMPTIONS OF LINEAR REGRESSION

This appendix contains a list of the assumptions associated with linear regression. To simplify the list, the assumptions are written for simple linear regression, although they apply to all of the independent variables in multiple regression.

The basic linear regression model is of the form $y_i = b_0 + b_1 x_i + e_i$ where:

y_i is the value of the ith response variable

b_0 is the intercept of the equation

b_1 is the slope of the equation

x_i is the ith value of the independent variable

e_i is the ith error term or ith residual

The assumptions concerning linear regression are:

1. The relationship between x and y is assumed to be linear rather than curvilinear.
2. The independent variable is assumed to be measured without error.
3. The mean of errors for each observation y_i over many replications is zero.
4. The population of errors associated with one observed value of y_i are not correlated with the population of errors associated with another observation y_j, for i not equal to j. For example the population of errors associated with y = 2 are not correlated with the population of errors associated with y = 3.
5. The variance of errors at each x_i is constant. This is where x_i is held fixed and y is allowed to vary.
6. The errors are assumed not to be correlated with x.
7. The population of errors are assumed to be normally distributed.

The first six assumptions are necessary to obtain the best linear unbiased estimators. An estimator is said to be unbiased if its average obtained from repeated samples of size N is equal to the (unknown) parameter. Assumption 7 is necessary for tests of significance.

Assumption 2 is not met in this study. One reason is that the Math ACT score is not measured without error. This problem will produce underestimates of R^2. This may cause the rejection of some models during some of the statistical tests.

Failure to meet all of the assumptions is not uncommon in this type of research. One major purpose of this study is to produce tools that can assist advisors in placing students into the correct courses. Some models may be eliminated needlessly because of the failure of assumptions, but the models that survive will be statistically sound. The errors associated with the failure of assumptions cause the rejection of models rather than the accepting them when they are not statistically valid. Evaluation based on Success and Misplaced percent will also help to determine the usefulness of the models.

The diagnostic techniques designed for evaluating failures of assumptions are beyond the scope of this study. More than 127 models are being considered in this research, and the time necessary to evaluate all of the failed models would be enormous. Future studies may involve looking at the models that were not statistically viable in terms of these assumptions.

Complete discussions regarding linear regression assumptions and diagnostic techniques for evaluating failures of assumptions can be found in Pedhazur (1982) and Neter, Wasserman, and Kutner (1989).

APPENDIX C

INFORMATION ABOUT ALL REGRESSION MODELS

This appendix contains the coefficient estimates and the p-values for all of the 127 models considered in this study. Information about each models is broken into two lines: one line listing the coefficient estimates and the next line contains the p-values for the coefficients. Each line is preceded by a model name with each variable represented by one letter: G=GPA, M=MACT, A=CACT, R=RANK, C=CODE, S=MSAT, T=TSAT (INTER=INTERCEPT). The number in each model represents the number of independent variables in the model. Each model name ends with an E or a P. The E represents the coefficients and the P represents the p-values. The p-values are associated with the test that the coefficient is zero. P-values that are less than .05 indicate that the coefficient is significantly different from zero. These p-values are highlighted.

The first two lines in Table C.1 are M1AE and M1AP. M1AE indicates that the one variable model using CACT is GRD = 1.6403 + .08896 (CACT) and that the R^2 for this model is .0433. The second line M1AP indicates that the coefficient for CACT is significantly different from zero, and that the R^2 is significantly different from zero.

TABLE C.1

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M1AE	0.16403			0.08896					0.0433
M1AP	0.4084			0.0001					0.0001
M1CE	0.00648					0.99845			0.0539
M1CP	0.9721					0.0001			0.0001
M1GE	-2.1919	1.28136							0.1868
M1GP	0.0001	0.0001							0.0001
M1ME	-1.071		0.14928						0.1083
M1MP	0.0001		0.0001						0.0001
M1RE	2.93475				-0.0307				0.1575
M1RP	0.0001				0.0001				0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M1SE	0.56816						0.00352		0.0441
M1SP	0.1076						0.0001		0.0001
M1TE	0.87478							0.00153	0.0266
M1TP	0.0216							0.0001	0.0001
M2ACE	-1.8263			0.08359		0.94967			0.0941
M2ACP	0.0001			0.0001		0.0001			0.0001
M2ARE	1.82169			0.04622	-0.0292				0.1715
M2ARP	0.0001			0.0001	0.0001				0.0001
M2ASE	-0.1492			0.0381			0.0032		0.0663
M2ASP	0.7485			0.0861			0.0005		0.0001
M2ATE	0.237			0.0534				0.0009	0.0459
M2ATP	0.6041			0.0668				0.1862	0.0001
M2CSE	-1.0373					0.76258	0.00326		0.0647
M2CSP	0.0688					0.0004	0.0001		0.0001
M2CTE	-0.8592					0.80981		0.00142	0.0499
M2CTP	0.1482					0.0002		0.0002	0.0001
M2GAE	-2.9063	1.24082		0.03645					0.1971
M2GAP	0.0001	0.0001		0.0001					0.0001
M2GCE	-3.7642	1.22622				0.79078			0.2225
M2GCP	0.0001	0.0001				0.0001			0.0001
M2GME	-4.0559	1.1467	0.10507						0.2403
M2GMP	0.0001	0.0001	0.0001						0.0001
M2GRE	-2.2236	1.2874			0.0002				0.1835
M2GRP	0.0001	0.0001			0.9507				0.0001
M2GSE	-2.9742	1.16697					0.00284		0.2323
M2GSP	0.0001	0.0001					0.0001		0.0001
M2GTE	-2.4752	1.16924						0.00096	0.2143
M2GTP	0.0001	0.0001						0.0113	0.0001
M2MAE	-1.0676		0.1496	-0.0004					0.1083
M2MAP	0.0001		0.0001	0.9691					0.0001
M2MCE	-2.8726		0.14139			0.88726			0.1525
M2MCP	0.0001		0.0001			0.0001			0.0001
M2MRE	0.30287		0.11506		-0.0271				0.2217
M2MRP	0.1295		0.0001		0.0001				0.0001
M2MSE	-1.0405		0.1459				0.0002		0.1327
M2MSP	0.0148		0.0001				0.8126		0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M2MTE	-1.0048		0.1497					-9E-06	0.1326
M2MTP	0.027		0.001					**0.9857**	0.0001
M2RCE	0.74153				-0.0306	0.97971			0.2105
M2RCP	0.0001				0.0001	0.0001			0.0001
M2RSE	1.32404				-0.0254		0.00339		0.1925
M2RSP	0.0002				0.0001		0.0001		0.0001
M2RTE	1.71414				-0.0251			0.00137	0.1731
M2RTP	0.0001				0.0001			0.0004	0.0001
M2STE	0.6441						0.004	-0.0004	0.0445
M2STP	0.0932						0.001	**0.6111**	0.0001
M3ACSE	-1.9919			0.0397		0.8638	0.0029		0.096
M3ACSP	0.0024			**0.0694**		0.0001	0.0014		0.0001
M3ACTE	-1.72			0.0566		0.9062		0.0007	0.0787
M3ACTP	0.0088			0.0483		0.0001		**0.2818**	0.0001
M3ARCE	-0.191			0.04125	-0.0291	0.95351			0.2226
M3ARCP	0.4594			0.0001	0.0001	0.0001			0.0001
M3ARSE	1.8699			-0.0282	-0.0267		0.0038		0.1961
M3ARSP	0.0002			**0.2058**	0.0001		0.0001		0.0001
M3ARTE	2.2641			-0.029	-0.0267			0.0016	0.174
M3ARTP	0.0001			**0.321**	0.0001			0.0147	0.0001
M3ASTE	-0.1719			0.0732			0.0051	-0.0018	0.0729
M3ASTP	0.7112			0.0125			0.0002	**0.0662**	0.0001
M3CSTE	-0.9967					0.761	0.0037	-0.0003	0.065
M3CSTP	0.102					0.0004	0.0024	**0.6498**	0.0001
M3GACE	-4.3729	1.18226		0.03464		0.76915			0.2313
M3GACP	0.0001	0.0001		0.0001		0.0001			0.0001
M3GARE	-3.0644	1.2866		0.035	0.0013				0.1948
M3GARP	0.0001	0.0001		0.0001	**0.7033**				0.0001
M3GASE	-2.5663	1.27044		-0.0463			0.00357		0.2397
M3GASP	0.0001	0.0001		0.0419			0.0001		0.0001
M3GATE	-2.1837	1.265		-0.0389				0.0013	0.2185
M3GATP	0.0001	0.0001		**0.1925**				0.0493	0.0001
M3GCSE	-4.9206	1.19324				0.88865	0.00252		0.2618
M3GCSP	0.0001	0.0001				0.0001	0.0001		0.0001
M3GCTE	-4.5616	1.1976				0.93492		0.00082	0.2472
M3GCTP	0.0001	0.0001				0.0001		0.0278	0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M3GMAE	-3.8347	1.17797	0.12934	-0.0374					0.2448
M3GMAP	0.0001	0.0001	0.0001	0.0002					0.0001
M3GMCE	-5.4019	1.09472	0.10071			0.72919			0.2709
M3GMCP	0.0001	0.0001	0.0001			0.0001			0.0001
M3GMRE	-4.1954	1.1742	0.106		0.0008				0.2395
M3GMRP	0.0001	0.0001	0.0001		0.8067				0.0001
M3GMSE	-3.4224	1.0589	0.0947				0.0002		0.2607
M3GMSP	0.0001	0.0001	0.0001				0.8494		0.0001
M3GMTE	-0.3158	1.0645	0.1109					-0.0006	0.2634
M3GMTP	0.0001	0.0001	0.0001					0.2055	0.0001
M3GRCE	-3.0537	1.0272			-0.0057	0.8346			0.2218
M3GRCP	0.0001	0.0001			0.0765	0.0001			0.0001
M3GRSE	-3.7084	1.3311			0.0054		0.0029		0.2198
M3GRSP	0.0002	0.0001			0.3585		0.0001		0.0001
M3GRTE	-3.1706	1.337			0.0054			0.001	0.2
M3GRTP	0.0015	0.0001			0.3564			0.0162	0.0001
M3GSTE	-2.7711	1.1859					0.0046	-0.0012	0.2373
M3GSTP	0.0001	0.0001					0.0001	0.0714	0.0001
M3MACE	-2.865		0.142	-0.0009		0.8873			0.1525
M3MACP	0.0001		0.0001	0.929		0.0001			0.0001
M3MARE	0.61332		0.13617	-0.0328	-0.0279				0.2251
M3MARP	0.0057		0.0001	0.0013	0.0001				0.0001
M3MASE	-0.9141		0.1523	-0.0155			0.0004		0.1335
M3MASP	0.0502		0.0001	0.5035			0.6665		0.0001
M3MATE	-0.9213		0.1559	-0.0223				0.0003	0.1336
M3MATP	0.0489		0.0001	0.4545				0.623	0.0001
M3MCSE	-2.8269		0.1454			0.8486	-1E-05		0.1614
M3MCSP	0.0001		0.0001			0.0001	0.9886		0.0001
M3MCTE	-2.7939		0.1473			0.85		-9E-05	0.1615
M3MCTP	0.0001		0.0001			0.0001		0.8513	0.0001
M3MRCE	-1.5393		0.1076		-0.0271	0.89999			0.267
M3MRCP	0.0001		0.0001		0.0001	0.0001			0.0001
M3MRSE	0.3344		0.1029		-0.0221		0.0006		0.2273
M3MRSP	0.4669		0.0001		0.0001		0.5207		0.0001
M3MRTE	0.5249		0.1182		-0.022			-0.0003	0.227
M3MRTP	0.2824		0.0001		0.0001			0.5896	0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M3MSTE	-0.994		0.1459				0.0005	-0.0002	0.1329
M3MSTP	0.0291		0.0001				**0.7058**	**0.7684**	0.0001
M3RCSE	-0.9004				-0.027	1.06893	0.00303		0.2304
M3RCSP	0.106				0.0001	0.0001	0.0001		0.0001
M3RCTE	-0.6008				-0.0269	1.10948		0.00118	0.214
M3RCTP	0.302				0.0001	0.0001		0.0017	0.0001
M3RSTE	1.5016				-0.0257		0.0045	-0.0008	0.1944
M3RSTP	0.0001				0.0001		0.0002	**0.2672**	0.0001
M4ACSTE	-2.0194			0.0752		0.8659	0.0048	-0.0018	0.1027
M4ACSTP	0.0021			0.0092		0.0001	0.0004	**0.0592**	0.0001
M4ARCSE	-0.4942			-0.0298	-0.0286	1.1472	0.0035		0.2447
M4ARCSP	0.4503			**0.1685**	0.0001	0.0001	0.0001		0.0001
M4ARCTE	-0.1992			-0.0291	-0.0286	1.1812		0.0014	0.2257
M4ARCTP	0.7616			**0.3051**	0.0001	0.0001		0.0258	0.0001
M4ARSTE	1.8216			-0.0074	-0.0264		0.0049	-0.001	0.1982
M4ARSTP	0.0003			**0.8024**	0.0001		0.0003	**0.278**	0.0001
M4GACSE	-4.5531	1.28792		-0.0457		0.91474	0.00326		0.274
M4GACSP	0.0001	0.0001		0.0403		0.0001	0.0002		0.0001
M4GACTE	-4.2832	1.2826		-0.0375		0.9546		0.0011	0.2559
M4GACTP	0.0001	0.0001		**0.199**		0.0001		**0.0773**	0.0001
M4GARCE	-3.7317	1.0161		0.0324	-0.0049	0.8092			0.2311
M4GARCP	0.0001	0.0001		0.0001	**0.1413**	0.0001			0.0001
M4GARSE	-3.7666	1.5698		-0.0483	0.0085		0.0036		0.2366
M4GARSP	0.0009	0.0001		0.0393	**0.2025**		0.0001		0.0001
M4GARTE	-3.4201	1.5763		-0.0379	0.007			0.0012	0.2141
M4GARTP	0.0027	0.0001		**0.2184**	**0.1851**			**0.071**	0.0001
M4GASTE	-2.547	1.2519		-0.0212			0.0048	-0.0012	0.2427
M4GASTP	0.0001	0.0001		**0.4764**			0.0003	**0.1946**	0.0001
M4GCSTE	-4.7188	1.2113				0.8835	0.0043	-0.0012	0.2665
M4GCSTP	0.0001	0.0001				0.0001	0.0003	**0.0765**	0.0001
M4GMACE	-5.1816	1.12521	0.1242	-0.0361		0.72575			0.2752
M4GMACP	0.0001	0.0001	0.0001	0.0003		0.0001			0.0001
M4GMARE	-3.8728	1.1888	0.1326	-0.041	0.0002				0.2449
M4GMARP	0.0001	0.0001	0.0001	0.0001	**0.9402**				0.0001
M4GMASE	-3.0372	1.1689	0.1219	-0.0827			0.0014		0.2821
M4GMASP	0.0001	0.0001	0.0001	0.0004			**0.1393**		0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M4GMATE	-3.0389	1.0679	0.1344	-0.0992				0.0009	0.2816
M4GMATP	0.0001	0.0001	0.0001	0.0011				0.1692	0.0001
M4GMCSE	-5.3806	1.0791	0.0934			0.907	-8E-05		0.2943
M4GMCSP	0.0001	0.0001	0.0001			0.0001	0.9257		0.0001
M4GMCTE	-5.1479	1.088	0.1074			0.9189		-0.0007	0.298
M4GMCTP	0.0001	0.0001	0.0001			0.0001		0.1354	0.0001
M4GMRCE	-4.8017	0.9201	0.1015		-0.005	0.7705			0.2723
M4GMRCP	0.0001	0.0001	0.0001		0.1189	0.0001			0.0001
M4GMRSE	-5.0353	1.429	0.1026		0.0106		-6E-06		0.2623
M4GMRSP	0.0001	0.0001	0.0001		0.1042		0.9951		0.0001
M4GMRTE	-4.7814	1.4471	0.1193		0.011			-0.0007	0.2667
M4GMRTP	0.0001	0.0001	0.0001		0.0932			0.1223	0.0001
M4GMSTE	-3.1782	0.10946	0.0926				0.0025	-0.0015	0.2689
M4GMSTP	0.0001	0.0001	0.0001				0.0751	0.0296	0.0001
M4GRCSE	-5.4174	1.2408			0.0017	0.9968	0.0026		0.2549
M4GRCSP	0.0001	0.0001			0.7726	0.0001	0.0002		0.0001
M4GRCTE	-4.9836	1.2442			0.0016	1.043		0.0008	0.2386
M4GRCTP	0.0001	0.0001			0.7847	0.0001		0.0413	0.0001
M4GRSTE	-3.5125	1.3625			0.0055		0.005	-0.0014	0.2262
M4GRSTP	0.0004	0.0001			0.3408		0.0001	0.0496	0.0001
M4MACSE	-2.7115		0.1509	-0.0134		0.8458	0.0002		0.162
M4MACSP	0.0001		0.0001	0.556		0.0001	0.8669		0.0001
M4MACTE	-2.7178		0.1521	-0.0175		0.8449		0.0002	0.1621
M4MACTP	0.0001		0.0001	0.5524		0.0001		0.7923	0.0001
M4MARCE	-1.2259		0.12907	-0.0334	-0.0279	0.9012			0.2706
M4MARCP	0.0001		0.0001	0.0008	0.0001	0.0001			0.0001
M4MARSE	1.0138		0.1271	-0.068	-0.0242		0.0015		0.2423
M4MARSP	0.0474		0.0001	0.0032	0.0001		0.1129		0.0001
M4MARTE	1.0128		0.1396	-0.0892	-0.0243			0.001	0.2426
M4MARTP	0.0475		0.0001	0.0027	0.0001			0.0991	0.0001
M4MASTE	-0.9228		0.1547	-0.0212			0.0001	0.0003	0.1336
M4MASTP	0.0489		0.0001	0.5156			0.9351	0.8026	0.0001
M4MCSTE	-2.7846		0.1454			0.8481	0.0003	0.0002	0.1615
M4MCSTP	0.0001		0.0001			0.0001	0.8496	0.7902	0.0001
M4MRCSE	-1.9848		1.008		-0.0239	1.1264	0.0003		0.2742
M4MRCSP	0.0015		0.0001		0.0001	0.0001	0.7389		0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M4MRCTE	-1.8048		0.1144		-0.0239	1.1402		-0.0004	0.2752
M4MRCTP	0.0049		0.0001		0.0001	0.0001		0.3975	0.0001
M4MRSTE	0.6061		0.1021		-0.0227		0.0023	-0.0011	0.2316
M4MRSTP	0.2162		0.0001		0.0001		0.1046	0.1129	0.0001
M4RCSTE	-0.7199				-0.0274	1.0716	0.0042	-0.0008	0.2325
M4RCSTP	0.2121				0.0001	0.0001	0.0004	0.2339	0.0001
M5ARCSTE	-0.5439			-0.0088	-0.0282	1.1476	0.0045	-0.001	0.2469
M5ARCSTP	0.407			0.7587	0.0001	0.0001	0.0005	0.2593	0.0001
M5GACSTE	-4.5311	1.2697		-0.021		0.9133	0.0045	-0.0012	0.2769
M5GACSTP	0.0001	0.0001		0.4704		0.0001	0.0005	0.1928	0.0001
M5GARCSE	-5.3134	1.4277		-0.0498	0.0036	1.0238	0.0033		0.2767
M5GARCSP	0.0001	0.0001		0.0294	0.5838	0.0001	0.0002		0.0001
M5GARCTE	-5.0397	1.4286		-0.0385	0.0039	1.0581		0.0011	0.257
M5GARCTP	0.0001	0.0001		0.1982	0.5584	0.0001		0.1005	0.0001
M5GARSTE	-3.798	1.5604		-0.0186	0.0088		0.0051	-0.0015	0.2409
M5GARSTP	0.0008	0.0001		0.5442	0.1844		0.0002	0.1356	0.0001
M5GMACSE	-4.9838	1.1875	0.1202	-0.0816		0.8993	0.0012		0.3152
M5GMACSP	0.0001	0.0001	0.0001	0.0004		0.0001	0.2211		0.0001
M5GMACTE	-4.9992	1.1876	0.1303	-0.096		0.9033		0.0006	0.3151
M5GMACTP	0.0001	0.0001	0.0001	0.0013		0.0001		0.2353	0.0001
M5GMARCE	-4.4799	0.9348	0.128	-0.0409	-0.0056	0.7701			0.2777
M5GMARCP	0.0001	0.0001	0.0001	0.0001	0.0831	0.0001			0.0001
M5GMARSE	-4.4949	1.5137	0.133	-0.0898	0.0098		0.0014		0.2873
M5GMARSP	0.0001	0.0001	0.0001	0.0002	0.1284		0.1709		0.0001
M5GMARTE	-4.4939	1.5136	0.1446	-0.1043	0.0098			0.0008	0.2866
M5GMARTP	0.0001	0.0001	0.0001	0.0009	0.1269			0.2228	0.0001
M5GMASTE	-3.0564	1.1718	0.1253	-0.0915			0.001	0.0004	0.2824
M5GMASTP	0.0001	0.0001	0.0001	0.005			0.5044	0.6978	0.0001
M5GMCSTE	-5.1329	1.1142	0.0913			0.9036	0.0022	-0.0015	0.3023
M5GMCSTP	0.0001	0.0001	0.0001			0.0001	0.1081	0.0285	0.0001
M5GMRCSE	-6.5459	1.2897	0.1008		0.0059	1.0016	-0.0003		0.3007
M5GMRCSP	0.0001	0.0001	0.0001		0.3647	0.0001	0.7807		0.0001
M5GMRCTE	-6.3083	1.3074	0.1158		0.0061	1.0172		-0.0008	0.3063
M5GMRCTP	0.0001	0.0001	0.0001		0.3462	0.0001		0.069	0.0001
M5GMRSTE	-4.7454	1.4623	0.1008		0.0105		0.0026	-0.0017	0.2727
M5GMRSTP	0.0001	0.0001	0.0001		0.106		0.0681	0.0169	0.0001

TABLE C.1 cont.

Model	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	R^2
M5GRCSTE	-5.2212	1.2721			0.0018	0.9963	0.0046	-0.0014	0.2613
M5GRCSTP	0.0001	0.0001			0.7473	0.0001	0.0002	0.0454	0.0001
M5MACSTE	-2.7176		0.1529	-0.0182		0.8453	-9E-05	0.0002	0.1621
M5MACSTP	0.0001		0.0001	0.572		0.0001	0.9561	0.8335	0.0001
M5MARCTE	-1.3118		0.1353	-0.0874	-0.0262	1.1329		0.0009	0.2901
M5MARCSP	0.0461		0.0001	0.0021	0.0001	0.0001	0.1818		0.0001
M5MARCTE	-1.3118		0.1353	-0.0874	-0.0262	1.1329		0.0009	0.2901
M5MARCTP	0.0452		0.0001	0.0024	0.0001	0.0001		0.1485	0.0001
M5MARSTE	1.0052		0.1329	-0.083	-0.0244		0.0007	0.0007	0.243
M5MARSTP	0.0495		0.0001	0.0102	0.0001		0.627	0.5058	0.0001
M5MRCSTE	-1.7114		0.0999		-0.0245	1.1302	0.0021	-0.0012	0.2789
M5MRCSTP	0.0079		0.0001		0.0001	0.0001	0.1327	0.0906	0.0001
M6GARCSTE	-5.3433	1.4185		-0.0203	0.0039	1.023	0.0048	-0.0014	0.2809
M6GARCSTP	0.0001	0.0001		0.497	0.5477	0.0001	0.0003	0.1287	0.0001
M6GMACSTE	-5.003	1.1904	0.1237	-0.0904		0.8993	0.0007	0.0004	0.3155
M6GMACSTP	0.0001	0.0001	0.0001	0.0046		0.0001	0.62	0.6912	0.0001
M6GMARCSE	-6.0104	1.3744	0.1314	-0.0908	0.005	1.0087	0.0011		0.3262
M6GMARCSP	0.0001	0.0001	0.0001	0.0001	0.4335	0.0001	0.2456		0.0001
M6GMARCTE	-6.0161	1.374	0.141	-0.1033	0.005	1.0122		0.0007	0.3259
M6GMARCTP	0.0001	0.0001	0.0001	0.0007	0.4328	0.0001		0.2899	0.0001
M6GMARSTE	-4.5023	1.5144	0.1354	-0.0961	0.0098		0.001	0.0003	0.2875
M6GMARSTP	0.0001	0.0001	0.0001	0.0042	0.1305		0.4972	0.7869	0.0001
M6GMRCSTE	-6.2578	1.323	0.0989		0.0057	1.0056	0.0024	-0.0018	0.3114
M6GMRCSTP	0.0001	0.0001	0.0001		0.3731	0.0001	0.085	0.0129	0.0001
M6MARCSTE	-1.3126		0.1308	-0.0832	-0.0262	1.1308	0.0005	0.0006	0.2903
M6MARCSTP	0.0453		0.0001	0.008	0.0001	0.001	0.7325	0.5166	0.0001
M7GRMASTCE	-6.0173	1.3751	0.1337	-0.0969	0.0049	1.0086	0.0008	0.0003	0.3264
M7GRMASTCP	0.0001	0.0001	0.0001	0.003	0.4377	0.0001	0.5844	0.7891	0.0001

APPENDIX D

INFORMATION ABOUT SURVIVING REGRESSION MODELS WITH GENDER ADDED

This appendix contains the coefficient estimates and the p-values for the surviving 35 models with GENDER added. Information about each models is broken into two lines: one line listing the coefficient estimates and the next line contains the p-values for the coefficients. Each line is preceded by a model name with each variable represented by one letter: G=GPA, M=MACT, A=CACT, R=RANK, C=CODE, S=MSAT, T=TSAT (INTER=INTERCEPT). Each model name ends with an E or a P. The E represents the coefficients and the P represents the p-values. The p-values are associated with the test that the coefficient is zero. P-values that are less than .05 indicate that the coefficient is significantly different from zero. These p-values are highlighted.

The first two lines in Table C.1 are M1AE and M1AP. M1AE indicates that the one variable model using CACT with GENDER added. The coefficient for CACT is .088 and GENDER is .3179. The second line M1AP indicates that the coefficient for CACT is significantly different from zero and the coefficient for GENDER is significantly different from zero. Coefficients that are not significantly different from zero are highlighted

TABLE D.1

MODEL	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	GENDER
M1AE	0.0025			0.0880					0.3179
M1AP	0.9900			0.0001					0.0001
M1CE	-0.2023					1.0085			0.3313
M1CP	0.2794					0.0001			0.0001
M1GE	-2.1794	1.2688							0.0540
M1GP	0.0001	0.0001							0.2970

TABLE D.1 cont.

MODEL	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	GENDER
M1ME	-1.4834		0.1568						0.4284
M1MP	0.0001		0.0001						0.0001
M1RE	2.8832				-0.0303				0.0719
M1RP	0.0001				0.0001				**0.1679**
M1SE	-0.1846						0.0043		0.6146
M1SP	0.6146						0.0001		0.0001
M1TE	0.4105							0.0017	0.5221
M1TP	0.2855							0.0001	0.0001
M2ACE	-1.9958			0.0826		0.9526			0.3216
M2ACP	0.0001			0.0001		0.0001			0.0001
M2ARE	1.7457			0.0467	-0.0286				0.0890
M2ARP	0.0001			0.0001	0.0001				**0.0928**
M2CSE	-1.8181					0.7738	0.0041		0.6182
M2CSP	0.0015					0.0002	0.0001		0.0001
M2CTE	-1.3866					0.8352		0.0016	0.5319
M2CTP	0.0191					0.0001		0.0001	0.0001
M2GAE	-2.8986	1.2241		0.0369					0.0679
M2GAP	0.0001	0.0001		0.0001					**0.1961**
M2GCE	-3.7549	1.2094				0.7944			0.0717
M2GCP	0.0001	0.0001				0.0001			**0.1572**
M2GME	-4.0991	1.0997	0.1100						0.1693
M2GMP	0.0001	0.0001	0.0001						0.0011
M2GSE	-3.0709	1.0933					0.0032		0.2717
M2GSP	0.0001	0.0001					0.0001		0.0123
M2GTE	-2.4933	1.1165						0.0010	0.1960
M2GTP	0.0001	0.0001						0.0060	**0.0697**
M2MCE	-3.2777		0.1488			0.8847			0.4261
M2MCP	0.0001		0.0001			0.0001			0.0001
M2MRE	0.0418		0.1203		-0.0257				0.1954
M2MRP	0.8428		0.0001		0.0001				0.0002
M2RCE	0.6790				-0.0300	0.9816			0.0815
M2RCP	0.0002				0.0001	0.0001			**0.1066**
M2RSE	0.7823				-0.0227		0.0039		0.3776
M2RSP	0.0413				0.0001		0.0001		0.0004
M2RTE	1.3773				-0.0230			0.0015	0.2929
M2RTP	0.0007				0.0001			0.0001	0.0063

TABLE D.1 cont.

MODEL	INTER	GPA	MACT	CACT	RANK	CODE	MSAT	TSAT	GENDER
M3ARCE	-0.2729			0.0418	-0.0285	0.9545			0.0934
M3ARCP	0.2976			0.0001	0.0001	0.0001			0.0686
M3GACE	-4.3701	1.1617		0.0352		0.7726			0.0824
M3GACP	0.0001	0.0001		0.0001		0.0001			0.1088
M3GASE	-2.6393	1.1849		-0.0486			0.0040		0.2936
M3GASP	0.0001	0.0001		0.0319			0.0001		0.0138
M3GCSE	-5.0092	1.1208				0.8833	0.0029		0.2666
M3GCSP	0.0001	0.0001				0.0001	0.0001		0.0123
M3GCTE	-4.5823	1.1445				0.9360		0.0009	0.1975
M3GCTP	0.0001	0.0001				0.0001		0.0155	0.0621
M3GMAE	-3.8653	1.1289	0.1365	-0.0402					0.1851
M3GMAP	0.0001	0.0001	0.0001	0.0001					0.0003
M3GMCE	-5.4577	1.0445	0.1059			0.7346			0.1794
M3GMCP	0.0001	0.0001	0.0001			0.0001			0.0004
M3MARE	0.3642		0.1440	-0.0362	-0.0264				0.2104
M3MARP	0.1121		0.0001	0.0004	0.0001				0.0001
M3MRCE	-1.7955		0.1128		-0.0256	0.8990			0.1933
M3MRCP	0.0001		0.0001		0.0001	0.0001			0.0001
M3RCSE	-1.3484				-0.0244	1.0391	0.0035		0.3555
M3RCSP	0.0176				0.0001	0.0001	0.0001		0.0007
M3RCTE	-0.8851				-0.0249	1.0931		0.0013	0.2769
M3RCTP	0.1329				0.0001	0.0001		0.0005	0.0082
M4GACSE	-4.5795	1.2080		-0.0478		0.8957	0.0037		0.2732
M4GACSP	0.0001	0.0001		0.0310		0.0001	0.0001		0.0194
M4GMACE	-5.2242	1.0732	0.1317	-0.0391		0.7313			0.1947
M4GMACP	0.0001	0.0001	0.0001	0.0001		0.0001			0.0001
M4MARCE	-1.4709		0.1368	-0.0367	-0.0264	0.9002			0.2085
M4MARCP	0.0001		0.0001	0.0002	0.0001	0.0001			0.0001

VITA

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OKLAHOMA STATE UNIVERSITY
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Principal Investigator(s): Dennis Bertholf, Kerry D. Johnson

Reviewed and Processed as: Exempt

Approval Status Recommended by Reviewer(s): Approved

APPROVAL STATUS SUBJECT TO REVIEW BY FULL INSTITUTIONAL REVIEW BOARD AT NEXT MEETING.
APPROVAL STATUS PERIOD VALID FOR ONE CALENDAR YEAR AFTER WHICH A CONTINUATION OR RENEWAL REQUEST IS REQUIRED TO BE SUBMITTED FOR BOARD APPROVAL.
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Comments, Modifications/Conditions for Approval or Reasons for Deferral or Disapproval are as follows:

Signature: John H. Wycoff

Chair of Institutional Review Board

Date: February 10, 1995