UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

THE IMPACT OF STUDENT DIVERSITY ON COMMUNITY COLLEGE GRADUATION RATES IN OKLAHOMA: WHAT CAN BE LEARNED USING STATE REGENTS DATA?

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

JAMES DENNIS ATKINSON
Norman, Oklahoma
2015

THE IMPACT OF STUDENT DIVERSITY ON COMMUNITY COLLEGE GRADUATION RATES IN OKLAHOMA: WHAT CAN BE LEARNED USING STATE REGENTS DATA?

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF EDUCATIONAL LEADERSHIP AND POLICY STUDIES

BY

Dr. David Tan, Chair

Dr. T. Elon Dancy

Dr. Alisa Hicklin-Fryar

Dr. Joan Smith

Dr. Juanita Gamez Vargas

Dedication

I dedicate this paper to my wife and best friend, Janet. She is an exemplar of what results when hard work, discipline, sacrifice, and tenacity meet opportunity at one of the many wonderful community colleges situated across rural America. My pride in her achievements is immense.

Acknowledgements

It is cliché to say that this space is too limited to acknowledge the many people who have made it possible for me to attain this milestone. I cannot fail to mention the patience, encouragement, and wisdom of Dr. David Tan; the highly qualified and dedicated faculty of the Jeannine Rainbolt College of Education; nor the shining example of a flagship public university that is the University of Oklahoma. I am especially indebted to the hardworking and professional Strategic Planning and Analysis staff at the Oklahoma State Regents for Higher Education, who invested many hours in becoming familiar with the data requirements of this study and methodically extracting the electronic records.

Table of Contents

List of Tables

List of Figures

Abstract

The United States federal government requires postsecondary schools, including community colleges, to calculate student completion rates and make them public information, which they do through the Integrated Postsecondary Education Data System (IPEDS). Stakeholders are keenly interested in completion rates as a measure of community college quality. Community colleges' mission compels them to admit nearly every student desiring an opportunity to earn a higher education credential. This policy results in great diversity among students in their academic preparedness and their propensity to complete a college program. Using discrete student records from Oklahoma's public two-year colleges, this research project seeks to determine how much of the difference in completion rates is attributable to diversity in the background of admitted students.

Chapter 1:

Introduction

Background

The proportion of citizens who believe in the American dream—the idea that anyone can achieve prosperity and success through hard work, determination, and initiative—has reached a decade low of 64% (Cillizza, 2014). Americans have always overestimated their prospects for upward class mobility (Deparle, 2012); perhaps what is surprising is that they continue to harbor the degree of faith they do, given the irrefutability of 21st-century macroeconomic trends. If the lower bound of middle class is defined as twice the poverty rate for a family of four, and the upper limit is a six-figure income, then from 1967 to 2000 using inflation-adjusted dollars, the middle income band shrank from 53% to 45%, not because Americans became poorer, but because they became more affluent. In the 21st century, however, this trend has reversed itself. From 2000 to 2013, the number of households fitting this definition declined from 45% to 43%, not because incomes have increased, but because they have decreased (Parlapiano, Gebeloff & Carter, 2015). Furthermore, household net worth has not increased in decades. For the typical home-owning family, real estate represents a large proportion of its net worth. Thus, when Wall Street's housing bubble collapsed in the Great Recession of 2007 and 2008, almost 20 years of what Main Street thought it had accumulated was lost, and the median household balance sheet was reset to levels last seen in the early 1990s (Appelbaum, 2012).

What has happened more recently, since President Obama took office in 2009? During the president's first term, recovery from the Great Recession eventually took hold. Emmanuel Saez (2013), an economics professor at the University of California, Berkeley, examined Internal Revenue Service data generated between 2009 and 2012, finding that average real family income increased by 6.0%. However, this modest growth mirrored the skewed distribution of the prior two decades: Incomes of the top 1% of households grew by 31.4%, whereas the incomes of the other 99% increased by just 0.4%, meaning that the top 1% captured 95% of the income gains from the nascent recovery. Saez concludes:

> Overall, these results suggest that the Great Recession has only depressed top income shares temporarily and will not undo any of the dramatic increase in top income shares that has taken place since the 1970s. Indeed, the top decile income share in 2012 is equal to 50.4%, the highest ever since 1917 when the series start (p. 1).

These trends may seem distant from the topic of this study—refining measures of quality for community colleges—but they are a necessary prelude to understanding the "why" of this research. In the popular vernacular, "sending the kids to college" is nearly always listed by parents as a milestone of having achieved a middle-class status, along with owning a home, saving for retirement, and perhaps having a late model car. It is an aspiration that is unattainable for many people in the lower income band; or, if they do attain it, they do so through Herculean sacrifice and self-discipline. A college degree never has, nor does it now, ensure upward economic mobility, but evidence suggests that not having at least a bachelor's degree greatly reduces one's chances of staking out a spot in the middle of the U.S. income distribution. In 1992, about 50% of middle-class households were headed by someone with a high school education or less;

today, only 37% of the middle class have not been to college (Searcey & Gebeloff, 2015).

President Obama has asserted that this relentless accumulation of immense riches by the few and the lack of upward mobility for the many is “the defining challenge of our time.” “Making sure the economy works for everyone” is “the reason why I ran for president”; “it drives everything I do in this office” (Obama, 2013). Consistent with his public statements, the president has made education policy changes to offer many more people the chance to earn a college credential. The president has consistently made the case that greater educational attainment among the workforce is necessary to improve economic mobility, and that much of this education should take place at community colleges (Pérez-Peña, 2012). To make progress towards this goal, the president’s most ambitious proposal is to transform the public financing of higher education by having the federal government pay 75% of the average cost of tuition charged by community colleges, if the states agree to pay the remaining 25%. Full- and part-time students will qualify for this assistance if they make steady progress in a program that transfers its credits towards a baccalaureate degree, or results in a certificate in designated high-demand fields. Up to nine million students may benefit if all states agree to participate (Davis & Lewin, 2015). The federal government already provides about $9.1 billion annually to community colleges, with students contributing $16.7 billion through tuition payments. President Obama’s free-tuition program, if authorized by Congress, will no doubt significantly expand the federal government’s investment in community colleges (Davis & Lewin, 2015).

Research Problem

Although the Obama Administration has channeled an unprecedented level of support to community colleges, the president has indicated clearly and consistently that he intends to reform what he regards as structural performance and accountability flaws in higher education institutions. He has made at least two attempts to link federal aid disbursements to college and university performance. In 2014, the Education Department (ED) published a rule (commonly known as the "gainful employment" rule) ending federal aid to career-oriented colleges whose students graduate or leave school with high debt-to-income ratios and low loan repayment rates. For-profit colleges challenged this rule and prevailed in court, but ED redrafted it, and it went into effect in July 2015. In a January 2012 speech at the University of Michigan, the president also proposed awarding additional Perkins Loan dollars to colleges that serve low-income students effectively, keep tuition down, and provide "good value" (Field, 2013). Such a change to a statutory loan program, however, would require Congress to authorize legislation; this has not happened.

ED has promoted some non-coercive consumer-choice initiatives to encourage colleges and universities to control costs and improve graduation rates. Unlike the mandatory reporting required by the Higher Education Act of 1965 and the Higher Education Opportunity Act of 2008, these consumer-choice programs are optional; ED merely encourages institutions to participate voluntarily. These programs encourage participating institutions to deliver information to families in a standardized format that makes it easy to make comparisons across schools—unlike the information traditionally provided by schools, which can be confusing and, in the case of some for-profit entities, outright deceptive. An example of a voluntary initiative with a high adoption rate is the Financial Aid Shopping Sheet, “a standardized form that is designed to simplify the information that prospective students receive about costs and financial aid so that they can easily compare institutions and make informed decisions about where to attend school” (Department of Education, 2014).

The White House College Scorecard webpage went live in 2013, greatly expanding on the cost-comparison information provided by the Shopping Sheet. The College Scorecard, an interactive tool published on the White House website, includes graduation rates, measures of affordability, and information about graduates’ success in finding employment related to their field of study (The White House, 2013). At the University of Buffalo in August 2013, the president proposed that students receive larger Pell Grants and lower interest rates on loans if they enroll at institutions with high scores on the College Scorecard—institutions that, in the White House’s view, offer good educational value (Lewin, 2013). Congress would need to pass legislation to enact any plan to link federal funding to College Scorecard measures. Such a prospect is nearly nonexistent in the current political climate, but this may not always be the case. An internet screenshot of the White House College Scorecard is shown in Appendix A, as it is no longer live on the internet, having been replaced by a later edition of the College Scorecard hosted on an ED webpage. This more elaborate consumer-choice tool provides much more data and is discussed later in this chapter.

The higher education sector—community colleges and vocational schools; public and private universities; trade and professional associations; and individual administrators, faculty, and students—have expressed somber reservations in writing and at public meetings to changes in federal funding formulas based on institutions' attainment of benchmarks like those measured by the College Scorecard. In response to these concerns, ED has pledged to work in consultation with colleges to develop measures that minimize "unintended consequences." One possible unintended consequence is that community colleges may creatively erect barriers to serving students who are at greatest risk of not completing. Alexander Astin, who studies college and university graduation rates, voiced this concern in 1997: "Perhaps the most dangerous aspect of such an approach to accountability is that it provides negative incentives for institutions to enroll underprepared students, since such students tend to lower the institution's absolute level of outcome performance" (Astin, 1997, p. 656).

Completion rates for community colleges are generally quite low compared to the rates of four-year institutions. The National Center for Education Statistics (NCES) reports in *The Condition of Education 2014* that, of the 17.8 million students enrolled in degree-granting postsecondary institutions in fall 2012, 40% of them (7.2 million) were enrolled at two-year institutions. But the students at two-year colleges have graduation rates starkly different from the students at four-year institutions. Based on a 2006 cohort tracked for six years (150% of normal completion time), the graduation rate for students at four-year institutions is 59%. Among a 2009 cohort of community college students, however, the graduation rate is found to be just 31% (using the "150% of normal completion time" rule, which means these students were tracked for three years). Enrollment patterns threaten to exacerbate the graduation problem in postsecondary education. By 2023, community college attendance is projected to grow by 1.1 million students (bringing the total to 8.3 million); for four-year colleges and universities, the projected growth is 1.3 million (bringing to the total to 11.9 million). This equates to a 16% growth rate for community colleges, compared to a 12% growth rate for four-year institutions (Kena et al., 2014). Whether meeting compulsory performance benchmarks or recruiting students armed with what the Obama Administration calls a “datapalooza” of competitive information, community colleges will likely continue to face pressure to show improvement in graduation rates, graduates’ employment prospects, and affordability.

The White House is not the first entity to take an interest in improving college completion rates. The Lumina Foundation’s Achieving the Dream (ATD) and the American Association of Community Colleges’ (AACC) Voluntary Framework of Accountability (VFA) are privately funded national programs designed to help community colleges raise graduation rates, but unlike the federal government, they do not control access to the $185 billion in undergraduate student aid expended by the federal government in 2012–13. The VFA, by establishing precise standards for reporting data and calculating metrics, has improved the comparability of data across the growing list of participating institutions (more than 300 are listed on the VFA website as of November 2015). The National Community College Benchmark Project (NCCBP) is another organization that aggregates data from participating institutions and reports measures such as persistence, retention, and graduation rates. These organizations allow member colleges to engage in benchmarking: comparing outcome measures for groups of colleges with similar attributes that are commonly thought to be related to graduation rates (such as the institution’s size or urbanicity). These organizations’ data collection standards assuage some of the weaknesses that many community college administrators believe are inherent in the Student-Right-To-Know (SRK) rates reported in the Integrated Postsecondary Education Data System (IPEDS), the mandatory federal reporting system administered by NCES. The commonly used benchmarking practice of comparing a college to a cohort of institutions with similar attributes—as is made possible by membership in the NCCBP—allows for limited comparisons, but much of the variability in community college outcomes remains unexplained (Bailey, Calcagno, Jenkins, Leinbach, & Kienzl, 2006).

Significance of the Problem

Community college advocates who criticize the College Scorecard point out that the core mission of community colleges is to open the door widely to higher education for as many people as possible. One cost of providing this breadth of opportunity is that community colleges admit populations of students who, simply due to the lottery of birth, have characteristics and circumstances that put them at a much higher risk of not completing a credential. Historically, society has regarded this cost as legitimate and necessary to safeguard all citizens' opportunity for personal betterment and enrichment through education. Community colleges are continuously experimenting with services and programs to bolster these students' retention and completion rates, but regardless of these interventions, even the staunchest advocates of community colleges acknowledge that a significant proportion of students will never complete a program of study. Critics of the College Scorecard argue that it will discourage institutions from providing services that attract and support at-risk students, such as mentoring, tutoring, childcare, and disability services (Shear, 2014). Because at-risk students often require more student support services than the typical student, and because these services cost money, and because such students are less likely to complete than a typical student even when they use such services, community college administrators might perceive an incentive to erect barriers to admitting some types of at-risk students when they are under pressure to improve completion rates (so the argument goes). In other words, the College Scorecard risks creating perverse incentives to discriminate against the kinds of students that the Obama Administration wants to help (Field, 2013).

The goal of the College Scorecard is to provide students, as consumers of higher education, with valuable information to help them make good choices. The College Scorecard is just the first step in the Obama Administration's long-term plan to create a standardized, government-sponsored rating system providing uniform measures to help students and their families make decisions. The College Scorecard puts forth five measures and, for each measure, rates institutions on a "low/medium/high" scale or as above or below the national average. But it does not take the next step of making an explicit judgment about relative institutional quality, nor does it link federal resource allocation to a ranking algorithm. The college ranking system envisioned by ED, if completed, would eliminate the College Scorecard's ambiguity about how to weigh the attributes of institutional performance and would add further metrics.

Because of colleges' fierce opposition to the Obama Administration's plan, ED has chosen not to publish the ranking system, which would group colleges into high-performing, low-performing, and middle-performing categories. Instead, ED is developing consumer-driven web-based tools to provide students with an unprecedented amount of data, enabling them to compare college costs and outcomes and form their own conclusions about a college's value (Stratford, 2015; https://collegescorecard.ed.gov).

The federal government is developing a gainful employment accountability apparatus geared toward stopping abuses by for-profit career and vocational colleges. ED plans gainful employment measures that compare earnings (as soon as eighteen months after graduation) to average student loan debt. As an indicator of the seriousness with which ED views these metrics, earnings data will come from the Social Security Administration master file, which archives the earnings of the U.S. working population. College stakeholders continue to exhort ED to take into account demographic factors, such as whether an institution serves predominately minority or low-income students, when applying gainful employment assessments. However, ED's position is that special metrics or thresholds for college programs serving predominantly low-income or minority students are not justified. This position is based on ED's analysis of the correlation of demographics with post-graduation earnings (Gallegos, 2015).

Until fairly recently, rankings publications and college guidebooks purporting to measure quality and value were mainly in the domain of undergraduate and graduate institutions. But about 10 years ago, this situation began to change significantly. In 2007, *Washington Monthly* introduced a ranking system that identifies the top 30 community college based (with a weight of 85%) on the Community College Survey of Student Engagement (CCSSE) and the college's graduation rate (weighted at 15%). This ranking was criticized by CCSSE, but, like the annual *U.S. News Best Colleges* edition, it continues to be published. It seems that, whether against other institutions or against absolute standards, rankings and scorecards have migrated into the space occupied by community colleges in the U.S. system of higher education, with no sign of abatement. Although the most public manifestations of this debate, such as the introduction of a federal ratings system, may have subsided for the moment, higher education stakeholders are fiercely contesting the very issues this study seeks to address.

Research Questions

The preceding discussion of the research problem and its significance give rise to the following research questions:

1. Is it possible to use data routinely collected by the Oklahoma State Regents for Higher Education (OSRHE) to compute an estimate of a given student's chance of graduating from each of the state's 14 community colleges?
2. If the 14 community colleges are listed in descending order by this student's probability of graduating, is this rank order different from an ordinal ranking of the colleges based on all enrolled students?
3. If a value measure for an individual student is calculated (i.e., marginal value), where average cost to the student of attending the college is divided by the student's probability of graduating, and the colleges are listed in ascending order by this marginal value measure, how does this list compare to the two lists mentioned in Research Question 2?

Contribution of the Study

This study contributes to the scholarly literature and contemporary policy debate about college access, quality, and affordability.

Completion rates are of the utmost concern to state policymakers. Adjusting these rates to account for disparities in student characteristics, using data routinely collected and reported to a state department of education, will contribute to rational discussions of college effectiveness. The Oklahoma community college system is a logical selection as the subject of the study because of important similarities with other predominantly rural states, as supported by the following observations. First, it is reasonable to hypothesize that the mix of student attributes and institutional characteristics in these states—states belonging to the U.S. Census Bureau's West North Central and Mountain areas—are comparable to Oklahoma's. This strengthens the external validity of the study with regard to both population and ecological features. Second, it is also a reasonable judgment that these states' education departments and data collection protocols are more comparable with Oklahoma's than those of states with opposite political orientations toward state government, such as California or Oregon.

A goal of this study is to make a key performance metric—student completion—more comparable across a state's system of community college. If the study design calls for data resources not available, it is not nearly as helpful a contribution. The need to refine student success measures is very pressing, but it must be accomplished, if possible, with data routinely collected by state governments. To answer the question of whether this is possible, we must find out whether the data converge on a statistically significant and meaningful conclusion—or whether the variables are so weakly correlated, with too many variables missing from the equation, or with so many unknown confounding variables excluded, that the model becomes unpersuasive.

Researchers usually hope for a statistically significant and compelling outcome from their data, and I hope for such an outcome from this study. However, regardless of whether the models converge with the data available, a contribution to the literature and policy implications can be derived from the effort either way.

This study calculates graduation rates in a way that avoids some of the objections commonly voiced by community college practitioners. ED's Committee on Measures of Student Success (CMSS) put forward a recommendation to include part-time and transfer students. ED acquiesced to this recommendation, but these changes will not be implemented for at least several years. The College Scorecard uses three-year cohorts and excludes part-time students, whereas using data from OSRHE makes it possible to calculate graduation rates based on three-year cohorts that include part-time students.

Precisely because this study uses data collected from Oklahoma's community colleges according to the guidelines and criteria specified by OSRHE, its findings and conclusions should have better credibility than those emanating from surveys and institutions not indigenous to the state. An objection often voiced by the state's education officials is that findings and recommendations originating outside Oklahoma do not take the state's unique circumstances and conditions into account.

Due to congressional concerns about privacy, ED declined to implement the CMSS recommendation to create a national student-record system. This means that when a student transfers credits earned at a community college to an out-of-state college or university (as is often the case), the community college generally does not get credit for the student's completion, even if the student graduates within six years. Likewise, if a student completes all the coursework for an associate's degree and transfers the credits to a four-year institution without applying for the associate's degree, the community college cannot count this student as a "completion." An exception to this situation occurs if the community college participates in the voluntary National Student Clearinghouse program and can track the student to completion, but this happens infrequently. This means that it generally is possible to conduct a study at the level of individual student records only within a single state. The lack of adequate student-level data at the federal level, due to congressional prohibitions, is a common theme among comments submitted in opposition to the federal college rating system proposed by ED (Stratford, 2013). Other researchers have specifically suggested that future research designs leverage state record systems, which have the advantage of providing much larger samples, including significant samples within single institutions. Bigger samples are obtainable for state record systems because reporting by institutions is compulsory and is invisible to the student. The typical community college registrar or institutional research office uploads a file consisting of individual student records with specific fields and definitions each semester to the state government entity overseeing higher education. For public institutions, these records usually form the foundation for state funding, so great care is taken in preparing and submitting the information. The critical dissimilarity between the files submitted to the state and the files submitted to IPEDS is the level of analysis. Only summary institution-level statistics are submitted to IPEDS, not discrete student records. The dramatically alters the nature of the research that is possible, as will be discussed in Chapter 3: Research Design and Methods. NCES administers national surveys, such as the Beginning Postsecondary Students

Longitudinal Study, but participation in these is strictly voluntary. At campuses across the country, students who meet the subject criteria are solicited to participate in these surveys, but even if the participation rate were extraordinarily high, these surveys' data could not match the amount and type of data generated by mandatory reporting to state governments. One research team noted that, although the number of institutions within a state is much smaller than the number of institutions in the entire nation, the kind of data available at the state level make it easier to develop comprehensive measures of institutional features (Calcagno, Bailey, Jenkins, Kienzl, & Leinbach, 2008, p. 644).

Assumptions and Limitations

Several simplifying assumptions about the 14 colleges are necessary. For the certificates and degrees that the colleges are accredited to teach, it is assumed that employers generally accept that students with these credentials have sufficient knowledge, skills, and expertise to perform the jobs associated with the credentials. It is thus assumed that, all other things being equal, employers are indifferent about which college awarded the credential, and that graduates of all colleges are equally prepared to succeed. This assumption of equivalence also applies to transfer students: It is assumed that baccalaureate institutions readily accept a degree from any of the 14 community colleges as evidence of adequate academic preparation and ability to complete the requirements of a bachelor degree. The emphasis on employment is not meant to suggest that students who start at or go no further than community college are incapable of intellectual aspirations other than vocational training. But just as transfer preparation is a key mission of community colleges, so is employment training and career preparation. Given the assumption of equality of credentials across all 14 colleges, the student should prefer the institution that affords similar students the best chance for achieving a successful outcome at the lowest costs. This emphatically does not mean that students should or will choose the college with the lowest absolute cost. Unless the institution makes sufficient investments in the facilities, programs, services, and faculty required to create a supportive and engaging academic environment, students are likely to depart the institution without graduating. Thus, it is useful to consider the student's probability of graduating in conjunction with the cost of the investments required to produce that probability.

The quality of data reported by the 14 institutions varies widely. One advantage of using data submitted to OSRHE is that it conforms to data governance criteria that enhance its cross-institutional comparability, and the state follows procedures to identify and correct flaws in its accuracy. However, despite these advantages, some irregularities are known to exist. Students who transfer credits toward a bachelor's degree program are counted as graduates of the community college, even though they may never complete the bachelor's degree. But students transferring to another community college are not counted as a success if they transfer to another community college. ED has plans to modify the graduation rate calculation for students who transfer out of community colleges, but the current practice is to exclude them, and this is how the OSRHE cohorts used in this study are compiled. Community colleges can count students transferring to out-of-state bachelor's programs only if they can track the student to the program and confirm that they enroll.

As will be discussed in the theory and review of literature sections, many confounding variables are correlated with student outcomes. Any correlations derived from the analysis of the study data are subject to the risk of unobserved and confounding variables, even when the model fit statistics are sound, because in the social sciences it is generally not possible to construct a true experimental design. Because of this limitation inherent in ex post facto designs, readers should exercise caution when extrapolating this study's results to populations of students and institutions uncharacteristic of those in the state of Oklahoma, which has low population densities, an economy dominated by agriculture and extractive industries, very conservative political and religious orientation, and other factors not measured but potentially influential. This study acknowledges these missing parameters and experiments with proxy variables for key parameters like socioeconomic status, rather than dropping them entirely due to lack of data. For example, subsets of data are available from the United States Census Bureau to describe income and poverty measures of the school districts containing the high schools attended by students studied in this project.

Definitions

This scope of this inquiry reflects theory, models, and research mainly from two disciplines: education and economics. It also involves topics of practical college administration and performance measurement, as well as very current topics in federal education policy that are sometimes contentious. Its ex post facto research design uses institutional and student-level records from state and national repositories that comply with carefully defined data governance criteria and standards. Given this context, it is important for the sake of clarity and precision to define the following terms:

Cohort—This is a specific group of students, established for tracking purposes, who meet the criteria for inclusion in the study. Students enrolled in college for the first time and seeking a degree or certificate are included. A student is considered first-time if they are in their first semester of college or if their only previous enrollment was in the summer immediately preceding the fall cohort year. In addition, high school students concurrently enrolled in college courses are also considered first-time students. Both part-time and full-time students will be included in the analysis of the OSRHE data. A part-time student is one who attempts at least six but fewer than 12 credits; a full-time student is one who attempts 12 or more credits. (Only full-time students are included in IPEDS reporting, but ED has accepted a study group recommendation to include part-time students in the future.) Membership in the cohort based on credential-seeking status and full- or part-time status is assessed in the first fall semester of enrollment and does not change. Student progress is assessed at three-year intervals. Six-year cohort data with identical variables was requested from and supplied by OSRHE. However, the six-year data were not used in this study because they turned out not to be needed to answer the three research questions. These data were retained for future research.

Graduation Rate. The graduation rate is the proportion of students who complete a certificate or degree within a specific time period. For IPEDS, this time period is 150% of the time it normally takes a full-time student to complete the program. For students seeking associate's degrees, this interval is three years; for certificate-seeking students it is one year. However, in this project, all students are assessed after three years, which means that certificate-seeking students have longer than 150% of the normal time to complete. But this simplification is necessary: Certificates vary in the length of time to complete, and without this simplification, the number of cohorts increases, adding complexity not justified by the additional explanatory power. The SRK graduation rates reported by IPEDS include students who transfer to bachelor's degree programs, if the transfer can verified and if transfer is a primary mission of the reporting institution. The graduation rates calculated in this study will include transfer students also; however, the College Scorecard website reports transfers and graduation rates separately. These rates will be summed back to a composite rate when used in this study.

Net Cost of Attendance. It is important to define the net cost of attendance because it is the numerator in the calculation needed to answer research question #3. The Higher Education Act of 1965, as amended, defines institutional net price as "the average yearly price actually charged to first-time, full-time undergraduate students receiving student aid at an institution of higher education after deducting such aid" (ED, 2015). This is the definition that will be used in this project.

Community College. This is a publicly funded institution that awards primarily two-year degrees and certificates. This is consistent with Cohen and Brawer's (2008) definition of the community college "as any institution regionally accredited to award the associate in arts or the associate in science as its highest degree" (2003, p. 5). Note: This study includes OSU-OKC as a two-year college, even though it offers two baccalaureate degree programs (http://www.osuokc.edu/academics/programs_AZ.aspx) at the time of this writing. This is because 6,689 student enrollments during the study period meet the criteria for inclusion, and most of its programs are, in fact, certificates or associates degrees.

College or University. This is an institution that awards primarily baccalaureate and graduate degrees. The University of Oklahoma, for example, offers certificate programs in addition to bachelor's, master's, and doctoral degrees, but does not offer any associate's degree programs.

Associate's Degrees. Associate of arts (AA), associate of science (AS), and associate of applied science (AAS) are degrees that generally can be earned in two years by a student attending community college full time. The college credits from AA and AS degrees are generally fully transferrable to bachelor's degree programs. AAS programs have more limited transferability and are intended to lead directly to employment.

Certificates. The certificate programs taught by community colleges are categorized into one of two groups: those taking more than one year but less than two years to complete, and those taking up to one year to complete. These programs are overwhelmingly vocationally oriented. Although certificate programs take variable amounts of time to complete, for the purposes of this project, the outcome interval for students enrolled in certificate programs is three years.

Because the terms "probability," "odds," "odds ratio," and "logit" are confusing and often misused in practice, non-technical descriptions are provided below. These terms are also defined contextually in Chapter 4. The following definitions are adapted from UCLA: Statistical Consulting Group (2014).

Probability. This is calculated by dividing the number of desired outcomes by the total number of opportunities. The “desired outcome” is sometimes also referred to as an “event,” whereas other outcomes are termed “non-events.” For example, the probability of rolling a six with a fair die is 1/6 or 0.167 or 16.7%. The probability of a non-event (not rolling a six) is 1 minus the probability of the event (rolling a six). The probability of not rolling a six is therefore 1 - 0.167 = 0.833, or 5/6, or 83.3%. Probabilities range from 0 to 1, with 0 meaning that the event cannot occur and 1 meaning that the event is certain to occur.

Odds—Odds is defined as the ratio of the probability of an event and the probability of the corresponding non-event. If 20% of students graduate or transfer in three years, it follows that 80% do not complete within three years. The odds of completing are therefore 0.20/0.80 = 1/4 = 0.25. The non-event is the odds of not graduating, which is 0.80/0.20 = 4. Conventionally, odds are stated as a relationship of two whole numbers in their simplest form. In the example above, if both sides of the expression are multiplied by five, the odds of graduating are 1 to 4, and the odds of not graduating are 4 to 1.

Odds ratio—This is the ratio of the odds of an event and its corresponding non-event. As an example, suppose that the 20% graduation rate describes the probability that a male student will graduate. The odds that he will graduate are thus 1 to 4, or ¼, or 0.25. Suppose that for a female, the probability of graduating is 30%, meaning that her odds are 0.30/0.70, or 0.48. The odds ratio for gender—a comparison of the odds that a male will graduate compared to the odds that a female will graduate—is therefore 0.25/0.48 = 0.52. In other words, the odds that a male will graduate are just slightly more than half of the odds that a female will graduate. Conversely, 0.48/0.25 = 1.96, meaning that a female's odds of graduating are almost twice a male's odds. It is evident that the odds ratio is a measure of effect size; that is, it quantifies the magnitude of the treatment effect. If the treatment is attending college, the effect is quite different depending on the student's gender. Another effect size measure commonly used in educational research is Cohen's d, which is calculated by dividing the difference between the group means by the pooled standard deviation.

Logit—The logit is the natural logarithm of the odds ("log of the odds"). The exponent that indicates the power to which the constant *e* is raised to produce a given number is its natural logarithm, so *e* raised to the odds is the logit. The terms in a logistic regression (dependent variable and coefficients) are in logit units. Logits are uninterpretable by most people, but if they are exponentiated, they transform into odds ratios, which are easier to understand.

Overview of Methodology

Answering this study's three research questions begins with creating a model that will generate the probability that a particular student will complete a program of study. The criterion variable is dichotomous, taking a value of either "completion" or "no completion," depending on whether the student completes the certificate or degree program within the prescribed interval or transfers to a bachelor's degree program. This model calculates probability estimates at three-year intervals, measured from the date of first enrollment. The predictor variables include continuous scale and multilevel categorical variables pertaining to students' background and attributes—factors that predate their enrollment. In the second phase of model building, the study attempts to enhance the prediction by including institutional characteristics deemed outside the college's control. The data for this study were provided by OSRHE and the IPEDS website.

Four potential outcomes from this study are possible, each of which would have significant policy implications. (1) The OSRHE data may results in a model that predicts outcomes no better than random chance. In this case, we would not be able to reject the null hypothesis, that the regression coefficients do not give useful information about graduation rates. This study includes 14 separate regression equations, one for each college. It is possible that the results will yield an acceptable predictive threshold for some colleges and not others. This may have policy implications with respect to OSRHE, and it would suggest a research agenda for identifying proxy variables. (2) Production functions might be found to be statistically strong and better than chance, but the predicted probability of graduating for the reference person might not be different from the simple frequency count rate. If this outcome occurs, the colleges will not be reordered by graduation rate, and therefore their performance and quality rankings likewise will remain the same. (3) The data might support a statistically significant model that can predict (more than 50% of the time) whether a student will graduate, and these predictions might result in a reordering of the community colleges compared to unmodified completion rates. (4) If outcome (2) or (3) occurs, this last option weights the graduation rate by the amount of money that the college must spend per student to achieve the student's graduation. This could produce a different ordering of the list, compared to the list ranked by the unmodified rates or the modified rates that do not account for net institutional cost (i.e., the lists generated via the second or third outcomes).

To simplify the task of acquiring and analyzing the data, this study intentionally obscures the distinction between certificates and associates degrees. OSRHE categorizes certificates according to whether they take less than one year or between one and two years. Analyzing certificates separately from associate's degrees would increase threefold the regressions and ancillary tables that would have to be prepared and interpreted. Moreover, even if the certificates were analyzed separately, there would be measurement error between the normal time to complete and the assumed time because, for example, for a student engaged in a program that takes a semester to complete would be assessed at one year (which is greater than 150% of the normal completion time). Perhaps most important, if the degree award goals stated by the student at admission are an indication of the actual proportion of certificates that the 14 institutions award, certificates represent less than 2% of the total.

There is a rich body of scholarly research evaluating performance-based funding experiments conducted by states (Tandberg, Hillman, & Barakat, 2014; Dougherty et al., 2014; Dougherty & Reddy, 2011). Williams, Tandberg, and Fryar (2015) assessed the state of Washington's foray into using performance-oriented incentives to improve completion rates within its community college system. Theoretically, colleges should be expected to maximize funding by taking full advantage of available incentives, so it makes sense for them to offer a profusion of short certificate programs to augment graduation rates. However, the 14 colleges in this study are not subject to performance-based funding, so their degree and certificate offerings have not been distorted in this way.

Chapter 2:

Review of Literature

For five years, I worked at one of Oklahoma's 14 community colleges, with a job title that was as descriptive as it was unwieldy: Director of Performance Measurement and Reporting. Years before that, after having completing an MBA, I had worked at a Hewlett Packard (HP) manufacturing division, producing measurement equipment descended from the product line that led to the company's founding in the Palo Alto garage that today is considered the birthplace of Silicon Valley. My interest in quality motivated me to study a performance-improvement methodology widely deployed in manufacturing and consider how it might apply to higher education. This background inspired me to undertake this study, although the pathway to the specific topic and research questions as written in the previous chapter was not direct.

When I began my inquiry into the subject of what constitutes quality in higher education and how to measure it, I discovered that the literature is dominated by research and debate about the practice of comparing and ranking higher education institutions. Each of these ranking systems invariably involves subjective judgments about what academic quality is, what variables measure it, how these variables should be weighted and scored, and what source should be used to obtain the data (Usher & Savino, 2007). College rankings almost constitute an industry in themselves, resulting in a plethora of publications in books, magazines, and journals as well as on websites.

Theories and Models of How Higher Education Affects Students

Reviewing the literature about how higher education affects students provides the theoretical justification needed to help support the selection of variables during the model building process. Sometimes higher education fails to bring about positive change, leading the student to depart the institution (Pascarella & Terenzini, 1991). In their 2005 review of three decades of research on how college affects students, Pascarella and Terenzini divided the literature pertaining to theories and models into two categories: (1) developmental theories weighted toward the nature and content of intra-individual development, and (2) college impact models focused primarily on the characteristics of the institutions that students attend or the nature of the experiences they have while they are enrolled. They note that the main distinction between developmental theories and college impact models is the degree of attention given to the changes that education causes in college students as opposed to the sources of student change.

Some developmental theories focusing on how college changes students emphasize psychosocial impacts, such as gender, ethnic, or racial identity formation; others theorize about the cognitive–structural changes that students undergo as they pass through hierarchical phases of increasingly complex epistemological or moral development. College impact models, on the other hand, seek to correlate environmental and inter-individual variables with one or more aspects of change observed in students, including variables that are barriers to student change (i.e., variables that prevent students from making progress and completing a program of study). Of the two categories, the college impact models are most helpful in choosing which independent variables to include in this study.

College impact models, according to Pascarella and Terenzini (2005, p. 18), utilize variables that are “student-related” (such as gender, academic achievement, socioeconomic status, race, and ethnicity), structural and organizational (such as institutional size, type of control, selectivity, and curricular mission), or environmental (for example, the academic cultural, social, or political climate created by faculty and students on a campus). Most of the literature reviewed by Pascarella and Terenzini is concerned with first-time, full-time students enrolling at four-year colleges and universities directly after graduating from high school. During the last decade, however, many more studies have been published specifically investigating community college students. Several of these studies are clearly relevant to this study proposal; these are summarized in the literature review section.

The input–environment–output (I–E–O) model proposed by Astin (1965; 1970a; 1970b) anchors decades of research on college outcomes. Astin's formulation has been used to study many college outcomes besides graduation rates; in fact, Astin originally adapted the model from research on the effect of different college environments on the career choices of high-aptitude students (Astin, 1965). Astin noted that an adequate study design must include student input data, student output data, and data about the college environment (p. 29). His formulation postulates that college outcomes are the result of interactions among these three groups of variables, as described below and depicted in Figure 1:

> The relationships among these three components of the model are shown schematically in Figure 1. The principal concern of research on college impact is to assess relationship "B," the effects of the college environment on relevant student outputs. Relationship "C" refers to the fact that outputs also are affected by inputs, and relationship "A" to the

fact that college environments are affected by the kinds of students who enroll (p. 225).

Influential variables from the student input group might include demographic and socioeconomic traits and academic qualifications like aptitude, preparation, and prior achievement. Environmental inputs include the wide range of faculty, programs, policies, facilities, and other institutional features with which the student is likely to interact. The proposed study is concerned with one particular student output, completion rate; however, the output of interest could be a construct like a desired attitude, belief, or moral code, rather than a credential.

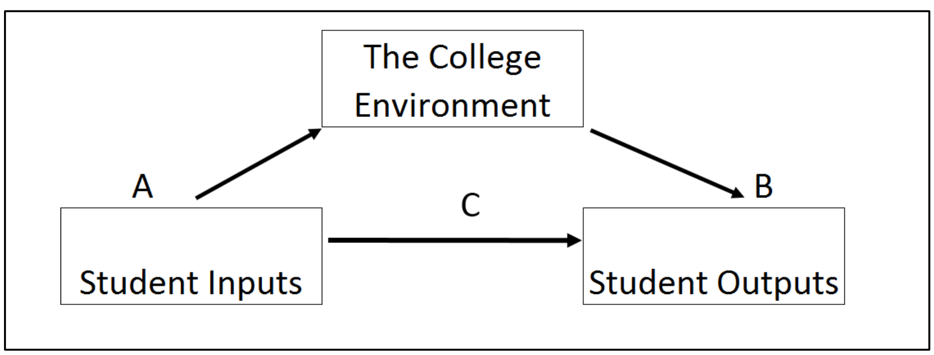


Figure 1: Astin's I-E-O Model
(Astin, 1970a, p. 225)

An example from Astin's research on predicting retention rates at colleges and universities (i.e., graduation rates for bachelor's degree students) illustrates the I–E–O model. Using a sample of 52,898 students from 365 colleges and universities, Astin used multiple linear regression analyses to calculate predicted retention at intervals of four, six, and nine years. Completion or non-completion of a bachelor's degree is the dichotomous criterion variable; the categorical predictor variables are high school grades, admission test scores, sex, and race. These four variables describing incoming freshman characteristics accounted for the majority of variance that can be predicted by the student input side of the model. Astin notes that the addition of other student input variables (socioeconomic status, religion, political orientation, and level of hedonism) significantly improves the prediction equation, but he excludes them because they are not commonly available to colleges and universities. Institutional variables (labelled “the college environment” in Figure 1) that contribute to higher retention rates include requirements that freshman live on campus and large numbers of business, psychology, and other social science majors. On the other hand, using the two longer time intervals—six or nine years rather than four—diminishes the accuracy of the model. Astin speculates this is because, as time passes, environment variables become more dominant in the retention equation. This result may have implications for this study, as a three-year outcome allows a certificate student proportionally more time than an associate’s degree student (because time is expressed as a percentage of the time normally expected for a full-time student to complete the credential).

In a study published in *Science* in 1968, Astin demonstrated that student traits over which the institution has no control can be confused with or wrongly attributed to the institution’s quality and performance. In the fall of 1961, Astin sampled 669 freshmen seeking bachelor’s degrees from 248 accredited colleges and universities to determine whether certain institutional traits commonly believed to indicate institutional quality actually affected student development and achievement. He discovered that, when he accounted for student inputs completely disassociated from the quality of the institution, the positive relationship between institutional quality and intellectual achievement was greatly diminished. These student inputs included standardized test scores; gender; high school grades and class size; nonacademic achievements; father's educational level and occupation; highest degree planned; intended field of study; and career choice. Astin concluded that "the student's achievement in social science, humanities, or natural science is not facilitated either by the intellectual level of his classmates or by the level of academic competitiveness," nor do bright students benefit more from supposed indices of institutional quality than average students (p. 667). This study will test similar parameters as permitted by the availability of data routinely collected by a state agency rather than a specialized survey instrument.

Tinto's theory of institutional departure may more aptly fit the definition of what constitutes a theory in the social sciences than the I–E–O model, because it provides a more complete and detailed explanation of the departure process (i.e., the events that lead students to leave the institution without a credential), but the variables involved are the same. Tinto's model of student departure theory is explicitly concerned with student attrition. As Pascarella and Terenzini conclude (2005, p. 56), "Tinto's comparatively more explicit theoretical structure…offers guidance in variable selection to researchers who wish to study the college student change process and to administrators who seek to design academic and social programs and experience intended to promote students' educational growth." As shown in Figure 2, when students have rewarding experiences with the formal and informal academic and social systems of their college or university, they become integrated into the institution and are more likely to persist in their studies and achieve their goals. Students undergo "integration" when they "share the normative attitudes and values of peers and faculty in the institution and abide by the formal and informal structural requirements for membership or in subgroups of it" (Pascarella & Terenzini, 2005, p. 54). On the other hand, negative interactions with the institution's academic and social systems have the opposite effect on students, which can lead to isolation from the external community and an outcome of a departure. It is important to note that the pre-entry attributes—family background, skills and abilities, prior schooling, and so forth—are the model's foundational variables and the focus of the proposed study. In later research, Tinto explores institutional conditions (classroom pedagogy, assessment, faculty development, learning communities, and proportion of part-time faculty) affecting retention (Tinto, 2010).

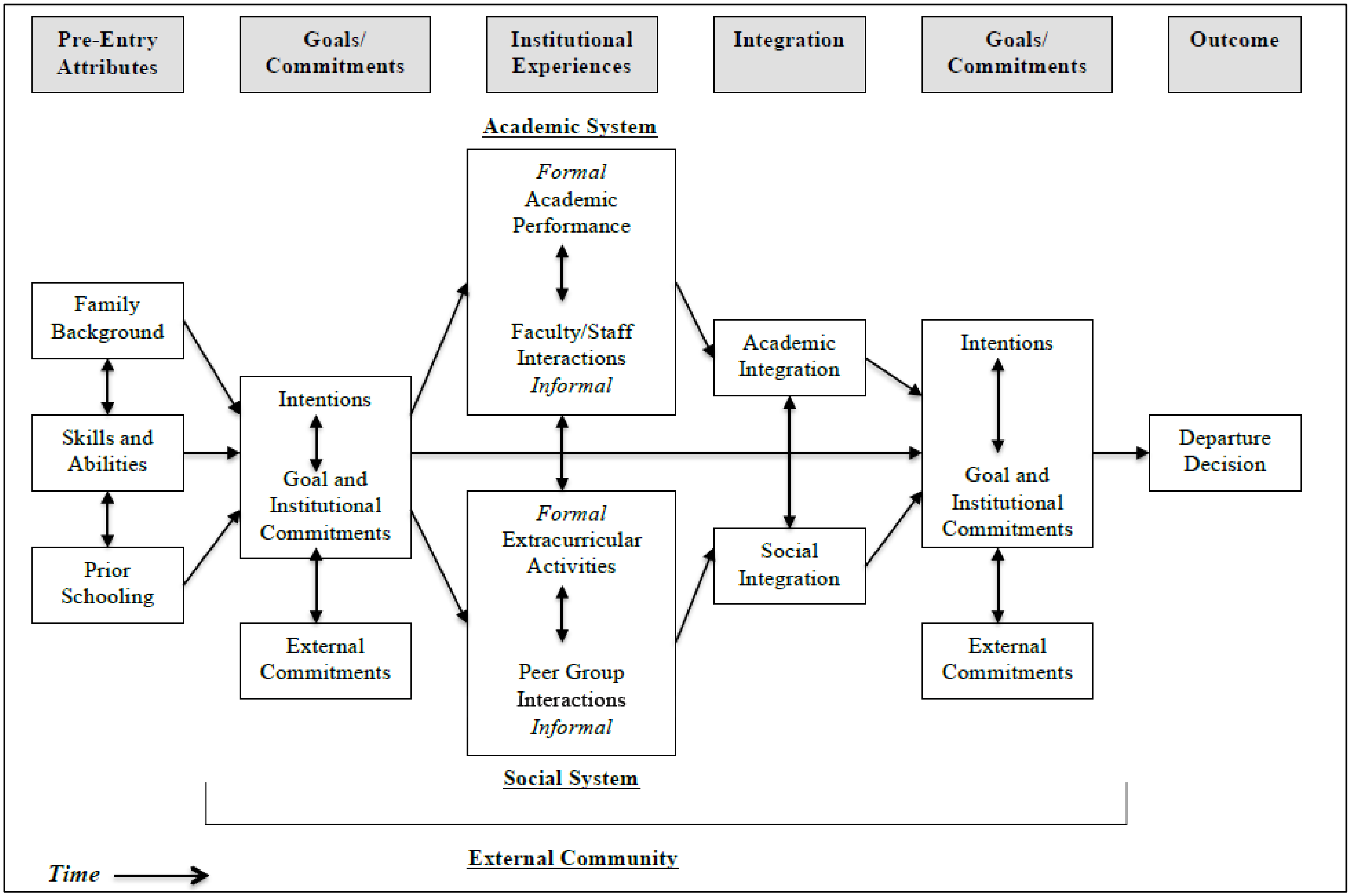


Figure 2: Tinto's Model of Student Departure (Tinto, 1993).

Figure 3 depicts Astin’s theory of student involvement (Astin, 1984). Involvement simply refers to the level of physical and psychological energy that the student dedicates to the academic experience. A highly involved student is one who “devotes considerable energy to studying, spends much time on campus, participates actively in student organizations, and interacts frequently with faculty members and other students” (p. 518). “Involvement.” in this model is analogous to the institutional experiences students accumulate as they navigate the formal and informal academic and social systems depicted in Tinto’s institutional departure model. Astin’s theory confirms the weight that the current study places on student attribute variables in the calculation of completion rates among community colleges to improve their usefulness as quality metrics. Astin asserts that “[t]he principal advantage of the student involvement theory over traditional pedagogical approaches…is that it directs attention away from subject matter and technique and toward the motivation and behavior of the student” (p. 529).

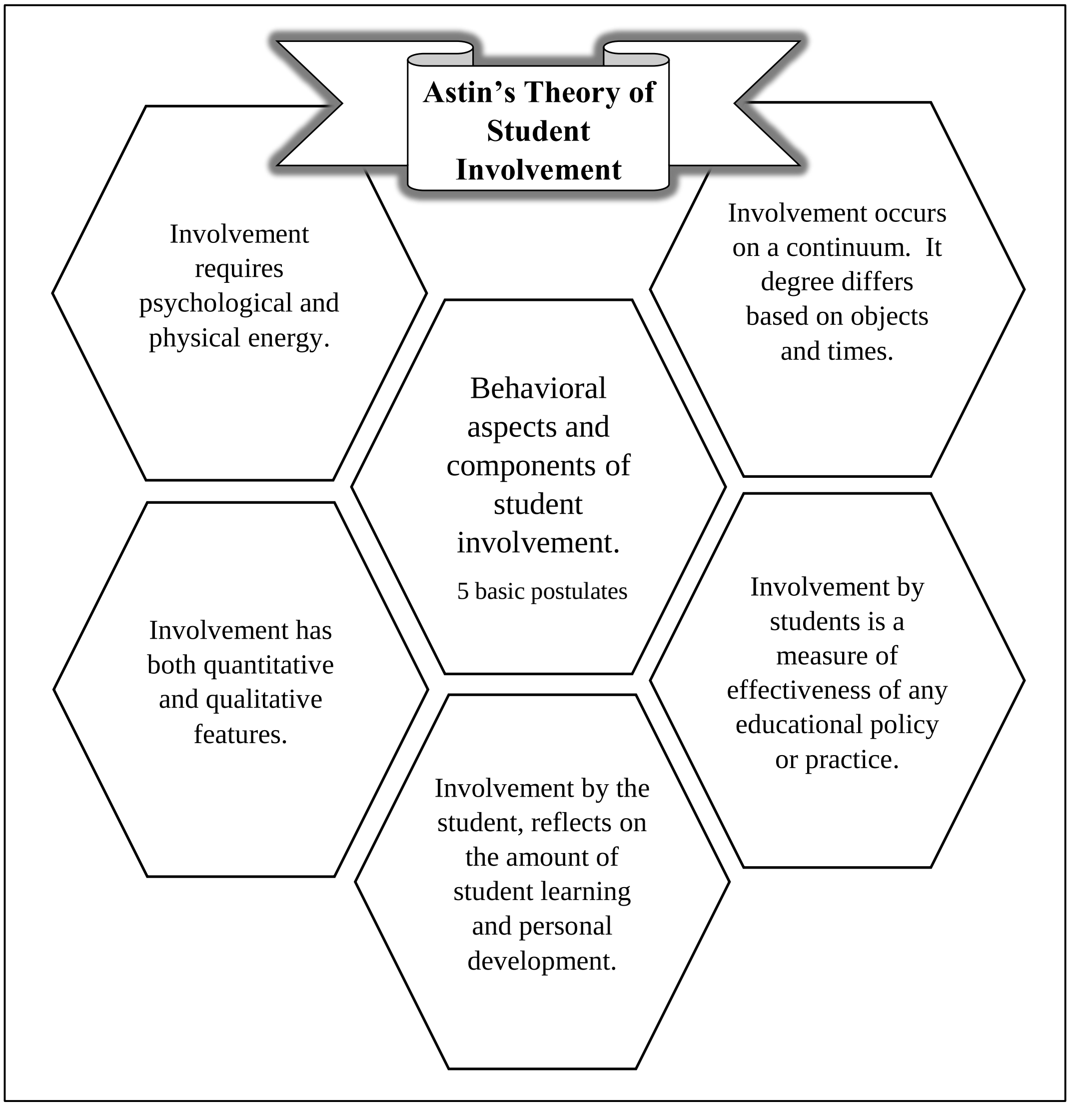


Figure 3: Astin's Theory of Student Involvement

This review of college-impact theories concludes with Pascarella and Terenzini's general causal model for assessing change (Pascarella & Terenzini, 2005). This model postulates the direct and indirect interactions of five sets of variables responsible for student development. Figure 4 shows that the set of student background and pre-college trait variables are integral to the growth and retention equation. These variables are directly correlated with learning and cognitive development; furthermore, because they influence the institutional environment, the structural and organizations features of the institution, and the quality of student effort, they also have an indirect correlation with student learning. Pascarella (1985) notes that, although he developed the model to assess changes in learning and cognitive development, it is equally suitable for other learning outcomes like completion.

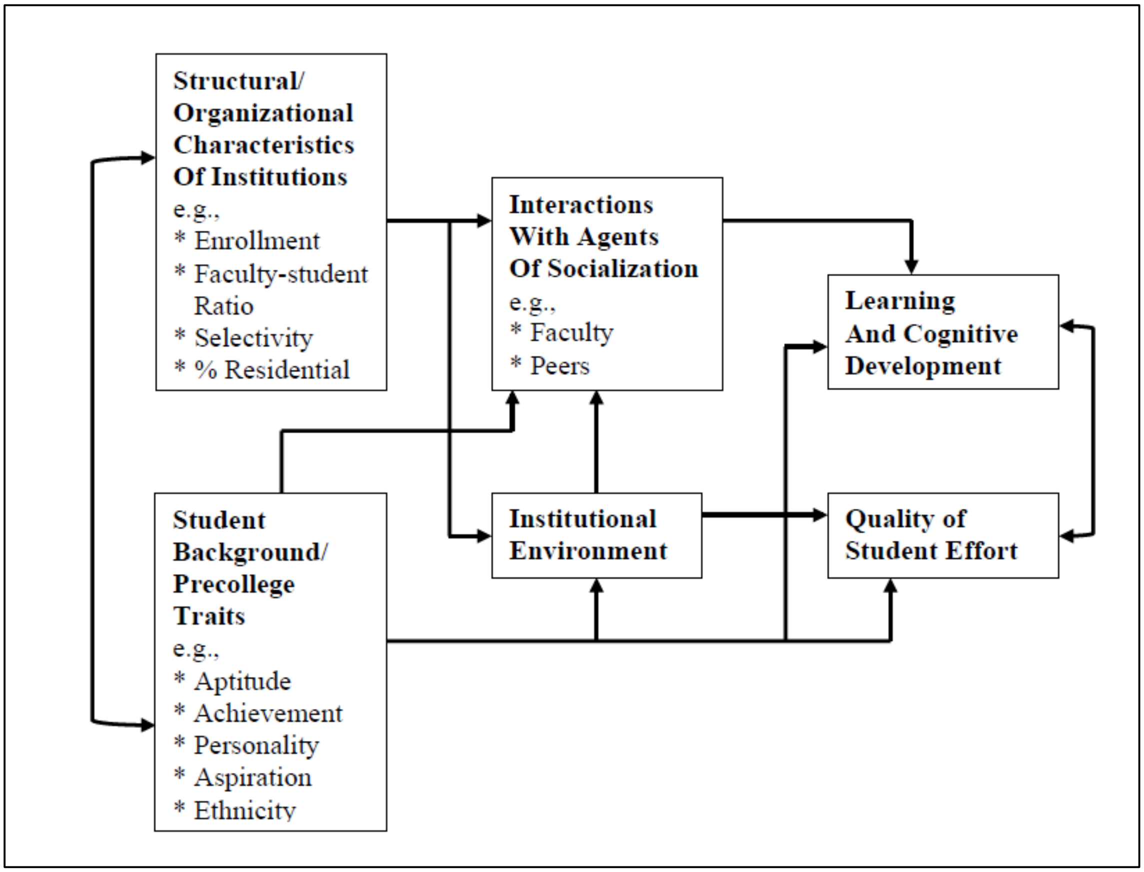


Figure 4: Pascarella's General Causal Model
(Pascarella, 1985, p. 10)

Studies of Community College Outcomes

The topic of graduation rates for students seeking bachelor's degrees—including predicting rates both at the institutional level and for individual students—has long received extensive treatment in the literature. However, scholarly interest in completion rates at community colleges is a relatively recent phenomenon. These studies' objectives vary. The literature relevant to the present inquiry has as its objective estimating completion rates from some combination of student and institutional variables, or measuring the efficacy of other programs or interventions while controlling for student and institutional variables.

OSRHE does not require community colleges to collect and report high school grade-point average (GPA) from applicants; at Oklahoma City Community College (OCCC), for example, high school GPA is archived for some but not all enrolled students in a seemingly random pattern. Astin (1997) has found that high school GPA and SAT scores are among the most predictive indicators of student retention in bachelor's degree programs, yet information about them is only sporadically reported by colleges awarding primarily associate's degrees. (Interestingly, ACT scores are more widely available, probably because the College Board reports them directly to OSRHE). As will be discussed later in the methodology section, this study proposes examining whether students report their high school GPA or standardized test scores, because, irrespective of the magnitude of the actual score, this may serve as a proxy for the student's *commitment* to a higher education program and *motivation* to complete it. (It has been observed at OCCC, for example, that easing late registration requirements or a downturn in the economy is followed by lower persistence rates in subsequent semesters, possibly reflecting weak commitment by some new entrants).

The practice of remedial or developmental education at community colleges is a topic of considerable interest and controversy among community college stakeholders. Attewell, Lavin, Domina, and Levey (2006) published a study using a model and variables similar to those in this proposal. They examined the correlation of remedial course-taking behavior by two- and four-year college students with graduation rates and time to degree. Using a sample of 6,879 students from the 1988 National Educational Longitudinal Study (NELS:88), the study estimated the probability that students attending two-year schools would earn a degree under four scenarios: if they enrolled in a single remedial course; if they enrolled in multiple remedial courses; if their remedial course work was in reading, English (writing), or math; and if they successfully completed all of the remedial requirements in reading, English, or math. The authors controlled for measures of academic skills and high school measures of academic achievement and orientation. The NELS:88 data also enabled them to control for demographic factors and socioeconomic status (using data about the proportion of classmates who were Black or Hispanic in eighth grade, the proportion of students who qualified for free lunches, and information about whether the high school was public or private, or in an urban, suburban or rural setting). The researchers reported results from three model designs: the raw effect with no controls (bivariate); conventional logistic regression with controls; and a counterfactual inference model with controls for covariates, intended to compensate for the selection effect.

The researchers found that, for two-year students who enrolled only in a remedial course, the uncontrolled bivariate calculation revealed a significantly lower probability of graduation. When controls were added, however, the effect disappeared. For two-year students who successfully completed all remedial courses in a subject area (reading, English, and math), the logistical model found that they had better chances of graduating compared to students with similar backgrounds who did not engage in remediation (11% in reading, 13% in English, and 8% in math). The authors conclude that taking some remedial coursework has no negative effects on two-year college graduation rates. This is different from the results for students at four-year colleges, whose chances of graduating are reduced by about 6% to 7% if they take remedial courses (when results are controlled for academic preparation and high school skills). Two-year college students who successfully completed remedial sequences were more likely to graduate than equivalent students who never took remediation.

Using a database of 256,672 student records from the Lumina Foundation's Achieving the Dream (ATD) project, Bailey, Jeong, and Cho (2010) found that 59% of first-time, credential-seeking community college students were advised to take one or more remedial math courses, and 33% were referred to developmental reading. Yet of these students, only 20% of the math students and 37% of the reading referrals went on to attempt a college-level ("gateway") course within three years. Given the prevalence of developmental referrals for two-year students and the low-level of matriculation from remedial to college-level classes, these researchers were interested in identifying student and institutional factors linked with successful progress through a developmental sequence and into college-level courses. The ATD project did not collect extensive data on student characteristics, so the researchers used the NELS:88 survey and college-level variables from IPEDS to carry out an ordered logistic regression testing the hypothesis “that success in developmental education depends on student demographics, college characteristics, and state-specific effects.” Student demographics included gender, ethnicity, race, age at entry, cohort year, intensity of first-term enrollment, major studied, developmental need in other subjects, and socioeconomic background. The model also incorporated other parameters: whether the student was employed while enrolled, whether the student was enrolled full-time or part-time, and whether the student required remediation. The authors discovered that failing or withdrawing generally was not the reason students exited their developmental sequences; it was because they simply did not enroll in the first or subsequent course in the sequence. (Informal analysis of OCCC’s year-one VFA also showed this result.) The study showed that men, older students, African American students, part-time students, and students in vocational programs were less likely to progress through their full remedial sequences.

These studies confirm the appropriateness of using remedial course-taking behavior as a predictor of credential completion. It is outside the scope of this study to investigate whether remedial education requirements influence student completion because they are an indicator of academic ability, or because they constitute a barrier to student engagement, or for some other reason. What is relevant is that the literature has identified it as a possibly significant variable. The type of credential that community college students seek also may be predictive of completion outcomes. Alfonso, Bailey, and Scott (2005) analyzed whether community college students’ selection of an occupational track versus an academic track was correlated with completion rates. This study chose a sample from each of two waves (1989–1994 and 1995–1998) of the Beginning Postsecondary Student Longitudinal Study (BPS). Using a categorization developed by Choy and Horn (1992), students were sorted into groups based on whether their declared major was occupational or academic, or whether they had not declared a major. OSRHE requires colleges to submit these records for individual students, so this kind of sorting can be used in the current study.

Disentangling the effects of multiple confounding variables was a critical issue in designing the current study. Although certificates require fewer credits to complete, certificate students as a group have more demographic characteristics associated with lower completion rates (such as minority status, lower socioeconomic status, and GED completion rather than a high school diploma). Conversely, certificate students are more likely to attend full-time, less likely to be employed, and less likely to interrupt their program; these factors are associated with higher completion rates. The associate's degree students were divided into academic and occupational subgroups (almost all certificate students, on the other hand, are occupational), and the descriptive statistics show that these groups are dissimilar along dimensions known to be predictive of completion, especially delayed enrollment, part-time enrollment, and responsibility for care of family members.

This study used logistical regression with a dichotomous dependent variable of completion and an independent variable of whether the student is enrolled in an academic or occupational program, along with demographic, socioeconomic, education, and attendance intensity (full-time or part-time status) variables. For the certificate cohort, most of the variables did not reveal statistically meaningful results; for the associates group, the regression variables explained some of the discrepancy between the academic (57%) and the occupational (38%) students' completion rates. The study concludes that the regression model can only partially explain the achievement gap within the associate's degree cohort, suggesting that institutional factors have a differential effect on a student's probability of completing, depending on the program type they chose.

Studies focused on estimating completion rates for community colleges from student or institutional characteristics (or both) using an input–output framework (as Astin proposed in 1965) are most relevant to the current study. Economists who study higher education have undertaken this kind of research using elaborate datasets and analytic models, so before discussing the methods and conclusions of these studies, a review of the theoretical framework commonly used in the economics literature will prove useful.

Economists use a theoretical framework known as a production function to study problems that involve relating the physical inputs to a production process to the outputs produced. A production function is a mathematical expression that relates the quantity of output that can be produced with a given combination of the factors of production—labor and capital. Defining a production function for a process makes it possible to answer questions such as "what is the marginal productivity of the factors of production?" or, in other words, "how much will output change with a one-unit change in a factor of production?" When applied to the study of education, this input–output relationship is called an educational production function (EPF). These types of studies are "generally statistical analyses relating observed student outcomes to characteristics of the students, their families, and other students in school, as well as characteristics of schools" (Hanushek, 1979, p. 354).

Academic economists are not the only professionals who envisage schools as taking heterogeneous student inputs (i.e., inputs with varying levels of "quality" or propensity to succeed academically) and producing outputs that meet a stipulated standard as measured by test scores, grades, persisting to the next grade-level, graduating with a high school diploma, or other outcomes. One of the very early studies to apply this framework was the *Equality of Educational Opportunity Study* (EEOS), published in 1966 as required by the Civil Rights Act of 1964. Its purpose was to assess the availability of equal educational opportunities to children of different races, religions, and national origins. Coleman gathered data on more than half a million students from the first through the 12th grades from more than 3,000 school districts. He discovered that variation in school resource levels (i.e., institutional variables) did not matter nearly as much as the variation among individual students (i.e., student characteristics). This result was unexpected and politically controversial; nevertheless, this groundbreaking finding in the sociology of education has inspired decades of subsequent research (Gamoran & Long, 2006). The current study proposal is a humble descendant of this line of inquiry, dedicated to elucidating how disparities in certain qualities of community college students influence completion rates at Oklahoma's 14 community colleges.

Hanushek (1979) points out that Coleman's work was groundbreaking for another reason, besides "direct[ing] attention to the importance of the relationship between school inputs and student achievement.” The report also introduced into the public policy lexicon a “bewildering array of technical and esoteric issues such as statistical significance, analysis of covariance, production efficiency, multicollinearity, residual variation, estimation bias, and simultaneous equations” (p. 352). Thinking of the production of education in this way enables the researcher to utilize quantitative techniques that can discriminate between the influences of multiple variables on a continuous, dichotomous, or multinomial criterion variable. The study proposed here will make use of statistical methods akin to those used by Coleman to determine whether any defensible conclusions can be drawn using data acquired from the state record system.

Fifty years after the publication of the Coleman Report, how is the theoretical construct of the production function, identical in many respects to Astin’s I–E–O formulation, being applied to the study of community colleges? Bailey, Calcagno, Jenkins, Leinbach, and Kienzl (2006) created a model to adjust community college graduation rates, as published in IPEDS, for institutional characteristics. The authors note that many community college students possess qualities identified in the literature with lower graduation rates. Because increasing the selectivity of admissions violates one of the underlying missions of community colleges—preserving an open-door admission policy to provide the widest possible access to any student who wants to learn—they chose to focus their research on the characteristics of institutions to judge performance. (This author is fully supportive of community colleges’ mission to offer unfettered access to any student desirous of a chance to learn. The proposed study, by seeking to explain the discrepancy in completion rates attributable to heterogeneous student input, effectively exposes what may be the differential attributable to variation in college quality. The difference between the Bailey et al. [2006] study and the current study lies in the emphasis on the production function coefficients calculated, not in differing philosophies about the role of community colleges.)

Bailey et al. have criticized IPEDS rates in other studies as overly pessimistic (Bailey, Jenkins, & Leinbach, 2005), but they point out that no other data source provides a sample of this size (almost a thousand community colleges report to IPEDS). IPEDS was the source for the 915 community colleges ultimately selected for the sample. The source of the graduation rates was the 2002–03 IPEDS Graduation Rate Survey (GRS), adjusted for transfer-out students who ultimately graduated from other institutions. Student-Right-To-Know (SRK) rates are based on the proportion of students who graduate within 150% of the time it would normally take for a full-time, academically prepared student to complete a degree. For an associate's degree, the expected length of time to complete is two years, and 150% of this is three years. Thus, the base year for collecting the predictor variable data is 1999–2000, and the sources are the IPEDS Institutional Characteristics, Fall Enrollment, and Finance surveys.

Bailey et al. use a multivariate statistical design to estimate an expected graduate rate for each college using institutional characteristics; they then compare actual outcomes to those predicted by the model. These results could be used to categorize colleges as "higher quality" if their graduation rates are greater than predicted by the regression equation could be considered higher quality; likewise, colleges with empirical rates below the prediction could be designated as lower quality. (This approach is similar to both Astin's and the study design proposed here.) The output of the production function (the probability of graduation or transfer within three years) is determined by fixed institutional characteristics: urbanicity; proportion of certificates awarded; compositional variables like enrollment, ethnicity, and gender; and financial variables (such as the budget allocation among instruction, academic support, student services, and administration). For technical reasons, the authors opted for a weighted least squares method for grouped data, as opposed to ordinary least squares or logistic regression. The first model uses only fixed characteristics (such as location and degree mix) to control for state differences; the second adds compositional characteristics (such as enrollment levels and gender mix); and the final one includes financial characteristics (such as tuition rates and expenditures). The final model explains 60% of the outcome variation, and it uncovered a negative effect on the proportion of females enrolled and graduation rates. This was explored in a separate regression for males and females, which uncovered an interaction between the proportion of part-time and female students, perhaps because female part-time students often care for children in addition to earning household income, greatly magnifying the intensity of the part-time effect.

Bailey et al., like most researchers working on this topic, built their model using national survey data, a richer collection of potential model variables than will be used in this document’s proposed study. The work of Bailey et al. does suggest the inclusion of several institutional-level parameters derived from the composition of the student population that are beyond the control of the institution to mediate. However, the research questions for the proposed study are not directed at building a comprehensive model to predict graduation rates; rather, this study’s purpose is to explore specifically the correlation of completion rates with the pre-college attributes of students. This very important dissimilarity between the two types of studies is linked to the source data and sample size. There are only 14 primarily two-year degree-awarding colleges in Oklahoma, meaning that the sample size is not nearly large enough to construct an econometric model (logit) based on institutional characteristics. Rather, the three research questions relate to the individual student's chances of completing and the marginal cost of that chance; in other words, this study is an attempt to measure individual, not ecological, correlation, so data collection should take place at the student-record level. The methodology section will expand upon this important study design issue.

In their work on estimating completion rates, Calcagno, Bailey, Jenkins, Kienzl, and Leinbach (2008) use student-level data and include students who attend multiple institutions. Their study merges 2,196 student records obtained from NELS:88 containing demographic, socioeconomic, and cognitive ability measures with institutional-level data from IPEDS describing various characteristics of the 536 schools attended by the students. The institutional variables of interest are general college characteristics (enrollment size, proportion of part-time faculty, and degree mix); student body composition (part-time status, gender, and ethnicity); financial characteristics (federal aid levels, tuition rates, and budget allocation mix); and a fixed location variable (urbanicity). As with their other econometric model, the binary outcome variable takes the value 1 if a credential (certificate, associate's degree, or bachelor's degree) is attained or the student transfers to a four-year institution; otherwise, the value is 0. The study divides the sample into associate's degree earners and all students to provide a subgroup with reduced variability.

The data is analyzed by constructing four regression models. Model 1 assumes that the probability of completion is a function only of observed institutional variables. Model 2 accounts for unobserved institution-specific effects (e.g., academic preparedness, faculty-administrative relations). By applying attendance weights, Model 3 acknowledges that more than 40% of students attend more than one college. Model 4 uses ordinary least squares regression, with the number of credits earned as a dependent variable instead of a binary as a measure of success. Across all four models, college size and the proportions of part-time faculty and minority students were negatively associated with completion. The authors observed that, in general, student attributes are more correlative than institutional attributes, at least for variables that are observable, a finding consistent with Coleman's and Astin's work. They also noted that further research using much larger samples from single institutions is needed. Both of these observations tend to support the study design described in this paper, which calls for a much larger, multi-cohort, multi-year sample with outcomes measured at three and six years.

In a 2007 study of 28 community colleges in Florida, Jenkins confronts the problem of comparing the quality of community colleges that serve populations of students with very divergent characteristics. The purpose of the study was to estimate each college's effect on the probability that a minority student will persist for three years, earn a certificate or degree, or transfer to a public university in Florida. Using ordinary least squares regression on transcript-level data from more than 150,000 degree-seeking students at the 28 schools, the study isolates an institutional effect that captures "all unobserved institutional characteristics factoring into the probability of a student's completing, transferring, or persisting" (p. 951). Higher values mean that the college increases the minority student's probability of achieving a positive outcome; a lower value means that the college was less effective in helping the student persist, complete, or transfer. The study controlled for age, gender, race and ethnicity, math and verbal placement test scores, first semester enrollment intensity, enrollment interruption during the period, financial aid status, cohort year, and whether the student transferred within the Florida community college system before completing or transferring. Data limitations precluded controlling for socioeconomic status. A second-stage regression that attempted to control for institutional parameters outside the colleges' control—like proportion of full- and part-time students or the ratio of certificates to degrees awarded—produced indeterminate results. Because the schools in the study were very similar to each other with respect to these variables, Jenkins concludes that their impact on the ranking of institutional effectiveness was immaterial.

A careful review of the Florida study conveys several helpful insights about the proposed Oklahoma research: It confirms the challenge of correlating institutional variables with student outcomes for a small sample of colleges. With 28 community colleges in the study, Jenkins was forced to conclude that the model was misspecified, and the population of primarily two-year degree-awarding colleges in Oklahoma is even smaller (precisely half the size of Jenkins' Florida sample). Even using a much bigger sample of 536 schools, Calcagno et al. (2008) found student-centered variables more helpful than institutional attributes in making predictions. Jenkins solved this problem by comparing the colleges along the institutional dimensions he included in the regression model and concluded that the variances in these institutional characteristics was probably insignificant anyway. If the size of the variances was big enough to influence the findings, one solution might be to group colleges with similar attributes and then rank them using the regression equations. It appears that nearly the all Florida fields are available in Oklahoma, based on a comparison of the student attributes acquired from the Florida Department of Education data to the fields listed in the OSRHE Data Request Manual. Jenkins notes that he is unable to identify a proxy for socioeconomic status; however, this variable may be captured for Oklahoma students by making inferences based on the school district of their high school. Working with records retrieved from actual state record repositories greatly abridges the array of available variables. This may present privacy and data quality challenges, but these records are most likely to result in findings with the most compelling state policy implications.

This review of the literature has focused on studies that estimate completion rates for community colleges by conceptualizing the higher education process as involving inputs and outputs that can be modeled using regression techniques (or, using the lexicon of the economist from whose research many of these studies were taken, by specifying an educational production function and an appropriate econometric model). Before closing this review and turning to an in-depth description of the methodology, some research from the United Kingdom (U.K.) is presented.

Why include research about U.K. university students in a review of literature about educational outcomes for U.S. community college students? The first rationale is the high quality of the dataset used in U.K. analyses. An administrative reorganization in the U.K. resulted in the creation of individual student records for all students who attended universities between 1972 and 1994. This dataset includes the student's complete university record, prior academic qualifications, and social class background—data not generally captured by public colleges and universities in the United States. For example, Smith and Naylor (2001) study the 1993–1994 cohort of undergraduates departing a U.K. university, a cohort of 117,801 students. The Jenkins study, based on Florida students, has a comparably large number of records; however, the student attributes available for study are, by comparison, very limited.

The authors' reasons for undertaking their research provides the second rationale for including U.K. work here. Both Smith and Naylor (2001) and Bratti (2002) embarked on their research at a time when the U.K. government sought to develop performance indicators that "improve on raw rankings or league tables of universities by comparing universities against a benchmark that takes account of the subject mix and variations in students' entry qualification" (Smith and Naylor, 2001, p. 389). The authors note that the performance indicators published by the government are "derived from a macro-level analysis of university-level data," whereas their "micro-level analysis" investigates the correlation of individual student characteristics across institutions with departure decisions.

Using a binary probit model, Smith and Naylor reached conclusions nearly identical to those of the research previously presented about American community colleges. They found that prior academic achievement, student demographic characteristics, degree subject, and department and university characteristics influence the probability of not completing. The U.K. dataset enabled the researchers to incorporate a predictor variable for economic conditions, which was not possible for any of the U.S. studies. Smith and Naylor found that an increase in the local unemployment rate of 5 percentage points increases the probability of non-completion by 1 percentage point; when the data were disaggregated by gender and social class, it was found that lower-class males were twice as likely not to graduate.

Bratti (2002) used a smaller sample (n=7,997) to predict the probability that life sciences students will reach one of five levels of academic achievement, from fail (lowest) to first-class honors (highest). Bratti controlled for student attributes similar to those studied by Smith and Naylor. He found that a quality index based on the probability of a reference student graduating from each institution, as calculated by the educational production function for that institution, was significantly different from the published "league tables" that are analogous to the *U.S. News and World Report Best Colleges* rankings. As with Jenkins (2007), when Bratti attempted to explain the differential in the predicted probability of the reference student's attaining a given level of academic achievement at each of the U.K. universities with measures commonly used in empirical studies, about 60% of the variance remains unexplained. This result seems to support other studies' conclusions: When researchers strive to compensate for differentials in the output of institutions by adjusting for inputs into the production function (i.e., pre-college characteristics of students), they are on a much firmer footing than when they seek to correlate the residual variance with environmental variables (i.e., institutional characteristics).

Chapter 3:

Research Design and Methodology

The goal of this study is to make it easier to compare the completion rates of a of state's community colleges using data routinely collected and submitted by each college to the state regents for higher education. The first phase of the data analysis involves attempting to construct a statistically meaningful production function that estimates the probability that the educational institution will produce the desired output of a student completion based on the attributes of the student enrolled. The second phase is to use the production function to calculate the probability of a completion outcome for a reference student with a particular set of attributes. Using a reference student will improve the comparability of institutional productivity because it simulates what would happen if the exact same student enrolled in the exact same program of study at the exact same time at each of the 14 schools simultaneously. This will result in a list of community colleges shown in descending order based on the probability the reference student will complete. The last phase of the study will calculate a marginal cost of the probability of completion for each community college.

Model Design and Rationale

A binary logit model is proposed for this study. Binary logit models are a variant of logistic regression in which the outcome variable has two possible categorical outcomes. Two other commonly used forms of logistic regression are multinomial and ordinal logit models. The multinomial logit is used for problems in which the dependent variable can take more than two categories, and ordinal logit is used when these categories have a hierarchy. Because the goal of this study is to predict whether a student will complete based on a single trial, the binary logit model is appropriate.

Probit models are also suitable for problems in which the dependent variable is binary. The difference between logit and probit models is the assumption about the probability distribution of the error terms. The logit model assumes that the errors are distributed according to the logistic function, whereas the probit model assumes a normal distribution of the errors. The coefficients of the models are different, but the marginal effects are usually similar. The preference for which model to use tends to vary by discipline. The predicted value of a logit model is the log odds of a case. If the log odds are exponentiated, the resultant value is the odds-ratio. Because odds-ratios are more intuitive to understand than z-scores and are widely used in the field of education research, the logit model was selected over the probit.

Linear regression is another model choice available for this study. Dey and Astin (1993) compared the relative efficacy of the linear, logistic, and probit models on an actual research problem using educational data. They reported no significant difference in the results for their test case, concluding that no practical difference exists, although logit and probit models have theoretical advantages. In a 1997 publication, Astin notes that he chose to present regression results “because regression is a more familiar form of multivariate analysis” (Astin, 1997, p. 658). Logit models actually are a special case of linear regression, using logarithmic transformations and linear regression to fit the criterion variable to the predictors. Multiple studies presented in the literature review employ linear models.

Nevertheless, because of the theoretical inconsistencies inherent in applying a linear model to the dichotomous outcome of completion versus non-completion, this study proposes to use a model from the logistic regression family, even though it may require more explanation to interpret. The sigmoid or “S” shape of the logistic curve produces probability estimations that intuitively make more sense than the constant slope of the equation for a straight line. The logistic transformation used in a logit model ensures that probability estimates are always between zero and one, whereas a linear model can give results that defy interpretation, such as negative numbers or values greater than one, because the dependent variable in a linear model is continuous. Linear regression assumes that the prediction errors are randomly distributed; however, this cannot be the case with a dichotomous outcome variable, because if the variable does not take one value it must necessarily take the other.

The research questions in this study involve using student characteristics to predict a student’s chances of completing at each community college. This research may help individual students make choices about where to enroll in college. If the correlation involves groups—such as many students attending a community college—the correlation is an ecological correlation. According to Robinson (2009), ecological correlations cannot be substituted for individual correlations except under very unusual circumstances not ordinarily encountered in social science data. This statistical reality governs the selection of study participants and data collection procedures for this study, as described below.

Study Participants

The cohorts consist of first-time college students who attended one of the 14 colleges in Oklahoma that award primarily two-year degrees. First-time students who enrolled the summer prior to the beginning of the fall cohort year are included in that year's cohort. This is compatible with OSRHE reporting guidelines that define the academic year as beginning in the summer and ending with the spring semester. In contrast to the College Scorecard data, but consistent with the planned changes in IPEDS reporting, part-time students (as measured the first semester of their enrollment), are included in the cohort. Oklahoma colleges are required to report on the summer cohort in October, the fall cohort in March, and the spring cohort in July.

Data Collection Procedures

Data were requested based on OSRHE's Student Enrollment File, the list of the student-level variables that are routinely collected by OSRHE and thus are available as potential predictors. Listing of the field in the Student Enrollment File is not an assurance that any of the colleges report the data; it is simply an assurance that the colleges could report it if they wished to. Requesting the field is the only way to know what fields are populated in sufficient quantity to include as possible variables in the model building process.

An interesting theme emerged from the literature reviewed for this inquiry: (1) student background and pre-college attributes are more strongly correlated with outcomes than the variables centered around institutional characteristics; (2) furthermore, when researchers attempted second-order regressions to correlate the variance unexplained by the student input with the environmental variables related to the college or university, the results were indeterminate. This has implications for the methodology and design of this study: One reason why the research design and methodology stress the acquisition of data about student background and attributes is that these data are more likely than the alternatives to bolster the statistical strength of the model. Colleges and universities are, of course, accountable for creating an environment where the students they serve can succeed, but in this study, the emphasis is on the individual student.

Data collection focused exclusively on the OSRHE Student Enrollment File because it is the only source for the information. As Robinson (2009) cautions, “In an individual correlation the variables are descriptive properties of individuals, such as height, income, eye color, or race, and not descriptive statistical constants such as rates or means” (p. 337). The descriptive statistics available to download on the NCES website are ecological correlations, meaning that they are not valid for answering the research questions in this study. However, descriptive information at the institutional level of analysis about the colleges and universities can be validly used in this study. The institutional data—enrollment, urbanicity, congressional district, cost, and so forth—are acquired directly from the NCES website.

Chapter 4:

Data Analysis

The goal of analyzing the data is to derive, for each of the 14 institutions, an educational production function that predicts the probability that a reference student will graduate. This will make it possible to make judgments about the relative performance of the colleges based on cost of attendance and graduation rates while controlling for variability in “input”—that is, variability in student characteristics. The analysis must be statistically sound, but in order to affect policy, it must be convincing and compelling to stakeholders who do not necessarily have deep knowledge of quantitative methods. Astin has used this approach to good effect in his work. The original data analysis plan was chosen because it follows a rigorous and sound method but avoids unnecessary embellishments. As the analysis proceeded, however, it became apparent that model fit was the overriding challenge, which was surprising, given the sample size. Because of this development, a very methodical check of the data was necessary prior to performing the final regression analyses.

Verifying and Preparing Data for Analysis

Data analysis begins by verifying that the data conform to the specifications outlined by Tabachnick and Fidell (2013) for binomial logistic regression. Although certain distributional assumptions, such as normality and homoscedascity, are absent from logistic regression, this type of regression is not devoid of all preconditions. The steps taken to assess and prepare the data for logistic regression are discussed next.

Adequacy of sample size. The guidelines for the adequacy of the ratio of cases to predictors when carrying out a logistic regression are the same for other forms of multivariate regression. A rule of thumb for testing multiple correlation is $N \geq 50 + 8m$, where m is the number of independent variables. With 97,929 valid records, the sample size clearly conforms to this guideline common in the literature; in fact, one concern is that the sample is so large that almost any multiple correlations are statistically significant. This concern about sample size is discussed in greater depth in Chapter 5.

Another facet of sample size determination is making sure that the expected frequencies are adequate for the categorical predictors. This rule is the same as the rule for chi-square tests of significance in cross-tabulation tables: No more than 20% of the cells should have expected values less than 5, and no cell should have an expected value of 1. Cross-tabulation tables for all pairwise combinations of all discrete variables confirm that the data meet this requirement.

Missing data. Missing data is not a problem with the data received from OSRHE. The data were missing 12 birth years and 18 age-at-college-entry values. Of the missing entry ages, six were imputed from birth years and the remaining 12 were replaced with the mode (age 19). For ethnicity, ACT score, and high school GPA, "unknown" is a possible value. In the case of ethnicity, missing values were changed to "unknown" for the purposes of this study. In many student records, ACT and high school GPA are missing; in fact, inspection of the cross-tabulation tables in Appendix D reveals that ACT scores are reported for 52.7% of the students, whereas high school GPA is reported for only 6.0% of students. Only three of the 14 institutions report high school GPAs: Connors State College (contributing 38.5% of all the GPAs in the dataset), Northeastern Oklahoma A&M College (contributing 61.5%), and Oklahoma State University at Oklahoma City (contributing one record). This compares with a distribution of reported ACT scores from a low of 37.3% for OCCC to a high of 89.0% for Northeastern Oklahoma A&M College. This inconsistent pattern of non-reporting precludes including high school GPA as a predictor in logistic regression. Omission of this variable (GPA) most assuredly will leave a significant void in the explanatory power of the production functions, as prior academic achievement is arguably the most important predictor of future academic success.

Why is there such a disparity between the reporting of ACT scores and the reporting of high school GPAs, and what does this mean about including, as an independent variable, whether ACT scores are reported or not? The master file provided by OSRHE includes a UDS_COMPOSITE_ACT_SCORE field and six ACT_xx fields. The notes state that the source of the UDS field is "ACT score submitted by institution in UDS" and that, for the ACT_xx fields, the source is "ACT files." Students do not need an ACT score to apply to any of the colleges. When students take the ACT, they can send score reports to up to four colleges, but only if they request the score reports at the time they register to take the ACT. If a college receives a score report, the score is recorded and reported to OSRHE. OSRHE may check with ACT for a score report if the college has reported an admission record for a student, regardless of whether the college has also reported have also received a UDS score. This is why a UDS_COMPOSITE_ACT_SCORE, an ACT_xx score, or both may exist for a given record in the data file. Students are not required to submit a high school GPA for admission to any of the 14 colleges, and because there is no external agency sending GPAs (as is the case for ACT score), GPAs simply are not recorded.

Detection and treatment of outliers. Outliers are values so extreme that they distort the calculation of statistics. Outliers can be present in both dichotomous and continuous variables, in the data used to calculate the regression (both the independent variable and the dependent variable), and in the predicted values output from the full equation. Methods have been developed for detecting outliers before and after performing a regression by evaluating the model output. Mahalanobis distance is an application of the principle behind a z-score, whereby the distance of a point away from the mean of the distribution is measured in standard deviations. Points with higher Mahalanobis distances have greater leverage and are more influential on the regression equation. To set an outlier threshold, an inferential test using a chi-square critical value is employed, with the degrees of freedom equaling the number of predictors.

Post-regression methods examine the residuals; that is, the quantity that remains after the predicted value is subtracted from the observed value. This difference is typically standardized (normalized to the Gaussian distribution) or studentized (normalized to the Student's *t*-distribution). Converting the residuals to z- or t-scores permits the rejection of cases that result in a residual (prediction error) falling outside an acceptable margin of error. The default margin of error in SPSS is +/– 2.0 standard deviations, which, if the data meets the specifications for random selection, normality, and independence, should bound approximately 95.5% of the residuals. A more rigorous threshold for expunging outliers is the three-sigma rule that theoretically will bound nearly all (99.7%) of the normally distributed residuals. Although the two- and three-sigma rules are commonly used, they are nevertheless arbitrary and may not be in themselves adequate justification for rejecting cases (which is the position I plan to take after giving due consideration to what constitutes good practice in multivariate statistics). Tabachnick and Fidell advise that cases identified as outliers may rightly belong to the population from which the sample was taken, so deleting them, although improving model fit, will reduce generalizability.

Potential outlier candidates were identified in this study by evaluating the standardized residuals. A preliminary regression was run with simultaneous introduction of all the variables that will be used in the final model, and the casewise listing of residuals option for 2.0 standard deviations was selected. This returned 3008 standardized residuals with z-scores of 2.0 or greater. Although not the final model, it includes the 14 predictor variables and provides a framework for covering the topic of outliers generally. Figure 5 is a histogram showing the frequency distribution of all the residuals. Inspection of the residual table shows that, for all 3008 cases, the model predicted no success, whereas the observed values are all successes. Because the reference case is coded zero, the residual is 1 minus the predicted probability of success.

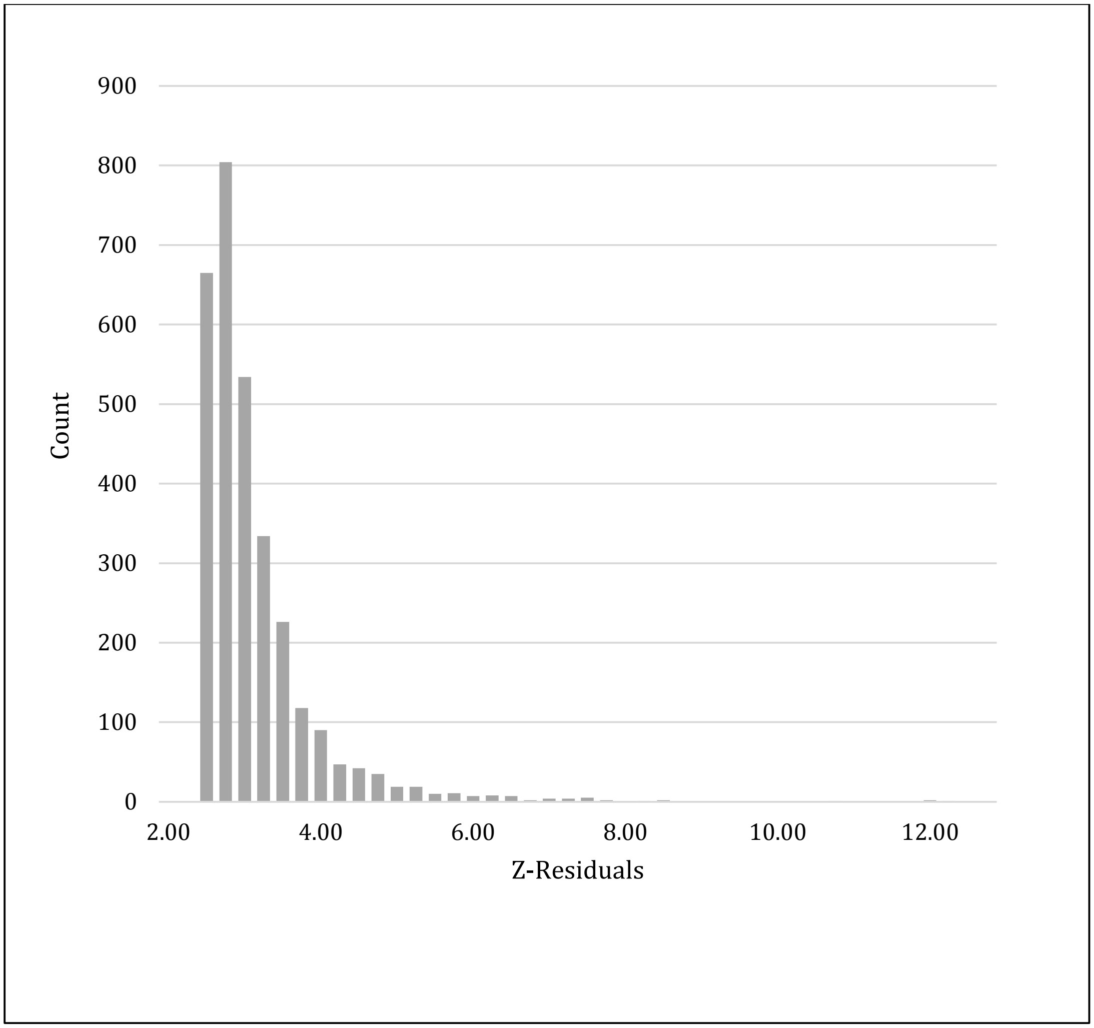


Figure 5: Histogram, Z-Residuals Outliers

The case of student 222 represents the most extreme outlier. Its deletion from the regression is easily justified by applying rules from the literature. This study, however, does not delete this case, nor does it delete any of the other 3007 cases meeting the 2.00 z-score threshold. The particulars of case 222 elucidate the reason for retaining it. The regression predicts a 12.6% chance of success for this student. Because 12.6% (0.126) is not greater than 0.50, the student is categorized as belonging to the reference (no success) group. The residual is 1.00 minus 0.126, which equals 0.874 and equates to a z-score of 12.3, far in excess of the 2.00 z-score threshold. This case is a Caucasian 19-year-old male attending OCCC who has no ACT score. This young man did not earn a credential, but transferred to a four-year institution within three years, which resulted in his assignment to the success group. He entered with a degree goal of AA or AS, received no financial aid, attempted three remedial English classes and two remedial math classes, and belongs to cohort year 2010. It is, admittedly, surprising that this student has a successful outcome. Multiple indictors strongly point to a “no completion” outcome—male, no ACT, and, very significantly, five remedial class attempts in two subjects. A plausible scenario is that this young man was a lackluster student in high school, yet did graduate; that he entered the workforce and learned first-hand how limited his employment prospects were, then enrolled in community college and bolstered his academic preparedness with the remedial programs; established a strong academic record and transferred to the flagship research university with a famous football program 18 miles to the south. Another scenario that is, sadly, more plausible is that when this young man left the community college, he stated to a college employee that he planned to transfer to a bachelor’s program; or perhaps OSRHE cross-checked records and discovered that he was enrolled at a nonselective four-year college in the state, but not the state’s most selective university. It is also possible that that this student had a superlative academic record at the community college and did not bother to complete the associate’s degree simply because he had been admitted to a bachelor’s degree program.

Depending on a model’s application, it may be a valid strategy to bolster its accuracy by narrowing the variability of the cases it must predict. The purpose of this study is to make more meaningful comparisons among institutions possible by using the common measurement instrument of the reference case to assess effectiveness. This method is philosophically distinct from a method that artificially constrains the amount of information that the model must contend with by screening out cases that happen very infrequently but nevertheless take place. A freak occurrence that is not foreseeable or explainable except by random chance is different from a very believable and understandable event that occurs with a low frequency. Every record in the database used in this study signifies the involvement of an actual community college student with the state's system of higher education. Everyone who works with community college students understands that they are an inherently diverse group and, if they work with them long enough, will not be surprised by even the most unusual circumstances. Pretending that these uncommon situations did not take place does not add to the credibility of the study, nor does it contribute to making the colleges commensurable.

Multicollinearity issues. Although it does not violate theoretical assumptions, the prevalence of multicollinearity in regression models can inflate standard errors and cause instability in beta coefficients. To test multicollinearity, a linear regression was performed with the dependent variable and the discrete independent variable. Dummy variables were created for the predictors with multinomial outcomes to facilitate application of a linear model and obtain collinearity statistics. SIZE, URBANIZATION, and CONGRESS_DISTRICT exhibited extreme collinearity, with variance inflation factors (VIFs) ranging from 5.9 to 15.3, resulting in a condition index (CI) of 31.3 for this set of discrete independent variables. Independent variables with a VIF value greater 10 generally are regarded as unacceptable, and it is ideal if the sum of the CI not exceed 30. Applying these criteria, URBANIZATION and CONGRESS_DISTRICT were dropped from the regression. This reduced the CI from 31.3 to 11.0. It is reasonable that a community college's enrollment is strongly correlated with whether the campus is set in a rural, suburban or urban setting, so SIZE plausibly captures the variance. CONGRESS_DISTRICT was originally introduced as an exploratory variable. These institutional-level variables are used in the regression only to specify a single production function for the state college system, because their values are equivalent for all the students attending the same college and therefore cannot explain any of the variance among student outcomes. Rerunning the linear regression without URBANIZATION and CONGRESS_DISTRICT reduced the highest VIF to 2.1 and the highest CI to 11.0. The complete table of diagnostics is presented in Appendix E.

Linearity in the logit. The concluding step in preparing the dataset for logistic regression is to check and perhaps explore the relationship between the logit of the dependent variable and its predictors. Osborne (2014) writes, "The essence of this assumption is that after we use the logit link function with our data, the relationship between the independent variables and the logit of the dependent variable is linear" (p. 92). Tabachnick and Fidell (2013) define this condition thus: "Logistic regression assumes a linear relationship between continuous predictors and the logit transform of the [dependent variable], although there are no assumptions about linear relationships among predictors themselves" (p. 445). It should be noted that this definition excludes categorical predictors (dummy variables coded zero or one) and is restricted to continuous predictors. In fact, continuous variables that have been dichotomized into unequal groups can cause spurious curvilinear effects that are not inherent in the underlying relationship being studied. Procedures for detecting curvilinearity (such as the Box-Tidwell transformation) are restricted to scale predictors, and if zero or negative values are part of the dataset, it is necessary to add a constant, because the base *e* log of numbers less than or equal to zero is undefined. When researchers apply logistic regression to data, they are asserting a linear relationship between the continuous predictors and the logit of the dependent variable. But this relationship is not with the actual value of the dependent variable; it is with the log of the odds that the case belongs to the outcome group (i.e., that it is not the reference case).

According to Osborne (2014), the Box-Tidwell transformation is widely used by statisticians and "is a more methodical approach to testing and specifying curvilinear effects" (p. 208) than ad hoc testing by adding squared and cubed terms to the equation, which Osborne says "tends to capture much of the curvilinearity if there is any" (p. 208). Tabachnick and Fidel concur, noting that the Box-Tidwell approach for testing linearity on the logit is among the simplest of the several graphical and statistical approaches available. These statisticians write: "In this approach, terms composed of interactions between each predictor and its natural lograrithm, are added to the logistic regression model. The assumption is violated if one or more of the added interaction terms are statistically significant" (p. 445). Because the log of zero and the log of negative numbers are undefined, these values are replaced with constants where they appear. The regression output relevant to the Box-Tidwell procedure is excerpted in Table 1.

Variables in the Equation	*B*	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
AGE_SCALE by LN_AGE	.042	.006	40.950	1	.000	1.042
LN_ENGLISH by REMEDIAL_3_YR_ENGLISH_SCALE	.421	.027	242.504	1	.000	1.524

LN_MATH by REMEDIAL_3_YR_MATH_SCALE	.290	.021	193.773	1	.000	1.337
LN_READ by REMEDIAL_3_YR_READ_SCALE	.036	.066	.298	1	.585	1.037

Table 1: Box-Tidwell Test

Because this data set is very large, the power of the inferential tests is extremely sensitive, with very small differentials in the data resulting in very large critical values that overshadow even miniscule levels of significance. This may be such a case, and it raises the question of what constitutes a practical effect size. Regression is a form of multivariate analysis that can be interpreted more easily through visual aids like scatter plots and line graphs. I experimented with plotting the scale predictors against the logit of the criterion, which are included in Appendix F, and doing power transformations by applying Tukey's ladder of transformations. Using visual inspection of the graph as a guide, I reran the regression when the line was approximately straight (given the perspective offered by a laptop computer screen), and, although the Wald chi-square had decreased, the p-value of the significance test was still too high to reject the null hypothesis.

Further exploration of the shape of the logit-criterion distribution may be a fascinating avenue for future research, but in the context of the research questions in this study, it is extraordinarily unlikely that misinterpreting the shape will invalidate the conclusions reached. To be sure, misidentifying the underlying relationship as linear rather than curviliner will weaken the model fit and is analogous to making the same error with ordinary least squares regression, but it is not a fatal error. These four predictors are only four out of 14, leaving 10 base variables to explain variance (plus interaction terms). That being said, remedial course work attempted is the best indicator of prior academic achievement in the dataset, given that GPA data is not collected, and it is throughly established in the literature that a student's past scholastic performance is strongly correlated with their future performance. This is why this particular model specification—linearity in the logit (a specification some researchers cover in a footnote, or not at all)—is explored in some detail.

Tabachnick and Fidel suggest that a reasonable criterion for determining significance for the Wald test is to divide the level of significance α by the number of predictors. Using a 0.05 level of significance and four predictors, the criterion is α=.0125. Comparing the *p*-values generated by the Wald tests to the threshold of 0.0125 shows that the interaction is clearly significant, suggesting a nonlinear relationship between the log of the odds predicted by the model and the continuous predictors. This raises the question of whether the relationship is actually nonlinear, which is often the case with many underlying processes in the social sciences, or whether the nonlinearity results from other data analysis problems that can be fixed.

Osborne describes three sources of curvilinearity not rightfully extant in a logistic regression: omission of important variables (model misspecification), violation of equal intervals in coding continuous variables, and poor data cleaning (e.g., when there are only a few cases, a severe outlier may distort the line). The equal intervals and data cleaning issues are straightforward (at least compared to misspecification), so they are tackled first.

The AGE_SCALE variable specifies the student's age at first enrollment. The frequency table in Appendix C, "Age Entered College Continuous," shows that 55.5%

of the students first enroll at age 18 or 19; however, 2.2% are under 18, and there is a very long right tail to the frequency distribution, stretching to a maximum of 86 years (grouped in the table only; continuous in regression). The skew in this distribution is evident by viewing the plot in Appendix F. I experimented with grouping this variable, but in the end, I decided against it because it seemed illogical to take one of the four ordinal continuous variables and arbitrarily convert it to a less powerful nominal predictor (and I later learned that Osborne warns against grouping in such cases precisely because of the skewed frequency count). Even though the AGE_SCALE variable is ungrouped, I speculate that the irregular clusters of students along the age spectrum causes the same effect. The histograms of the remedial English and math course attempts suggest that perhaps the same principle is at work to create curvilinearity in these relationships between the independent variable and the dependent variable.

Thorough data cleaning is the next step Osborne stresses when curvilinearity is discovered in a logistic regression, and he especially emphasizes the need to identify outliers. Osborne writes that he “repeatedly came across relatively powerful and interesting examples of how data cleaning enhanced curvilinear effects” (2014, p. 228). However, the presence of outliers can, theoretically, cause curvilinear effects. He points out that he could not “find a reasonable example that used appropriate data cleaning to remove a curvilinear effect” when writing his book, despite trying lots of different methods, including the standardized residuals procedure, the procedure calculated and discussed in this paper in the section dedicated to outliers. Osborne did note, however, that he found many cases in which a curvilinear effect was revealed by correcting the flaws in the data (2014, p. 228).

Although this study certainly includes an abundance of cases, I have followed a policy of retaining cases that might qualify as outliers according to popular statistical screening algorithms. About 3.0% of the total population of 97,929 would be deleted if residuals exceeding 2.00 standard deviation were removed from the analysis. Neither Osborn nor Tabachnick and Fidel suggest deleting outliers solely on the basis of statistical tests. Researchers should use such tests to indicate which cases require deeper consideration to determine whether they fit with the underlying theory, whether the theory should be revised, or whether the model specification needs attention. These records represent actual contact between students and colleges. Even though the colleges generally follow a nonselective, open enrollment policy, students still make a major investment: It requires capital and time to apply for admission and financial aid, meet with an advisor, select classes, purchase books, and generally adopt a school-centered lifestyle, especially given that 66.7% of students report that they plan to attend full-time. The rationale for retaining all the cases is humanistic, not statistical. Everyone who works with community college students knows that “outlier” situations are typical and expected, even if infrequent. Thus, it is appropriate to include them.

Model misspecification is the last area to consider in light of a significant Box-Tidwell result. Misspecification occurs when relevant and important variables are excluded from the regression, or when extraneous variables are included. This is why theory and prior research are essential guides to the selection of variables. If important predictors are excluded, the variance that these variables may share with included variables is misallocated; conversely, if irrelevant variables are included, they may absorb variance that they should not. Some statistical programs have advanced procedures for testing for misspecification (typically involving extensive graphing), and segments of code shared by other scholars can be downloaded from the internet for this purpose (UCLA: Statistical Consulting Group, 2015c).

The selection of predictors for this study was constrained by the availability of data from OSRHE; in fact, the idea behind the study was to determine whether meaningful analysis could be carried out with the data routinely collected by government. This contrasts to research that uses carefully designed survey instruments requiring students to consent to voluntary participation, such as the surveys sponsored by the NCES and used by many of the scholars cited in the literature review. It also contrasts to the work of Smith and Naylor, and that of Bratti, which took advantage of a unique opportunity afforded by a bureaucratic restructuring in the U.K. to apply a production function theoretical framework to a database of individual student records (larger [n=117,801] than the OSRHE records used in this study) documenting actual student experiences with the U.K. higher education system. The critical difference between the U.K. records and the OSRHE records is that, because of profound dissimilarities in ideology about the role of government and the social contract, the data used by the U.K. researchers was vastly richer and more detailed. It is almost surely the case that predictors that should be in the model are not, so misspecification may be a cause of the positive Box-Tidwell test. Yet, in practical terms, there is scant utility in searching for other variables to include, because the fields supported by theory and prior research that are available from state government are included in the model building process.

Exploring Determinants of Completion with Logistic Regression

Four views of the OSRHE records are presented, ranging from a simple arithmetic treatment to a full multivariate exploration that splits the database by college to create 14 production functions with main effects and interactions between nominal and scale predicators. Of course, it is this concluding and most complicated treatment that will be used to answer the three research questions, but the first three views are logical and intuitive interpretations of the data given the limits of the design. These interim steps are shared for their explanatory benefit and as a cross-check on the model building process. Commonly used terms in logistic regression that are often confusing are explained in the Definitions section of Chapter 1. Table 2 is a list of the names and abbreviations of the colleges in the study.

Institution Name	Abbreviation
Oklahoma City Community College	OCCC
Connors State College	CSC
Eastern Oklahoma State College	EOSC
Murray State College	MSC
Northeastern Oklahoma A&M	NEOK
Northern Oklahoma College	NOC
Carl Albert State College	CASC
Oklahoma State University-Oklahoma City	OSUO
Oklahoma State University Institute of Technology-Okmulgee	OSUT
Redlands Community College	RCC
Rose State College	RSC
Seminole State College	SSC
Tulsa Community College	TCC
Western Oklahoma State College	WOSC

Table 2: List of Colleges and Abbreviations

The software used to perform the calculations is IBM's SPSS Statistics 23, which uses a computationally intensive process known as maximum likelihood estimation (MLE) to calculate the regression coefficients. MLE estimates parameters that maximize the probability of obtaining the observed data; it is an iterative estimation method that is different from OLS regression. The categorical variables were coded in SPSS by using the "categorical" option in the regression binary logistic selection, creating k-1 dummy variables. The contrast is not changed from the default setting of "indicator," which returns the presence or absence of category membership. The threshold for assigning membership to the outcome (completion) group is $p \geq 0.50$. The reference category is changed from its default of "last" to "first," meaning that the reference category for a predictor becomes the mode, except for OUTCOME_YEAR. Because community colleges are susceptible to enrollment spikes from exogenous events, such as economic downturns or changes to financial aid policies, the ending cohort year with the highest enrollment (2013) was not used; instead, 2007 was used, because it has an enrollment closer to the mean and avoids the Great Recession turmoil. The data will be split by college, and a separate regression will be performed for each college, resulting in 14 separate production functions. These 14 predictive equations are the foundation for answering the three research questions. Peng, Lee, and Ingersoll (2002) make recommendations about how to report logistic regression results for publication in the scholarly higher education literature; these recommendations are followed for each of the data views. Each regression will evaluate the model's overall goodness-of-fit with the data, statistical tests of individual predictors, goodness-of-fit statistics, and an assessment of the predicted probabilities.

View #1. Probability of completion by college: simple frequency count. The simplest way to view the data is as a frequency count in which the sum of student completions is divided by the sum of students in the cohort. Although the algorithm for reporting is slightly different, this is the way dates are reported on the federally reported SRK IPEDS rates on the NCES website and the College Scorecard.

Table 3 is arranged with OCCC at the top to designate it as the reference case. This is not a logistic regression, it is a simple frequency count; therefore, this is not a true reference to which the odds of the other cases occurring are compared. In fact, with a probability of success of 0.163, if OCCC were placed in sort order with the other colleges, it would be second to the bottom, above RSC. The general probability of success for students attending two-year colleges in Oklahoma is 0.309. If the college attended is known, it is possible to make a better estimate of the student's chances. Table 3 is labeled a conditional probability table because the probability is conditional on knowing which college the student attended. To make the view comparable, however, the concept of the reference is introduced here. Without any other information available except the completion rates as measured in seven three-year cohorts, the student who wanted to have the greatest probability of completing would logically choose the college at the top of the table, which is CASC.

	No success	*(1 - p)*	*Success*	*(p)*	*Total*	*Odds (success)*	*Odds(no success)*	*Odds ratio*
OCCC	16343	0.837	3186	0.163	19529	0.195	5.130	
CSC	3369	0.621	2059	0.379	5428	0.611	1.636	3.135
EOSC	4721	0.626	2823	0.374	7544	0.598	1.672	3.067
MSC	3145	0.664	1592	0.336	4737	0.506	1.976	2.597
NEOK	2141	0.686	981	0.314	3122	0.458	2.182	2.350
NOC	2231	0.724	850	0.276	3081	0.381	2.625	1.954
CASC	2843	0.733	1034	0.267	3877	0.364	2.750	1.866
OSUO	2875	0.735	1035	0.265	3910	0.360	2.778	1.847
OSUT	2835	0.739	1000	0.261	3835	0.353	2.835	1.809
RCC	5517	0.741	1930	0.259	7447	0.350	2.859	1.794
RSC	2274	0.765	698	0.235	2972	0.307	3.258	1.575
SSC	13349	0.799	3367	0.201	16716	0.252	3.965	1.294
TCC	5533	0.827	1156	0.173	6689	0.209	4.786	1.072
WOSC	7611	0.842	1431	0.158	9042	0.188	5.319	0.964
Total	74787	0.764	23142	0.309	97929	0.405	0.309	

Table 3: Conditional Probability Student Award or Transfer Within Three Years

View #2. Probability of completion by college: univariate regression. A simple single predictor logistic regression model can be created by regressing the dichotomous criterion SUCCESS_3_YR against COLLEGE_CODE. Logically, because the college the student attended and whether they succeeded in three years are the only two data inputs into the logistic regression, the results will be exactly the same as the frequency count table. This intuitive perception turns out to be correct; however, to assess the validity of a logistic regression model, it is necessary to follow a specific protocol and examine several indicators to reach a conclusion about its usefulness. The process of assessing this relatively simple univariate regression, in which student success is regressed against institution attended using 97,929 records provided by OSRHE, will demonstrate the utility of logistic regression powered by MLE to elucidate extremely valuable information that is opaque in a view of institutional-level percentages.

Goodness-of-fit statistics are listed in Table 4. The omnibus test *p*-value of 0.000 is the probability of obtaining a chi-square of 2942 if the independent variables have no effect on the dependent variable. The null hypothesis, that the variance explained by the model is statistically insignificant, is rejected. There are 13 degrees of freedom, one for every college except OCCC, which, as the reference case, is always coded zero and, therefore, cannot influence the criterion. Nagelkerke/Cragg & Uhler's R-squared and Cox & Snell's R-squared are pseudo R-squareds, meaning that they were developed to measure model fit for categorical variables in logistic regressions (UCLA: Statistical Consulting Group, 2015a). Ordinary least squares regression minimizes variance; MLE iteratively searches for parameters that maximize the probability of getting the sample data, so pseudo R-squareds are not equivalent to the R-squareds used in ordinary least squares such as Pearson's. Both of the pseudo R-squareds in the regression output compare the fitted model to the null model (the null model being a model with no predictors except the constant). The constant is the y-intercept; it is the mean value of y when the values of the predictors are zero. With no predictors, the best guess for the value of y is the mean, the identical logic that would lead a student to choose CASC based on the sorting of institutions shown in Table 3. Cox & Snell's R-squared and Nagelkerke's R-squared indicate the benefit of the fitted model in explaining variance over the intercept-only model that predicts the mean. Perfect correlation results in a Nagelkerke R-squared of one; perfect correlation for Cox & Snell is less than one. The -2 log likelihood of 104151 is for the final model, which in this regression involved only one step and therefore is not very useful. The -2 log likelihood is helpful in assessing models in which the data is entered in blocks, as is the case with the third view of the data explained in the next section. Table 4 shows that there is strong evidence, X^2 (13, N = 97,929) = 2942.07, $p \leq 0.001$, of a correlation between the college that a student attends and their chances of success within three years, but the size of the effect is very small with the single predictor of COLLEGE_CODE explaining only 4.5% more variance than the null.

Omnibus Tests of Model Coefficients				
		Chi-square	***df***	***Sig.***
Step	Model	2924.065	13	0.000
Model Summary				
		-2 Log likelihood	***Cox & Snell R Square***	***Nagelkerke R Square***
Step	1	104151.885[a]	.030	.045
a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.				

Table 4: Overall Model Fit Univariate Regression

The magnitude of the effect that the choice of college has on the student's odds of success is delineated in Table 5. It is evident that OCCC is the reference case, because there no coefficient is listed, meaning that it is not in the model. The Wald chi-square value, degrees of freedom, and *p*-value are for the COLLEGE_CODE predictor, which is decomposed into 13 dummy variables as indicated by the 13 degrees of freedom. The Wald chi-square strongly suggests that the college attended is correlated with the dependent variable overall; however, OSUO and RSC are exceptions with *p*-values above the 0.05 significance threshold for a two-tailed test. The coefficients listed in column B are used to construct the equation that predicts the probability of the dependent variable. The equation is $\log(p/1\text{-}p) = b_0 + b_1x_1 + b_2x_2 \ldots + b_ix_i$, where *p* is the probability of the dummy taking the value of one, which for this study represents student completion. It is important to note that this equation is the same as for ordinary least squares regression, except that the coefficients and criterion are the natural logarithm of the odds, also called log odds or the logit. In Table 6, if the coefficients of

B are a positive number, they represent the amount by which the log odds of student success increase (i.e., dependent variable = 1) when the predictor increases by one unit, holding all the other predictors constant. If the coefficient is negative, it represents the decrease in the log odds that the dependent variable will equal 1, all other predictors constant.

Variables in the Equation								
	B	***S.E.***	***Wald***	***df***	***Sig,***	***Exp(B)***	***Predicted logit(Y)***	***p(success| college)***
OCCC			2916.364	13	.000		-1.635	0.163
CASC	1.143	.034	1127.910	1	.000	3.135	-0.492	0.379
NOC	1.121	.031	1334.824	1	.000	3.067	-0.514	0.374
NEOK	.954	.036	689.177	1	.000	2.597	-0.681	0.336
EOSC	.855	.043	392.319	1	.000	2.350	-0.780	0.314
WOSC	.670	.045	224.520	1	.000	1.954	-0.965	0.276
SSC	.624	.041	229.578	1	.000	1.866	-1.011	0.267
CSC	.613	.041	222.748	1	.000	1.847	-1.022	0.265
MSC	.593	.042	203.519	1	.000	1.809	-1.042	0.261
OSUT	.585	.033	318.205	1	.000	1.794	-1.050	0.259
RCC	.454	.047	91.692	1	.000	1.575	-1.181	0.235
TCC	.258	.027	88.845	1	.000	1.294	-1.377	0.201
OSUO	.069	.038	3.377	1	.066	1.072	-1.566	0.173
RSC	-.036	.035	1.087	1	.297	.964	-1.671	0.158
Constant	-1.635	.019	7127.723	1	.000	0.195		

Table 5: Regression Coefficients Univariate Model

The coefficients B in Table 5 are in log odds units. If the independent variable changes by 1 unit, this implies a change in the dependent variable magnitude of the coefficient. Because the predictor COLLEGE_CODE is categorical, it is represented by k-1 dummies in the regression. RCC is represented by COLLEGE_CODE(10) in the categorical variables coding section of the regression output (Appendix H). If a student decides to attend RCC rather than OCCC, the variable changes from 0 to 1, meaning the log odds of completion are increased by 0.454. Reading across the table, Exp(B) for RCC is 1.575, which is the odds ratio. The odds of a student succeeding at RSC is 1.575 times the odds of succeeding at OCCC, holding all other predictors constant. In terms of relative risk, the student's probability of completing improves by 0.235 by attending RCC; or, stated in terms most familiar, students have a 23.5% better chance of completing at RCC than they do at OCCC. Based on this very simple model, all the other two-year colleges in the state offer a better chance for completion than OCCC except RSC, which has a negative logit for the coefficient of minus 0.036. The Wald test is insignificant for the RSC coefficient, so the null hypothesis that it is zero cannot be rejected. If the test indicated that the coefficient for the RSC dummy was, in fact, statistically significant, it could be said that the odds that a RSC student will complete an award or transfer to a four-year college are 0.964 those of an OCCC student.

Thinking in terms of changes in log odds is difficult, so reporting logistic regressions models typically involves exponentiating both sides of the regression equation, which converts the coefficients to odds ratios instead of logits. The odds ratios for each college is listed in the column labeled Exp(B). The odds that a student at CASC will have a "succeed" outcome are slightly more than 3 times (Exp(B) = 3.135) that of an OCCC student. Table 5 shows only one college with a negative B, RSC, which means that an RSC student has lower odds (odds ratio <1) of graduating compared to an OCCC student. However, because the Wald test is insignificant, the null hypothesis that the coefficient is zero cannot be rejected, and it cannot be concluded the odds of completing at RSC are lower than OCCC. If the Wald chi-square value were significant, the odds ratio of 0.964 means that the odds a student will complete in three years are (1 - 0.964) = 0.036 (3.6%) lower if they attend RSC than if they attend OCCC. The last value in Table 5 is the constant, which equals negative 1.635 in log odds units and 0.195 in odds ratio units. The X^2 value is 7128, resulting in very strong rejection of the null hypothesis that the coefficient is zero. The constant negative 1.635 is the expected value of the SUCCESS_3_YR logit when all the predictors are equal to zero. The odds ratio Exp(B) = 0.195, and when all the dummy variables for COLLEGE_CODE = 0, the college indicated is OCCC, therefore the odds ratio of a student completing at OCCC is 0.195

Because log odds are not readily interpretable by most researchers in the social sciences or their intended audiences, software programs like SPSS routinely calculate odds ratios. However, converting logits to odds ratios may solve one problem while introducing another, as there are important distinctions among odds, odds ratios, log odds, and probabilities that are not always respected in practice, as Osborne (2014) writes:

> [O]dds ratios are problematic in that the lay public often don’t intuitively understand odds—although they often think they do...and ratios of things that people don’t understand are necessarily even more fraught with difficulty. Odds are not intuitive like probabilities are, and the language needed to technically describe an odds ratio is (as you can see) a bit convoluted (p. 34).

Osborne further amplifies his concern: “The situation is not helped by authors’ tendency to whitewash this important distinction and use probabilistic language when discussing odds ratios” (p. 34). Osborne worries that even sophisticated researchers mistakenly summarize odds ratios and imply probabilistic statements that misconstrue study outcomes, citing research by Holcomb et al. (2001) showing that 26% of authors in top-tier medical journals misinterpreted odds ratios as “relative risk ratios, which are ratios of probabilities rather than odds” (Osborne, 2014, p. 34).

Clearly, researchers should consider their intended readers when choosing the language they use to interpret quantitative research. When Osborne’s book, *Best Practices in Logistic Regression*, was published in 2014, he was a faculty member of the College of Education and Human Development at the University of Louisville (in 2015, he joined Clemson University as associate provost and dean of graduate studies), and his groundbreaking works in educational statistics have been cited more than 8000 times. Yet even Osborne says, “[t]hose of us who use logistic regression routinely have trouble conceptualizing logits. . . . Most researchers and consumers of research would be more comfortable talking about odds or probabilities” (2014, p. 39). Reading this, I was relieved to learn that other educators and even statisticians do not find it easy to comprehend log odd and odds ratios or to communicate about them correctly.

Fortunately, a remedy to this problem is available: It is possible to convert the predicted logit to a conditional probability by dividing Exp(B) by 1+Exp(B). That is to say, the log odds is exponentiated and divided by one plus the exponentiated log odds. With this transformation, the output of the logistic regression is the *probability* of achieving group membership (which for this study is completion of a certificate, degree, or transfer within three years). Then, by converting the decimal to a percentage, it is possible to make statements such as "Of all community college students in Oklahoma, those who attend CASC have the best chance of graduating, at 37.9%. Students at OCCC have a lower chance of graduating, at 16.3%."

Regressing the outcome success against the single predictor of college attended calculates a probability of group membership, shown in Table 6, that matches the frequencies in cross-tabulation shown in Table 3. Logically, this is what we would expect. If the only data in the 97,929 records is the college attended, and if the student completed an award or transfer in three years, the model most likely to result in the sample data is a model with a slope (B) and intercept (constant) that are the mean for the predictor (college). The subsequent sections of this study explore more fully the data with multivariate models. Although the logits and odds ratios of the individual predictors are presented in these sections, the conditional probability of group membership is the unit of measure that will be emphasized.

	B	*Exp(B)*	*Predicted logit(Y)*	*P(success|college)*
OCCC			-1.635	0.163
CASC	1.143	3.135	-0.492	0.379
NOC	1.121	3.067	-0.514	0.374
NEOK	0.954	2.597	-0.681	0.336
EOSC	0.855	2.350	-0.780	0.314
WOSC	0.670	1.954	-0.965	0.276
SSC	0.624	1.866	-1.011	0.267
CSC	0.613	1.847	-1.022	0.265
MSC	0.593	1.809	-1.042	0.261
OSUT	0.585	1.794	-1.050	0.259
RCC	0.454	1.575	-1.181	0.235
TCC	0.258	1.294	-1.377	0.201
OSUO	0.069	1.072	-1.566	0.173
RSC	-0.036	0.964	-1.671	0.158
Constant	-1.635	0.195		

Table 6: Prediction in Odds Ratio, Log Odds, and Probability Units

The classification table, Table 7, is the last section of output to consider in evaluating the regression. The classification table compares the observed outcomes to those predicted by the model and displays the overall percentage of correct predictions made by the model. Observed values of the dependent variable are shown in the rows of the classification table, and the predicted values are represented in the columns.

		Predicted Award or Transfer within 3 years		Percentage Correct
		No success	***Success***	
Observed Award or Transfer Within 3 Years	***No success***	74787	0	100.0
	Success	23142	0	0.0
Overall Percentage				76.4

Table 7: Classification Table Univariate Regression

It is helpful to understand how the model predicts group assignment. In this regression, it is predicting group membership solely based on the college attended. The predicted y is compared to a threshold value that, for this regression, is the SPSS default score of 0.50. If the predicted y is equal to or greater than 0.50, it assigns the case to the "success" group; if it is less than 0.50, it assigns the case to the "no success" group. Statewide, the probability of a student belonging to the "success" group ranges from 0.158 to 0.379. Because no college in the model has a probability of student success equal to or greater than 0.50, and because the model applies the probability of a success independently to each discrete case, the model will predict "no success" for every student at every college.

Sensitivity and specificity are the measures used to describe the capability of a model to distinguish accurately between dichotomous outcomes. As shown in Table 7, the model predicts that no students belong to the "success" group, whereas, in the observed data, 23,142 do in fact belong to this group. This reflects the sensitivity of the model: its ability to predict whether the cases meet the criteria for group membership. For the univariate regression, the sensitivity is zero. Specificity measures model accuracy in predicting cases that do not meet the criteria for inclusion in the target group. As shown in Table 7, specificity for the regression is 100%, because it correctly classified all the cases that did not belong to the success group. For a model that exhibits 100% sensitivity and specificity, the entries in the classification table will be on a diagonal. The intersection of the overall percentage row and the percentage correct column in the bottom rightmost cell (showing the number 76.4) is the total number correctly predicted divided by the number of cases attempted. It is important to note that, although the classification table shows that the model predicts correctly 76.4% of the time, this is merely the same as the percentage in the data and therefore has no practical utility.

The default score of 0.50 was used in the univariate regression and throughout this study. It is possible to modify the cutoff score, and for some types of analysis—epidemiological research, for example—changing the cutoff threshold is a sound methodology to follow. A receiver operating characteristic curve plots the rate of false negatives against the rate of false positives for various threshold values. The intent of this study is to make college performance measures like completion rates more commensurable by accounting for the impact that a student’s precollege characteristics may have on the efficacy of college production functions. False positives and false negatives both detracts from this measurement; therefore, the cutoff score used is not changed based on a receiver operating characteristic curve analysis.

To say that the model makes correct predictions for approximately 75% of the cases is extremely misleading without distinguishing between sensitivity and specificity. Because slightly more than three-quarters of Oklahoma students fit the criteria for inclusion in the target group, a model that predicts zero completions will be correct three times out of four over the long term.

View #3. Probability of completion: system-wide multivariate regression. This logistic regression excludes the college attended as a predictor and treats the records as if the students all attended the same institution. It is as if Oklahoma is the college, and only the precollege attributes of the students are relevant in estimating whether they will become a member of the success group. The model is split by college and recalculated in view #4, resulting in an estimated production function for each of the 14 colleges, information that is foundational to answering the three research questions posited in Chapter 1.

The predictors are entered into the model in blocks intended to represent constructs such as "commitment," "preparedness," "social capital," and so forth. Entering variables by blocks helps with model. Block 1 is ACT_REPORTED, DEGREE_GOAL, CONCURRENT, and ATTEND_INTENSITY. This group of predictors represents the construct "commitment." Attending college classes concurrently in high school and sitting for a college entrance exam like the ACT are the actions of a person considering higher education months before fall semester begins. Attending college full-time requires a major lifestyle and financial commitment, especially if the student is seeking an associate's degree, which is normally a two-year commitment.

The second block of predictors GENDER, AGE_SCALE, ETHNIC_CLASS, ENTRY_OHLAP, ENTRY_OTAG, and ENTRY_PELL indicate the construct "social capital." Prior research correlates delaying postsecondary education after high school with lower completion rates. The continuous predictor AGE_SCALE captures this potential effect. The OHLAP (Oklahoma Higher Learning Access Program, a tuition assistance program) has an income restriction; the OTAG (Oklahoma Tuition Aid Grant) is completely need-based; and PELL is the federal grant program based on family expected contribution. Because eligibility for these programs is based on a student's family's financial resources, it is hoped that they will serve as a proxy for socioeconomic effects when they are taken in conjunction with the three other demographic variables. To further strengthen the socioeconomic value of these variables, an interaction term between ENTRY_PELL and ETHNIC_CLASS is entered in Block 4.

Remedial courses attempts for math, reading, and English comprise the measure for the construct "preparedness" entered in Block 3. As previously noted, high school GPA is available for only 6% of the records and only from CSC, NEOK, and OSUO. This highly uneven pattern of reporting shows that the lack of a reported GPA is not linked to student behavior and therefore is not tested as an indicator of student preparedness. Even if it were, there is insufficient data to include it in the regression, which, as noted previously, is highly unfortunate because, if prior research is any guide, it is probably the strongest possible predictor of student success.

Block 4 explores second-order effects by adding five interaction terms: the student's ethnicity and financial situation (ETHNIC_CLASS by ENTRY_PELL); ethnicity and freshman class size (ETHNIC_CLASS by SIZE); age at entry and quantitative skills (AGE_ENTRY by REMEDIAL_MATH); and multi-subject deficiencies that span math and English (REMEDIAL_MATH by

REMEDIAL_ENGLISH) or math and reading proficiency (REMEDIAL MATH by REMEDIAL_ENGLISH). The ethnicity-financial interaction is introduced based on anecdotal knowledge of survey results at OCCC showing that students of color are especially unlikely to pass remedial courses when they have financial problems. The interaction between ethnicity and enrollment size is introduced because size is typically related to campus urbanicity for community colleges, which in turn may correlate with the presence of supportive cultural or social networks that promote student engagement off campus; this can be particularly valuable for vulnerable subpopulations. The motivation behind introducing an interaction between age at entry and math preparedness is that delayed-entry students and older returning students may have special difficulty establishing or regaining academic momentum in traditionally challenging gateway courses like mathematics. Multi-subject deficiencies may cause learning challenges to be multiplicative rather than additive, which is the rationale for the interaction between remedial math-English and math-reading.

Block 5 is composed of SIZE and OUTCOME_YEAR, the two institutional-level variables remaining after CONGRESS_DISTRICT and URBANICITY were expunged for violating multicollinearity norms. SIZE is the categorical IPEDS variable with three response levels corresponding to FTE enrollment. OUTCOME_YEAR is an exploratory term introduced to explain variance arising from cyclical factors like the unemployment rate.

Block 6 enters into the model the four diagnostic terms required by the Box-Tidwell procedure to determine whether the dependent variable logit is linear with the continuous independent variable predictors. These four terms are the product of the age at entry and remedial course attempts variables and their natural logs.

SPSS provides goodness-of-fit measures after each block is entered to assess their contribution to model fit. Table 8 shows that each block of variables entered explains a statistically significant quantity of variance ($p < 0.001$) compared to the null model with the constant and zero coefficients. The block line displays the test results for each separate block, and the model line is additive of the preceding blocks.

Omnibus Tests of Model Coefficients				
	Block	***Chi-square***	***df***	***Sig.***
1	Block	8765.676	7	.000
	Model	8765.676	7	.000
2	Block	555.792	10	.000
	Model	9321.468	17	.000
3	Block	2111.454	3	.000
	Model	11432.922	20	.000
4	Block	438.408	18	.000
	Model	11871.330	38	.000
5	Block	284.122	8	.000
	Model	12155.452	46	.000

Table 8: Statistical Significance of Variable Blocks

Table 9 presents overall model fit measures for the multivariate regression in View #3. When the college-only regressions were presented, -2 log likelihood (-2LL) was mentioned but, because -2LL is used to compare nested models in which predictors are entered in steps, it was not interpreted. -2LL is analogous to total sums of squares in regression, meaning that if the independent variables are related to the dependent variable as they are introduced, -2LL will decrease. Subtracting the -2LLs shows a steady decline, indicating better model fit with each block. It should be noted that Block 3 produces the biggest jump in explained variance, with a four-fold increase over Block 2. As already mentioned, Block 3 is remedial course course-taking behavior representing the construct "preparedness." The influence of preparedness on the model is consistent with the research presented in Chapter 2 and the literature generally.

It is possible to calculate a test statistic by subtracting the null model and final model -2LLs and comparing this difference to a critical value from the chi-square distribution for the desired alpha with degrees of freedom equal to the number of predictors in the final model. SPSS 23 does not provide the *p*-value for this test, but the pseudo R-squared values factor into log likelihoods in quantifying the variance explained. Both the Cox & Snell R-square and Nagelkerke R-square show a steady increase from block to block in the variance explained.

-2 Log likelihood	***Change -2 Log likelihood***	***Cox & Snell R Square***	***Nagelkerke R Square***
98328.275		.086	.129
97772.482	555.793	.091	.137
95661.028	2111.454	.110	.166
95222.620	438.408	.114	.172
94938.498	284.122	.117	.176

Table 9: Overall Model Fit System-wide Regression

Correlation measures, like the widely reported Pearson product-moment correlation (Pearson's r) for linear regression, are often misinterpreted and misunderstood. The risk of misjudging pseudo R-squareds is amplified because they are neither qualitatively nor quantitatively analogous to linear correlation coefficient. A much more intuitive tool for assessing the utility of the predictive model produced by the regression of the student records is the classification table. Table 10 summarizes how the model would predict group membership for every student in the OSRHE database covering the study period 2003 to 2009. Unlike the college-only regression, this model generates the probabilities of group membership of greater than 0.50 resulting in their assignment to the success group. Model sensitivity is 13.8%; that is, the model correctly predicts group membership for 13.8% of the cases. Correct prediction of non-membership, or model specificity, is 97.0%.

		Predicted Award or Transfer Within 3 Years		
		No success	***Success***	*Percentage Correct*
Observed Award or Transfer Within 3 Years	***No success***	72553	2234	97.0
	Success	19937	3205	13.8
Overall Percentage				77.4

Table 10: Classification Table System-wide Regression

View #4. Full model: production functions for all 14 colleges. The concluding data analysis step is the disaggregation of the 97,929 records by college and the calculation of 14 discrete production functions for each of the two-year colleges in the study. Block 6 is dropped as superfluous because the Box-Tidwell diagnostic was completed. The variables were entered as blocks in the system-wide regression to facilitate overall model validation and to elucidate the rationale for their inclusion. With the variables legitimated by statistical evidence and qualitative rationales in View #3, and to avoid the complexity of adding four block levels and their sublevels to each of the 14 colleges, the variables are entered into the regression in a single step. Table 11 suggests that the predictors are highly significant, compared to the null model, which consists of the y-intercept only. Table 12 summarizes the full model fit statistics for each college. The Nagelkerke R-squared measure ranges from a low of 0.110 for CASC to a maximum of 0.241 for SSC. The -2LL values are not interpreted because the models are not nested. The regression coefficients, tests of significance, and odds ratios for each college's individual predictors are included in Appendix J.

			Chi-square	*df*	*Sig.*
OCCC	Step 1	Model	1440.451	32	.000
CSC	Step 1	Model	433.439	31	.000
EOSC	Step 1	Model	413.686	31	.000
MSC	Step 1	Model	568.201	31	.000
NEOK	Step 1	Model	400.567	32	.000
NOC	Step 1	Model	1303.889	30	.000
CASC	Step 1	Model	455.562	32	.000
OSUO	Step 1	Model	570.819	32	.000
OSUT	Step 1	Model	1275.767	30	.000
RCC	Step 1	Model	361.026	32	.000
RSC	Step 1	Model	1023.534	32	.000
SSC	Step 1	Model	700.154	31	.000
TCC	Step 1	Model	1584.191	32	.000
WOSC	Step 1	Model	539.930	31	.000

Table 11: Omnibus Tests of Model Coefficients Full Model

Appended to the bottom of Table 12 are important footnotes that require explanation. These notes state that five of the models did not converge within the default 20 attempts that SPSS is programmed to perform. The production functions that did not converge are for CSC, MSC, NOC, RSC, and SSC. This phenomenon, known as separation or quasi-separation, is not uncommon with logistic regression. A complete separation occurs when the outcome variable separates a predictor or combination of predictors completely; that is, there is a vector that correctly allocates all the cases to a group (UCLA: Statistical Consulting Group, 2015b).

			-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
OCCC	Step	1	15934.246[a]	.071	.121
CSC	Step	1	4085.910[b]	.105	.153
EOSC	Step	1	3472.810[c]	.124	.174
MSC	Step	1	3833.201[d]	.138	.202
NEOK	Step	1	5647.630[e]	.081	.112
NOC	Step	1	8671.627[f]	.159	.216
CASC	Step	1	6749.944[g]	.081	.110
OSUO	Step	1	5587.493[h]	.082	.136
OSUT	Step	1	7246.304[i]	.157	.231
RCC	Step	1	2878.934[j]	.114	.172
RSC	Step	1	6875.117[k]	.107	.184
SSC	Step	1	3796.778[l]	.165	.241
TCC	Step	1	15211.039[m]	.090	.143
WOSC	Step	1	3089.637[n]	.161	.232

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = OCCC.

b. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file Institution ID = CSC.

c. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = EOSC.

d. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file Institution ID = MSC.

e. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = NEOK.

f. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = NOC.

g. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001 for split file Institution ID = CBSC.

h. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = OSUO.

i. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = OSUT.

j. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file Institution ID = RCC.

k. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file Institution ID = RSC.

l. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file Institution ID = SSC.

m. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = TCC.

n. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001 for split file Institution ID = WOSC.

Table 12: Overall Model Fit Full Model

The classification percentages are recapped in Table 13. Appendix K presents the complete classification results for each college. The value in the Change column is the difference between the Block 1 model, replete with all predictors, and the null model, with only the y-intercept. The very best improvement is only 5.8 percentage points, and the least efficacious model showed no improvement over the null at all. Clearly, these production functions cannot be regarded as having any practical utility.

			Overall Percentage		
	Specificity	***Sensitivity***	***Block 1***	***Null***	***Change***
OCCC	99.6	3.1	83.8	83.7	0.1
CSC	97.0	14.3	75.1	73.5	1.6
EOSC	91.8	29.4	72.2	68.6	3.6
MSC	95.5	21.3	76.1	73.9	2.2
NEOK	93.3	20.0	68.7	66.4	2.3
NOC	80.3	48.6	68.4	62.6	5.8
CASC	90.6	26.8	66.4	62.1	4.3
OSUO	99.0	5.0	82.7	82.7	0.0
OSUT	92.0	34.6	77.1	74.1	3.0
RCC	97.8	9.3	77.0	76.5	0.5
RSC	98.7	8.9	84.5	84.2	0.3
SSC	93.0	28.3	75.8	73.3	2.5
TTC	99.7	1.6	79.9	79.9	0.1
WOSC	94.4	28.5	76.2	72.4	3.8

Table 13: Classification Table Full Model

Chapter 5: Findings, Conclusions, and Recommendations

Findings

An experienced analyst who works for OSRHE carefully constructed this database with the approval of a vice chancellor. It represents many hours of work on the part of the analyst, and we consulted multiple times to make sure it met the requirements of the research project within the limitations of data routinely collected by OSRHE. To my knowledge, this is the best data available for this project. When I embarked upon my dissertation project, I had two important goals in mind. The first was to acquire a large database of professionally curated records that would allow me to apply the kinds of multivariate statistics methods widely used in the social science research literature. The second goal was to apply these methods to data that closely represents the students and colleges that make up the system of postsecondary education in the United States. Data collected with meticulously designed surveys administered through carefully executed processes with the primary objective of supporting scholarly research are invaluable, but so is data that reflects the extremely limited resources and political constraints of states that struggle to provide postsecondary education opportunities to as many of its residents as it can. When stakeholders are presented with findings based on data that has been transparently derived from administrative recording keeping processes that they themselves specified and put into place, the conclusions are more compelling, and if the findings do not conform to their preconceived expectations, it is more challenging for stakeholders to dismiss them.

Research Question One

The first study questions asks “Is it possible to use data routinely collected by the Oklahoma State Regents for Higher Education (OSRHE) to compute an estimate of a given student’s chance of graduating from each of the state’s 14 community colleges?” Based on the data and mathematics applied here, it is not possible to calculate a probabilistic estimate of group membership superior to the null model, which is simply an estimate of the mean value of y. The regression output for the predictor blocks and the individual predictors reveals that most of the predictors are significantly associated with membership in the outcome group under one or more of the three views. Results from the chi-square test (shown in Table 11) and the Cox & Snell and Nagelkerke R-squareds (shown in Table 12) depict college production functions that have statistically significant predictive power over the null hypothesis; however, the classification table (Table 13) exhibits practically no benefit over null predictions. The correct interpretation of the seemingly conflicting messages is that the association between the independent variables and the dependent variable is significant, but insufficient to make accurate predictions. Most of the variance is unexplained, overshadowing the variance that is accounted for.

Research Question Two

This question assumes that it was possible to construct production functions with enough sensitivity (i.e., ability to correctly predict a student’s completion) to be convincing. If the colleges are listed in descending order by this student’s probability of graduating, is this rank order different from an ordinal ranking of the colleges based on all enrolled students? Although the predictive capability of the model is disappointing, I follow through with the analysis as if the indices of model fit and percentage of cases correctly classified were indicative of a statistically well-specified model. Table 14 presents the completion probabilities of the reference student as calculated by models, with the change in rank shown in the rightmost column. The values in the *Univariate Rank* and *College* $p(y_{univariate})$ columns are from the univariate regression presented in View #2; they are equivalent to the values produced by the simple frequency count in View #1. The *Multivariate Rank* and *Reference* $p(y_{multivariate})$ values are from the individual college production functions presented in View #4, and, therefore, they exemplify the maximum effort to compensate for the variability in student attributes that are linked to graduation rates for which data is available. Not only does the probability and rank change from model to model, but, as Table 15 illustrates, all the descriptive statistics point towards the same conclusion: reduced variability among the state's community colleges graduation rates—the single measure that stakeholders are most interested in (with the possible exception of post-graduation employment rates, which cannot be tracked for lack of data). The worst completion rate improves (*Minimum*); the best rate is not as high (*Maximum*); the variance decreases fivefold; and the standard deviation of the system decreases by more than 50%. Based on this assessment of the statistics presented in Tables 14 and 15, Research Question Two is unequivocally affirmed.

	Univariate Rank	*College[a] $p(y_{univariate})$*	*Multivariate Rank*	*Reference $p(y_{multivariate})$*	*Change p(y)*	*Change p(y) Rank*
OCCC	13	0.163	3	0.346	+ 0.183	+ 10
CSC	1	0.379	8	0.311	- 0.068	- 7
EOSC	2	0.374	10	0.293	- 0.082	- 8
MSC	3	0.336	11	0.287	- 0.049	- 8
NEOK	4	0.314	2	0.347	+ 0.033	+ 2
NOC	5	0.276	12	0.271	- 0.005	- 7
CASC	6	0.267	1	0.375	+ 0.108	+ 5
OSUO	7	0.265	4	0.323	+ 0.058	+ 3
OSUT	8	0.261	6	0.316	+ 0.055	+ 2
RCC	9	0.259	5	0.319	+ 0.060	+ 4
RSC	10	0.235	13	0.258	+ 0.023	- 3
SSC	11	0.201	14	0.255	+ 0.053	- 3
TTC	12	0.173	9	0.293	+ 0.120	+ 3
WOSC	14	0.158	7	0.316	+ 0.158	+ 7

[a] As shown previously, p(success) is identical to college simple frequency county (view #1)

Table 14: Comparison Predicted Graduation Probabilities

Descriptive statistics	*$p(y_{univariate})$*	*$p(y_{multivariate})$*	*Change p(y)*
Mean	0.262	0.308	+ 0.046
Minimum	0.158	0.225	+ 0.096
Maximum	0.379	0.375	- 0.005
Range	0.221	0.120	- 0.101
Variance	0.005	0.001	- 0.004
Standard Deviation	0.072	0.035	- 0.038

Table 15: Descriptive Statistics Model Comparison

Research Question Three

This research question introduces the element of cost into the quality equation. From the literature on how higher education affects students, an institution that is able to spend large sums of money on facilities, programs, faculty, and athletics that foster academic and social integration should benefit from higher persistence rates. The probability of a student's having a positive outcome should be weighted by the cost to create that outcome. Therefore, the concluding step in this analysis is to determine whether dividing the probability of completion by the average cost to complete shakes up the perception of the "best" performing college among the 14 in the state system. The average net cost of attendance, shown in Figure 16, comes from the IPEDS website. It is an average of the last three cohort years of the study, 2010 through 2013. The probability of graduating and the rank associated with that probability are from the multivariate model, meaning that student diversity is controlled for up to the limits of the data. The column *Marginal Cost* $p(y_{multivariate})$ is the *3-Year Average Net Cost of Attendance* divided by *Reference* $p(y_{multivariate})$. With the average net cost fixed, if the graduation rate decreases, this index increases; if the average net cost increases with the graduation rate fixed, the index also increases. Therefore, for this ratio, lower values are preferable. Inspecting the rightmost column, *Change p(y) Rank*, in Table 16 provides the evidence to answer Research Question Three affirmatively, because 11 of the 14 colleges have a rank change as signified by a nonzero value.

Index #	*College*	*3-Year Average Net Cost of Attendance*	*Reference $p(y_{multivariate})$*	*Marginal Cost $p(y_{multivariate})$*	*Rank Marginal Cost $p(y_{multivariate})$*	*Change p(y) Rank*
1	**OCCC**	7274	0.346	21040	8	- 5
2	**CSC**	7428	0.311	23870	11	- 3
3	**EOSC**	5574	0.293	19053	4	+ 6
4	**MSC**	7917	0.287	27580	12	- 1
5	**NEOK**	6324	0.347	18223	3	- 1
6	**NOC**	5420	0.271	20033	6	+ 6
7	**CASC**	3958	0.375	10561	1	0
8	**OSUO**	6397	0.323	19810	5	- 1
9	**OSUT**	6620	0.316	20942	7	- 1
10	**RCC**	5809	0.319	18190	2	+ 3
11	**RSC**	8583	0.258	33289	13	0
12	**SSC**	9701	0.255	38094	14	0
13	**TTC**	6503	0.293	22184	10	- 1
14	**WOSC**	6676	0.316	21126	9	- 2

Table 16: Marginal Cost of Completion Probability by College

Conclusions

Among the 50 states, Oklahoma ranks 45th in the percentage of its residents in 2010 between the ages of 25 and 34 who have some kind of postsecondary degree, and the state is projected to drop two spots to 47th by 2020 (U.S. Department of Education, 2012). This study sought to explore a timely and controversial topic in higher education using data routinely collected by a state agency from a rural state that is politically and socially conservative. The goal of this study was to explore the pressing topic of student success at two-year colleges at a macro level using the tools at hand, which, from the perspective of this practitioner, include a database of carefully and methodically extracted anonymized student records from OSRHE, SPSS Statistics 23 software, a MacBook Pro laptop computer, and a keen interest in the bedrock quantitative modeling techniques of social science research, techniques to which logistic regression clearly belongs.

Chapter 1 discusses the Obama Administration's College Scorecard; the Administration's blueprint for a standardized college ratings system; the morphing of that plan into a consumer-oriented tool due to the inexorable opposition from colleges and their proxies; and the unrelenting lobbying by trade groups (especially for-profit colleges) to consider some of the predictors used in this study in its gainful employment rule. I hope that this backdrop has convinced the reader of the relevance of this work. I would be engaging in egregious errors of overfitting and misinterpretation if I argued that this study provided a practical predictive model for student success—it most certainly does not. However, I believe that two-year institutions' stakeholders can apply this framework to enrich their understanding of community colleges' strengths and weakness. With a rapidly changing demographic, community colleges will have an even greater responsibility than they do now for providing their students a gateway to perhaps some semblance of economic security and, it is hoped, a deeper understanding of the world and a greater capacity to serve as discriminating global citizen.

Policy Implications

In concluding this study, I will consider its implications—first for the legislators, regents, and administrators who apportion, oversee, and spend community college budgets, and second, for the faculty who teach and students strive to learn at these colleges. It is expected that these colleges will become increasingly important parts of the American system of postsecondary education, as their enrollment is projected to increase in over the next decade.

With regard to the first group—elected officials and senior academic managers tasked with funding and policy—this study should help clarify the limits of the use of data analysis and predictive modeling. Institutions should use extreme caution about adopting the latest rage—predictive modeling of data mining output, enabled by powerful personal computers and academic licensing of software that is heavily marketed to administrators, like SPSS Modeler. Consider this statement excerpted from a national newspaper story: “The use of computer models by local law enforcement agencies to forecast crime is part of a larger trend by governments and corporations that are increasingly turning to predictive analytics and data mining in looking at behaviors” (Eligon and Williams, 2015). When institutions experiment with institutional data by applying the superfluity of modeling algorithms and transformations in these programs, searching for the best correlation, they risk finding and circulating results that are devoid of any theoretical grounding or critical evaluation of model assumptions or diagnostics.

Yet, the context of how performance measures like graduation rates are calculated and evaluated matters. Using them ahistorically—that is, without regard to the “life stories” of the people whose success or failure they ultimately reflect—is a mistake as grievous as reaching erroneous conclusions from improper modeling and the misapplication of institutional data. Taking stock of context does not excuse a vacuum where “academic grit”—discipline, perseverance, and a commitment to succeed no matter what—exists anymore than it excuses the abysmal post-completion employment rates of “career colleges” that evidence shows deliver little more than exorbitant pay packages to private equity executives and billions in unpaid student loan obligations to taxpayers. But it is irrational to pretend students matriculate at community colleges with backgrounds that will not inevitably have an influence on their likelihood of success. This will impact institutional performance measures. It is reasonable that institutions are apprehensive about connections between access, performance, and funding. A productive pathway for expressing these reservations that can support credible discussions with stakeholders and potentially influence policy is using student-level data as was done here. Despite any risks of misinterpretation or misuse, community colleges should continue to investigate and study this data looking for answers that satisfy all the stakeholders.

The public, which invests enormous sums of money, credibility, and prestige in the American higher education system, deserves administrators (and students) who honor this investment by taking seriously the public’s fear—as articulated by President Obama and his Department of Education—that highly paid college presidents and senior administrators are failing to reap the best possible results from this investment. The performance-based funding movement, imperfect though it may be, is a legitimate expression of this worry. Although the correlations found in this study are weak, one correlation that perseveres is the bond between postsecondary education and the ambitions, dreams, hopes, and fears of generations of people. This leads to the principal message for the second group of stakeholders who have an interest in this type of research, a message best conveyed by the classification table for the models. It is the safer bet to assume that a student will not succeed in completing a degree, but the safer bet will be wrong much of the time, and that is why it is important to continue the policy of open enrollment and the funding needed to support such a policy.

Community college personnel are rightly concerned that the changes in federal policy may not adequately take into account the difficulties that they confront in teaching and mentoring people from profoundly disparate backgrounds, and they are right to express their misgivings. A useful way to express those misgivings is through scholarly analysis of student records, such as the study attempted here, to quantify the impact that students' disparate traits may have on performance-oriented measures like the probability of completion. Administrators at legitimate community colleges reacted with fear and outrage to ED proposals, when, in fact, most of the new rules are targeted at for-profit colleges and intended to quash some of the most egregious abuses that the for-profit education industry has engaged in for many years, protected by a congress influenced by lobbyists.

Prior academic achievement is strongly correlated with successful completion of an associates or bachelor's degree; this is thoroughly substantiated in the literature. A very conspicuous gap in the database used in this study is the absence of recorded high school GPA. GPA is one of only four variables in Astin's (1997) retention equation. CSC and NEOK reported high school GPAs for early cohorts. If they were not recorded because high school GPA is not an admission criterion, then an outstanding question is why ACT scores were recorded and when GPAs were not. If colleges are interested in pressing their case against performance-based measures on the grounds that the precollege characteristics of students invalidate cross-institutional comparisons of production functions, it seems that archiving this data would be a relatively simple step towards bolstering their case.

The literature supports the value of socioeconomic variables as predictors of college completion, but these are much more difficult to locate and access. Bratti (2002) obtained data from the U.K. government, including parental occupation, which was mapped into nine levels of a social class variable. In the United States, it is implausible that data this sensitive will be routinely collected by a state agency and made available to U.S. researchers. But researchers may find creative methods of developing better proxies than those used in this study. Although high school GPA is not used in the OSRHE records, for many students the high school attended is listed. I hypothesized that a proxy for socioeconomic status might be the percentage of students eligible for free or reduced-price lunches at the high school for the year the student graduated.

However, as I worked to obtain missing volumes of reports that the state is supposed to archive with this information, I learned from federal sources this is a poor socioeconomic status indicator because, in practice, eligibility for free and reduced-price lunches is more highly subject to political vagaries than objective poverty measures. NCES is experimenting with applying Education Demographic and Geographic Estimates (EDGE) (http://nces.ed.gov/programs/edge/demographic.aspx) derived from the U.S. Census Bureau's American Community Survey and Decennial Census Long Form to school attendance boundaries. EDGE's economic data includes income and benefits, poverty status, employment status, industry and occupation, transportation to work, and class of worker. As NCES progresses with this work, it may be possible to obtain EDGE estimates for high school attendance boundaries in

Oklahoma. It would then be necessary to assess whether the estimates are still valid for the years students in the OSRHE database attended high school by examining relative changes in the demographics of standard census polygons like block groups. It might be possible to infer that the mean EDGE characteristics for the school boundary apply to the student. This work is exploratory, but NCES's efforts to find pathways to extrapolate from existing datasets it is important, due to both the paucity of socioeconomic information at the individual level and the relevance of such data to research on student success.

Recommendations for Future Research

A very large sample may not be a benefit. When statistics textbooks discuss samples, they usually emphasize adequate size and selection protocol to ensure that it is representative of the population. Obtaining a sample is often difficult and expensive, and weighting techniques like clustering or stratification ensure representativeness while minimizing the size. Although counterintuitive, reducing the size of the sample will lower the sensitivity of the inferential tests, and studying subpopulations may reveal stronger correlations that can be applied to the research questions.

Why separation precluded four of the schools in the full model from finding a solution is a question that remains to be answered. There are clues suggesting that the logit linearity assumption is suspect. If the distribution approximating a relationship the predictors and the criterion is something other than a straight line, it will not be the first example of this in the social science. There are many precedents for curvilinear distributions in the social sciences.

Lastly, the three research questions in this study were constructed to take a system-level view of the State of Oklahoma's two-year colleges over a ten year period. This same data could be used to answer entirely different research questions, such as questions that concern a single institution or subsets of institutions that share similar characteristics, or to compare changes in institutions over time.

Summary

This study used data routinely gathered by a state education department reflecting the actual experiences of students with the Oklahoma system of two-year colleges over a ten year period to reassess graduation rates and make them more comparable. Although the model fit statistics and classification table were not statistically compelling, a comparison of the simple graduation rates derived from frequency counts and the full multivariate model did clearly suggest that accounting for student diversity closes the graduation gap among the system's schools. Further data collection and research is suggested which may help strengthen the model fit.

References

Appelbaum, B. (2012). Family net worth drops to level of early ’90s, Fed says. *The New York Times*. Retrieved from http://www.nytimes.com/2012/06/12/business/economy/family-net-worth-drops-to-level-of-early-90s-fed-says.html?_r=0

Astin, A. W. (1965). Effect of different college environments on the vocational choices of high aptitude students. *Journal of Counseling Psychology*, *12*(1), 28–34.

Astin, A. W. (1970a). The methodology of research on college impact, part one. *Sociology of Education*, *43*(3), 223–254.

Astin, A. W. (1970b). The methodology of research on college impact, part two. *Sociology of Education*, *43*(4)437–450.

Astin, A. W. (1984). Student involvement: A developmental theory for higher education. *Journal of College Student Personnel*, *25*(4), 297–308.

Astin, A. W. (1997). How “good” is your institution’s retention rate? *Research in Higher Education*, *38*(6), 647–658.

Bailey, T., Calcagno, J. C., Jenkins, D., Leinbach, T., & Kienzl, G. (2006). Is Student-Right-to-Know all you should know? An analysis of community college graduation rates. *Research in Higher Education*, *47*(5), 491–519. http://doi.org/10.1007/s11162-005-9005-0

Bailey, T., Jenkins, D., & Leinbach, T. (2005, September). *Graduation rates, student goals, and measuring community college effectiveness* (Community College Research Center Brief No. 28). New York, NY: Community College Research Center. Retrieved from http://files.eric.ed.gov/fulltext/ED489098.pdf

Bratti, M. (2002). Does the choice of university matter?: A study of the differences across UK universities in life sciences students' degree performance. *Economics of Education Review*, *21*(5), 431–443. http://doi.org/10.1016/S0272-7757(01)00035-8

Calcagno, J. C., Bailey, T., Jenkins, D., Kienzl, G., & Leinbach, T. (2008). Community college student success: What institutional characteristics make a difference? *Economics of Education Review*, *27*(6), 632–645. http://doi.org/10.1016/j.econedurev.2007.07.003

Cillizza, C. (2014, December 11). Work hard, get rich? Maybe not anymore. *The Washington Post*. Retrieved from http://www.washingtonpost.com/blogs/the-fix/wp/2014/12/11/work-hard-get-rich-maybe-not-anymore/

Cohen, A. M., & Brawer, F. B. (2003). *The American community college* (4th ed.). San Francisco, CA: Jossey-Bass.

Coleman, J. S., Campbell, E., Hobson, C., McPartland, J., Mood, A., Weinfeld, F., & York, R. (1966). The Coleman Report. *Equality of Educational Opportunity*.

DeParle, J. (2012, January 4). Harder for Americans to rise from lower rungs. *The New York Times*. Retrieved from http://www.nytimes.com/2012/01/05/us/harder-for-americans-to-rise-from-lower-rungs.html

Department of Education. (2015, April 16). *Financial Aid Shopping Sheet*. Retrieved November 12, 2015, from http://www2.ed.gov/policy/highered/guid/aid-offer/index.html

Dey, E. L., & Astin, A. W. (1993). Statistical alternatives for studying college student retention: A comparative analysis of logit, probit, and linear regression. *Research in Higher Education, 34*(5), 569–581.

Dougherty, K. J., Jones, S. M., Lahr, H., Natow, R. S., Pheatt, L., & Reddy, V. (2014, September). *Envisioning performance funding impacts: The espoused theories of action for state higher education performance funding in three states* (CCRC Working Paper No. 63.) New York, NY: Community College Research Center. Retrieved from http://ccrc.tc.columbia.edu/publications/envisioning-performance-funding-impacts.html

Dougherty, K. J., & Reddy, V. (2011). *The impacts of state performance funding systems on higher education institutions: Research literature review and policy recommendations* (CCRC Working Paper No. 37). New York, NY: Community College Research Center. Retrieved from http://ccrc.tc.columbia.edu/publications/impacts-state-performance-funding.html

Field, K. (2013, August 22). Obama plan to tie student aid to college ratings draws mixed reviews. *The Chronicle of Higher Education*. Retrieved from http://chronicle.com/article/Obama-Plan-to-Tie-Student-Aid/141229/

Gallegos, Y. R. (2015). *The new college ratings tool: do you know what to expect?* [DVD]. Durham, NC: AudioSolutionz.

Gamoran, A., & Long, D. A. (2006, December). *Equality of educational opportunity: A 40-year retrospective* (WCER Working Paper No. 2006-9). Madison, WI: Wisconsin Center for Education Research. Retrieved from http://www.wcer.wisc.edu/publications/workingpapers/Working_Paper_No_2006_09.pdf

Hanushek, E. A. (1979). Conceptual and empirical issues in the estimation of educational production functions. *The Journal of Human Resources*, *14*(3), 351–388. http://doi.org/10.2307/145575

Obama, B. (2013, December 4). *Remarks by the President on economic mobility*. Retrieved from http://www.whitehouse.gov/the-press-office/2013/12/04/remarks-president-economic-mobility

Osborne, J. W. (2014). *Best Practices in Logistic Regression*. Los Angeles, CA: SAGE Publications.

Parlapiano, A. Gebeloff, R., & Carter, S. (2015, January 26). The shrinking American middle class. *The New York Times*. Retrieved from http://www.nytimes.com/interactive/2015/01/25/upshot/shrinking-middle-class.html

Pascarella, E. T. (1985). College environmental influences on learning and cognitive development: A critical review and synthesis. In J. Smart (ed.), *Higher Education: Handbook of Theory and Research* (Vol. 1, pp. 1–61). New York, NY: Agathon Press.

Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students: A third decade of research*. San Francisco, CA: Jossey-Bass.

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

Pérez-Peña, R. (2012, October 17). Rising college costs pose test for Obama on education policies. *The New York Times*. Retrieved from http://www.nytimes.com/2012/10/18/us/politics/college-costs-test-obamas-education-policies.html

Robinson, W. S. (2009). Ecological correlations and the behavior of individuals. *International Journal of Epidemiology*, *38*(2), 337–341. http://doi.org/10.1093/ije/dyn357

Searcey, D., & Gebeloff, R. (2015, January 25). Middle class shrinks further as more fall out instead of climbing up. *The New York Times*. Retrieved from http://www.nytimes.com/2015/01/26/business/economy/middle-class-shrinks-further-as-more-fall-out-instead-of-climbing-up.html

Smith, J. P., & Naylor, R. A. (2001). Dropping out of university: A statistical analysis of the probability of withdrawal for UK university students. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *164*(2), 389–405.

Stratford, M. (2013, November 7). Education Department kicks off public hearings on college ratings system. Retrieved from https://www.insidehighered.com/news/2013/11/07/education-department-kicks-public-hearings-college-ratings-system

Tandberg, D. A., Hillman, N., & Barakat, M. (2014). State higher education performance funding for community colleges: Diverse effects and policy implications. *Teachers College Record*, *116*(12). Retrieved from http://www.tcrecord.org.ezproxy.lib.ou.edu/library/Issue.asp?volyear=2014&number=12&volume=116

Terenzini, P. E., & Pascarella, E. (1991). *How college affects students: Findings and insights from twenty years of research*.San Francisco, CA: Jossey-Bass.

The White House. (2013). College Scorecard. Retrieved January 2, 2015, from http://www.whitehouse.gov/issues/education/higher-education/college-score-card

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). Chicago, IL: University of Chicago Press.

Tinto, V. (2010). From theory to action: Exploring the institutional conditions for student retention. In J. C. Smart (Ed.), *Higher Education: Handbook of Theory and Research* (Vol. 25, pp. 51–89). Dordrecht, Netherlands: Springer. Retrieved from http://link.springer.com.ezproxy.lib.ou.edu/chapter/10.1007/978-90-481-8598-6_2

UCLA: Statistical Consulting Group. (2015a). FAQ: What are pseudo R-squareds? Retrieved from http://www.ats.ucla.edu/stat/mult_pkg/faq/general/Psuedo_RSquareds.htm

UCLA: Statistical Consulting Group. (2015b). FAQ: What is complete or quasi-complete separation in logistic/probit regression and how do we deal with them? Retrieved from http://www.ats.ucla.edu/stat/mult_pkg/faq/general/complete_separation_logit_models.htm

UCLA: Statistical Consulting Group. (2015c). Lesson 3: Logistic regression diagnostics. Retrieved from http://www.ats.ucla.edu/stat/stata/webbooks/logistic/chapter3/statalog3.htm

U.S. Department of Education. (2012, July 12). New state-by-state college attainment numbers show progress toward 2020 goal. Retrieved from http://www.ed.gov/news/press-releases/new-state-state-college-attainment-numbers-show-progress-toward-2020-goal

Usher, A., & Savino, M. (2007). A global survey of university ranking and league tables. *Higher Education in Europe*, *32*(1), 5–15. http://doi.org/10.1080/03797720701618831

Appendix A: White House College Scorecard

College Affordability and Transparency Center
College Scorecard

Northeastern Oklahoma A&M College (NEO A&M College)

Miami, OK
Primarily associate's degree granting
Undergraduate enrollment: 2,347

Back to Search | More Information | Print Profile

Costs

$6,900 / yr

What does it typically cost to attend NEO A&M College?

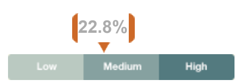
The average net price for undergraduate in-state students is $6,900 per year. Net price is what undergraduate students pay after grants and scholarships (financial aid you don't have to pay back) are subtracted from the institution's cost of attendance.

The average net price has increased 33.3% from 2009 to 2011.

Click here to see listings of changes in college costs.

Click here to go to the Net Price Calculator for a better estimate of what your costs would be.

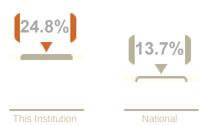
Graduation Rate



What percentage of students graduate?

22.8% of full-time students graduated within 150% of the expected time for completion and 19.6% transferred to another institution. Graduation rate data are based on undergraduate students who enrolled full-time and have never enrolled in college before. This may not represent all undergraduates that attend this institution.

Loan Default Rate



Are students able to repay their loans after they graduate?

24.8% of borrowers defaulted on their Federal student loans within three years of entering repayment.

Median Borrowing

$67.87 / mo

What is the typical amount borrowed for a student's undergraduate study?

Families typically borrow $6,500 in Federal loans for a student's undergraduate study. The Federal loan payment over 10 years for this amount is approximately $67.87 per month. Your borrowing may be different.

To learn about loan repayment options, go to:
http://studentaid.ed.gov/repay-loans/understand/plans

Employment

What kinds of jobs do students have when they graduate?

The U.S. Department of Education is working to provide information about the average earnings of former undergraduate students at NEO A&M College who borrowed Federal student loans. In the meantime, ask NEO A&M College to tell you about how many of its graduates get jobs, what kinds of jobs they get, and how much those graduates typically earn.

Visit http://www.mynextmove.org to explore what potential careers a particular postsecondary program or major prepares you to enter. The site has information about current earnings and potential growth in those occupations.

The College Scorecard has been designed by the U.S. Department of Education to provide better information to students and parents about college affordability and value. More information about the data included in the scorecard is available here. Note that the information included in the scorecard may not apply to all students. Students should contact the institution for more information about these measures.

Appendix B: Frequency Table, State College System

End of Cohort Status	*Frequency*	*Percent*	*Cumulative Percent*
No award, not enrolled	54539	55.7	55.7
Still enrolled	20248	20.7	76.4
Transferred to four-year	11128	11.4	87.7
Degree or certificate earned	12014	12.3	100.0
Total	**97929**	**100.0**	
Award or Transfer 3 years	***Frequency***	***Percent***	***Cumulative Percent***
No success	74787	76.4	76.4
Success	23142	23.6	100.0
Total	**97929**	**100.0**	
Reported ACT Score	***Frequency***	***Percent***	***Cumulative Percent***
ACT reported	51585	52.7	52.7
No ACT reported	46344	47.3	100.0
Total	**97929**	**100.0**	
Reported High School GPA	***Frequency***	***Percent***	***Cumulative Percent***
No GPA reported	92052	94.0	94.0
Student GPA reported	5877	6.0	100.0
Total	**97929**	**100.0**	
High School Concurrent	***Frequency***	***Percent***	***Cumulative Percent***
Not concurrent	94166	96.2	96.2
Concurrent	3763	3.8	100.0
Total	**97929**	**100.0**	
Full or Part-Time Attend	***Frequency***	***Percent***	***Cumulative Percent***
Full-time	65279	66.7	66.7
Part-time	32650	33.3	100.0
Total	**97929**	**100.0**	
Degree Goal When Admitted	***Frequency***	***Percent***	***Cumulative Percent***
AA or AS (transfer)	51082	52.2	52.2
Certificate 1 to 2 years	391	.4	52.6
Certificate less than 1 year	1030	1.1	53.6
AAS (limited transfer)	27058	27.6	81.2

No program leading to credential	18368	18.8	100.0
Total	**97929**	**100.0**	
Male or Female	***Frequency***	***Percent***	***Cumulative Percent***
Female	54271	55.4	55.4
Male	43658	44.6	100.0
Total	**97929**	**100.0**	
Age Entered College Continuous	***Frequency***	***Percent***	***Cumulative Percent***
<=17	2197	2.2	2.2
18	25945	26.5	28.7
19	28412	29.0	57.8
20	7610	7.8	65.5
21	3923	4.0	69.5
22	3152	3.2	72.7
23	2637	2.7	75.4
24	2466	2.5	78.0
25	2166	2.2	80.2
26	1886	1.9	82.1
27	1653	1.7	83.8
28	1513	1.5	85.3
29	1310	1.3	86.7
30	1169	1.2	87.9
31	1098	1.1	89.0
32	976	1.0	90.0
33	878	.9	90.9
34	775	.8	91.7
35	691	.7	92.4
36	674	.7	93.1
37	577	.6	93.6
38	578	.6	94.2
39	519	.5	94.8
40	471	.5	95.2
41	474	.5	95.7
42	467	.5	96.2
43	396	.4	96.6
44	386	.4	97.0
45	341	.3	97.4
46	342	.3	97.7

47	307	.3	98.0
48	282	.3	98.3
49	243	.2	98.6
50	224	.2	98.8
51	186	.2	99.0
52	159	.2	99.1
53	161	.2	99.3
54	114	.1	99.4
55	96	.1	99.5
56	89	.1	99.6
57	89	.1	99.7
58	49	.1	99.7
59	47	.0	99.8
60	34	.0	99.8
61	31	.0	99.9
62	14	.0	99.9
63	12	.0	99.9
64	12	.0	99.9
65	11	.0	99.9
66	16	.0	99.9
67	7	.0	99.9
>=68	64	.1	100.0
Total	**97929**	**100.0**	
Ethnic Group Membership	***Frequency***	***Percent***	***Cumulative Percent***
White	63324	64.7	64.7
Hispanic	4664	4.8	69.4
Black	9956	10.2	79.6
Native American	12203	12.5	92.1
Asian	1665	1.7	93.8
Other group	6117	6.2	100.0
Total	**97929**	**100.0**	
OK Higher Learning Access Program	***Frequency***	***Percent***	***Cumulative Percent***
No OHLAP award	91925	93.9	93.9
OLAP award 1st semester	6004	6.1	100.0
Total	**97929**	**100.0**	
OK Tuition Aid Grant	***Frequency***	***Percent***	***Cumulative Percent***

No Oklahoma Tuition Aid Grant	90889	92.8	92.8
Oklahoma Tuition Aid Grant 1st semester	7040	7.2	100.0
Total	**97929**	**100.0**	
Pell Award	***Frequency***	***Percent***	***Cumulative Percent***
No Pell award	70198	71.7	71.7
Pell award 1st semester	27731	28.3	100.0
Total	**97929**	**100.0**	
English Remedial Attempts 3 Years Scale	***Frequency***	***Percent***	***Cumulative Percent***
0	68790	70.2	70.2
1	17350	17.7	88.0
2	7014	7.2	95.1
3	2834	2.9	98.0
4	1143	1.2	99.2
5	447	.5	99.6
6	217	.2	99.9
7	76	.1	99.9
8	25	.0	100.0
9	13	.0	100.0
10	9	.0	100.0
11	3	.0	100.0
12	4	.0	100.0
13	1	.0	100.0
14	1	.0	100.0
18	2	.0	100.0
Total	97929	100.0	
Math Remedial Attempts 3 Years Scale	***Frequency***	***Percent***	***Cumulative Percent***
0	44683	45.6	45.6
1	24531	25.0	70.7
2	16313	16.7	87.3
3	7518	7.7	95.0
4	3122	3.2	98.2
5	1173	1.2	99.4
6	439	.4	99.8
7	121	.1	100.0
8	21	.0	100.0

9	8	.0	100.0
Total	**97929**	**100.0**	
Reading Remedial Attempts 3 Years Scale	***Frequency***	***Percent***	***Cumulative Percent***
0	90760	92.7	92.7
1	5738	5.9	98.5
2	1060	1.1	99.6
3	184	.2	99.8
4	46	.0	99.9
5	122	.1	100.0
6	9	.0	100.0
7	3	.0	100.0
8	2	.0	100.0
9	2	.0	100.0
10	2	.0	100.0
13	1	.0	100.0
Total	**97929**	**100.0**	
IPEDS Student Enrollment	***Frequency***	***Percent***	***Cumulative Percent***
1,000 - 4,999	54367	55.5	55.5
5,000 - 9,999	24033	24.5	80.1
10,000 - 19,999	19529	19.9	100.0
Total	**97929**	**100.0**	
IPEDS Urbanization	***Frequency***	***Percent***	***Cumulative Percent***
City	43692	44.6	44.6
Suburb	24445	25.0	69.6
Town	9661	9.9	79.4
Rural	20131	20.6	100.0
Total	**97929**	**100.0**	
Congressional District	***Frequency***	***Percent***	***Cumulative Percent***
District 5	30853	31.5	31.5
District 2	27721	28.3	59.8
District 3	13597	13.9	73.7
District 4	9042	9.2	82.9
District 1	16716	17.1	100.0
Total	**97929**	**100.0**	
3-Year Cohort Ends	***Frequency***	***Percent***	***Cumulative Percent***

Cohort ends 2007	14155	14.5	14.5
Cohort ends 2008	13726	14.0	28.5
Cohort ends 2009	14042	14.3	42.8
Cohort ends 2010	13192	13.5	56.3
Cohort ends 2011	13707	14.0	70.3
Cohort ends 2012	12883	13.2	83.4
Cohort ends 2013	16224	16.6	100.0
Total	**97929**	**100.0**	

Appendix C: Frequency Table Grouped by College

End of Cohort Status		*Frequency*	*Percent*	*Cumulative Percent*
Oklahoma City Community College	No award, not enrolled	11520	59.0	59.0
	Still enrolled	4823	24.7	83.7
	Transferred to four-year	2237	11.5	95.1
	Degree or certificate earned	949	4.9	100.0
	Total	19529	100.0	
Connors State College	No award, not enrolled	2194	56.1	56.1
	Still enrolled	681	17.4	73.5
	Transferred to four-year	419	10.7	84.2
	Degree or certificate earned	616	15.8	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	No award, not enrolled	1761	56.4	56.4
	Still enrolled	380	12.2	68.6
	Transferred to four-year	361	11.6	80.1
	Degree or certificate earned	620	19.9	100.0
	Total	3122	100.0	
Murray State College	No award, not enrolled	2193	57.2	57.2
	Still enrolled	642	16.7	73.9
	Transferred to four-year	476	12.4	86.3
	Degree or certificate earned	524	13.7	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	No award, not enrolled	2435	51.4	51.4
	Still enrolled	710	15.0	66.4
	Transferred to four-year	561	11.8	78.2
	Degree or certificate earned	1031	21.8	100.0
	Total	4737	100.0	
Northern Oklahoma College	No award, not enrolled	3547	47.0	47.0
	Still enrolled	1174	15.6	62.6
	Transferred to four-year	1544	20.5	83.0
	Degree or certificate earned	1279	17.0	100.0
	Total	7544	100.0	

Carl Albert State College	No award, not enrolled	2545	46.9	46.9
	Still enrolled	824	15.2	62.1
	Transferred to four-year	519	9.6	71.6
	Degree or certificate earned	1540	28.4	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	No award, not enrolled	3801	56.8	56.8
	Still enrolled	1732	25.9	82.7
	Transferred to four-year	855	12.8	95.5
	Degree or certificate earned	301	4.5	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	No award, not enrolled	4601	61.8	61.8
	Still enrolled	916	12.3	74.1
	Transferred to four-year	511	6.9	80.9
	Degree or certificate earned	1419	19.1	100.0
	Total	7447	100.0	
Redlands Community College	No award, not enrolled	1825	61.4	61.4
	Still enrolled	449	15.1	76.5
	Transferred to four-year	249	8.4	84.9
	Degree or certificate earned	449	15.1	100.0
	Total	2972	100.0	
Rose State College	No award, not enrolled	5499	60.8	60.8
	Still enrolled	2112	23.4	84.2
	Transferred to four-year	874	9.7	93.8
	Degree or certificate earned	557	6.2	100.0
	Total	9042	100.0	
Seminole State College	No award, not enrolled	2261	58.3	58.3
	Still enrolled	582	15.0	73.3
	Transferred to four-year	352	9.1	82.4
	Degree or certificate earned	682	17.6	100.0
	Total	3877	100.0	
Tulsa Community College	No award, not enrolled	8600	51.4	51.4
	Still enrolled	4749	28.4	79.9
	Transferred to four-year	1797	10.8	90.6

	Degree or certificate earned	1570	9.4	100.0
	Total	16716	100.0	
Western Oklahoma State College	No award, not enrolled	1757	57.0	57.0
	Still enrolled	474	15.4	72.4
	Transferred to four-year	373	12.1	84.5
	Degree or certificate earned	477	15.5	100.0
	Total	3081	100.0	
Award or Transfer 3 years		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	No success	16343	83.7	83.7
	Success	3186	16.3	100.0
	Total	19529	100.0	
Connors State College	No success	2875	73.5	73.5
	Success	1035	26.5	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	No success	2141	68.6	68.6
	Success	981	31.4	100.0
	Total	3122	100.0	
Murray State College	No success	2835	73.9	73.9
	Success	1000	26.1	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	No success	3145	66.4	66.4
	Success	1592	33.6	100.0
	Total	4737	100.0	
Northern Oklahoma College	No success	4721	62.6	62.6
	Success	2823	37.4	100.0
	Total	7544	100.0	
Carl Albert State College	No success	3369	62.1	62.1
	Success	2059	37.9	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	No success	5533	82.7	82.7
	Success	1156	17.3	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	No success	5517	74.1	74.1
	Success	1930	25.9	100.0
	Total	7447	100.0	
	No success	2274	76.5	76.5

Redlands Community College	Success	698	23.5	100.0
	Total	2972	100.0	
Rose State College	No success	7611	84.2	84.2
	Success	1431	15.8	100.0
	Total	9042	100.0	
Seminole State College	No success	2843	73.3	73.3
	Success	1034	26.7	100.0
	Total	3877	100.0	
Tulsa Community College	No success	13349	79.9	79.9
	Success	3367	20.1	100.0
	Total	16716	100.0	
Western Oklahoma State College	No success	2231	72.4	72.4
	Success	850	27.6	100.0
	Total	3081	100.0	
Reported ACT Score		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	ACT reported	7279	37.3	37.3
	No ACT reported	12250	62.7	100.0
	Total	19529	100.0	
Connors State College	ACT reported	2692	68.8	68.8
	No ACT reported	1218	31.2	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	ACT reported	1874	60.0	60.0
	No ACT reported	1248	40.0	100.0
	Total	3122	100.0	
Murray State College	ACT reported	2211	57.7	57.7
	No ACT reported	1624	42.3	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	ACT reported	4216	89.0	89.0
	No ACT reported	521	11.0	100.0
	Total	4737	100.0	
Northern Oklahoma College	ACT reported	5556	73.6	73.6
	No ACT reported	1988	26.4	100.0
	Total	7544	100.0	
Carl Albert State College	ACT reported	3453	63.6	63.6
	No ACT reported	1975	36.4	100.0
	Total	5428	100.0	
	ACT reported	2585	38.6	38.6
	No ACT reported	4104	61.4	100.0

Oklahoma State University – Oklahoma City	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	ACT reported	3382	45.4	45.4
	No ACT reported	4065	54.6	100.0
	Total	7447	100.0	
Redlands Community College	ACT reported	1174	39.5	39.5
	No ACT reported	1798	60.5	100.0
	Total	2972	100.0	
Rose State College	ACT reported	3840	42.5	42.5
	No ACT reported	5202	57.5	100.0
	Total	9042	100.0	
Seminole State College	ACT reported	1787	46.1	46.1
	No ACT reported	2090	53.9	100.0
	Total	3877	100.0	
Tulsa Community College	ACT reported	9730	58.2	58.2
	No ACT reported	6986	41.8	100.0
	Total	16716	100.0	
Western Oklahoma State College	ACT reported	1806	58.6	58.6
	No ACT reported	1275	41.4	100.0
	Total	3081	100.0	
High School Concurrent		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	Not concurrent	19110	97.9	97.9
	Concurrent	419	2.1	100.0
	Total	19529	100.0	
Connors State College	Not concurrent	3697	94.6	94.6
	Concurrent	213	5.4	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	Not concurrent	3042	97.4	97.4
	Concurrent	80	2.6	100.0
	Total	3122	100.0	
Murray State College	Not concurrent	3590	93.6	93.6
	Concurrent	245	6.4	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	Not concurrent	4427	93.5	93.5
	Concurrent	310	6.5	100.0
	Total	4737	100.0	
	Not concurrent	6950	92.1	92.1

Northern Oklahoma College	Concurrent	594	7.9	100.0
	Total	7544	100.0	
Carl Albert State College	Not concurrent	5259	96.9	96.9
	Concurrent	169	3.1	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	Not concurrent	6475	96.8	96.8
	Concurrent	214	3.2	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	Not concurrent	7208	96.8	96.8
	Concurrent	239	3.2	100.0
	Total	7447	100.0	
Redlands Community College	Not concurrent	2914	98.0	98.0
	Concurrent	58	2.0	100.0
	Total	2972	100.0	
Rose State College	Not concurrent	8524	94.3	94.3
	Concurrent	518	5.7	100.0
	Total	9042	100.0	
Seminole State College	Not concurrent	3602	92.9	92.9
	Concurrent	275	7.1	100.0
	Total	3877	100.0	
Tulsa Community College	Not concurrent	16661	99.7	99.7
	Concurrent	55	.3	100.0
	Total	16716	100.0	
Western Oklahoma State College	Not concurrent	2707	87.9	87.9
	Concurrent	374	12.1	100.0
	Total	3081	100.0	
Full or Part-Time Attend		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	Full-time	10523	53.9	53.9
	Part-time	9006	46.1	100.0
	Total	19529	100.0	
Connors State College	Full-time	3119	79.8	79.8
	Part-time	791	20.2	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	Full-time	2415	77.4	77.4
	Part-time	707	22.6	100.0
	Total	3122	100.0	
	Full-time	2957	77.1	77.1

Murray State College	Part-time	878	22.9	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	Full-time	4362	92.1	92.1
	Part-time	375	7.9	100.0
	Total	4737	100.0	
Northern Oklahoma College	Full-time	6109	81.0	81.0
	Part-time	1435	19.0	100.0
	Total	7544	100.0	
Carl Albert State College	Full-time	3726	68.6	68.6
	Part-time	1702	31.4	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	Full-time	3358	50.2	50.2
	Part-time	3331	49.8	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	Full-time	4825	64.8	64.8
	Part-time	2622	35.2	100.0
	Total	7447	100.0	
Redlands Community College	Full-time	1886	63.5	63.5
	Part-time	1086	36.5	100.0
	Total	2972	100.0	
Rose State College	Full-time	5726	63.3	63.3
	Part-time	3316	36.7	100.0
	Total	9042	100.0	
Seminole State College	Full-time	3057	78.8	78.8
	Part-time	820	21.2	100.0
	Total	3877	100.0	
Tulsa Community College	Full-time	10977	65.7	65.7
	Part-time	5739	34.3	100.0
	Total	16716	100.0	
Western Oklahoma State College	Full-time	2239	72.7	72.7
	Part-time	842	27.3	100.0
	Total	3081	100.0	
Degree Goal When Admitted		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	AA or AS (transfer)	9931	50.9	50.9
	Certificate 1 to 2 years	153	.8	51.6
	Certificate less than 1 year	291	1.5	53.1
	AAS (limited transfer)	5786	29.6	82.8

	No program leading to credential	3368	17.2	100.0
	Total	19529	100.0	
Connors State College	AA or AS (transfer)	3629	92.8	92.8
	Certificate 1 to 2 years	1	.0	92.8
	Certificate less than 1 year	14	.4	93.2
	AAS (limited transfer)	266	6.8	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	AA or AS (transfer)	2401	76.9	76.9
	Certificate less than 1 year	11	.4	77.3
	AAS (limited transfer)	579	18.5	95.8
	No program leading to credential	131	4.2	100.0
	Total	3122	100.0	
Murray State College	AA or AS (transfer)	2348	61.2	61.2
	Certificate less than 1 year	18	.5	61.7
	AAS (limited transfer)	1467	38.3	99.9
	No program leading to credential	2	.1	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	AA or AS (transfer)	3514	74.2	74.2
	Certificate 1 to 2 years	50	1.1	75.2
	Certificate less than 1 year	26	.5	75.8
	AAS (limited transfer)	1069	22.6	98.4
	No program leading to credential	78	1.6	100.0
	Total	4737	100.0	
Northern Oklahoma College	AA or AS (transfer)	5845	77.5	77.5
	AAS (limited transfer)	1345	17.8	95.3
	No program leading to credential	354	4.7	100.0
	Total	7544	100.0	
Carl Albert State College	AA or AS (transfer)	4621	85.1	85.1
	Certificate 1 to 2 years	12	.2	85.4
	Certificate less than 1 year	197	3.6	89.0
	AAS (limited transfer)	372	6.9	95.8
	No program leading to credential	226	4.2	100.0
	Total	5428	100.0	
	AA or AS (transfer)	329	4.9	4.9

Oklahoma State University – Oklahoma City	Certificate 1 to 2 years	37	.6	5.5
	Certificate less than 1 year	163	2.4	7.9
	AAS (limited transfer)	5728	85.6	93.5
	No program leading to credential	432	6.5	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	AA or AS (transfer)	345	4.6	4.6
	AAS (limited transfer)	2949	39.6	44.2
	No program leading to credential	4153	55.8	100.0
	Total	7447	100.0	
Redlands Community College	AA or AS (transfer)	1723	58.0	58.0
	Certificate 1 to 2 years	7	.2	58.2
	Certificate less than 1 year	34	1.1	59.4
	AAS (limited transfer)	1089	36.6	96.0
	No program leading to credential	119	4.0	100.0
	Total	2972	100.0	
Rose State College	AA or AS (transfer)	4206	46.5	46.5
	Certificate 1 to 2 years	1	.0	46.5
	Certificate less than 1 year	34	.4	46.9
	AAS (limited transfer)	2256	25.0	71.9
	No program leading to credential	2545	28.1	100.0
	Total	9042	100.0	
Seminole State College	AA or AS (transfer)	3342	86.2	86.2
	Certificate 1 to 2 years	50	1.3	87.5
	AAS (limited transfer)	480	12.4	99.9
	No program leading to credential	5	.1	100.0
	Total	3877	100.0	
Tulsa Community College	AA or AS (transfer)	7180	43.0	43.0
	Certificate 1 to 2 years	80	.5	43.4
	Certificate less than 1 year	235	1.4	44.8
	AAS (limited transfer)	2336	14.0	58.8
	No program leading to credential	6885	41.2	100.0
	Total	16716	100.0	
	AA or AS (transfer)	1668	54.1	54.1
	Certificate less than 1 year	7	.2	54.4

Western Oklahoma State College	AAS (limited transfer)	1336	43.4	97.7
	No program leading to credential	70	2.3	100.0
	Total	3081	100.0	
Ethnic Group Membership		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	White	11177	57.2	57.2
	Hispanic	1323	6.8	64.0
	Black	1879	9.6	73.6
	Native American	1036	5.3	78.9
	Asian	622	3.2	82.1
	Other group	3492	17.9	100.0
	Total	19529	100.0	
Connors State College	White	2219	56.8	56.8
	Hispanic	86	2.2	59.0
	Black	463	11.8	70.8
	Native American	1094	28.0	98.8
	Asian	22	.6	99.3
	Other group	26	.7	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	White	1920	61.5	61.5
	Hispanic	66	2.1	63.6
	Black	174	5.6	69.2
	Native American	854	27.4	96.5
	Asian	21	.7	97.2
	Other group	87	2.8	100.0
	Total	3122	100.0	
Murray State College	White	2490	64.9	64.9
	Hispanic	176	4.6	69.5
	Black	256	6.7	76.2
	Native American	545	14.2	90.4
	Asian	100	2.6	93.0
	Other group	268	7.0	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	White	3026	63.9	63.9
	Hispanic	109	2.3	66.2
	Black	545	11.5	77.7
	Native American	943	19.9	97.6
	Asian	5	.1	97.7

	Other group	109	2.3	100.0
	Total	4737	100.0	
Northern Oklahoma College	White	5803	76.9	76.9
	Hispanic	310	4.1	81.0
	Black	490	6.5	87.5
	Native American	722	9.6	97.1
	Asian	72	1.0	98.1
	Other group	147	1.9	100.0
	Total	7544	100.0	
Carl Albert State College	White	3505	64.6	64.6
	Hispanic	124	2.3	66.9
	Black	206	3.8	70.7
	Native American	1361	25.1	95.7
	Asian	59	1.1	96.8
	Other group	173	3.2	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	White	4279	64.0	64.0
	Hispanic	463	6.9	70.9
	Black	878	13.1	84.0
	Native American	337	5.0	89.1
	Asian	143	2.1	91.2
	Other group	589	8.8	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	White	4903	65.8	65.8
	Hispanic	296	4.0	69.8
	Black	509	6.8	76.6
	Native American	1633	21.9	98.6
	Asian	52	.7	99.3
	Other group	54	.7	100.0
	Total	7447	100.0	
Redlands Community College	White	2103	70.8	70.8
	Hispanic	139	4.7	75.4
	Black	292	9.8	85.3
	Native American	299	10.1	95.3
	Asian	27	.9	96.2
	Other group	112	3.8	100.0
	Total	2972	100.0	
Rose State College	White	5664	62.6	62.6
	Hispanic	416	4.6	67.2

	Black	1676	18.5	85.8
	Native American	624	6.9	92.7
	Asian	158	1.7	94.4
	Other group	504	5.6	100.0
	Total	9042	100.0	
Seminole State College	White	2416	62.3	62.3
	Hispanic	111	2.9	65.2
	Black	319	8.2	73.4
	Native American	946	24.4	97.8
	Asian	9	.2	98.0
	Other group	76	2.0	100.0
	Total	3877	100.0	
Tulsa Community College	White	11779	70.5	70.5
	Hispanic	578	3.5	73.9
	Black	1945	11.6	85.6
	Native American	1642	9.8	95.4
	Asian	327	2.0	97.3
	Other group	445	2.7	100.0
	Total	16716	100.0	
Western Oklahoma State College	White	2040	66.2	66.2
	Hispanic	467	15.2	81.4
	Black	324	10.5	91.9
	Native American	167	5.4	97.3
	Asian	48	1.6	98.9
	Other group	35	1.1	100.0
	Total	3081	100.0	
OK Higher Learning Access Program		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	No OHLAP award	19120	97.9	97.9
	OLAP award 1st semester	409	2.1	100.0
	Total	19529	100.0	
Connors State College	No OHLAP award	3502	89.6	89.6
	OLAP award 1st semester	408	10.4	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	No OHLAP award	2733	87.5	87.5
	OLAP award 1st semester	389	12.5	100.0

	Total	3122	100.0	
Murray State College	No OHLAP award	3521	91.8	91.8
	OLAP award 1st semester	314	8.2	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	No OHLAP award	4092	86.4	86.4
	OLAP award 1st semester	645	13.6	100.0
	Total	4737	100.0	
Northern Oklahoma College	No OHLAP award	6627	87.8	87.8
	OLAP award 1st semester	917	12.2	100.0
	Total	7544	100.0	
Carl Albert State College	No OHLAP award	5294	97.5	97.5
	OLAP award 1st semester	134	2.5	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	No OHLAP award	6245	93.4	93.4
	OLAP award 1st semester	444	6.6	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	No OHLAP award	7295	98.0	98.0
	OLAP award 1st semester	152	2.0	100.0
	Total	7447	100.0	
Redlands Community College	No OHLAP award	2848	95.8	95.8
	OLAP award 1st semester	124	4.2	100.0
	Total	2972	100.0	
Rose State College	No OHLAP award	8329	92.1	92.1
	OLAP award 1st semester	713	7.9	100.0
	Total	9042	100.0	
Seminole State College	No OHLAP award	3401	87.7	87.7
	OLAP award 1st semester	476	12.3	100.0
	Total	3877	100.0	
Tulsa Community College	No OHLAP award	16222	97.0	97.0
	OLAP award 1st semester	494	3.0	100.0

	Total	16716	100.0	
Western Oklahoma State College	No OHLAP award	2696	87.5	87.5
	OLAP award 1st semester	385	12.5	100.0
	Total	3081	100.0	
OK Tuition Aid Grant		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	No Oklahoma Tuition Aid Grant	19239	98.5	98.5
	Oklahoma Tuition Aid Grant 1st semester	290	1.5	100.0
	Total	19529	100.0	
Connors State College	No Oklahoma Tuition Aid Grant	3246	83.0	83.0
	Oklahoma Tuition Aid Grant 1st semester	664	17.0	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	No Oklahoma Tuition Aid Grant	2788	89.3	89.3
	Oklahoma Tuition Aid Grant 1st semester	334	10.7	100.0
	Total	3122	100.0	
Murray State College	No Oklahoma Tuition Aid Grant	3668	95.6	95.6
	Oklahoma Tuition Aid Grant 1st semester	167	4.4	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	No Oklahoma Tuition Aid Grant	3972	83.9	83.9
	Oklahoma Tuition Aid Grant 1st semester	765	16.1	100.0
	Total	4737	100.0	
Northern Oklahoma College	No Oklahoma Tuition Aid Grant	6673	88.5	88.5
	Oklahoma Tuition Aid Grant 1st semester	871	11.5	100.0
	Total	7544	100.0	
Carl Albert State College	No Oklahoma Tuition Aid Grant	5001	92.1	92.1

	Oklahoma Tuition Aid Grant 1st semester	427	7.9	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	No Oklahoma Tuition Aid Grant	6074	90.8	90.8
	Oklahoma Tuition Aid Grant 1st semester	615	9.2	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	No Oklahoma Tuition Aid Grant	6850	92.0	92.0
	Oklahoma Tuition Aid Grant 1st semester	597	8.0	100.0
	Total	7447	100.0	
Redlands Community College	No Oklahoma Tuition Aid Grant	2812	94.6	94.6
	Oklahoma Tuition Aid Grant 1st semester	160	5.4	100.0
	Total	2972	100.0	
Rose State College	No Oklahoma Tuition Aid Grant	8283	91.6	91.6
	Oklahoma Tuition Aid Grant 1st semester	759	8.4	100.0
	Total	9042	100.0	
Seminole State College	No Oklahoma Tuition Aid Grant	3332	85.9	85.9
	Oklahoma Tuition Aid Grant 1st semester	545	14.1	100.0
	Total	3877	100.0	
Tulsa Community College	No Oklahoma Tuition Aid Grant	16178	96.8	96.8
	Oklahoma Tuition Aid Grant 1st semester	538	3.2	100.0
	Total	16716	100.0	
Western Oklahoma State College	No Oklahoma Tuition Aid Grant	2773	90.0	90.0
	Oklahoma Tuition Aid Grant 1st semester	308	10.0	100.0
	Total	3081	100.0	
Pell Award		***Frequency***	***Percent***	***Cumulative Percent***

Oklahoma City Community College	No Pell award	18964	97.1	97.1
	Pell award 1st semester	565	2.9	100.0
	Total	19529	100.0	
Connors State College	No Pell award	2062	52.7	52.7
	Pell award 1st semester	1848	47.3	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	No Pell award	1831	58.6	58.6
	Pell award 1st semester	1291	41.4	100.0
	Total	3122	100.0	
Murray State College	No Pell award	2445	63.8	63.8
	Pell award 1st semester	1390	36.2	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	No Pell award	2359	49.8	49.8
	Pell award 1st semester	2378	50.2	100.0
	Total	4737	100.0	
Northern Oklahoma College	No Pell award	4650	61.6	61.6
	Pell award 1st semester	2894	38.4	100.0
	Total	7544	100.0	
Carl Albert State College	No Pell award	4218	77.7	77.7
	Pell award 1st semester	1210	22.3	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	No Pell award	5363	80.2	80.2
	Pell award 1st semester	1326	19.8	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	No Pell award	5291	71.0	71.0
	Pell award 1st semester	2156	29.0	100.0
	Total	7447	100.0	
Redlands Community College	No Pell award	1877	63.2	63.2
	Pell award 1st semester	1095	36.8	100.0
	Total	2972	100.0	
Rose State College	No Pell award	5726	63.3	63.3
	Pell award 1st semester	3316	36.7	100.0
	Total	9042	100.0	
Seminole State College	No Pell award	1963	50.6	50.6
	Pell award 1st semester	1914	49.4	100.0
	Total	3877	100.0	
Tulsa Community College	No Pell award	11616	69.5	69.5
	Pell award 1st semester	5100	30.5	100.0
	Total	16716	100.0	

Western Oklahoma State College	No Pell award	1833	59.5	59.5
	Pell award 1st semester	1248	40.5	100.0
	Total	3081	100.0	
English Remedial Attempts 3 Years Scale		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	0	13225	67.7	67.7
	1	2458	12.6	80.3
	2	1713	8.8	89.1
	3	1337	6.8	95.9
	4	377	1.9	97.9
	5	225	1.2	99.0
	6	126	.6	99.7
	7	38	.2	99.8
	8	15	.1	99.9
	9	6	.0	100.0
	10	5	.0	100.0
	11	2	.0	100.0
	12	2	.0	100.0
	Total	19529	100.0	
Connors State College	0	2131	54.5	54.5
	1	973	24.9	79.4
	2	451	11.5	90.9
	3	217	5.5	96.5
	4	76	1.9	98.4
	5	45	1.2	99.6
	6	8	.2	99.8
	7	5	.1	99.9
	8	3	.1	100.0
	9	1	.0	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	0	2225	71.3	71.3
	1	614	19.7	90.9
	2	236	7.6	98.5
	3	38	1.2	99.7
	4	8	.3	100.0
	7	1	.0	100.0
	Total	3122	100.0	
Murray State College	0	2777	72.4	72.4
	1	549	14.3	86.7

	2	359	9.4	96.1
	3	84	2.2	98.3
	4	42	1.1	99.4
	5	16	.4	99.8
	6	6	.2	99.9
	7	1	.0	100.0
	9	1	.0	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	0	2997	63.3	63.3
	1	916	19.3	82.6
	2	513	10.8	93.4
	3	117	2.5	95.9
	4	143	3.0	98.9
	5	30	.6	99.6
	6	10	.2	99.8
	7	8	.2	99.9
	8	1	.0	100.0
	9	2	.0	100.0
	Total	4737	100.0	
Northern Oklahoma College	0	5401	71.6	71.6
	1	1716	22.7	94.3
	2	361	4.8	99.1
	3	49	.6	99.8
	4	11	.1	99.9
	5	6	.1	100.0
	Total	7544	100.0	
Carl Albert State College	0	4495	82.8	82.8
	1	829	15.3	98.1
	2	100	1.8	99.9
	3	3	.1	100.0
	4	1	.0	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	0	4814	72.0	72.0
	1	1364	20.4	92.4
	2	377	5.6	98.0
	3	99	1.5	99.5
	4	15	.2	99.7
	5	13	.2	99.9
	6	5	.1	100.0

	7	1	.0	100.0
	9	1	.0	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	0	6001	80.6	80.6
	1	1204	16.2	96.8
	2	199	2.7	99.4
	3	32	.4	99.9
	4	9	.1	100.0
	5	1	.0	100.0
	6	1	.0	100.0
	Total	7447	100.0	
Redlands Community College	0	2359	79.4	79.4
	1	440	14.8	94.2
	2	148	5.0	99.2
	3	17	.6	99.7
	4	5	.2	99.9
	5	2	.1	100.0
	6	1	.0	100.0
	Total	2972	100.0	
Rose State College	0	6057	67.0	67.0
	1	2197	24.3	91.3
	2	603	6.7	98.0
	3	129	1.4	99.4
	4	37	.4	99.8
	5	8	.1	99.9
	6	7	.1	100.0
	7	3	.0	100.0
	8	1	.0	100.0
	Total	9042	100.0	
Seminole State College	0	2553	65.8	65.8
	1	952	24.6	90.4
	2	333	8.6	99.0
	3	33	.9	99.8
	4	4	.1	99.9
	5	2	.1	100.0
	Total	3877	100.0	
Tulsa Community College	0	11443	68.5	68.5
	1	2454	14.7	83.1
	2	1553	9.3	92.4

	3	665	4.0	96.4
	4	413	2.5	98.9
	5	98	.6	99.5
	6	53	.3	99.8
	7	19	.1	99.9
	8	5	.0	99.9
	9	2	.0	99.9
	10	4	.0	100.0
	11	1	.0	100.0
	12	2	.0	100.0
	13	1	.0	100.0
	14	1	.0	100.0
	18	2	.0	100.0
	Total	16716	100.0	
Western Oklahoma State College	0	2312	75.0	75.0
	1	684	22.2	97.2
	2	68	2.2	99.4
	3	14	.5	99.9
	4	2	.1	100.0
	5	1	.0	100.0
	Total	3081	100.0	
Math Remedial Attempts 3 Years Scale		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	0	9004	46.1	46.1
	1	5163	26.4	72.5
	2	3141	16.1	88.6
	3	1376	7.0	95.7
	4	542	2.8	98.4
	5	222	1.1	99.6
	6	61	.3	99.9
	7	16	.1	100.0
	8	4	.0	100.0
	Total	19529	100.0	
Connors State College	0	1103	28.2	28.2
	1	961	24.6	52.8
	2	844	21.6	74.4
	3	509	13.0	87.4
	4	257	6.6	94.0
	5	113	2.9	96.9

	6	78	2.0	98.8
	7	30	.8	99.6
	8	10	.3	99.9
	9	5	.1	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	0	1477	47.3	47.3
	1	1183	37.9	85.2
	2	381	12.2	97.4
	3	66	2.1	99.5
	4	12	.4	99.9
	5	3	.1	100.0
	Total	3122	100.0	
Murray State College	0	1449	37.8	37.8
	1	1067	27.8	65.6
	2	792	20.7	86.3
	3	336	8.8	95.0
	4	123	3.2	98.2
	5	46	1.2	99.4
	6	19	.5	99.9
	7	3	.1	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	0	1874	39.6	39.6
	1	1406	29.7	69.2
	2	859	18.1	87.4
	3	334	7.1	94.4
	4	171	3.6	98.0
	5	54	1.1	99.2
	6	29	.6	99.8
	7	8	.2	100.0
	8	2	.0	100.0
	Total	4737	100.0	
Northern Oklahoma College	0	3025	40.1	40.1
	1	1611	21.4	61.5
	2	1782	23.6	85.1
	3	700	9.3	94.4
	4	288	3.8	98.2
	5	101	1.3	99.5
	6	25	.3	99.8
	7	11	.1	100.0

	8	1	.0	100.0
	Total	7544	100.0	
Carl Albert State College	0	3220	59.3	59.3
	1	1520	28.0	87.3
	2	531	9.8	97.1
	3	125	2.3	99.4
	4	30	.6	100.0
	5	2	.0	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	0	2790	41.7	41.7
	1	1610	24.1	65.8
	2	1045	15.6	81.4
	3	642	9.6	91.0
	4	334	5.0	96.0
	5	156	2.3	98.3
	6	82	1.2	99.6
	7	24	.4	99.9
	8	4	.1	100.0
	9	2	.0	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	0	4996	67.1	67.1
	1	1434	19.3	86.3
	2	742	10.0	96.3
	3	204	2.7	99.0
	4	52	.7	99.7
	5	18	.2	100.0
	6	1	.0	100.0
	Total	7447	100.0	
Redlands Community College	0	1670	56.2	56.2
	1	604	20.3	76.5
	2	400	13.5	90.0
	3	220	7.4	97.4
	4	64	2.2	99.5
	5	10	.3	99.9
	6	3	.1	100.0
	7	1	.0	100.0
	Total	2972	100.0	
Rose State College	0	3669	40.6	40.6
	1	2408	26.6	67.2

	2	1497	16.6	83.8
	3	827	9.1	92.9
	4	389	4.3	97.2
	5	165	1.8	99.0
	6	67	.7	99.8
	7	19	.2	100.0
	9	1	.0	100.0
	Total	9042	100.0	
Seminole State College	0	1716	44.3	44.3
	1	953	24.6	68.8
	2	718	18.5	87.4
	3	335	8.6	96.0
	4	113	2.9	98.9
	5	33	.9	99.8
	6	8	.2	100.0
	7	1	.0	100.0
	Total	3877	100.0	
Tulsa Community College	0	7090	42.4	42.4
	1	4032	24.1	66.5
	2	3130	18.7	85.3
	3	1582	9.5	94.7
	4	625	3.7	98.5
	5	202	1.2	99.7
	6	51	.3	100.0
	7	4	.0	100.0
	Total	16716	100.0	
Western Oklahoma State College	0	1600	51.9	51.9
	1	579	18.8	70.7
	2	451	14.6	85.4
	3	262	8.5	93.9
	4	122	4.0	97.8
	5	48	1.6	99.4
	6	15	.5	99.9
	7	4	.1	100.0
	Total	3081	100.0	
Reading Remedial Attempts 3 Years Scale		***Frequency***	***Percent***	***Cumulative Percent***
	0	19185	98.2	98.2
	1	181	.9	99.2

	2	31	.2	99.3
	3	8	.0	99.4
	4	7	.0	99.4
	5	109	.6	100.0
	6	4	.0	100.0
	7	1	.0	100.0
	9	1	.0	100.0
	10	1	.0	100.0
	13	1	.0	100.0
Oklahoma City Community College	Total	19529	100.0	
	0	3872	99.0	99.0
	1	33	.8	99.9
	2	5	.1	100.0
Connors State College	Total	3910	100.0	
	0	3098	99.2	99.2
	1	21	.7	99.9
	2	3	.1	100.0
Eastern Oklahoma State College	Total	3122	100.0	
	0	3782	98.6	98.6
	1	47	1.2	99.8
	2	6	.2	100.0
Murray State College	Total	3835	100.0	
	0	4064	85.8	85.8
	1	578	12.2	98.0
	2	74	1.6	99.6
	3	15	.3	99.9
	4	5	.1	100.0
	5	1	.0	100.0
Northeastern Oklahoma A&M College	Total	4737	100.0	
	0	6311	83.7	83.7
	1	954	12.6	96.3
	2	236	3.1	99.4
	3	24	.3	99.7
	4	7	.1	99.8
	5	4	.1	99.9
	6	4	.1	99.9
	7	2	.0	100.0
	9	1	.0	100.0
Northern Oklahoma College	10	1	.0	100.0

	Total	7544	100.0	
Carl Albert State College	0	5418	99.8	99.8
	1	8	.1	100.0
	2	2	.0	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	0	5108	76.4	76.4
	1	1175	17.6	93.9
	2	326	4.9	98.8
	3	67	1.0	99.8
	4	7	.1	99.9
	5	5	.1	100.0
	6	1	.0	100.0
	Total	6689	100.0	
Oklahoma State University Institute of Technology – Okmulgee	0	6469	86.9	86.9
	1	863	11.6	98.5
	2	103	1.4	99.8
	3	11	.1	100.0
	8	1	.0	100.0
	Total	7447	100.0	
Redlands Community College	0	2579	86.8	86.8
	1	333	11.2	98.0
	2	52	1.7	99.7
	3	8	.3	100.0
	Total	2972	100.0	
Rose State College	0	8810	97.4	97.4
	1	214	2.4	99.8
	2	15	.2	100.0
	3	3	.0	100.0
	Total	9042	100.0	
Seminole State College	0	3180	82.0	82.0
	1	599	15.5	97.5
	2	69	1.8	99.3
	3	13	.3	99.6
	4	13	.3	99.9
	5	2	.1	100.0
	8	1	.0	100.0
	Total	3877	100.0	
Tulsa Community College	0	16306	97.5	97.5
	1	364	2.2	99.7

	2	25	.1	99.9
	3	19	.1	100.0
	4	1	.0	100.0
	5	1	.0	100.0
	Total	16716	100.0	
Western Oklahoma State College	0	2578	83.7	83.7
	1	368	11.9	95.6
	2	113	3.7	99.3
	3	16	.5	99.8
	4	6	.2	100.0
	Total	3081	100.0	
3-Year Cohort Ends		***Frequency***	***Percent***	***Cumulative Percent***
Oklahoma City Community College	Cohort ends 2007	2704	13.8	13.8
	Cohort ends 2008	2881	14.8	28.6
	Cohort ends 2009	3307	16.9	45.5
	Cohort ends 2010	2813	14.4	59.9
	Cohort ends 2011	2687	13.8	73.7
	Cohort ends 2012	2280	11.7	85.4
	Cohort ends 2013	2857	14.6	100.0
	Total	19529	100.0	
Connors State College	Cohort ends 2007	591	15.1	15.1
	Cohort ends 2008	613	15.7	30.8
	Cohort ends 2009	559	14.3	45.1
	Cohort ends 2010	524	13.4	58.5
	Cohort ends 2011	518	13.2	71.7
	Cohort ends 2012	532	13.6	85.3
	Cohort ends 2013	573	14.7	100.0
	Total	3910	100.0	
Eastern Oklahoma State College	Cohort ends 2007	456	14.6	14.6
	Cohort ends 2008	498	16.0	30.6
	Cohort ends 2009	472	15.1	45.7
	Cohort ends 2010	483	15.5	61.1
	Cohort ends 2011	351	11.2	72.4
	Cohort ends 2012	334	10.7	83.1
	Cohort ends 2013	528	16.9	100.0
	Total	3122	100.0	
Murray State College	Cohort ends 2007	560	14.6	14.6
	Cohort ends 2008	564	14.7	29.3

	Cohort ends 2009	524	13.7	43.0
	Cohort ends 2010	509	13.3	56.2
	Cohort ends 2011	499	13.0	69.3
	Cohort ends 2012	526	13.7	83.0
	Cohort ends 2013	653	17.0	100.0
	Total	3835	100.0	
Northeastern Oklahoma A&M College	Cohort ends 2007	674	14.2	14.2
	Cohort ends 2008	685	14.5	28.7
	Cohort ends 2009	673	14.2	42.9
	Cohort ends 2010	649	13.7	56.6
	Cohort ends 2011	634	13.4	70.0
	Cohort ends 2012	643	13.6	83.6
	Cohort ends 2013	779	16.4	100.0
	Total	4737	100.0	
Northern Oklahoma College	Cohort ends 2007	850	11.3	11.3
	Cohort ends 2008	1100	14.6	25.8
	Cohort ends 2009	1276	16.9	42.8
	Cohort ends 2010	1117	14.8	57.6
	Cohort ends 2011	1157	15.3	72.9
	Cohort ends 2012	960	12.7	85.6
	Cohort ends 2013	1084	14.4	100.0
	Total	7544	100.0	
Carl Albert State College	Cohort ends 2007	1172	21.6	21.6
	Cohort ends 2008	1044	19.2	40.8
	Cohort ends 2009	678	12.5	53.3
	Cohort ends 2010	596	11.0	64.3
	Cohort ends 2011	707	13.0	77.3
	Cohort ends 2012	607	11.2	88.5
	Cohort ends 2013	624	11.5	100.0
	Total	5428	100.0	
Oklahoma State University – Oklahoma City	Cohort ends 2007	978	14.6	14.6
	Cohort ends 2008	848	12.7	27.3
	Cohort ends 2009	932	13.9	41.2
	Cohort ends 2010	780	11.7	52.9
	Cohort ends 2011	881	13.2	66.1
	Cohort ends 2012	1011	15.1	81.2
	Cohort ends 2013	1259	18.8	100.0
	Total	6689	100.0	
	Cohort ends 2007	1108	14.9	14.9

Oklahoma State University Institute of Technology – Okmulgee	Cohort ends 2008	673	9.0	23.9
	Cohort ends 2009	1111	14.9	38.8
	Cohort ends 2010	1464	19.7	58.5
	Cohort ends 2011	1490	20.0	78.5
	Cohort ends 2012	890	12.0	90.5
	Cohort ends 2013	711	9.5	100.0
	Total	7447	100.0	
Redlands Community College	Cohort ends 2007	491	16.5	16.5
	Cohort ends 2008	427	14.4	30.9
	Cohort ends 2009	450	15.1	46.0
	Cohort ends 2010	415	14.0	60.0
	Cohort ends 2011	410	13.8	73.8
	Cohort ends 2012	330	11.1	84.9
	Cohort ends 2013	449	15.1	100.0
	Total	2972	100.0	
Rose State College	Cohort ends 2007	1342	14.8	14.8
	Cohort ends 2008	1194	13.2	28.0
	Cohort ends 2009	1189	13.1	41.2
	Cohort ends 2010	1187	13.1	54.3
	Cohort ends 2011	1255	13.9	68.2
	Cohort ends 2012	1306	14.4	82.6
	Cohort ends 2013	1569	17.4	100.0
	Total	9042	100.0	
Seminole State College	Cohort ends 2007	611	15.8	15.8
	Cohort ends 2008	559	14.4	30.2
	Cohort ends 2009	532	13.7	43.9
	Cohort ends 2010	439	11.3	55.2
	Cohort ends 2011	526	13.6	68.8
	Cohort ends 2012	540	13.9	82.7
	Cohort ends 2013	670	17.3	100.0
	Total	3877	100.0	
Tulsa Community College	Cohort ends 2007	2075	12.4	12.4
	Cohort ends 2008	2206	13.2	25.6
	Cohort ends 2009	1887	11.3	36.9
	Cohort ends 2010	1812	10.8	47.7
	Cohort ends 2011	2240	13.4	61.1
	Cohort ends 2012	2498	14.9	76.1
	Cohort ends 2013	3998	23.9	100.0
	Total	16716	100.0	

Western Oklahoma State College	Cohort ends 2007	543	17.6	17.6
	Cohort ends 2008	434	14.1	31.7
	Cohort ends 2009	452	14.7	46.4
	Cohort ends 2010	404	13.1	59.5
	Cohort ends 2011	352	11.4	70.9
	Cohort ends 2012	426	13.8	84.7
	Cohort ends 2013	470	15.3	100.0
	Total	3081	100.0	
Age Entered College				
	N	*Maximum*	*Mean*	*Std. Deviation*
Oklahoma City Community College	19529	86	22.9	7.6
Connors State College	3910	81	22.7	7.3
Eastern Oklahoma State College	3122	69	21.8	6.8
Murray State College	3835	66	22.9	8.2
Northeastern Oklahoma A&M College	4737	70	20.6	5.6
Northern Oklahoma College	7544	69	21.4	6.4
Carl Albert State College	5428	83	24.7	9.2
Oklahoma State University – Oklahoma City	6689	76	24.0	8.2
Oklahoma State University Institute of Technology – Okmulgee	7447	79	22.4	8.5

Redlands Community College	2972	86	24.8	10.4
Rose State College	9042	69	22.1	6.5
Seminole State College	3877	65	22.6	7.7
Tulsa Community College	16716	77	21.6	6.4
Western Oklahoma State College	3081	60	22.3	7.3

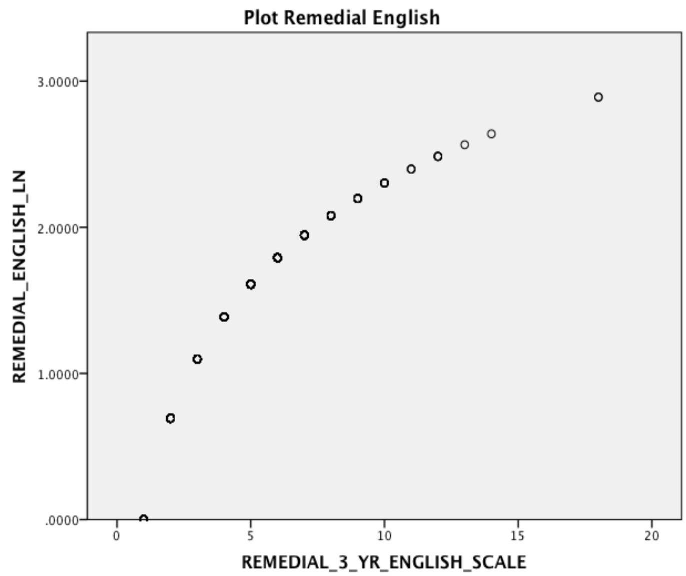
Appendix D: Selected Cross-Tabulation Tables

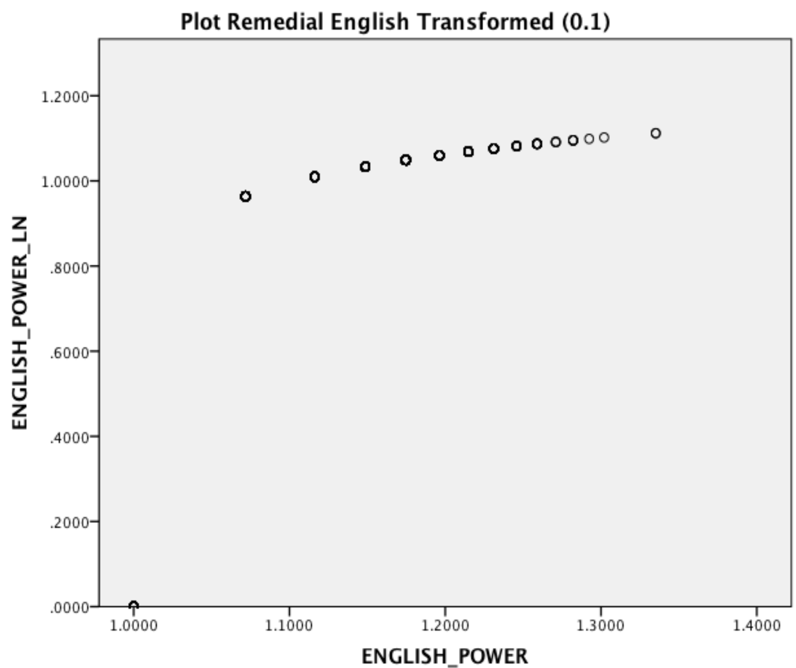
*Institution ID * Reported ACT Score Crosstabulation*		ACT reported	No ACT reported
Oklahoma City Community College	Count	7279	12250
	Expected Count	10287	9242
	% within Institution ID	37.3%	62.7%
Connors State College	Count	2692	1218
	Expected Count	2060	1850
	% within Institution ID	68.8%	31.2%
Eastern Oklahoma State College	Count	1874	1248
	Expected Count	1645	1477
	% within Institution ID	60.0%	40.0%
Murray State College	Count	2211	1624
	Expected Count	2020	1815
	% within Institution ID	57.7%	42.3%
Northeastern Oklahoma A&M College	Count	4216	521
	Expected Count	2495	2242
	% within Institution ID	89.0%	11.0%
Northern Oklahoma College	Count	5556	1988
	Expected Count	3974	3570
	% within Institution ID	73.6%	26.4%
Carl Albert State College	Count	3452	1976
	Expected Count	2859	2569
	% within Institution ID	63.6%	36.4%
Oklahoma State University – Oklahoma City	Count	2585	4104
	Expected Count	3523	3166
	% within Institution ID	38.6%	61.4%
Oklahoma State University Institute of Technology – Okmulgee	Count	3382	4065
	Expected Count	3923	3524
	% within Institution ID	45.4%	54.6%
Redlands Community College	Count	1174	1798
	Expected Count	1565	1407
	% within Institution ID	39.5%	60.5%

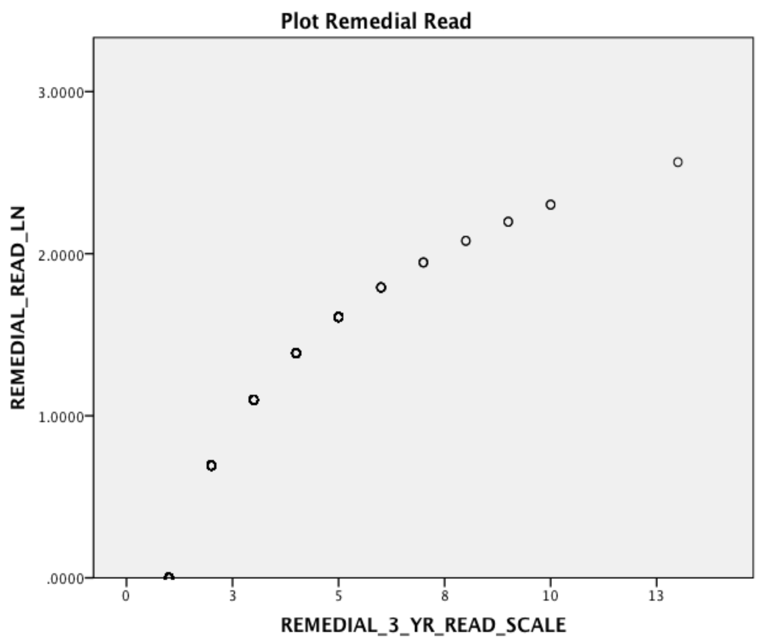
Rose State College	Count	3840	5202
	Expected Count	4763	4279
	% within Institution ID	42.5%	57.5%
Seminole State College	Count	1787	2090
	Expected Count	2042	1835
	% within Institution ID	46.1%	53.9%
Tulsa Community College	Count	9730	6986
	Expected Count	8805	7911
	% within Institution ID	58.2%	41.8%
Western Oklahoma State College	Count	1806	1275
	Expected Count	1623	1458
	% within Institution ID	58.6%	41.4%
Total	Count	51584	46345
	Expected Count	51584	46345
	% within Institution ID	52.7%	47.3%

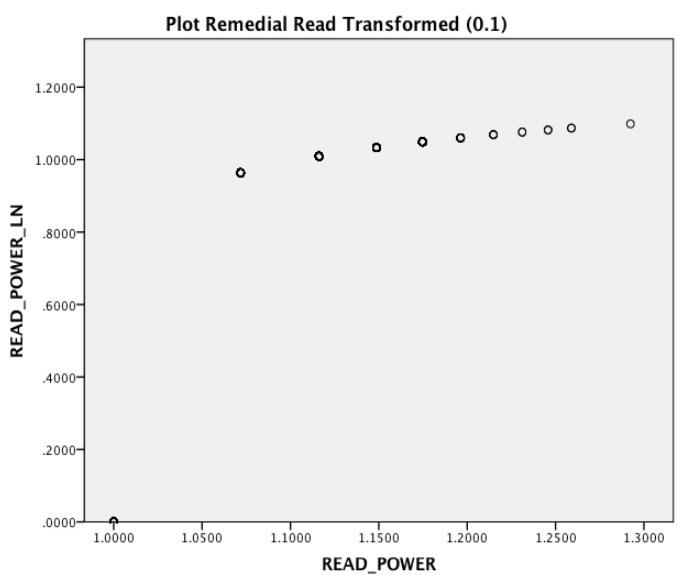
Institution ID * Reported High School GPA Crosstabulation		**No GPA reported**	**GPA reported**
Oklahoma City Community College	Count	19529	0
	Expected Count	18357	1172
	% within Institution ID	100.0%	0.0%
Connors State College	Count	1649	2261
	Expected Count	3675	235
	% within Institution ID	42.2%	57.8%
Eastern Oklahoma State College	Count	3122	0
	Expected Count	2935	187
	% within Institution ID	100.0%	0.0%
Murray State College	Count	3835	0
	Expected Count	3605	230
	% within Institution ID	100.0%	0.0%
Northeastern Oklahoma A&M College	Count	1122	3615
	Expected Count	4453	284
	% within Institution ID	23.7%	76.3%
Northern Oklahoma College	Count	7544	0
	Expected Count	7091	453
	% within Institution ID	100.0%	0.0%
Carl Albert State College	Count	5428	0
	Expected Count	5102.3	325.7

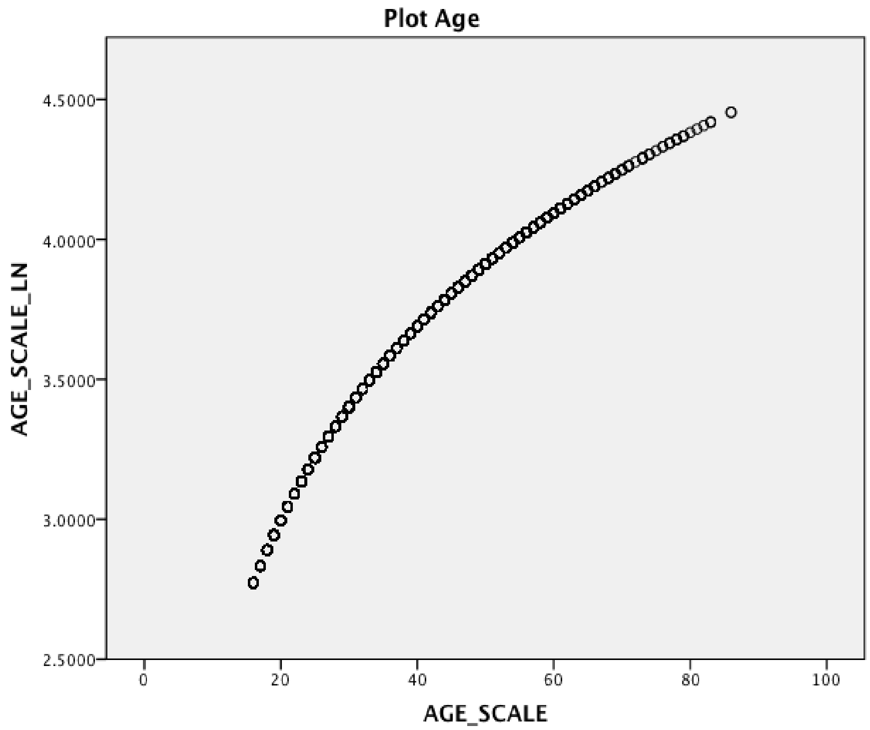
	% within Institution ID	100.0%	0.0%
Oklahoma State University - Oklahoma City	Count	6688	1
	Expected Count	6288	401
	% within Institution ID	100.0%	.0%
Oklahoma State University Institute of Technology – Okmulgee	Count	7447	0
	Expected Count	7000	447
	% within Institution ID	100.0%	0.0%
Redlands Community College	Count	2972	0
	Expected Count	2794	178
	% within Institution ID	100.0%	0.0%
Rose State College	Count	9042	0
	Expected Count	8499	543
	% within Institution ID	100.0%	0.0%
Seminole State College	Count	3877	0
	Expected Count	3644	233
	% within Institution ID	100.0%	0.0%
Tulsa Community College	Count	16716	0
	Expected Count	15713	1003
	% within Institution ID	100.0%	0.0%
Western Oklahoma State College	Count	3081	0
	Expected Count	2896	185
	% within Institution ID	100.0%	0.0%
Total	Count	92052	5877
	Expected Count	92052	5877
	% within Institution ID	94.0%	6.0%

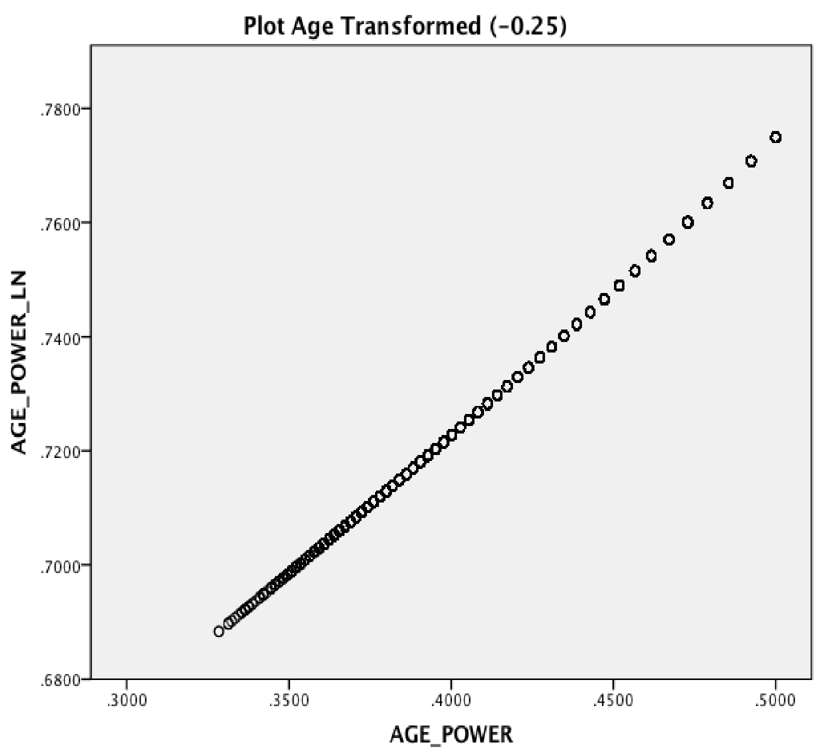

Plot Remedial English
REMEDIAL_ENGLISH_LN
REMEDIAL_3_YR_ENGLISH_SCALE
3.0000
2.0000
1.0000
.0000
0
5
10
15
20


Plot Remedial English Transformed (0.1)
ENGLISH_POWER_LN
ENGLISH_POWER
1.2000
1.0000
.8000
.6000
.4000
.2000
.0000
1.0000
1.1000
1.2000
1.3000
1.4000


Plot Remedial Read
3.0000
2.0000
1.0000
.0000
0
3
5
8
10
13
REMEDIAL_READ_LN
REMEDIAL_3_YR_READ_SCALE


Plot Remedial Read Transformed (0.1)
1.2000
1.0000
.8000
.6000
.4000
.2000
.0000
1.0000
1.0500
1.1000
1.1500
1.2000
1.2500
1.3000
READ_POWER_LN
READ_POWER


Plot Age
4.5000
4.0000
3.5000
3.0000
2.5000
AGE_SCALE_LN
0
20
40
60
80
100
AGE_SCALE


Plot Age Transformed (-0.25)
.7800
.7600
.7400
.7200
.7000
.6800
AGE_POWER_LN
.3000
.3500
.4000
.4500
.5000
AGE_POWER

Appendix E: Collinearity Diagnostics

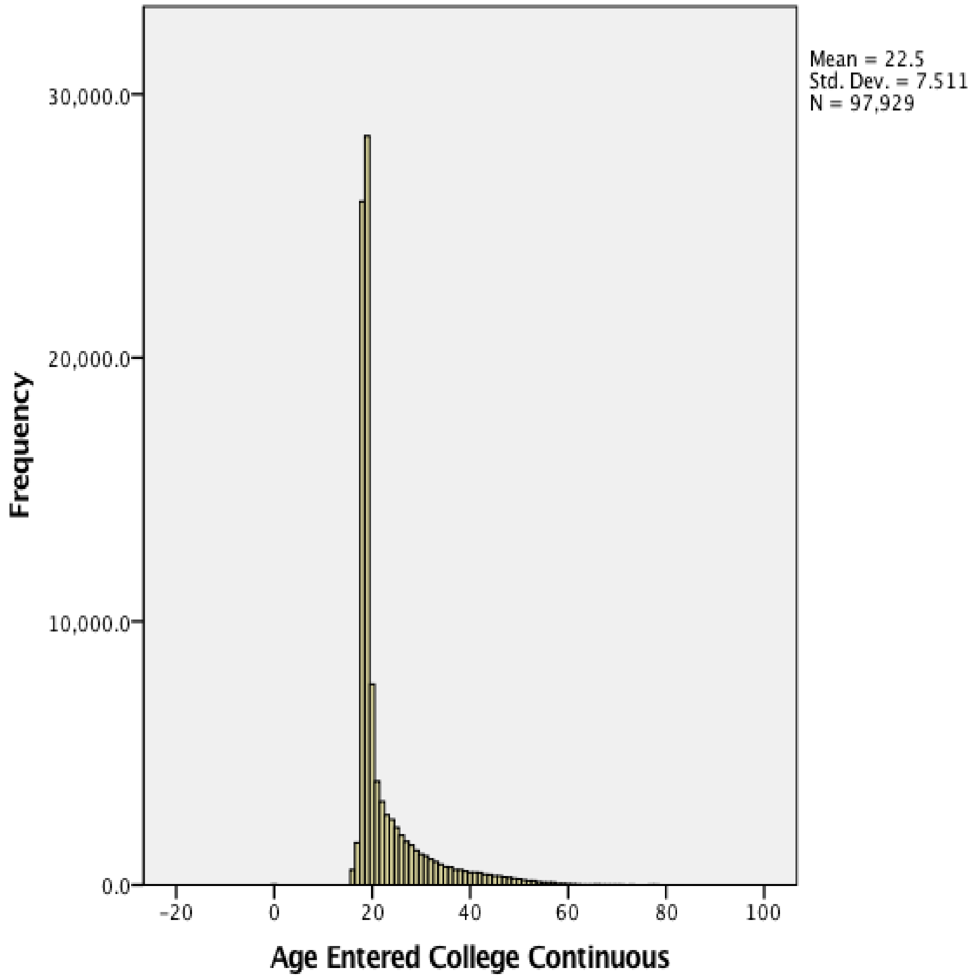
Pre-Correction Collinearity Statistics							
	Unstandardized Coefficients		*Standardized Coefficients*			*Collinearity Statistics*	
	B	*Std. Error*	*Beta*	*t*	*Sig.*	*Tolerance*	*VIF*
(Constant)	.316	.012		27.318	.000		
Reported ACT Score	-.140	.003	-.165	-46.778	0.000	.740	1.351
Reported High School GPA	-.019	.007	-.010	-2.839	.005	.678	1.475
High School Concurrent	.218	.007	.098	31.542	.000	.941	1.063
Full or Part-Time Attend	-.080	.003	-.089	-26.528	.000	.812	1.231
Male or Female	.005	.003	.006	1.970	.049	.967	1.034
OK Higher Learning Access Program	.095	.006	.054	17.085	.000	.923	1.084
OK Tuition Aid Grant	.009	.005	.006	1.699	.089	.863	1.159
Pell Award	-.038	.003	-.040	-11.505	.000	.760	1.315
DEGREE_GOAL= AA or AS (transfer)	.035	.004	.041	8.504	.000	.385	2.597
DEGREE_GOAL= Certificate 1 to 2 years	.089	.021	.013	4.307	.000	.972	1.029
DEGREE_GOAL= Certificate less than 1 year	.121	.013	.029	9.310	.000	.936	1.069
DEGREE_GOAL= AAS (limited transfer)	-.024	.004	-.025	-5.631	.000	.449	2.226
ETHNIC_CLASS= Hispanic	-.054	.006	-.027	-8.871	.000	.967	1.035
ETHNIC_CLASS= Black	-.028	.004	-.020	-6.264	.000	.928	1.078

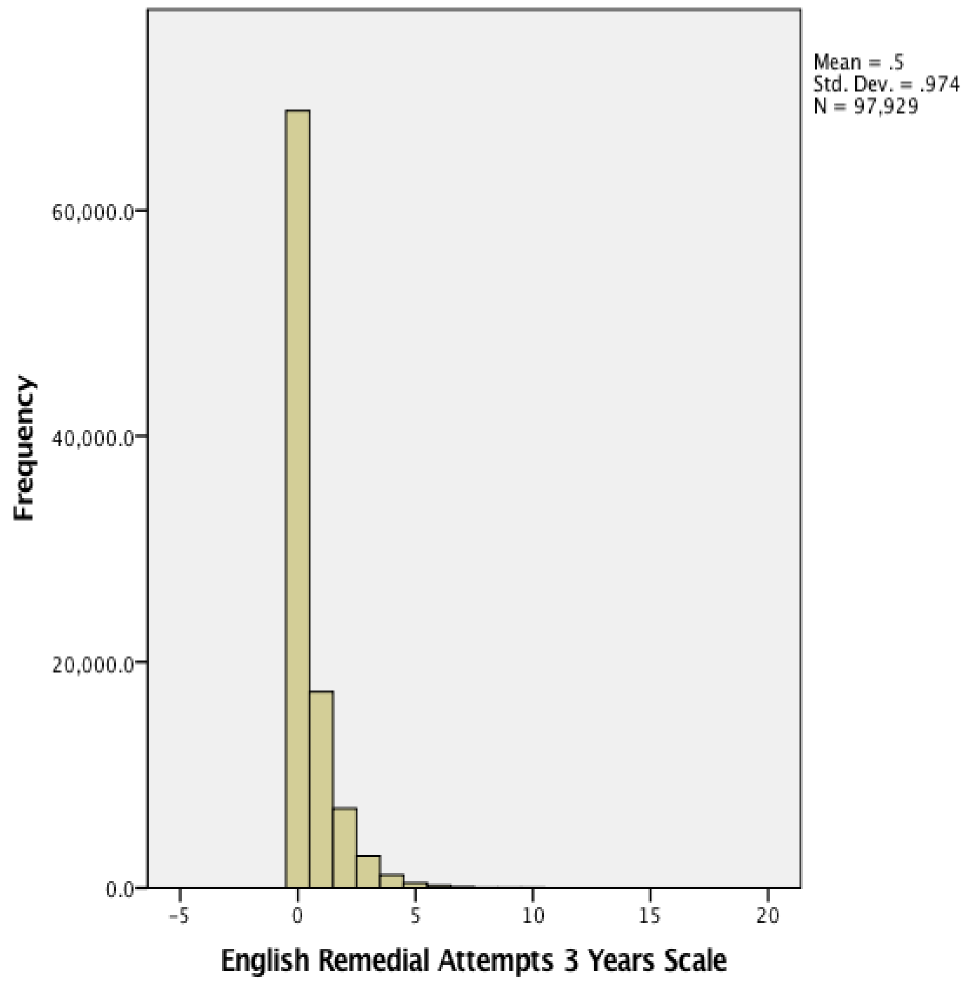
ETHNIC_CLASS= Native American	-.028	.004	-.022	-6.934	.000	.919	1.088
ETHNIC_CLASS= Asian	.074	.010	.022	7.333	.000	.984	1.016
ETHNIC_CLASS= Other group	.016	.006	.009	2.716	.007	.844	1.184
SIZE=5,000 - 9,999	.036	.009	.037	3.987	.000	.107	9.389
SIZE=10,000 - 19,999	-.074	.011	-.069	-6.714	.000	.086	11.623
OUTCOME_YEAR=Cohort ends 2007	.053	.005	.044	11.022	.000	.575	1.740
OUTCOME_YEAR=Cohort ends 2008	.038	.005	.031	7.867	.000	.587	1.702
OUTCOME_YEAR=Cohort ends 2009	.035	.005	.029	7.248	.000	.580	1.723
OUTCOME_YEAR=Cohort ends 2010	.019	.005	.015	3.879	.000	.590	1.694
OUTCOME_YEAR=Cohort ends 2011	.020	.005	.016	4.162	.000	.589	1.699
OUTCOME_YEAR=Cohort ends 2012	.021	.005	.017	4.394	.000	.612	1.633
URBANIZATION =Suburb	-.011	.011	-.012	-1.014	.311	.070	14.253
URBANIZATION =Town	-.045	.014	-.032	-3.255	.001	.097	10.350
URBANIZATION =Rural	-.014	.012	-.013	-1.092	.275	.065	15.269
CONGRESS_DISTRICT=District 2	.025	.007	.026	3.360	.001	.148	6.762
CONGRESS_DISTRICT=District 3	.024	.009	.020	2.765	.006	.182	5.499
CONGRESS_DISTRICT=District 4	-.111	.011	-.076	-10.286	.000	.168	5.939
CONGRESS_DISTRICT=District 1	-.054	.011	-.048	-5.013	.000	.099	10.102
a. Dependent Variable: Award or Transfer 3 years							

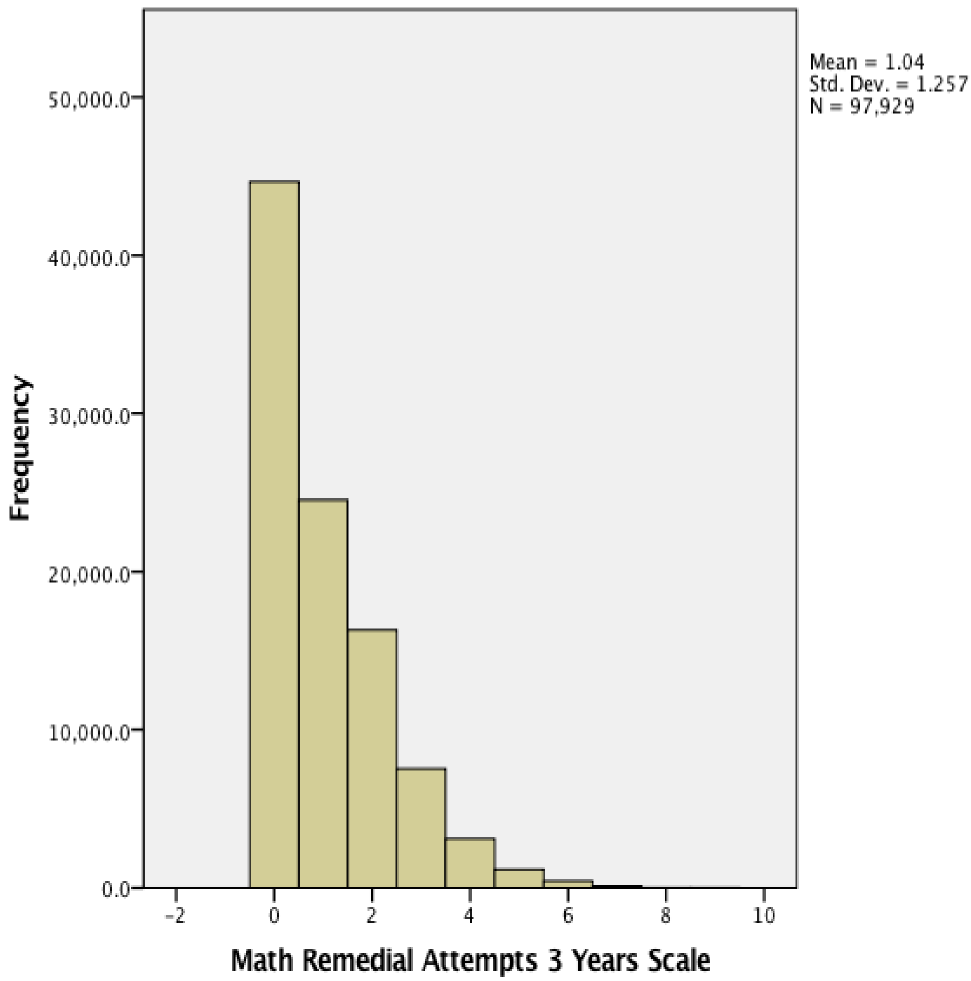
Post-Correction Collinearity Statistics							
	Unstandardized Coefficients		***Standardized Coefficients***			***Collinearity Statistics***	
	B	***Std. Error***	***Beta***	***t***	***Sig.***	***Tolerance***	***VIF***
(Constant)	.338	.005		64.320	0.000		
Reported ACT Score	-.142	.003	-.166	-47.801	0.000	.761	1.313
Reported High School GPA	.008	.006	.004	1.339	.180	.889	1.125
High School Concurrent	.224	.007	.101	32.580	.000	.954	1.048
Full or Part-Time Attend	-.082	.003	-.091	-27.184	.000	.817	1.223
Male or Female	.008	.003	.010	3.215	.001	.978	1.023
OK Higher Learning Access Program	.096	.006	.054	17.190	.000	.931	1.074
OK Tuition AId Grant	.015	.005	.009	2.839	.005	.868	1.152
Pell Award	-.039	.003	-.041	-11.851	.000	.770	1.299
DEGREE_GOAL= AA or AS (transfer)	.052	.004	.061	13.926	.000	.480	2.082
DEGREE_GOAL= Certificate 1 to 2 years	.103	.021	.015	4.955	.000	.977	1.023
DEGREE_GOAL= Certificate less than 1 year	.133	.013	.032	10.259	.000	.948	1.055
DEGREE_GOAL= AAS (limited transfer)	-.008	.004	-.008	-2.003	.045	.531	1.883
ETHNIC_CLASS= Hispanic	-.054	.006	-.027	-8.826	.000	.971	1.030
ETHNIC_CLASS= Black	-.039	.004	-.028	-8.806	.000	.937	1.068
ETHNIC_CLASS= Native American	-.019	.004	-.015	-4.734	.000	.941	1.063

ETHNIC_CLASS= Asian	.066	.010	.020	6.547	.000	.986	1.015
ETHNIC_CLASS= Other group	.014	.006	.008	2.376	.018	.850	1.176
SIZE=5,000 - 9,999	.015	.003	.015	4.631	.000	.852	1.174
SIZE=10,000 - 19,999	-.053	.004	-.050	-14.296	.000	.764	1.308
OUTCOME_YEAR=Cohort ends 2008	-.016	.005	-.013	-3.376	.001	.589	1.698
OUTCOME_YEAR=Cohort ends 2009	-.017	.005	-.014	-3.609	.000	.583	1.716
OUTCOME_YEAR=Cohort ends 2010	-.032	.005	-.026	-6.601	.000	.595	1.682
OUTCOME_YEAR=Cohort ends 2011	-.033	.005	-.027	-6.737	.000	.586	1.707
OUTCOME_YEAR=Cohort ends 2012	-.037	.005	-.029	-7.352	.000	.589	1.699
OUTCOME_YEAR=Cohort ends 2013	-.062	.005	-.055	-13.032	.000	.524	1.907
a. Dependent Variable: Award or Transfer 3 years							

Appendix F: Linearity in the Logit Diagnostics Equal Intervals




Mean = .5
Std. Dev. = .974
N = 97,929
Frequency
60,000.0
40,000.0
20,000.0
0.0
-5
0
5
10
15
20
English Remedial Attempts 3 Years Scale


Mean = 1.04
Std. Dev. = 1.257
N = 97,929
Frequency
50,000.0
40,000.0
30,000.0
20,000.0
10,000.0
0.0
-2
0
2
4
6
8
10
Math Remedial Attempts 3 Years Scale

Appendix G: Sample of 100 Cases with Largest Z-Residuals

Casewise List[b]	*Student ID*	Selected Status[a]	*Observed Award or Transfer 3 years*	*Predicted*	*Predicted Group*	*Temporary*	
						Resid	*ZResid*
1	222	S	S**	.126	N	.874	12.275
2	262	S	S**	.133	N	.867	12.043
3	341	S	S**	.035	N	.965	12.037
4	382	S	S**	.124	N	.876	10.769
5	386	S	S**	.121	N	.879	8.736
6	487	S	S**	.088	N	.912	8.669
7	621	S	S**	.102	N	.898	8.418
8	666	S	S**	.132	N	.868	7.829
9	754	S	S**	.117	N	.883	7.794
10	835	S	S**	.116	N	.884	7.720
11	960	S	S**	.118	N	.882	7.709
12	969	S	S**	.125	N	.875	7.701
13	1589	S	S**	.090	N	.910	7.596
14	1650	S	S**	.118	N	.882	7.593
15	1973	S	S**	.117	N	.883	7.489
16	2577	S	S**	.079	N	.921	7.381
17	2636	S	S**	.126	N	.874	7.376
18	2652	S	S**	.119	N	.881	7.349
19	2728	S	S**	.129	N	.871	7.243
20	2815	S	S**	.083	N	.917	7.147
21	2851	S	S**	.090	N	.910	7.076
22	3001	S	S**	.089	N	.911	7.020
23	3010	S	S**	.043	N	.957	6.993
24	3040	S	S**	.071	N	.929	6.755
25	3191	S	S**	.097	N	.903	6.700
26	3201	S	S**	.108	N	.892	6.638
27	3235	S	S**	.069	N	.931	6.609
28	3247	S	S**	.121	N	.879	6.587
29	3387	S	S**	.134	N	.866	6.561
30	3395	S	S**	.110	N	.890	6.540
31	3405	S	S**	.098	N	.902	6.529
32	3502	S	S**	.094	N	.906	6.466
33	3532	S	S**	.109	N	.891	6.419
34	3585	S	S**	.135	N	.865	6.359
35	3605	S	S**	.092	N	.908	6.345
36	3635	S	S**	.093	N	.907	6.331
37	3779	S	S**	.088	N	.912	6.320

38	3800	S	S**	.049	N	.951	6.268
39	3963	S	S**	.109	N	.891	6.255
40	4399	S	S**	.119	N	.881	6.223
41	4495	S	S**	.097	N	.903	6.208
42	4653	S	S**	.113	N	.887	6.105
43	4900	S	S**	.110	N	.890	6.085
44	5103	S	S**	.048	N	.952	6.057
45	5203	S	S**	.132	N	.868	6.014
46	5224	S	S**	.096	N	.904	6.003
47	5380	S	S**	.125	N	.875	5.974
48	5402	S	S**	.085	N	.915	5.969
49	5534	S	S**	.058	N	.942	5.893
50	5567	S	S**	.128	N	.872	5.892
51	5876	S	S**	.026	N	.974	5.891
52	5905	S	S**	.055	N	.945	5.831
53	5997	S	S**	.129	N	.871	5.815
54	6062	S	S**	.097	N	.903	5.783
55	6148	S	S**	.109	N	.891	5.782
56	6356	S	S**	.134	N	.866	5.774
57	6476	S	S**	.083	N	.917	5.758
58	6641	S	S**	.126	N	.874	5.731
59	6658	S	S**	.086	N	.914	5.654
60	6662	S	S**	.087	N	.913	5.634
61	6684	S	S**	.125	N	.875	5.631
62	6686	S	S**	.111	N	.889	5.611
63	6697	S	S**	.084	N	.916	5.603
64	6704	S	S**	.122	N	.878	5.551
65	6882	S	S**	.116	N	.884	5.535
66	7002	S	S**	.125	N	.875	5.524
67	7078	S	S**	.104	N	.896	5.519
68	7138	S	S**	.116	N	.884	5.491
69	7226	S	S**	.105	N	.895	5.480
70	7241	S	S**	.109	N	.891	5.457
71	7313	S	S**	.017	N	.983	5.457
72	7321	S	S**	.075	N	.925	5.390
73	7341	S	S**	.074	N	.926	5.389
74	7394	S	S**	.100	N	.900	5.376
75	7406	S	S**	.089	N	.911	5.355
76	7407	S	S**	.079	N	.921	5.345
77	7409	S	S**	.108	N	.892	5.341
78	7430	S	S**	.107	N	.893	5.325
79	7444	S	S**	.113	N	.887	5.324
80	7448	S	S**	.071	N	.929	5.323

81	7456	S	S**	.061	N	.939	5.307
82	7469	S	S**	.103	N	.897	5.276
83	7481	S	S**	.109	N	.891	5.268
84	7502	S	S**	.119	N	.881	5.264
85	7534	S	S**	.041	N	.959	5.257
86	7535	S	S**	.077	N	.923	5.253
87	7543	S	S**	.072	N	.928	5.245
88	7564	S	S**	.081	N	.919	5.207
89	7578	S	S**	.111	N	.889	5.196
90	7594	S	S**	.114	N	.886	5.176
91	7597	S	S**	.085	N	.915	5.142
92	7617	S	S**	.107	N	.893	5.111
93	7646	S	S**	.118	N	.882	5.110
94	7649	S	S**	.079	N	.921	5.109
95	7651	S	S**	.118	N	.882	5.097
96	7665	S	S**	.107	N	.893	5.093
97	7722	S	S**	.075	N	.925	5.059
98	7746	S	S**	.073	N	.927	5.055
99	7769	S	S**	.099	N	.901	5.038
100	7773	S	S**	.007	N	.993	5.038

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2.000 are listed.

Appendix H: Coding of Categorical Variables

Dependent Variable Encoding

		Internal Value
Original Value	No success	0
	Success	1

Categorical Variables Codings

			Parameter coding					
		Frequency	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
3-Year Cohort Ends	Cohort ends 2007	14155	0	0	0	0	0	0
	Cohort ends 2008	13726	1	0	0	0	0	0
	Cohort ends 2009	14042	0	1	0	0	0	0
	Cohort ends 2010	13192	0	0	1	0	0	0
	Cohort ends 2011	13707	0	0	0	1	0	0
	Cohort ends 2012	12883	0	0	0	0	1	0
	Cohort ends 2013	16224	0	0	0	0	0	1
Ethnic Group Membership	White	63324	0	0	0	0	0	
	Hispanic	4664	1	0	0	0	0	
	Black	9956	0	1	0	0	0	
	Native American	12203	0	0	1	0	0	
	Asian	1665	0	0	0	1	0	
	Other group	6117	0	0	0	0	1	
Degree Goal When Admitted	AA or AS (transfer)	51082	0	0	0	0		
	Certificate 1 to 2 years	391	1	0	0	0		
	Certificate less than 1 year	1030	0	1	0	0		
	AAS (limited transfer)	27058	0	0	1	0		
	No program leading to credential	18368	0	0	0	1		
IPEDS Student Enrollment	1,000 - 4,999	54367	0	0				
	5,000 - 9,999	24033	1	0				
	10,000 - 19,999	19529	0	1				
Pell Award	No Pell award	70198	0					
	Pell award 1st semester	27731	1					
High School Concurrent	Not concurrent	94166	0					
	Concurrent	3763	1					

Full or Part-Time Attend	Full-time	65279	0
	Part-time	32650	1
Male or Female	Female	54271	0
	Male	43658	1
OK Tuition Aid Grant	No Oklahoma Tuition Aid Grant	90889	0
	Oklahoma Tuition Aid Grant 1st semester	7040	1
OK Higher Learning Access Program	No OHLAP award	91925	0
	OLAP award 1st semester	6004	1
Reported ACT Score	ACT reported	51585	0
	No ACT reported	46344	1

Appendix I: Multivariate System-Wide Regression Coefficients

Variables in the Equation by Block	*B*	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
Block 0						
Constant	-1.173	.008	24316.885	1	0.000	.309
Block 1	-0.173					
ACT_REPORTED(1)	0.827					
CONCURRENT(1)	1.827					
ATTEND_INTENSITY(1)	2.827					
DEGREE_GOAL	3.827					
DEGREE_GOAL(1)	.328	.129	6.446	1	.011	1.388
DEGREE_GOAL(2)	.446	.076	34.655	1	.000	1.562
DEGREE_GOAL(3)	-.423	.020	444.614	1	.000	.655
DEGREE_GOAL(4)	-.324	.025	171.283	1	.000	.723
Block 2						
GENDER(1)	.031	.016	3.490	1	.062	1.031
ETHNIC_CLASS			55.291	5	.000	
ETHNIC_CLASS(1)	-.324	.069	22.423	1	.000	.723
ETHNIC_CLASS(2)	.073	.051	2.089	1	.148	1.076
ETHNIC_CLASS(3)	-.023	.035	.407	1	.524	.978
ETHNIC_CLASS(4)	.330	.097	11.515	1	.001	1.391
ETHNIC_CLASS(5)	.260	.064	16.471	1	.000	1.296
ENTRY_OHLAP(1)	.383	.030	164.527	1	.000	1.467
ENTRY_OTAG(1)	.121	.032	14.305	1	.000	1.129
ENTRY_PELL(1)	-.143	.024	34.325	1	.000	.867
AGE_SCALE	-.203	.029	49.311	1	.000	.816
Block 3						
REMEDIAL_3_YR_ENGLISH_SCALE	-.605	.023	704.086	1	.000	.546
REMEDIAL_3_YR_MATH_SCALE	-.496	.025	380.401	1	.000	.609
REMEDIAL_3_YR_READ_SCALE	-.067	.043	2.459	1	.117	.935
Block 4						
ENTRY_PELL * ETHNIC_CLASS			10.956	5	.052	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.235	.095	6.050	1	.014	1.265
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.043	.064	.437	1	.508	1.043
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.030	.052	.329	1	.566	1.030
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.035	.154	.051	1	.822	1.035
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.254	.128	3.959	1	.047	.775

ETHNIC_CLASS * SIZE			44.985	10	.000	
ETHNIC_CLASS(1) by SIZE(1)	.095	.100	.896	1	.344	1.099
ETHNIC_CLASS(1) by SIZE(2)	-.055	.117	.220	1	.639	.946
ETHNIC_CLASS(2) by SIZE(1)	-.312	.070	20.137	1	.000	.732
ETHNIC_CLASS(2) by SIZE(2)	.030	.092	.104	1	.747	1.030
ETHNIC_CLASS(3) by SIZE(1)	-.097	.058	2.760	1	.097	.908
ETHNIC_CLASS(3) by SIZE(2)	-.178	.104	2.926	1	.087	.837
ETHNIC_CLASS(4) by SIZE(1)	-.102	.165	.379	1	.538	.903
ETHNIC_CLASS(4) by SIZE(2)	.401	.136	8.615	1	.003	1.493
ETHNIC_CLASS(5) by SIZE(1)	-.291	.116	6.299	1	.012	.748
ETHNIC_CLASS(5) by SIZE(2)	-.025	.085	.090	1	.765	.975
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.008	.001	67.656	1	.000	1.008
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	.073	.008	83.587	1	.000	1.075
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.020	.014	1.988	1	.159	1.020
Block 5						
SIZE			140.661	2	.000	
SIZE(1)	.099	.023	18.702	1	.000	1.104
SIZE(2)	-.294	.030	93.559	1	.000	.745
OUTCOME_YEAR			150.681	6	.000	
OUTCOME_YEAR(1)	-.078	.030	6.991	1	.008	.925
OUTCOME_YEAR(2)	-.099	.030	11.180	1	.001	.905
OUTCOME_YEAR(3)	-.194	.030	40.478	1	.000	.824
OUTCOME_YEAR(4)	-.192	.030	40.336	1	.000	.826
OUTCOME_YEAR(5)	-.193	.031	39.459	1	.000	.825
OUTCOME_YEAR(6)	-.336	.030	123.948	1	.000	.714
Block 6						
ENGLISH_LNENGLISH	.083	.020	18.099	1	.000	1.087
MATH_LNMATH	.161	.012	182.530	1	.000	1.174
READ_LNREAD	-.039	.035	1.249	1	.264	.962
Constant	1.362	.192	50.347	1	.000	3.904

Appendix J: Full Model Regression Coefficients by Institution

COLLEGE_CODE Institution ID = 1 Oklahoma City Community College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.709	.048	222.737	1	.000	.492
CONCURRENT(1)	.632	.108	34.045	1	.000	1.881
ATTEND_INTENSITY(1)	-.273	.045	36.378	1	.000	.761
DEGREE_GOAL			187.994	4	.000	
DEGREE_GOAL(1)	-.271	.258	1.107	1	.293	.763
DEGREE_GOAL(2)	-.811	.232	12.216	1	.000	.444
DEGREE_GOAL(3)	-.641	.053	145.858	1	.000	.527
DEGREE_GOAL(4)	.113	.053	4.501	1	.034	1.120
GENDER(1)	-.017	.041	.171	1	.679	.983
ETHNIC_CLASS			107.304	5	.000	
ETHNIC_CLASS(1)	-.471	.099	22.876	1	.000	.624
ETHNIC_CLASS(2)	-.067	.080	.694	1	.405	.935
ETHNIC_CLASS(3)	-.200	.099	4.068	1	.044	.819
ETHNIC_CLASS(4)	.660	.096	47.060	1	.000	1.934
ETHNIC_CLASS(5)	.370	.074	24.685	1	.000	1.448
ENTRY_OHLAP(1)	.258	.121	4.543	1	.033	1.294
ENTRY_OTAG(1)	-.132	.183	.519	1	.471	.876
ENTRY_PELL(1)	.570	.127	20.110	1	.000	1.768
OUTCOME_YEAR			77.367	6	.000	
OUTCOME_YEAR(1)	-.202	.073	7.627	1	.006	.817
OUTCOME_YEAR(2)	-.026	.070	.142	1	.706	.974
OUTCOME_YEAR(3)	-.303	.076	16.021	1	.000	.739
OUTCOME_YEAR(4)	-.350	.078	20.025	1	.000	.705
OUTCOME_YEAR(5)	-.326	.081	16.323	1	.000	.722
OUTCOME_YEAR(6)	-.700	.097	51.748	1	.000	.497
AGE_SCALE	-.018	.004	19.037	1	.000	.982
REMEDIAL_3_YR_MATH_SCALE	-.239	.072	11.043	1	.001	.788
ENTRY_PELL * ETHNIC_CLASS			1.359	5	.929	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	-.304	.402	.573	1	.449	.738
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.185	.346	.285	1	.593	.831
ENTRY_PELL(1) by ETHNIC_CLASS(3)	-.219	.466	.221	1	.638	.803

ENTRY_PELL(1) by ETHNIC_CLASS(4)	-.362	.547	.438	1	.508	.696
ENTRY_PELL(1) by ETHNIC_CLASS(5)	.121	.531	.052	1	.820	1.128
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.006	.003	3.428	1	.064	1.006
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.122	.013	89.905	1	.000	.885
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.040	.038	1.113	1	.291	1.041
Constant	-.207	.109	3.611	1	.057	.813

COLLEGE_CODE Institution ID = 2 Connors State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.833	.131	40.161	1	.000	.435
CONCURRENT(1)	.882	.154	32.994	1	.000	2.417
ATTEND_INTENSITY(1)	-1.096	.135	65.835	1	.000	.334
DEGREE_GOAL			10.566	3	.014	
DEGREE_GOAL(1)	-19.329	######	.000	1	1.000	.000
DEGREE_GOAL(2)	.588	.791	.553	1	.457	1.800
DEGREE_GOAL(3)	-.557	.177	9.914	1	.002	.573
GENDER(1)	.088	.081	1.178	1	.278	1.092
ETHNIC_CLASS			7.604	5	.179	
ETHNIC_CLASS(1)	-.086	.343	.063	1	.802	.918
ETHNIC_CLASS(2)	-.309	.211	2.151	1	.143	.734
ETHNIC_CLASS(3)	-.295	.123	5.726	1	.017	.744
ETHNIC_CLASS(4)	-.124	.621	.040	1	.842	.884
ETHNIC_CLASS(5)	-.556	.560	.985	1	.321	.574
ENTRY_OHLAP(1)	.518	.117	19.704	1	.000	1.678
ENTRY_OTAG(1)	.078	.118	.432	1	.511	1.081
ENTRY_PELL(1)	-.400	.114	12.328	1	.000	.671
OUTCOME_YEAR			32.304	6	.000	
OUTCOME_YEAR(1)	-.200	.137	2.131	1	.144	.819
OUTCOME_YEAR(2)	-.360	.144	6.234	1	.013	.698
OUTCOME_YEAR(3)	-.752	.152	24.608	1	.000	.471
OUTCOME_YEAR(4)	-.421	.144	8.508	1	.004	.656

OUTCOME_YEAR(5)	-.293	.143	4.189	1	.041	.746
OUTCOME_YEAR(6)	-.581	.146	15.920	1	.000	.559
AGE_SCALE	-.007	.011	.386	1	.534	.993
REMEDIAL_3_YR_MATH_SCALE	-.171	.088	3.812	1	.051	.843
ENTRY_PELL * ETHNIC_CLASS			3.060	5	.691	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	-.403	.618	.425	1	.514	.669
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.391	.267	2.139	1	.144	1.478
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.046	.180	.064	1	.800	1.047
ENTRY_PELL(1) by ETHNIC_CLASS(4)	-.675	1.261	.287	1	.592	.509
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.132	.977	.018	1	.893	.877
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.005	.004	1.993	1	.158	1.005
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.038	.013	8.576	1	.003	.963
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.087	.089	.958	1	.328	1.091
Constant	.148	.254	.339	1	.561	1.159

COLLEGE_CODE Institution ID = 3 Eastern Oklahoma State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.895	.108	68.479	1	.000	.409
CONCURRENT(1)	.700	.248	7.926	1	.005	2.013
ATTEND_INTENSITY(1)	-.864	.130	44.194	1	.000	.421
DEGREE_GOAL			45.933	3	.000	
DEGREE_GOAL(1)	-.206	.661	.097	1	.755	.814
DEGREE_GOAL(2)	-.860	.127	45.870	1	.000	.423
DEGREE_GOAL(3)	-.095	.246	.150	1	.698	.909
GENDER(1)	-.107	.086	1.551	1	.213	.899
ETHNIC_CLASS			15.364	5	.009	

ETHNIC_CLASS(1)	-.714	.435	2.694	1	.101	.489
ETHNIC_CLASS(2)	-.676	.290	5.420	1	.020	.509
ETHNIC_CLASS(3)	-.391	.127	9.436	1	.002	.676
ETHNIC_CLASS(4)	-.230	.560	.168	1	.682	.795
ETHNIC_CLASS(5)	-.014	.299	.002	1	.961	.986
ENTRY_OHLAP(1)	.629	.121	27.060	1	.000	1.875
ENTRY_OTAG(1)	.187	.141	1.755	1	.185	1.205
ENTRY_PELL(1)	-.417	.115	13.115	1	.000	.659
OUTCOME_YEAR			9.182	6	.164	
OUTCOME_YEAR(1)	-.045	.150	.089	1	.765	.956
OUTCOME_YEAR(2)	-.127	.150	.712	1	.399	.881
OUTCOME_YEAR(3)	-.210	.151	1.916	1	.166	.811
OUTCOME_YEAR(4)	-.382	.166	5.303	1	.021	.682
OUTCOME_YEAR(5)	-.316	.173	3.321	1	.068	.729
OUTCOME_YEAR(6)	-.282	.152	3.455	1	.063	.754
AGE_SCALE	.015	.009	2.708	1	.100	1.015
REMEDIAL_3_YR_MATH_SCALE	-.635	.174	13.338	1	.000	.530
ENTRY_PELL * ETHNIC_CLASS			11.783	5	.038	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	1.297	.643	4.060	1	.044	3.656
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.786	.406	3.743	1	.053	2.194
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.279	.193	2.092	1	.148	1.322
ENTRY_PELL(1) by ETHNIC_CLASS(4)	-.326	1.272	.066	1	.798	.722
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-1.094	.699	2.449	1	.118	.335
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.025	.007	11.925	1	.001	1.025
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.180	.052	12.116	1	.000	.836
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.576	.234	6.086	1	.014	1.780
Constant	.022	.227	.010	1	.921	1.023

COLLEGE_CODE Institution ID = 4 Murray State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.941	.108	76.082	1	.000	.390
CONCURRENT(1)	1.069	.150	51.137	1	.000	2.914
ATTEND_INTENSITY(1)	-1.338	.139	92.303	1	.000	.262
DEGREE_GOAL			5.044	3	.169	
DEGREE_GOAL(1)	1.027	.520	3.891	1	.049	2.792
DEGREE_GOAL(2)	-.081	.088	.839	1	.360	.922
DEGREE_GOAL(3)	-18.515	######	.000	1	.999	.000
GENDER(1)	.186	.084	4.899	1	.027	1.205
ETHNIC_CLASS			7.035	5	.218	
ETHNIC_CLASS(1)	-.658	.273	5.820	1	.016	.518
ETHNIC_CLASS(2)	-.201	.236	.722	1	.395	.818
ETHNIC_CLASS(3)	-.098	.149	.428	1	.513	.907
ETHNIC_CLASS(4)	.193	.320	.365	1	.546	1.213
ETHNIC_CLASS(5)	-.084	.194	.185	1	.667	.920
ENTRY_OHLAP(1)	.569	.133	18.288	1	.000	1.767
ENTRY_OTAG(1)	.495	.197	6.297	1	.012	1.641
ENTRY_PELL(1)	-.239	.119	4.061	1	.044	.787
OUTCOME_YEAR			13.195	6	.040	
OUTCOME_YEAR(1)	.101	.146	.482	1	.488	1.107
OUTCOME_YEAR(2)	.020	.162	.015	1	.903	1.020
OUTCOME_YEAR(3)	-.055	.155	.127	1	.721	.946
OUTCOME_YEAR(4)	.010	.155	.004	1	.951	1.010
OUTCOME_YEAR(5)	-.453	.167	7.373	1	.007	.636
OUTCOME_YEAR(6)	-.173	.157	1.212	1	.271	.841
AGE_SCALE	.002	.008	.033	1	.856	1.002
REMEDIAL_3_YR_MATH_SCALE	-.158	.096	2.716	1	.099	.854
ENTRY_PELL * ETHNIC_CLASS			5.297	5	.381	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.650	.415	2.451	1	.117	1.915
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.203	.343	.352	1	.553	1.226
ENTRY_PELL(1) by ETHNIC_CLASS(3)	-.006	.238	.001	1	.981	.994
ENTRY_PELL(1) by ETHNIC_CLASS(4)	-.765	.544	1.979	1	.160	.466
ENTRY_PELL(1) by ETHNIC_CLASS(5)	.219	.341	.413	1	.520	1.245

AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.010	.004	5.974	1	.015	1.010
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.119	.026	21.605	1	.000	.888
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.846	.162	27.223	1	.000	2.330
Constant	-.555	.226	6.034	1	.014	.574

COLLEGE_CODE Institution ID = 5 Northeastern Oklahoma A&M College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.716	.162	19.592	1	.000	.489
CONCURRENT(1)	.916	.127	51.779	1	.000	2.499
ATTEND_INTENSITY(1)	-1.009	.167	36.471	1	.000	.365
DEGREE_GOAL			27.078	4	.000	
DEGREE_GOAL(1)	.181	.355	.261	1	.610	1.199
DEGREE_GOAL(2)	-.479	.481	.991	1	.319	.620
DEGREE_GOAL(3)	-.403	.082	24.198	1	.000	.668
DEGREE_GOAL(4)	-.418	.270	2.388	1	.122	.658
GENDER(1)	-.040	.068	.342	1	.559	.961
ETHNIC_CLASS			3.768	5	.583	
ETHNIC_CLASS(1)	-.146	.305	.228	1	.633	.865
ETHNIC_CLASS(2)	.202	.185	1.190	1	.275	1.223
ETHNIC_CLASS(3)	.112	.113	.976	1	.323	1.118
ETHNIC_CLASS(4)	-.045	1.498	.001	1	.976	.956
ETHNIC_CLASS(5)	-.334	.299	1.243	1	.265	.716
ENTRY_OHLAP(1)	.636	.091	48.661	1	.000	1.889
ENTRY_OTAG(1)	.122	.093	1.708	1	.191	1.129
ENTRY_PELL(1)	-.210	.085	6.014	1	.014	.811
OUTCOME_YEAR			5.534	6	.477	
OUTCOME_YEAR(1)	-.175	.122	2.053	1	.152	.839
OUTCOME_YEAR(2)	-.205	.121	2.881	1	.090	.815
OUTCOME_YEAR(3)	-.176	.121	2.118	1	.146	.838
OUTCOME_YEAR(4)	-.114	.125	.827	1	.363	.892
OUTCOME_YEAR(5)	-.001	.123	.000	1	.992	.999
OUTCOME_YEAR(6)	-.128	.120	1.142	1	.285	.880

AGE_SCALE	.026	.010	6.460	1	.011	1.026
REMEDIAL_3_YR_MATH_SCALE	.007	.126	.003	1	.954	1.007
ENTRY_PELL * ETHNIC_CLASS			1.176	5	.947	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	-.214	.456	.220	1	.639	.808
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.195	.220	.784	1	.376	1.215
ENTRY_PELL(1) by ETHNIC_CLASS(3)	-.022	.165	.018	1	.893	.978
ENTRY_PELL(1) by ETHNIC_CLASS(4)	-.328	1.959	.028	1	.867	.720
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.046	.566	.007	1	.936	.955
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.011	.006	3.240	1	.072	.989
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	.013	.013	.978	1	.323	1.013
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.140	.046	9.498	1	.002	.869
Constant	-.733	.228	10.286	1	.001	.481

COLLEGE_CODE Institution ID = 6 Northern Oklahoma College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.996	.096	108.341	1	.000	.370
CONCURRENT(1)	.971	.100	95.251	1	.000	2.641
ATTEND_INTENSITY(1)	-1.136	.088	164.914	1	.000	.321
DEGREE_GOAL			46.203	2	.000	
DEGREE_GOAL(1)	-.542	.080	45.917	1	.000	.582
DEGREE_GOAL(2)	-.013	.131	.010	1	.922	.987
GENDER(1)	.043	.053	.644	1	.422	1.044
ETHNIC_CLASS			14.582	5	.012	
ETHNIC_CLASS(1)	-.532	.185	8.276	1	.004	.588
ETHNIC_CLASS(2)	.098	.158	.382	1	.536	1.103
ETHNIC_CLASS(3)	-.207	.122	2.878	1	.090	.813

ETHNIC_CLASS(4)	.411	.354	1.343	1	.246	1.508
ETHNIC_CLASS(5)	.251	.213	1.387	1	.239	1.285
ENTRY_OHLAP(1)	.310	.078	15.925	1	.000	1.363
ENTRY_OTAG(1)	.010	.086	.013	1	.908	1.010
ENTRY_PELL(1)	-.448	.067	44.701	1	.000	.639
OUTCOME_YEAR			.589	6	.997	
OUTCOME_YEAR(1)	.001	.110	.000	1	.989	1.001
OUTCOME_YEAR(2)	-.017	.105	.028	1	.868	.983
OUTCOME_YEAR(3)	-.056	.108	.267	1	.606	.946
OUTCOME_YEAR(4)	.003	.105	.001	1	.974	1.003
OUTCOME_YEAR(5)	-.031	.110	.082	1	.774	.969
OUTCOME_YEAR(6)	-.008	.109	.006	1	.938	.992
AGE_SCALE	-.039	.010	15.555	1	.000	.962
REMEDIAL_3_YR_MATH_SCALE	-.600	.078	59.735	1	.000	.549
ENTRY_PELL * ETHNIC_CLASS			2.620	5	.758	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.274	.281	.950	1	.330	1.315
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.103	.212	.236	1	.627	.902
ENTRY_PELL(1) by ETHNIC_CLASS(3)	-.131	.185	.499	1	.480	.877
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.170	.520	.107	1	.744	1.185
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.384	.451	.727	1	.394	.681
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.026	.004	53.043	1	.000	1.026
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.087	.021	16.489	1	.000	.917
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.050	.023	4.666	1	.031	.951
Constant	.955	.216	19.556	1	.000	2.599

COLLEGE_CODE Institution ID = 7 Carl Albert State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.498	.079	39.917	1	.000	.608
CONCURRENT(1)	1.176	.174	45.823	1	.000	3.243
ATTEND_INTENSITY(1)	-.379	.074	26.105	1	.000	.685
DEGREE_GOAL			56.507	4	.000	
DEGREE_GOAL(1)	.448	.594	.570	1	.450	1.565
DEGREE_GOAL(2)	1.231	.165	55.962	1	.000	3.425
DEGREE_GOAL(3)	.131	.116	1.266	1	.261	1.140
DEGREE_GOAL(4)	.146	.156	.874	1	.350	1.157
GENDER(1)	-.294	.063	21.821	1	.000	.745
ETHNIC_CLASS			14.106	5	.015	
ETHNIC_CLASS(1)	-.464	.253	3.360	1	.067	.629
ETHNIC_CLASS(2)	.459	.174	6.927	1	.008	1.582
ETHNIC_CLASS(3)	.034	.080	.181	1	.670	1.034
ETHNIC_CLASS(4)	.283	.286	.980	1	.322	1.327
ETHNIC_CLASS(5)	.307	.183	2.802	1	.094	1.359
ENTRY_OHLAP(1)	.443	.191	5.409	1	.020	1.558
ENTRY_OTAG(1)	.589	.127	21.432	1	.000	1.802
ENTRY_PELL(1)	-.095	.113	.711	1	.399	.909
OUTCOME_YEAR			25.095	6	.000	
OUTCOME_YEAR(1)	-.251	.092	7.453	1	.006	.778
OUTCOME_YEAR(2)	-.189	.117	2.590	1	.108	.828
OUTCOME_YEAR(3)	-.336	.122	7.552	1	.006	.715
OUTCOME_YEAR(4)	-.272	.117	5.468	1	.019	.762
OUTCOME_YEAR(5)	-.401	.125	10.287	1	.001	.669
OUTCOME_YEAR(6)	-.584	.128	20.709	1	.000	.558
AGE_SCALE	.004	.004	.643	1	.423	1.004
REMEDIAL_3_YR_MATH_SCALE	-.499	.122	16.799	1	.000	.607
ENTRY_PELL * ETHNIC_CLASS			2.533	5	.772	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.309	.499	.382	1	.537	1.361
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.166	.380	.190	1	.663	.847
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.006	.160	.001	1	.969	1.006
ENTRY_PELL(1) by ETHNIC_CLASS(4)	1.284	1.169	1.207	1	.272	3.612

ENTRY_PELL(1) by ETHNIC_CLASS(5)	.650	.755	.742	1	.389	1.916
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.010	.004	5.595	1	.018	1.011
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.264	.061	18.441	1	.000	.768
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	1.319	.405	10.593	1	.001	3.738
Constant	.088	.148	.357	1	.550	1.093

COLLEGE_CODE Institution ID = 8 Oklahoma State University – Oklahoma City

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.796	.083	91.259	1	.000	.451
CONCURRENT(1)	.663	.153	18.663	1	.000	1.940
ATTEND_INTENSITY(1)	-.481	.076	39.896	1	.000	.618
DEGREE_GOAL			71.552	4	.000	
DEGREE_GOAL(1)	.681	.447	2.327	1	.127	1.977
DEGREE_GOAL(2)	-.606	.304	3.982	1	.046	.545
DEGREE_GOAL(3)	-.228	.157	2.116	1	.146	.796
DEGREE_GOAL(4)	.751	.190	15.543	1	.000	2.118
GENDER(1)	.167	.070	5.756	1	.016	1.182
ETHNIC_CLASS			29.048	5	.000	
ETHNIC_CLASS(1)	-.369	.170	4.724	1	.030	.691
ETHNIC_CLASS(2)	-.119	.145	.676	1	.411	.888
ETHNIC_CLASS(3)	-.296	.202	2.143	1	.143	.744
ETHNIC_CLASS(4)	.742	.231	10.322	1	.001	2.101
ETHNIC_CLASS(5)	.374	.129	8.469	1	.004	1.454
ENTRY_OHLAP(1)	.261	.122	4.618	1	.032	1.299
ENTRY_OTAG(1)	.129	.131	.968	1	.325	1.138
ENTRY_PELL(1)	-.245	.132	3.444	1	.063	.782
OUTCOME_YEAR			18.251	6	.006	
OUTCOME_YEAR(1)	-.044	.134	.109	1	.742	.957
OUTCOME_YEAR(2)	.265	.126	4.399	1	.036	1.304
OUTCOME_YEAR(3)	-.105	.137	.583	1	.445	.901
OUTCOME_YEAR(4)	-.002	.135	.000	1	.987	.998
OUTCOME_YEAR(5)	.238	.130	3.328	1	.068	1.269

OUTCOME_YEAR(6)	-.115	.134	.737	1	.391	.891
AGE_SCALE	-.004	.006	.532	1	.466	.996
REMEDIAL_3_YR_MATH_SCALE	-.122	.088	1.932	1	.164	.885
ENTRY_PELL * ETHNIC_CLASS			2.672	5	.750	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.212	.438	.234	1	.629	1.236
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.067	.269	.061	1	.804	.936
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.485	.358	1.836	1	.175	1.625
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.249	.446	.311	1	.577	1.282
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.231	.596	.150	1	.698	.794
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.002	.004	.319	1	.572	1.002
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.129	.039	11.118	1	.001	.879
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.057	.040	2.012	1	.156	.945
Constant	-.667	.229	8.479	1	.004	.513

COLLEGE_CODE Institution ID = 9 Oklahoma State University Institute of Techı

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.768	.078	97.546	1	.000	.464
CONCURRENT(1)	.791	.146	29.440	1	.000	2.206
ATTEND_INTENSITY(1)	-.538	.095	32.257	1	.000	.584
DEGREE_GOAL			111.981	2	.000	
DEGREE_GOAL(1)	.341	.137	6.218	1	.013	1.407
DEGREE_GOAL(2)	-.560	.140	15.908	1	.000	.571
GENDER(1)	-.029	.071	.170	1	.680	.971
ETHNIC_CLASS			2.278	5	.809	
ETHNIC_CLASS(1)	-.152	.189	.650	1	.420	.859
ETHNIC_CLASS(2)	-.048	.179	.073	1	.786	.953

COLLEGE_CODE Institution ID = 10 Redlands Community College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.796	.110	51.980	1	.000	.451
CONCURRENT(1)	.913	.292	9.781	1	.002	2.492
ATTEND_INTENSITY(1)	-.853	.130	42.825	1	.000	.426
DEGREE_GOAL			64.687	4	.000	
DEGREE_GOAL(1)	-.386	1.100	.123	1	.726	.680
DEGREE_GOAL(2)	1.693	.378	20.090	1	.000	5.433
DEGREE_GOAL(3)	-.607	.111	29.743	1	.000	.545
DEGREE_GOAL(4)	-1.169	.395	8.744	1	.003	.311
GENDER(1)	-.031	.097	.103	1	.748	.969
ETHNIC_CLASS			16.719	5	.005	
ETHNIC_CLASS(1)	.006	.279	.001	1	.982	1.006
ETHNIC_CLASS(2)	.176	.242	.531	1	.466	1.193
ETHNIC_CLASS(3)	-.649	.250	6.758	1	.009	.523
ETHNIC_CLASS(4)	.844	.514	2.700	1	.100	2.326
ETHNIC_CLASS(5)	.634	.263	5.827	1	.016	1.885
ENTRY_OHLAP(1)	.419	.205	4.194	1	.041	1.521
ENTRY_OTAG(1)	-.075	.219	.117	1	.732	.928
ENTRY_PELL(1)	-.219	.124	3.109	1	.078	.803
OUTCOME_YEAR			1.597	6	.953	
OUTCOME_YEAR(1)	-.123	.169	.531	1	.466	.884
OUTCOME_YEAR(2)	-.166	.168	.981	1	.322	.847
OUTCOME_YEAR(3)	-.139	.171	.659	1	.417	.871
OUTCOME_YEAR(4)	-.036	.173	.042	1	.837	.965
OUTCOME_YEAR(5)	-.026	.182	.021	1	.884	.974
OUTCOME_YEAR(6)	-.073	.170	.183	1	.668	.930
AGE_SCALE	.010	.007	1.856	1	.173	1.010
REMEDIAL_3_YR_MATH_SCALE	-.323	.145	4.968	1	.026	.724
ENTRY_PELL * ETHNIC_CLASS			7.121	5	.212	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	-.314	.495	.401	1	.526	.731
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.114	.319	.127	1	.722	1.120
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.333	.356	.874	1	.350	1.395
ENTRY_PELL(1) by ETHNIC_CLASS(4)	-20.655	######	.000	1	.999	.000

ENTRY_PELL(1) by ETHNIC_CLASS(5)	-1.629	.703	5.376	1	.020	.196
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.006	.006	1.126	1	.289	1.006
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.096	.057	2.828	1	.093	.908
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.058	.078	.555	1	.456	.943
Constant	-.202	.211	.915	1	.339	.817

COLLEGE_CODE Institution ID = 11 Rose State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-1.136	.079	204.523	1	.000	.321
CONCURRENT(1)	.961	.103	86.438	1	.000	2.614
ATTEND_INTENSITY(1)	-.557	.078	50.495	1	.000	.573
DEGREE_GOAL			74.474	4	.000	
DEGREE_GOAL(1)	-19.408	######	.000	1	1.000	.000
DEGREE_GOAL(2)	-.763	.761	1.004	1	.316	.466
DEGREE_GOAL(3)	-.743	.090	67.417	1	.000	.476
DEGREE_GOAL(4)	.027	.076	.127	1	.722	1.027
GENDER(1)	.068	.064	1.138	1	.286	1.071
ETHNIC_CLASS			9.671	5	.085	
ETHNIC_CLASS(1)	-.241	.186	1.670	1	.196	.786
ETHNIC_CLASS(2)	-.007	.119	.003	1	.954	.993
ETHNIC_CLASS(3)	-.140	.158	.793	1	.373	.869
ETHNIC_CLASS(4)	.586	.232	6.394	1	.011	1.796
ETHNIC_CLASS(5)	.096	.155	.383	1	.536	1.101
ENTRY_OHLAP(1)	.216	.100	4.684	1	.030	1.242
ENTRY_OTAG(1)	-.009	.133	.005	1	.946	.991
ENTRY_PELL(1)	-.394	.098	16.073	1	.000	.674
OUTCOME_YEAR			4.992	6	.545	
OUTCOME_YEAR(1)	-.055	.115	.228	1	.633	.946
OUTCOME_YEAR(2)	-.068	.116	.340	1	.560	.935
OUTCOME_YEAR(3)	-.117	.116	1.019	1	.313	.889
OUTCOME_YEAR(4)	-.209	.117	3.204	1	.073	.811
OUTCOME_YEAR(5)	-.067	.113	.349	1	.554	.936

OUTCOME_YEAR(6)	-.185	.111	2.777	1	.096	.831
AGE_SCALE	-.015	.009	2.500	1	.114	.985
REMEDIAL_3_YR_MATH_SCALE	-.179	.093	3.696	1	.055	.836
ENTRY_PELL * ETHNIC_CLASS			9.744	5	.083	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.785	.300	6.839	1	.009	2.192
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.064	.189	.116	1	.733	.938
ENTRY_PELL(1) by ETHNIC_CLASS(3)	-.471	.334	1.993	1	.158	.624
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.007	.463	.000	1	.988	1.007
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-.016	.292	.003	1	.956	.984
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.010	.004	4.775	1	.029	1.010
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.119	.024	25.505	1	.000	.888
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.280	.065	18.601	1	.000	1.323
Constant	-.414	.203	4.161	1	.041	.661

COLLEGE_CODE Institution ID = 12 Seminole State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-1.157	.103	126.929	1	.000	.314
CONCURRENT(1)	.737	.145	25.659	1	.000	2.090
ATTEND_INTENSITY(1)	-.784	.137	32.819	1	.000	.456
DEGREE_GOAL			48.346	3	.000	
DEGREE_GOAL(1)	1.468	.351	17.536	1	.000	4.340
DEGREE_GOAL(2)	-1.011	.199	25.807	1	.000	.364
DEGREE_GOAL(3)	-19.100	######	.000	1	.999	.000
GENDER(1)	.123	.084	2.141	1	.143	1.130
ETHNIC_CLASS			15.652	5	.008	
ETHNIC_CLASS(1)	.338	.338	1.005	1	.316	1.403

ETHNIC_CLASS(2)	-.190	.295	.417	1	.518	.827
ETHNIC_CLASS(3)	-.255	.146	3.037	1	.081	.775
ETHNIC_CLASS(4)	-19.807	######	.000	1	.999	.000
ETHNIC_CLASS(5)	.846	.272	9.661	1	.002	2.329
ENTRY_OHLAP(1)	.467	.114	16.764	1	.000	1.595
ENTRY_OTAG(1)	.145	.123	1.403	1	.236	1.156
ENTRY_PELL(1)	-.362	.114	10.163	1	.001	.696
OUTCOME_YEAR			8.043	6	.235	
OUTCOME_YEAR(1)	-.115	.150	.586	1	.444	.892
OUTCOME_YEAR(2)	-.031	.150	.043	1	.835	.969
OUTCOME_YEAR(3)	-.253	.159	2.537	1	.111	.776
OUTCOME_YEAR(4)	-.182	.152	1.431	1	.232	.833
OUTCOME_YEAR(5)	.050	.149	.114	1	.736	1.051
OUTCOME_YEAR(6)	-.253	.146	2.983	1	.084	.777
AGE_SCALE	-.024	.011	5.065	1	.024	.976
REMEDIAL_3_YR_MATH_SCALE	-.484	.116	17.487	1	.000	.616
ENTRY_PELL * ETHNIC_CLASS			4.337	5	.502	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.035	.467	.006	1	.940	1.036
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.519	.348	2.229	1	.135	1.681
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.189	.199	.898	1	.343	1.208
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.900	######	.000	1	1.000	2.459
ENTRY_PELL(1) by ETHNIC_CLASS(5)	-1.628	1.362	1.429	1	.232	.196
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.019	.005	14.890	1	.000	1.020
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.108	.035	9.685	1	.002	.898
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.052	.051	1.046	1	.306	.949
Constant	.455	.253	3.241	1	.072	1.576

COLLEGE_CODE Institution ID = 13 Tulsa Community College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.949	.060	248.080	1	.000	.387
CONCURRENT(1)	.052	.340	.023	1	.879	1.053
ATTEND_INTENSITY(1)	-.930	.054	301.873	1	.000	.394
DEGREE_GOAL			82.258	4	.000	
DEGREE_GOAL(1)	.728	.256	8.114	1	.004	2.071
DEGREE_GOAL(2)	.578	.158	13.351	1	.000	1.782
DEGREE_GOAL(3)	-.346	.064	29.481	1	.000	.708
DEGREE_GOAL(4)	-.296	.053	31.377	1	.000	.744
GENDER(1)	-.176	.042	17.545	1	.000	.839
ETHNIC_CLASS			12.660	5	.027	
ETHNIC_CLASS(1)	-.247	.143	3.000	1	.083	.781
ETHNIC_CLASS(2)	-.188	.101	3.423	1	.064	.829
ETHNIC_CLASS(3)	-.041	.081	.255	1	.613	.960
ETHNIC_CLASS(4)	.333	.161	4.287	1	.038	1.395
ETHNIC_CLASS(5)	-.215	.158	1.846	1	.174	.806
ENTRY_OHLAP(1)	.453	.104	19.115	1	.000	1.573
ENTRY_OTAG(1)	-.222	.128	3.019	1	.082	.801
ENTRY_PELL(1)	-.226	.059	14.635	1	.000	.797
OUTCOME_YEAR			19.167	6	.004	
OUTCOME_YEAR(1)	.032	.078	.172	1	.678	1.033
OUTCOME_YEAR(2)	-.099	.082	1.465	1	.226	.905
OUTCOME_YEAR(3)	-.099	.084	1.380	1	.240	.906
OUTCOME_YEAR(4)	-.127	.080	2.561	1	.110	.881
OUTCOME_YEAR(5)	-.094	.081	1.350	1	.245	.910
OUTCOME_YEAR(6)	-.253	.076	11.119	1	.001	.777
AGE_SCALE	.007	.005	1.663	1	.197	1.007
REMEDIAL_3_YR_MATH_SCALE	-.283	.065	18.755	1	.000	.753
ENTRY_PELL * ETHNIC_CLASS			5.105	5	.403	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.031	.274	.013	1	.910	1.032
ENTRY_PELL(1) by ETHNIC_CLASS(2)	-.012	.152	.006	1	.937	.988
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.046	.150	.092	1	.761	1.047
ENTRY_PELL(1) by ETHNIC_CLASS(4)	.204	.281	.528	1	.468	1.227

ENTRY_PELL(1) by ETHNIC_CLASS(5)	.675	.315	4.585	1	.032	1.965
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.011	.003	13.138	1	.000	1.011
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	-.101	.012	71.023	1	.000	.904
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	.162	.061	7.021	1	.008	1.176
Constant	-.432	.123	12.232	1	.000	.649

COLLEGE_CODE Institution ID = 14 Western Oklahoma State College

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*
ACT_REPORTED(1)	-.777	.129	36.389	1	.000	.460
CONCURRENT(1)	1.043	.135	59.952	1	.000	2.839
ATTEND_INTENSITY(1)	-.643	.130	24.433	1	.000	.526
DEGREE_GOAL			68.263	3	.000	
DEGREE_GOAL(1)	.615	.909	.458	1	.498	1.850
DEGREE_GOAL(2)	-.688	.102	45.704	1	.000	.502
DEGREE_GOAL(3)	1.033	.297	12.126	1	.000	2.809
GENDER(1)	-.187	.093	4.090	1	.043	.829
ETHNIC_CLASS			8.082	5	.152	
ETHNIC_CLASS(1)	-.479	.204	5.515	1	.019	.620
ETHNIC_CLASS(2)	-.122	.236	.269	1	.604	.885
ETHNIC_CLASS(3)	-.094	.258	.132	1	.716	.910
ETHNIC_CLASS(4)	-.368	.440	.700	1	.403	.692
ETHNIC_CLASS(5)	-1.141	.764	2.232	1	.135	.320
ENTRY_OHLAP(1)	.586	.129	20.719	1	.000	1.796
ENTRY_OTAG(1)	-.050	.160	.096	1	.757	.952
ENTRY_PELL(1)	-.414	.125	10.995	1	.001	.661
OUTCOME_YEAR			4.863	6	.561	
OUTCOME_YEAR(1)	.118	.162	.535	1	.465	1.126
OUTCOME_YEAR(2)	-.079	.164	.229	1	.632	.924
OUTCOME_YEAR(3)	.169	.164	1.062	1	.303	1.184
OUTCOME_YEAR(4)	-.031	.172	.033	1	.855	.969
OUTCOME_YEAR(5)	-.027	.164	.028	1	.868	.973
OUTCOME_YEAR(6)	.182	.157	1.333	1	.248	1.199

AGE_SCALE	-.017	.011	2.307	1	.129	.983
REMEDIAL_3_YR_MATH_SCALE	-.380	.111	11.586	1	.001	.684
ENTRY_PELL * ETHNIC_CLASS			10.860	5	.054	
ENTRY_PELL(1) by ETHNIC_CLASS(1)	.112	.282	.157	1	.692	1.118
ENTRY_PELL(1) by ETHNIC_CLASS(2)	.200	.316	.399	1	.527	1.221
ENTRY_PELL(1) by ETHNIC_CLASS(3)	.112	.410	.075	1	.785	1.119
ENTRY_PELL(1) by ETHNIC_CLASS(4)	2.196	.723	9.230	1	.002	8.989
ENTRY_PELL(1) by ETHNIC_CLASS(5)	1.244	.988	1.584	1	.208	3.470
AGE_SCALE by REMEDIAL_3_YR_MATH_SCALE	.017	.005	12.694	1	.000	1.018
REMEDIAL_3_YR_ENGLISH_SCALE by REMEDIAL_3_YR_MATH_SCALE	.004	.043	.009	1	.926	1.004
REMEDIAL_3_YR_MATH_SCALE by REMEDIAL_3_YR_READ_SCALE	-.052	.039	1.774	1	.183	.949
Constant	.089	.266	.112	1	.738	1.093

Appendix K: Full Model Classification Table

Classification Table[a]			*Predicted Award or Transfer Within 3 years*		*Percentage Correct*		
			No success	*Succes*	*Block*	*Block*	*Chan*
OCCC	***Observed Award or Transfer Within 3***	*No success*	16271	72	99.6	100.0	
		Success	3088	98	3.1	0.0	
	Overall %				83.8	83.7	0.13
CSC	***Observed Award or Transfer Within 3***	*No success*	2788	87	97.0	100.0	
		Success	887	148	14.3	0.0	
	Overall %				75.1	73.5	1.56
EOSC	***Observed Award or Transfer Within 3***	*No success*	1966	175	91.8	100.0	
		Success	693	288	29.4	0.0	
	Overall %				72.2	68.6	3.62
MSC	***Observed Award or Transfer Within 3***	*No success*	2707	128	95.5	100.0	
		Success	787	213	21.3	0.0	
	Overall %				76.1	73.9	2.22
NEOK	***Observed Award or Transfer Within 3***	*No success*	2935	210	93.3	100.0	
		Success	1273	319	20.0	0.0	
	Overall %				68.7	66.4	2.30
NOC	***Observed Award or Transfer Within 3***	*No success*	3789	932	80.3	100.0	
		Success	1452	1371	48.6	0.0	
	Overall %				68.4	62.6	5.82
CASC	***Observed Award or Transfer Within 3***	*No success*	3051	318	90.6	100.0	
		Success	1507	552	26.8	0.0	
	Overall Percentage				66.4	62.1	4.31
OSUO	***Observed Award or Transfer Within 3***	*No success*	5475	58	99.0	100.0	
		Success	1098	58	5.0	0.0	
	Overall %				82.7	82.7	0.00
OSUT	***Observed Award or Transfer Within 3***	*No success*	5077	440	92.0	100.0	
		Success	1263	667	34.6	0.0	
	Overall %				77.1	74.1	3.05
RCC	***Observed Award or Transfer Within 3***	*No success*	2223	51	97.8	100.0	
		Success	633	65	9.3	0.0	
	Overall %				77.0	76.5	0.47
RSC	***Observed Award or Transfer Within 3***	*No success*	7513	98	98.7	100.0	
		Success	1304	127	8.9	0.0	
	Overall %				84.5	84.2	0.32
SSC	***Observed Award or Transfer Within 3***	*No success*	2645	198	93.0	100.0	
		Success	741	293	28.3	0.0	
	Overall %				75.8	73.3	2.45
TCC	***Observed Award or Transfer Within 3***	*No success*	13310	39	99.7	100.0	
		Success	3314	53	1.6	0.0	
	Overall %				79.9	79.9	0.08
WOSC	***Observed Award or Transfer Within 3***	*No success*	2106	125	94.4	100.0	
		Success	608	242	28.5	0.0	
	Overall %				76.2	72.4	3.80
a. The cut value is .500							