

THE USE OF ACADEMIC AND DEMOGRAPHIC DATA FROM
RECENTLY GRADUATED HIGH SCHOOL STUDENTS TO PREDICT
ACADEMIC SUCCESS AT SAUK VALLEY COMMUNITY COLLEGE

by

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ABSTRACT

In order to determine which academic and demographic factors were the most important predictors of academic success at Sauk Valley Community College (SVCC), data from 699 recently graduated high school students were analyzed. College success was defined in five manners: (1) fall semester grade-point-average (FGPA), (2) Momentum (number of credit hours students accumulated), (3) Persistence (the percentage of student credit hours they completed), (4) Grade Points (Momentum \times FGPA), and (5) semester-to-semester retention (did the student reenroll in the following semester?). Five demographic variables and 16 academic variables were used to create statistical models that could predict college success.

The analysis indicated that females are better prepared for college than males and moderately outperformed males once enrolled at the college. A similar trend was found for White students who were better prepared for college than both Hispanic and Black students. White students outperformed students from other minority groups at SVCC in all but one academic measure. Students that declared a goal of eventually transferring to a four-year postsecondary institution were also better prepared for college than students who wanted to attain a certificate or two-year vocational degree. However, there was only a slight difference in academic performance at SVCC.

High school grade-point-average (HSGPA) was the number one or number two best predictor variable in all five college success models. The number of credits a student enrolled in during the first semester in college was also a powerful predictor in three of the five models. Other demographic and academic variables were not related to or only weakly related to college success. The most important significant remaining predictor variables were the high school a student attended and the number of science and weighted classes a student completed in high school. ACT scores and COMPASS scores were generally not important predictors of college success at the college.

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TABLE OF CONTENTS

	Page
LIST OF TABLES.....	x
LIST OF FIGURES.....	xiv
CHAPTER ONE: INTRODUCTION AND IMPORTANCE OF THE STUDY.....	1
History of the Growth in American Postsecondary Education.....	1
Global Competition and the Completion Agenda.....	4
Recruitment and Retention: Obstacles to the Completion Agenda.....	7
Importance of the First Year of College.....	9
Assessment and Remediation of Academic Unpreparedness.....	11
Academic Preparedness, the Open Door, and Remediation.....	14
Academic Forecasting.....	16
Research Questions.....	18
CHAPTER TWO: LITERATURE REVIEW.....	19
Introduction.....	19
How Is College Success Defined?.....	20
Predictors of College Success.....	23
The ACT and SAT as Predictors of College Success.....	24
Why Were the ACT and SAT Developed?.....	24
Evidence That the ACT and SAT Can Predict College GPA.....	27
ACT and SAT Scores and Their Relationship to HSGPA When Predicting College GPA.....	30
Using the ACT and SAT to Predict Retention and Graduation Rates.....	33
Evidence Against Using the ACT and SAT for Predicting College Success.....	34
The ACT, SAT, and Gender.....	37
The ACT, SAT, and Ethnicity.....	40

The Effect of Parents' Educational Level on Admission Exam Scores	46
The Effect of Family Income on Admission Exam Scores	47
Using Admission Exams to Predict Student Success: Conclusion	49
Using High School GPA and Academic Rank to Predict College Success	54
Introduction	54
Using HSGPA and HSR to Predict College GPA	58
Using HSGPA to Predict College Momentum	68
Using HSGPA to Predict Semester to Semester Retention	70
Using HSGPA to Predict Graduation from College.....	73
HSGPA as a Predictor of Future College Success: Conclusion	75
High School Academic Rigor.....	76
High School Academic Rigor: Conclusion.....	83
U.S. Department of Education Study: The Toolbox Revisited	84
The Use of Placement Tests to Predict College Success and Determine Class Placement	87
Other Student Data as Predictors of College Success.....	90
Conclusion	91
CHAPTER THREE: METHODOLOGY.....	93
Introduction	93
Research Questions.....	93
Study Population	94
Independent Variables (Possible Predictors of College Success)	95
Demographic Data	95
Student Academic Data	97
Dependent Variables (Measures of College Success)	101
Quantitative Research Design.....	104
Identifying Differences in Central Tendency.....	106
ANOVA and Kruskal-Wallis.....	106
Chi Square	108
Regression Analysis.....	108
Reliability and Validity.....	117

Summary	120
CHAPTER FOUR: RESULTS	121
Introduction	121
Section 1: Analysis of Central Tendency	121
Analysis of Central Tendency by High School	126
Academic Preparedness	126
Enrollment Data	128
College Success	128
Analysis of Central Tendency by Gender	130
Academic Preparedness	130
Enrollment Data	131
College Success	131
Analysis of Central Tendency by Race	132
Academic Preparedness	132
Enrollment Data	133
College Success	134
Analysis of Central Tendency by Program Declaration	135
Academic Preparedness	135
Enrollment Data	136
College Success	136
Analysis of Central Tendency by FAFSA Completion	137
Section 2. Regression Analysis: Can College Success Be Predicted?	138
Introduction	138
Hypothesis Testing	139
Hypothesis A: HSGPA Is a Better Predictor of College Success Than Compass Scores	139
Hypothesis B: HSGPA Is a Better Predictor of College Success Than Total Income	141
Hypothesis C: HSGPA Is the Best Predictor of All the Remaining Predictor Variables	142
Model 1: Using Stepwise Regression as a Way to Predict FGPA	143

Model 1A. Using Compass Scores and HSGPA to Predict FGPA	143
Model 1B. Using Total Income and HSGPA to Predict FGPA	144
Model 1C. Predicting FGPA Using the Remaining Fifteen Predictor Variables.....	145
Model 2: Using Stepwise Regression as a Way to Predict Momentum	150
Model 2A: Using Compass Scores, HSGPA, and Number of Credit Hours Enrolled to Predict Momentum	150
Model 2B. Using Total Income and HSGPA to Predict Momentum.....	151
Model 2C. Predicting Momentum Using the Remaining Fifteen Predictor Variables.....	152
Model 3: Using Stepwise Regression as a Way to Predict Persistence	154
Model 3A: Using Compass Scores and HSGPA to Predict Persistence	154
Model 3B. Using Total Income and HSGPA to predict Persistence.....	155
Model 3C. Predicting Persistence Using the Remaining Fifteen Predictor Variables.....	156
Model 4: Using Stepwise Regression as a Way to Predict Grade Points	159
Model 4A: Using Compass Scores and HSGPA to Predict Grade Points	159
Model 4B. Using Total Income and HSGPA to predict Grade Points	160
Model 4C. Predicting Grade Points Using the Remaining Fifteen Predictor Variables.....	161
Model 5: Using Binary Logistic Regression as a Way to Predict Retention	163
Model 5A: Using Compass Scores and HSGPA to Predict Retention	164
Model 5B. Using Total Income and HSGPA to predict Retention	164
Model 5C. Predicting Retention Using the Remaining Fifteen Predictor Variables.....	165
Regression Models Summary	167
Models A & B: Hypothesis Testing.....	170
CHAPTER FIVE: FINDINGS, RECOMMENDATIONS FOR SVCC, AND RECOMMENDATIONS FOR FUTURE RESEARCH	171
Introduction	171
Study Limitations.....	171
The Findings	173
What Does It Mean To Be Successful in College?.....	173

Recently Graduated High School Students Attending SVCC Are Not Prepared for College.....	175
Freshmen Were Only Moderately Successful at SVCC	178
The Effect of High School Attended and Academic Preparation on College Success.....	179
Females Were Better Prepared for College, but Were Not the Clear Academic Winners at SVCC	184
The College Success Gap for Blacks and Hispanics Is Real.....	186
Career-Technical Students Are Less Prepared for College	187
Predicting FGPA to Forecast the Need for Early Academic Intervention	188
Students with a Good HSGPA Should Be Encouraged to Enroll in More Classes	189
When It Comes to Predicting College Success, HSGPA Is King, but Credits Enrolled Is No Slouch	192
Surprise! Some Expected Predictors Were Not Related to College Success	193
Recommendations for Sauk Valley Community College.....	195
Future Research	198
Conclusion	202
REFERENCES	204
APPENDIX A: FERRIS STATE UNIVERSITY IRB APPROVAL.....	217
APPENDIX B: ASSUMPTIONS FOR TESTING CENTRAL TENDENCY	219
APPENDIX C: SPEARMAN CORRELATION TABLES FOR PREDICTOR AND COLLEGE SUCCESS VARIABLES.....	238

LIST OF TABLES

	Page
Table 1: <i>PISA Scores for Math, Science, and Reading and U.S. Rank Compared to Other Countries</i>	5
Table 2: <i>The Percentage of Universities That Gives Each Category “Considerable Importance” in the Admission Decision of Applying Students</i>	20
Table 3: <i>High School Rank and SAT Sub-scores Are Compared</i>	30
Table 4: <i>Success Rates of HSGPA, ACT and ACT Combined With HSGPA in Predicting FGPA</i>	39
Table 5: <i>ACT Average Composite Scores Ranked by Racial Group</i>	41
Table 6: <i>SAT Average Sub-scores Ranked by Racial Group</i>	42
Table 7: <i>Success Rates of HSGPA, ACT, and ACT Combined With HSGPA in Predicting FGPA by Racial Category</i>	43
Table 8: <i>Correlation r Values Between Socioeconomic and Academic Scores</i>	49
Table 9: <i>HSGPA and College GPA by Type of Student</i>	65
Table 10: <i>Number of Students Used in Study by Year and High School</i>	94
Table 11: <i>Five Student Demographic Variables Analyzed Within This Study</i>	96
Table 12: <i>Sixteen Student Academic Variables Analyzed Within This Study</i>	98
Table 13: <i>Five College Success Variables (Dependent Variables) Examined in This Study</i>	104
Table 14: <i>Five Nominal Variables Recoded Into Interval Data</i>	108
Table 15: <i>All Independent Variables Used in Statistical Analyses With Number of Data Points for Each Variable</i>	110
Table 16: <i>Example of Two Regression Models and Associated Statistics</i>	114

Table 17: <i>Example of an SPSS Output for Binary Logistic Regression That Shows Significance Values and Exp(B)</i>	116
Table 18: <i>Example of an SPSS Output for Binary Logistic Regression That Shows the -2 Log Likelihood and R² Values</i>	117
Table 19: <i>Number and Percentage of Students Representing Each High School by Year of Graduation</i>	123
Table 20: <i>Academic Preparedness Descriptive Statistics for 699 Students Represented in This Study</i>	124
Table 21: <i>ACT Descriptive Statistics for 699 Students Represented in This Sample</i>	124
Table 22: <i>College Success Descriptive Statistics for 699 Students Within the Sample</i> ...	126
Table 23: <i>Mean or Median Academic Preparedness Values by High School</i>	127
Table 24: <i>Mean or Median College Success Values by High School</i>	129
Table 25: <i>Academic Preparedness Mean and Median Values by Gender</i>	130
Table 26: <i>College Success Mean and Median Values by Gender</i>	131
Table 27: <i>Number and Percentage of Students of Different Racial Classifications</i>	132
Table 28: <i>Academic Preparedness Mean and Median Values by Race</i>	133
Table 29: <i>College Success Mean and Median Values by Race</i>	134
Table 30: <i>Academic Preparedness Mean and Median Values by Program of Study</i>	136
Table 31: <i>College Success Mean and Median Values by Program of Study</i>	137
Table 32: <i>Model 1A – Significant Predictors of FGPA and Related Regression Statistics</i>	143
Table 33: <i>Model 1B – Significant Predictors of FGPA and Related Regression Statistics</i>	145
Table 34: <i>Remaining Predictor Variables and Related Sample Size Used in Model 1C</i>	146
Table 35: <i>Model 1C – Significant Predictors of FGPA and Related Regression Statistics</i>	147
Table 36: <i>HSGPA Predicts FGPA</i>	149

Table 37: <i>Model 2A – Significant Predictors of Momentum and Related Regression Statistics</i>	151
Table 38: <i>Model 2B – Significant Predictors of Momentum and Related Regression Statistics</i>	152
Table 39: <i>Model 2C – Significant Predictors of Momentum and Related Regression Statistics</i>	153
Table 40: <i>Model 3A – Significant Predictors of Persistence and Related Regression Statistics</i>	155
Table 41: <i>Model 3B – Significant Predictors of Persistence and Related Regression Statistics</i>	156
Table 42: <i>Model 3C – Significant Predictors of Persistence and Related Regression Statistics</i>	157
Table 43: <i>Model 4A – Significant Predictors of Grade Points and Related Regression Statistics</i>	160
Table 44: <i>Model 4B – Significant Predictors of Grade Points and Related Regression Statistics</i>	161
Table 45: <i>Model 4C – Significant Predictors of Grade Points and Related Regression Statistics</i>	162
Table 46: <i>Model 5A – Significant Predictors of Retention and Related Regression Statistics</i>	164
Table 47: <i>Model 5B – Significant Predictors of Retention and Related Regression Statistics</i>	165
Table 48: <i>Model 5C – Significant Predictors of Retention and Related Regression Statistics</i>	166
Table 49: <i>Five College Success Models, Their R2 and the Number of Variables Required to Produce the Result</i>	168
Table 50: <i>College Success Predictor Variables and Their Use in Five College Success Models</i>	169
Table 51: <i>ACT Scores for SVCC Students Compared to National Averages of All Students Taking the ACT</i>	176

Table 52: <i>Academic Preparedness Variables Ranked From Highest (1) to Lowest (5) by High School</i>	181
Table 53: <i>College Success Variables and the Number of Science Classes Ranked by High School</i>	183
Table 54: <i>Predicted Momentum for New SVCC Students Based on HSGPA</i>	191
Table 55: <i>A Hypothetical Example of “Academic Forecasting” for a Newly Enrolled Freshman Student at SVCC</i>	201

LIST OF FIGURES

	Page
Figure 1. SAT scores in reading, math, and writing compared the number of years of English/language arts studied.....	82
Figure 2. SAT scores in reading, math, and writing compared to the number of years of math studied.....	82
Figure 3. Hypothetical linear regression model showing the relationship between HSGPA and FGPA	105
Figure 4. Histogram of the number of credits students enrolled in during the fall semester	125
Figure 5. Scatterplot of FGPA against HSGPA.....	148
Figure 6. Histogram of actual FGPA and predicted FGPA using only HSGPA	149
Figure 7. Histogram of actual FGPA and predicted FGPA using HSGPA and ACT science scores	150
Figure 8. Histograms of actual Momentum scores and predicted Momentum scores using HSGPA and Credits Enrolled.....	154
Figure 9. A scatterplot of HSGPA and Persistence.....	158
Figure 10. Histograms of actual Persistence and predicted Persistence using HSGPA and Credits Enrolled as predictor variables.....	159
Figure 11. Histograms of actual Grade Points and predicted Grade Points using HSGPA and Credits Enrolled as predictor variables	163
Figure 12. Histogram of number of students and number of credits enrolled and completed	179

CHAPTER ONE: INTRODUCTION AND IMPORTANCE OF THE STUDY

HISTORY OF THE GROWTH IN AMERICAN POSTSECONDARY EDUCATION

In the early 20th century, access to higher education in the United States was, for the most part, exclusive to the children of the rich and influential (Educational Testing Service, 1980). In part, this was because the need for a college degree, or a high school degree for that matter, was not required to access employment opportunities in the agriculture and industrial economies for much of the pre-21st century U.S. history. In 1900, fewer than 7% of adult citizens even attained high school degrees and only 1.9% attained bachelor degrees (Snyder, 1993).

The number of people interested in a postsecondary education increased dramatically as the 20th century progressed. Statistically, only 5% of 18-year-olds entered college in 1910, but this expanded to more than 45% by the 1960s (Cohen & Brawer, 2008). Concurrently, public two-year colleges increased in number from 19 institutions in 1915 to 405 institutions by 1960 (Cohen & Brawer, 2008). This increase can be partially explained by (1) the rapidly expanding U.S. population size; (2) increased interest in attaining a college education; (3) additional financial resources available to veterans, especially after World War II; (4) an economic shift away from agriculture and industry; and (5) the expansion of the community college system that increased access

to a college education to millions of individuals. As postsecondary access increased, interest in completing a high school degree also increased (Cohen & Brawer, 2008).

The 1950s were marked with vibrant growth in public, secondary education as children of the “baby boomer” generation enrolled in large numbers (Snyder, 1993). High school graduation rates concurrently increased to 70% by 1959 (Snyder, 1993). Therefore by the late 1950s, a much larger pool of students had entered high school *and* a larger fraction of them were graduating compared to the earliest part of the century. This created a large pool of applicants who were qualified and interested in a postsecondary education as employment opportunities for college graduates were also increasing quickly.

Scholars suggest the major interest and growth in higher education came as soldiers returned from WWII with educational benefits associated with the GI Bill (ACT, 2009). In order to meet the needs of a growing population interested in postsecondary education, the community college system grew to meet these needs and was instrumental in creating supplementary opportunities for many to attain a postsecondary degree (Cohen & Brawer, 2008). The GI Bill provided the financial resources necessary for many soldiers returning from war to attend college (ACT, 2009), and the growing number of community colleges provided additional opportunities for people to attain a postsecondary degree, especially those focused on vocational degrees and certifications (Cohen & Brawer, 2008).

It is also important to note that it was not just the GI Bill that contributed to expanding financial opportunities to those interested in postsecondary education. The

expansion of the Federal Student Loan program also provided additional resources necessary for many to attend college (Cohen & Brawer, 2008). The overall effect is that today over 54% of 18- to 24-year-olds in the U.S. are enrolled in some postsecondary institution (Snyder, 1993) though certainly not all of them will attain a postsecondary credential (Knapp, Kelly-Reid, & Ginder, 2012).

Access (through the GI bill and Federal Student Loans) to postsecondary education does not alone tell the whole story of the expansion of higher education. Equally important were the changing needs of employers. In the early 1900s, the number of jobs that required a postsecondary degree was few and, therefore, only 1.9% of the populace attained a bachelor's degree. Today, 27% of U.S. jobs require at least an associate degree and another 7% require some additional college (e.g., a certificate) (Bureau of Labor Statistics, n.d.).

The demand today for highly skilled and highly educated individuals in the workforce continues to rise. The Illinois ACT Report (ACT, 2010a) indicates that 65% of the top 50 occupations required some form of postsecondary education. A study by Georgetown University Center on Education and the Workforce indicated that, by 2018, over 37 million new jobs will require additional postsecondary training (Carnevale, Smith, & Strohl, 2010). Ultimately, up to two-thirds of ALL future jobs will require some additional college credentialing (Klepfer & Hull, 2012). Unfortunately, the demand for educated workers in this country is growing faster than the supply of graduates. By 2018, it is expected that the U.S. will have produced nearly three million fewer college graduates than the labor market demands (Carnevale et al., 2010).

GLOBAL COMPETITION AND THE COMPLETION AGENDA

Recent U.S. Presidents have cited the importance of enhancing our educational system (George W. Bush Institute, 2014; White House at Work, 2000). President Obama has followed his predecessors and indicated in a number of speeches that he believes that the U.S. educational system is faltering and has contended that fixing the educational problems, especially in science and math, is important to maintaining the U.S. technological and military advantage. He deems fixing our educational system a “national imperative” and one of “national security”:

So make no mistake: Our future is on the line. The nation that out-educates us today is going to out-compete us tomorrow. To continue to cede our leadership in education is to cede our position in the world. That’s not acceptable to me and I know it’s not acceptable to any of you. And that’s why my administration has set a clear goal: to move from the middle to the top of the pack in science and math education over the next decade. (Moravec, 2013, n.p.)

Data accumulated over the last 14 years clearly indicate that the U.S. is no longer leading the world in educational attainment. The Program for International Student Assessment (PISA) is an international evaluation that measures 15-year-old students’ academic ability in areas of reading, math, science, and problem solving. PISA was first administered in 2000 and has been conducted every three years since, with the last test administered in 2012 (National Center for Education Statistics [NCES], 2012). What PISA data indicate is that the typical U.S. 15-year-old is average or below average in educational attainment when compared to 15-year-old students of 50 other countries (Table 1). A number of countries easily outperform the U.S. in math, science, and reading scores.

Table 1: *PISA Scores for Math, Science, and Reading and U.S. Rank Compared to Other Countries*

	MATH	SCIENCE	READING	ALL THREE SCORES
Highest score	613 (Shanghai)	580 (Shanghai)	570 (Shanghai)	1763 (Shanghai)
Lowest score	368 (Peru)	373 (Peru)	384 (Peru)	1125 (Peru)
U.S. score	481 (lower than average)	497 (average)	498 (average)	1476 (average)
# of countries scoring above U.S. score ^a	29	22	19	18
# of countries scoring below U.S. score ^a	26	29	34	47

^a It is possible to have the same average score as another country.

Despite government initiatives like No Child Left Behind, Race to the Top, and others, the individual U.S. scores in math, science, and reading are not measurably different from scores in the year 2000. Further, large amounts of evidence from multiple sources suggests that the U.S.’s worldwide position is at best static and may have slid backward over the last decade (Cavanaugh, 2012; NCES, 2012; National Science Foundation, 2014).

In order to address this problem, President Obama has set a national goal to produce 8 million more college graduates by 2020. In an address to the National Governors Association, Obama focused his speech on higher education and its economic role:

The jobs of the future are increasingly going to those with more than a high school degree. And I have to make a point here. When I speak about higher education, we’re not just talking about a four-year degree. We’re talking about somebody going to a community college and getting trained for that

manufacturing job that now is requiring somebody walking through the door, handling a million-dollar piece of equipment. And they can't go in there unless they've got some basic training beyond what they received in high school. We all want Americans getting those jobs of the future. So we're going to have to make sure that they're getting the education that they need. (Wood, 2012, n.p.)

It is a widely held viewpoint that the economic future of the U.S. is linked directly to educational attainment of its citizens. As countries like India and China become more industrialized and as their educational systems produce additional high caliber students, the technological edge the U.S. has enjoyed for decades has quickly dissipated (National Science Foundation, 2014).

There are additional pressures that are driving colleges to increase their completion and retention rates. For example, many performance-based funding measures either directly or indirectly measure retention and completion rates (National Conference of State Legislatures, 2014). Further, accrediting agencies like the Higher Learning Commission (HLC) have become more focused on the completion of degrees and the retention of students. For example, Criterion 4C for HLC accreditation says, "The institution demonstrates a commitment to educational improvement through ongoing attention to retention, persistence, and completion rates in its degree and certificate programs" (HLC, 2014, n.p.). For all of these reasons, colleges have begun to move away from using enrollment metrics alone as a way to define "success" and are finally focusing more on the retention and graduation of students, truly the most important mission of higher education.

RECRUITMENT AND RETENTION: OBSTACLES TO THE COMPLETION AGENDA

There are significant obstacles in meeting President Obama's goal of creating 8 million new college graduates. Certainly in order to produce that many additional graduates, more students must attend college and a greater percentage of them must graduate from college (National Center for Public Policy and Higher Education, 2010). This requires colleges and universities to be better recruiters and retain more of these students until graduation. As budgets become tighter, it is difficult for colleges to find the resources to do all things well (Fuller, 2010). Recruitment (Noel-Levitz, 2013a), and, to a lesser extent, retention (Cuseo, 2003) are exceptionally expensive functions of most colleges.

The recruitment offices at most institutions tend to have some of the largest budgets at postsecondary institutions. Certainly, community colleges tend to have dramatically smaller recruiting budgets than do four-year institutions as it costs considerably less to recruit a student to a community college than to a four-year university (Noel-Levitz, 2013a). According to Noel-Levitz's report on recruitment costs, community colleges expend, on average, \$123 to recruit each new student. For even a small community college like Sauk Valley Community College (SVCC) located in Dixon, Illinois, this equates to more than \$500,000 annually including salaries and benefits of staff along with advertising and promotional item costs. This accounts for nearly 3.7% of SVCC's operating expenses annually (SVCC internal data). However, as budgets become tighter nationwide, recruiting and marketing budgets are either decreasing or staying the same despite inflation (Noel-Levitz, 2013a). Therefore, less real money is being

spent on recruitment today than a few years ago. Over the last few years, postsecondary institutions, including community colleges, experienced, on average, a 2 to 3% drop in enrollment (Lipka, 2013). This is a direct impediment to President Obama's Completion Agenda as more students must enter the educational pipeline in order to reach President Obama's ambitious goal; even the White House admits it is just not possible to reach that goal unless higher education is affordable to and accessible by large numbers of U.S. citizens ("Higher Education," n.d.).

While declining college enrollment is worrisome, the retention and completion statistics of students who have already entered the educational pipeline of higher education are even more troublesome. The percentage of enrolled students who graduate from four-year colleges/universities is very low; it is even lower for community college students. Annually, the U.S. Department's National Center for Education Statistics (NCES) collects data on every U.S. postsecondary institution that participates in federal student financial aid programs and inputs the data in an online data warehouse called the Integrated Postsecondary Education Data System or IPEDS (NCES, n.d.). The IPEDS data warehouse contains information on tuition and fees, enrollment, student financial aid, degrees and certificates conferred, student retention rates, and human and fiscal resources of those institutions. IPEDS contains graduation data from over 7,500 postsecondary institutions (Knapp et al., 2012). While there are critics of using IPEDS data to calculate graduation rates, particularly for community college students (Offenstein & Shulock, 2009), IPEDS data indicate that only 37% of first-time, full-time bachelor degree-seeking students will graduate in four years. This number increases to

over 60% that graduate with bachelor degrees in eight years. In comparison, the graduation statistics for public two-year colleges (community colleges) are only 12.9% of first-time, full-time students graduate with an associate degree in two years and only 28% graduate in even four years or 200% the recommended time of completion. Graduation statistics are much worse for students of color and for part-time students who may make up, on average, two-thirds of the student population at community colleges (Complete College America [CCA], 2011). According to The Completion Arc report (College Board Advocacy and Policy Center, 2012), only 6% of part-time students will complete an associate degree with an additional 8% earning certificates within *six* years of initial enrollment. And very few part-time students (<1%) will ever earn a bachelor's degree. This longstanding track record indicates that colleges and universities must do better in the future.

IMPORTANCE OF THE FIRST YEAR OF COLLEGE

Retaining students from semester to semester is key to increasing graduation rates. For example, if students can be retained past the first year, the likelihood of completing a degree or credential will increase dramatically (Cuseo, 2003).

Unfortunately, students are more likely to drop out in the first year than any other year in college (National Information Center for Higher Education Policymaking and Analysis [NICHEPA], 2014). Therefore, colleges often focus retention efforts on the first-year student, easing the transition of the student into a higher education setting (Noel-Levitz, 2013b). For even a small community college like SVCC, if these efforts can successfully

raise retention rates even 10 percentage points, the number of degrees or certificates completed will increase by the hundreds.

Of all entering first-time college freshmen in the U.S. in 2004, 79% returned for the second year of college (Klepfer & Hull, 2012). However, the one-year retention rate for students enrolled in two-year institutions was much lower with only 64% persisting (Klepfer & Hull, 2012). It is important to note that community college retention rates are calculated by removing those students who transferred to another institution or have completed a degree or certificate. Therefore, the community college rate is a true measure of how many students did not attain their degrees or certificates, and yet did not return to their higher education institution the following semester to complete their academic goals. For community colleges, one-third of students never make it past their first year of college before they drop out of school.

Certainly some students may only temporarily withdrawal from college, but then later return when life permits. These students are sometimes referred to as “stopping out” because they “stop” their collegiate progress, but return at a later time (Fain, 2013). However, if students “stop out” more than once, the possibility of that student returning to college at some later point drops dramatically. It is imperative to keep the student enrolled if that student is ever expected to complete a degree (Fain, 2013).

The student retention problems at community colleges are much different than the retention problems of most four-year schools. For example, community colleges must be able to accommodate a large population of academically unprepared students while most universities often only select the best, most academically prepared students

to attend their university. So, the most successful retention programs at community colleges focus on tutoring and providing additional academic support programs or services to these academically underprepared students (Noel-Levitz, 2013b).

ASSESSMENT AND REMEDIATION OF ACADEMIC UNPREPAREDNESS

There is no single factor that can easily be fixed that will dramatically increase completion rates at community colleges; the problem is multifaceted and complex. However, properly evaluating the academic aptitude of students when they enroll, academically remediating any underprepared students, and providing them additional “intrusive” assistance may help alleviate some of the problems immediately. It is therefore important to provide an accurate method to evaluate and place students into classes that they can succeed in at the college. This is the first step to increasing retention and completion rates.

According to Parsad, Lewis, and Greene (2003), nearly 92% of two-year colleges use high-stakes exams like ACCUPLACER and Compass as a way to assess academic preparedness of entering students to then enroll them into classes at their college. Assessment is often as simple as placing students into remedial classes based on a “cut score,” that is, if a student’s score is below a certain score on the Compass or ACCUPLACER exam, then he/she will be placed within a developmental class instead of a college-level class. There is significant evidence that suggests that using a single placement exam (like Compass or ACCUPLACER) to academically place students is

extremely unreliable even though it is the norm (Belfield & Crosta, 2012; Scott-Clayton, 2012).

Some institutions may use high-stakes admission exam scores (e.g., the ACT) as a method, or as a supplementary method, for placing students into either college-level or developmental classrooms (ACT, 2014). Admission test data are widely available as the ACT and SAT tests are each administered to over 1.6 million prospective college students annually. In Illinois, the ACT has historically been administered to all public high school students in their junior year, although it is no longer mandatory as of the 2014 school year (Rado, 2014). The organizations that administer the ACT and SAT claim that their exams can predict college readiness (ACT, 2005; Kobrin, Patterson, Shaw, Mattern, & Barbuti, 2008). But in reality, the ACT and SAT scores become much more predictive when used along with students' high school grade point average (HSGPA). The evidence is overwhelming that HSGPA is the best predictor of college success, but certainly additional data from ACT or SAT scores can increase the predictive ability of college success for many students (Crouse & Trusheim, 1988).

Most entering community college students need academic remediation. In fact, a study of 57 community colleges showed that 59% of their students needed academic remediation in math and 33% needed academic remediation in English (Bailey, Jeong, & Cho, 2010). Of course, while students must pay for the tuition and fees charged for these remedial courses, passing the courses does not count toward graduation requirements. This situation creates serious financial aid concerns as students may deplete available funds before completing a degree, sometimes leaving students a few

credits shy of a degree but with no financial resources to complete it. And certainly, the cost of providing remedial education, which was not an original charge of the community college system, has exceeded \$1 billion and drains college financial resources (Noble, Schiel, & Sawyer, 2004).

But does developmental education make a difference? Despite the cost and the loss of time, one could argue that if students are being adequately prepared for college-level work, then the system *is* working. Unfortunately, the evidence suggests otherwise. Bailey et al. (2010) found that those students who ignored the advice of an advisor and enrolled into a college-level class instead of a developmental class (as recommended) had slightly lower success rates than the students who placed into those college-level classes. However, students who enrolled in developmental classes, as an advisor recommended, were substantially less successful at completing the college-level class. Why? Because most of the students relegated to developmental coursework never passed the developmental coursework to take the college-level equivalent or ran out of funds to support their educational endeavors. In the end, students are not completing the prerequisite developmental classes, so it is not much of a surprise that they then cannot complete the associated college-level course successfully. At Sauk Valley Community College, less than 50% complete a developmental class the first time (internal SVCC data). Only half of students taking one or more developmental classes their first semester will be retained one year later (internal SVCC data). It is pretty clear that if we are going to admit students to developmental courses, then we must do a better job at helping these students be successful the first time.

The current postsecondary education model looks something like this. Many students are recruited to community colleges with dreams of completing degrees or certificates with hopes of attaining better jobs and futures. The cost of recruitment can be substantial to the community college, costing around \$123 per student (for both full-time and part-time) which easily costs the college hundreds of thousands of dollars per year (Noel-Levitz, 2013a). Approximately one-third of these newly recruited students, who do not complete or transfer, will not enroll for the second year of college and while the reasons for this are numerous, being academically underprepared for college-level work is generally an important cause. Colleges try but are often unsuccessful at identifying and then remediating the academic unpreparedness of such students. Also, about two of every three community college students are part-time (American Association of Community Colleges, 2014) and while being part-time provides more convenience and flexibility for the student, it interferes with degree completion (Adelman, 2006; CCA, 2011). IPEDS data show that only 28% of full-time students complete their degrees or certificates in 200% suggested completion time (that is four years for an associate degree) and only 6% for part-time students in six years.

ACADEMIC PREPAREDNESS, THE OPEN DOOR, AND REMEDIATION

Most two-year public colleges do not have selective admission policies. Maintaining this open enrollment policy, often called an Open Door to higher education, has been cited as one of the most important missions of the community college system (Myran, 2009b). Open admission policies allow anyone with a high school degree or

equivalent and the proper financial support to enroll. This Open Door policy has often been cited as a way to increase college attainment for people of color and of low income (Myran, 2009a). However, with the focus shifting away from the Open Door policy to the Completion Agenda, it is vitally important to understand what “types” of students are succeeding in college and to understand why those students are succeeding. This information could then be used as a way to increase student retention and completion rates.

Community colleges could simply implement selective academic admission standards and this would, of course, raise retention and graduation rates. However, not only does this not meet the mission of most community colleges, the impact on enrollment could be significant. The challenge is not to raise the admission standards and further restrict access to postsecondary education; the challenge for community colleges is to meet students “where they are at” academically, remediate any academic concerns, and propel students toward a degree or certificate. Access and opportunity are the cornerstones of the community college system. The goal is to link access and opportunity to student success. This goal, however, has been exceptionally challenging.

In order to positively affect retention and completion rates, it is important to focus on high school to college transition and quickly identify at-risk students. Students must be properly counseled in order to enroll them into college classes that they can succeed in, but often the only hard data used for academic placement is a student’s score on a placement exam (e.g., Compass) or possibly admission exam scores (e.g., ACT or SAT). In essence, academic advisors are expected to enroll students based more on

intuition and experience than statistically reliable models based on the students' demographic and former academic records.

The community college system also needs to better identify the variables of college success, creating predictive models that will allow them to better serve the individual needs of students and help create a positive link between access and opportunity while simultaneously improving student success. Using student data to predict future performance of newly enrolled students is already effectively being conducted at a number of higher education institutions including Southern Methodist University, Georgia State University, and hundreds more of postsecondary institutions (Marcus, 2014). By using data analytics to make informed decisions about what classes students can succeed in, many of these universities have seen dramatic increases in retention and graduation rates (Marcus, 2014). The White House has applauded these efforts to use predictive modeling as a way to raise graduation rates (Marcus, 2014). If higher education can do a better job of identifying variables related to student success (and failure), then there is a chance at both increasing retention and completion rates while simultaneously maintaining the foundational values of access and opportunity.

ACADEMIC FORECASTING

This dissertation will investigate the academic (ACT scores, HSGPA, etc.) and demographic records (e.g., gender, race, etc.) of local, recently graduated high school students and correlate these data to “success” at Sauk Valley Community College. The goal is to explore the creation of statistical models that will better predict

success/failure rates of students in their first semester at SVCC. By understanding students more completely, academic remediation and student intervention strategies may be successfully implemented earlier in order to increase college success of the student population as a whole. As Grumman (2014) said when discussing how higher education can boost the completion of college credentials, “Behold the power of paying attention to the right things, at the right time, by the right people” (n.p.). The “right counselor” with the “right data” could help at-risk students make more informed, life-changing decisions about their college education or help college staff intervene before these students stop out or drop out of college completely (Grumman, 2014). Ultimately, it is hoped that using predictive modeling will not only increase completion rates at SVCC, but also have students successfully navigate college more efficiently, graduate more quickly, and enter the workforce more rapidly than before. This needs to begin by better understanding the nature of the students that are enrolling at SVCC.

While statistical models like these have become more ubiquitous (Marcus, 2014), this particular predictive model will be tailored specifically for the students of SVCC. Each postsecondary institution is unique as it recruits students with various academic and demographic backgrounds; it is therefore imperative to tailor predictive models for each unique institution. For example, a predictive model created for the students of Georgia State University would, more than likely, be ineffective for students attending SVCC; the students are just too different. It is imperative that this specific model is created using data from previous SVCC students in order to increase its effectiveness and reliability.

RESEARCH QUESTIONS

This research project was designed to answer the following two questions.

1. Could high school student academic data be used to predict academic success at SVCC?
 - a. What variables were most important in the prediction of college success?
 - b. What variables were insignificant to the prediction of college success?
2. What role will demographic data have on the robustness and reliability of the statistical models created? Can a “one size fits all” model be created for all genders, races and income levels, or will separate models need to be created? In order to answer this question thoroughly, a multiple linear regression will be conducted on each college success variable. This technique should highlight the most important academic and demographic predictor variables found in the data set.

If robust statistical models can be generated successfully, it is possible in the future to use this information as a way to place students into classes they can be successful in during the first semester in college. It is hoped that this “academic forecasting” will increase semester-to-semester and year-to-year retention rates and ultimately positively impact completion rates for future students.

CHAPTER TWO: LITERATURE REVIEW

INTRODUCTION

Many universities, especially elite universities, annually have more applicants than seats (Urist, 2014) and must, by definition, be more selective than open-enrollment colleges in the number and types of students that they admit. In order to increase their own completion rates, university admission officers must predict which applicants will most likely succeed at their university—only qualifying students will be admitted and academically risky students will often be excluded. Academic studies have clearly shown that robust enrollment models can be generated using applicant data. These robust models often contain a plethora of applicant variables. The National Association of College Admission Counseling (NACAC, 2008, 2015) indicates that greater than 80% of selective universities and colleges find that HSGPA in college preparatory classes is of “considerable importance” for determining admission into their institutions (Table 2). Further, approximately 60% of universities and colleges still find the ACT/SAT to be of considerable importance in admission determination even though a significant number of institutions are now ACT/SAT optional (Bruno, 2006; McDermott, 2008). HSGPA in all courses was ranked third in admission importance at approximately 50%. College preparatory grades, which had decreased in significance in the late 1990s and early 2000s, have rebounded in significance in 2011 (NACAC, 2008, 2015) coinciding with a

larger proportion of institutions that no longer require the ACT or SAT for admittance (Bruno, 2006; McDermott, 2008). Other admissions criteria (e.g., admission essays, portfolios, interviews, etc.) are generally of less importance on average (NACAC, 2008).

Table 2: *The Percentage of Universities That Gives Each Category “Considerable Importance” in the Admission Decision of Applying Students*

	1993	2000	2006	2011
Grades in college prep courses	82%	78%	76%	84%
Admission tests (ACT, SAT)	46%	54%	60%	59%
Grades in all classes	39%	43%	51%	52%

(Data from NACAC, 2008, 2015)

For universities and colleges with more open enrollment policies, for instance most community colleges, high school transcript data and ACT/SAT scores are of considerably less significance. However, student transcript information may be used as a way to determine if students need remediation and may help the counseling/advising staff of those colleges properly enroll students into classes they can pass. So, in essence, even community colleges can use high school academic information as a way to influence college success of their enrolling students.

HOW IS COLLEGE SUCCESS DEFINED?

What exactly does it mean for a student to be “successful” in college? Even academic researchers cannot come to a consensus as they have defined college success in a multitude of ways. Conley (2007) has defined success in a complex way:

. . . completing entry level courses at a level of understanding and proficiency that makes it possible for the student to consider taking the next course in the sequence or the next level of course in the subject area. If students are prepared to succeed in [these] courses, they will be able to cope with the full range of college courses they are likely to encounter [in college]. The college-ready student envisioned by this definition is able to understand what is expected in a college course, can cope with the content knowledge that is presented, and can take away from the course the key intellectual lessons and dispositions the course was designed to convey and develop. In addition, the student is prepared to get the most out of the college experience by understanding the culture and structure of postsecondary education and the ways of knowing and intellectual norms of this academic and social environment. The student has both the mindset and disposition necessary to enable this to happen. (p. 5)

While Conley's definition of college success is precise, it is complex and somewhat qualitative. In order to do statistical analyses, many researchers have defined college success in a more quantitative manner. Some researchers have broadly defined college success as degree attainment and is measured simply as successful (completion) or not successful (no completion) (Adelman, 2006; Geiser & Santelices, 2007; Mattern, Patterson, & Wyatt, 2013). Other researchers have focused on semester-to-semester retention (Clements, 1969; Harrell & Bower, 2011; Hoffman & Lowitzki, 2005), grades in specific college classes (Belfield & Crosta, 2012; Hopper, 1968), the speed of attaining college credits (called momentum) (Adelman, 2006; Beecher & Fischer, 1999) or the accuracy of placing students into either college level or developmental classes (Scott-Clayton, 2012). However, most researchers have used college GPA as their criterion to determine success. Since GPA can be calculated by semester or cumulatively over years of academic study, most researchers have narrowly defined success as just a student's GPA during their first semester (first semester GPA or FGPA) or first academic year only

(freshman GPA). FGPA is the most common criterion for determining college success for two reasons:

1. The composition of students being studied will morph from one semester to the next so it is best to measure college success, as a group, early in their college career instead of later. In other words, the students at the institution the first semester will not necessarily be the same group of students the second, third, and fourth semesters because students may drop out, transfer to another institution, or new students may transfer in from a different institution. When the measured student population changes with time, this will create statistical validity concerns called a “history effect” (Vogt, 2007). It is best to avoid history effects, so therefore, from a statistical point of view, FGPA is most valid to use than other college success variables that measure GPA later in the academic careers of students.
2. All freshmen take similar courses (“gen eds.”) (Zwick, 2007), while students that have progressed past freshman year will begin to specialize in major level classes. Again, from a statistical perspective, measuring the grade point average of juniors or seniors is not necessarily as statistically reliable as measuring the grades of freshmen only. As an example, the students with the highest ACT scores may advance into more difficult majors and therefore have lower cumulative GPAs in their junior or senior years as compared to students in easier majors.

Predictably, many of the “college success” variables listed above are interrelated. For example, students’ FGPA are strongly correlated to the cumulative GPAs of college seniors (Geiser & Santelices, 2007) or to the total number of credit hours students attained each semester (momentum) (Belfield & Crosta, 2012). FGPA is also strongly associated with classroom persistence and college retention (Clements, 1969). There is also strong evidence to associate FGPA with the completion of a degree (Adelman, 2006). Therefore, FGPA and other “early” college success indicators (e.g., class persistence rates) may be considered indicators of future college completion.

Throughout this document, “*r*” scores will regularly be mentioned. These *r* values are statistical measures of association between two variables, where *r* values can range from –1 to 1. When an *r* score is close to 0, that indicates that two variables are not strongly correlated. When scores are close to –1 or 1, that indicates that two variables are strongly correlated. For example, if ACT scores and FGPA are found to have an $r = 0.60$, then the two variables are moderately correlated within one another. Correlation does not indicate causation, only a relationship.

PREDICTORS OF COLLEGE SUCCESS

This section discusses the predictors of college success in great detail. However, many of the educational papers examined here looked at more than one predictor variable at a time. For example, some authors have discussed the value of the ACT or SAT at predicting FGPA, but have also looked at the value of HSGPA as a predictor as well. Of course, in many cases the predictive variables themselves may correlate. For

instance, there is a high degree of correlation between HSGPA and ACT scores or between ACT scores and the rigor of students' HS curriculum (Noble, Davenport, Schiel, & Pommerich, 1999). In order to have complete discussion on each subject, each predictive variable will be discussed in its own subcategory.

THE ACT AND SAT AS PREDICTORS OF COLLEGE SUCCESS

Why Were the ACT and SAT Developed?

Before 1900, college admission in the U.S. was unsystematic in nature, where each particular institution used its own evaluation method to determine which students were college ready (Leslie, 2007). Some colleges used oral examinations from faculty to evaluate prospective students; others evaluated prospective students on their knowledge of classical authors or their knowledge of contemporary science (Leslie, 2007). Academic admission criteria were as numerous as the universities/colleges administering them. In many cases, college admittance was often determined by one's socioeconomic status alone; those students that could afford to attend the university were admitted (Educational Testing Service, 1980) and, therefore, affluent, but academically underprepared students would need to be remediated to correct any academic deficiencies (Leslie, 2007). Since wealth in the U.S. was heavily centered upon White males of European descent, this particular admission policy was also an effective way to screen out students of a lower socioeconomic status (ACT, 2009) or certain racial groups (Levine, 2007).

As higher education became more accessible to the masses at the turn of the 20th century, U.S. universities were, really for the first time, turning away prospective students (Levine, 2007). University officials began to realize that the enrollment policy of “first come, first served” was an ineffective way of admitting the most qualified students (Levine, 2007), but struggled to find an objective and reliable evaluation tool as prospective students attended high schools with varying curricula and standards for academic rigor. Therefore, the forthcoming standardized admission examinations were really the first attempt to evaluate students’ abilities in a consistent and objective way (Crouse & Trusheim, 1988).

In 1900, the College Entrance Examination Board (now known as the College Board) was formed with the charge of standardizing entrance examinations for 12 participating “elite” institutions represented on the Board (Zwick, 2007). In 1901, the first standardized college entrance exam was administered (Zwick, 2007). The original College Board examination was built around a series of essay questions from ancient and modern language and mathematics (ACT, 2009). However, some considered the College Board examination as arbitrary and therefore felt that the exam remained an inconsistent evaluator of student academic preparedness for college (ACT, 2009).

In response to criticism, the College Board fostered the creation of the SAT. The SAT was first administered in 1926 as the first standardized multiple-choice admissions test. At the time, the SAT was considered less of a way to measure a student’s academic achievement and more of a way to measure a student’s IQ and in many ways the SAT and the IQ test were synonymous (ACT, 2009; Lemann, 1999). By 1941, the SAT had

been adopted by most of the elite private universities as their college admissions exam. In 1947, the Educational Testing Service (ETS) was created from the College Board assets and became the SAT's central administrator (Crouse & Trusheim, 1988). In the late 1940s and 1950s, the doors of higher education opened substantially, thanks in large part to the Servicemen's Readjustment Act of 1944, later known as the GI Bill (ACT, 2009). In fact, by 1949-1950 college enrollments were 80% higher than they were in 1939-1940 (ACT, 2009). By 1959, even though the ranks of college enrollees swelled substantially, the use of the SAT was still confined to a small group of elite universities—a vacuum that would soon be filled by the creation of the ACT (ACT, 2009).

By the 1950s, many individual states administered their own college admissions examinations. E. F. Lindquist and Ralph Tyler were instrumental in pushing states to consolidate their admissions exams into a single, consistent college admissions test. The test was designed to be strongly correlated to high school instructional goals; therefore, this test, they reasoned, could be used for more than just governing admissions, but could also be used for student advisement and placement once enrolled in college (ACT, 2009; Zwick, 2007). Their proposal planted the seeds for the creation of the American College Testing Program (now known strictly as the "ACT") and in 1958, the ACT program made its official public debut. Ultimately, the ACT Program was designed to:

- measure the skills and abilities required for college success;
- have students perform tasks that were comparable to college level work;
- require students to read, interpret, and evaluate material they would study in college;

- and allow high school administrators to evaluate their curricula and instruction. (ACT, 2009)

In short, the ACT was designed specifically as a tool to predict college success while the SAT was designed to measure a student's cognitive ability. Much later, in response to criticism, the newest version of the SAT in 2005 more closely aligned the exam to current high school curricula, and therefore, enhanced the SAT's ability to predict college success (Zwick, 2007).

Today the SAT and ACT are ubiquitous college entrance exams. In 2011, the ACT and SAT tests were each administered to over 1.6 million prospective college students and 1,500 universities and colleges still either require the ACT/SAT or strongly recommend students take the exams for possible admission into their institution (Crouse & Trusheim, 1988; Zwick, 2007). Nevertheless, 80% of two-year colleges and 8% of four-year colleges are "open door" and therefore do not require students to take these exams.

Evidence That the ACT and SAT Can Predict College GPA

The College Board and Educational Testing Service (ETS), that administer the SAT, and ACT, Inc., that administers the ACT, unambiguously claim that their tests can predict FGPA (Crouse & Trusheim, 1988; Noble, 1991; Noble et al., 1999; Noble & Sawyer, 2002; Zwick, 2007). In fact, the ACT organization claims that their College Readiness Benchmarks can determine which students have at least a 75% or greater chance of obtaining a grade of "C" or better in college classes (ACT, 2005). The College

Board makes similar claims for the SAT exam (Wyatt, Kobrin, Wiley, Camara, & Proestler, 2011). In essence the prediction is that the higher the score on the ACT/SAT, the higher the FGPA will be in college. Noble (1991) indicated that using admission exam scores to predict future college grades rests on two assumptions:

1. Admission scores and high school coursework must “directly measure” or be “closely related to the academic skills and knowledge required for success.”
2. Grades in college must reliably and validly measure real educational outcomes.

Only if these two factors are true can there be a positive relationship between admission scores and FGPA. But this relationship between FGPA and ACT/SAT scores has been shown numerous times by researchers that are affiliated or not affiliated with the ACT/SAT organizations.

ACT has strong evidence that test scores positively correlated with college FGPA for students that attended high schools in Illinois. ACT generates statistical reports for the state of Illinois because the State required high school students to take the exam to meet No Child Left Behind requirements. The *2008-2010 High School to College Success Report* (ACT, 2010a) for Illinois shows a clear relationship between college FGPA and their ACT scores. For example, those students who earned a score of 16-19 on their composite ACT earned a 2.38 FGPA in Illinois colleges and universities and those students who earned a 33-36 ACT composite score performed significantly better by earning a FGPA of 3.39. The same trend is also seen in Sauk Valley Community College (SVCC) students. The ACT *2008-2010 High School to College Success Report* (ACT,

2010b), specifically designed to report on SVCC students, shows that the higher the ACT score the higher the FGPA was for SVCC students. This trend remains absolutely consistent by ACT subject area scores. For example, students who have higher ACT scores in the English subtest will generally have higher college GPAs than students with lower ACT scores in English. This trend holds true for other subtests in science, reading, and math for Illinois college students (ACT, 2010a) and Sauk Valley Community College students (ACT 2010b).

While this dissertation is focused on the community college student, ACT and SAT scores have been found to reliably predict college GPA in a variety of other postsecondary institutions, across a wide range of test scores and also beyond a student's freshman year. Examples include both public universities (Chase & Jacobs, 1989; Geiser & Santelices, 2007) and private postsecondary institutions (DeBerard, Spielmans, & Julka, 2004; Paszyk, 1994). This attests to the robust predictive powers of both the ACT and SAT across a multitude of institutions and circumstances.

However, despite very strong evidence to support their claims, the College Board and ACT are careful to point out that their college readiness assessments are only one factor that selective postsecondary institutions should use to admit students, and in fact, no institution uses just the ACT/SAT score as the single way to choose students for admissions (NACAC, 2008).

ACT and SAT Scores and Their Relationship to HSGPA When Predicting College GPA

It should not be surprising that academic researchers have found an association between ACT/SAT scores and HSGPA. Even the ACT and the College Board, in their own private research studies, admit that students' test scores on the ACT/SAT are related to students' HSGPA. For example, in the Total Group Profile Report (SAT, 2012), a positive correlation was found between HSGPA and SAT composite, critical reading, mathematics, and writing scores. High school rank (HSR), a proxy for HSGPA, is another variable that is also strongly related to SAT scores (SAT, 2012) (Table 3).

Table 3: *High School Rank and SAT Sub-scores Are Compared*

HIGH SCHOOL RANK	MEAN SAT CRITICAL READING	MEAN SAT MATHEMATICS	MEAN SAT WRITING
90 th -100 th percentile	572	606	569
80 th -89 th percentile	508	534	499
60 th -79 th percentile	481	497	468
Below 60 th percentile	436	445	423

(SAT, 2012)

Similar correlations exist between HSGPA and ACT scores. Noble et al. (1999) found that the two variables were moderately correlated ($r = 0.62$). Also, those same authors noted that when the high school attended was entered into the analysis, that 5 to 7% additional variance could be accounted for in their statistical models. In essence, this means that some high schools prepare students better for the ACT than others.

Many would argue that a robust predictive model for college success must include either HSGPA or HSR *and* an admission test at a minimum. HSGPA or HSR “are

the most important indicators [for predicting future college success, but] . . . the addition of scores on good [admission] tests add significantly to the prediction of success” (Crouse & Trusheim, 1988, p.43). When the ACT/SAT score is used together with HSGPA/HSR to predict FGPA, correlation values (r) may exceed 0.80 (Crouse & Trusheim, 1988) with the SAT boosting the correlation rates by approximately 6 to 8% (Crouse & Trusheim, 1988). According to a synopsis written for Education Partnerships, Inc. (Bleyaert, 2010), using the combination of both HSGPA and the ACT or SAT composite scores is most often “a much stronger predictor of future [college] success for students regardless of race or gender than using either of these scores alone as a predictor” (p. 1). As Noble and Sawyer (2002) stated, HSGPA may be a way to measure academic performance, but it also measures other personal characteristics including motivation, effort, and attendance, while the ACT primarily measures academic achievement in college preparatory courses. So in some ways, admission exams and HSGPA may really measure different attributes of a student and hence both are important when predicting future college success.

Event ACT, Inc. researchers agree that both HSGPA and ACT scores should be used to predict FGPA. In a 2013 study by ACT (Sanchez, 2013), data from 137,000 first-year entering students from 259 two- and four-year colleges and universities were analyzed (though most were from four-year universities). In this study, median ACT composite scores were 21.5 and a median HSGPA was 3.3. The analysis indicated that ACT and HSGPA are related, as expected, with a moderate correlation value (r) of 0.43. However, when predicting FGPA, HSGPA had significantly better correlation value (r) of

0.43 than the ACT ($r = 0.36$). However, when HSGPA and the ACT scores are used together, the correlation value did increase ($r = 0.48$) as was expected. Therefore in this study, around 23% of the FGPA variance can be explained by using the ACT and HSGPA together.

Some would say that the ACT, since it measures purely cognitive abilities of students, should better predict FGPA of the highest-achieving students, while HSGPA would be able to better predict FGPA of moderately achieving students (with a GPA less than 3.0) (Noble & Sawyer, 2002). A study of ACT data of 218,000 students who attended one of 301 postsecondary institutions indicated that HSGPA was slightly more inaccurate when compared to the ACT composite score in predicting FGPA above 3.75. This partially supported their hypothesis that the ACT is better at predicting grades of high-achieving students (Noble & Sawyer, 2002).

Sanchez (2013) also studied how accurately the ACT and HSGPA could accurately predict FGPA. Specifically, Sanchez (2013) was interested in how well HSGPA and the ACT could predict attainment of a B or C average for students in college. The analysis indicated that HSGPA was slightly more accurate than the ACT at predicting a 2.5 and 3.0 grade point average in college. For instance, the ACT could reliably predict a 2.5 FGPA or higher 70% of the time, while HSGPA could predict a 2.5 FGPA or higher 72% of the time. As expected, when used together in a single model, HSGPA and ACT could reliably predict FGPA slightly better than either variable alone. All models became less effective when predicting FGPA of 3.0 or higher as was suggested by Noble and Sawyer (2002).

Using the ACT and SAT to Predict Retention and Graduation Rates

Admission tests like the ACT or SAT were designed to predict FGPA specifically. Since ACT/SAT scores are correlated to FGPA and FGPA is correlated to retention and graduation rates (Adelman, 2006; Clements, 1969), it is likely that ACT/SAT scores will also correlate, albeit weakly, to retention and graduation rates. A number of studies have supported this contention.

The High School to College Success Reports (ACT, 2010a) also show that “persisters” (those that return to the same campus for a second year of college) have higher ACT scores on average than “non-persisters” in Illinois. Statewide persisters averaged 21.7 on their ACT composite, while non-persisters averaged more than two points less (19.3). The general trend also holds true for Sauk Valley Community College students where persisters average 20.6 and non-persisters average 19.1 (ACT, 2010b). These data tie in nicely with what the ACT organization already claims, that the ACT score can be used to predict future college success.

The College Board also conducts a plethora of research studies on the reliability of the SAT at predicting college success. A recent report investigated whether the SAT could be used to predict graduation rates (Mattern et al., 2013). Since FGPA and graduation rates are often strongly correlated, the researchers believed that the SAT could reliably predict this ultimate indicator of success. Studying data from 54 institutions and nearly 79,000 students, the research indicated that those students with higher SAT composite scores were more likely to graduate than those with lower SAT composite scores. For example, while 75% of students with SAT composite scores of

2100 or higher graduated, only 18% with SAT composite scores 600 to 890 graduated.

This predictability held true even when HSGPA was controlled for. This led the researchers to state that HSGPA and SAT composite scores each “provided unique information to the prediction of graduation, indicating the utility of using both measures in the admission process to select applicants who are most likely be successful”

(Mattern et al., 2013, p. 3).

In a very large study of 1,429 higher education institutions, Stumpf and Stanley (2002), using College Board data, found a strong correlation with ACT/SAT and HSGPA and graduation rates. In this study, the authors compared, using a multiple regression model, the graduation rates of institutions with the percentage of freshmen having GPAs of at least 3.0 and SAT verbal and math and ACT scores at the 25th and 75th percentiles. Not surprisingly, those institutions that admitted more students with higher ACT or SAT scores would graduate a larger percentage of students within six years. In this particular study, the ACT and SAT outperformed HSGPA by almost 50% in the forecasting. It is important to note that, in this study, actual ACT and SAT scores were not used, but only the percentages of students attaining scores above a certain standard (25th or 75th percentile).

Evidence Against Using the ACT and SAT for Predicting College Success

In the past, HSGPA would have been considered by many as an unreliable way of predicting college success, so admission exams were originally created as a standardized method to ascertain academic knowledge for admission purposes (Crouse & Trusheim,

1988). Universities, especially elite universities, wanted only the best and the brightest high school students to attend their university. Why wouldn't a university want to attract and admit students that can successfully graduate? Certainly the College Board and the ACT believe their exams provide valuable information that can, at best, accurately predict college success and, at least, be an important piece of a robust model that can successfully predict college success. The evidence, detailed above, is robust and comes from multiple independent sources that verify the exams' power. With that said, certainly some researchers are less impressed with the ability of the ACT or SAT to predict college success (Bordes-Edgar, Arredondo, Kurpius, & Rund, 2011; Bryson, Smith, & Vineyard, 2002; Crouse & Trusheim, 1988; Mattson, 2007; Thornell & Jones, 1986; Truell & Woosley, 2008).

Crouse and Trusheim (1988) wrote a controversial book, called *The Case Against the SAT*, that details the problems associated with using the SAT when making admission decisions. While somewhat dated, the book provides a strong argument that still has relevance today. Their research indicates that if universities or colleges used solely HSGPA or HSR to make admission decisions they would nearly be as accurate as if those same institutions used the high-stakes admission exams and HSGPA/HSR together (Crouse & Trusheim, 1988, p. 6). According to the authors' own analysis, because the SAT and HSGPA can both be used to predict FGPA, a strong majority (>74%) of applicants would have been accepted into college using either the SAT or HSGPA/rank alone (when the criterion for admittance was a predicted FGPA of 2.5). The probability rises to 83.8% when the criterion was a predicted FGPA of 2.8 instead. Therefore, the

authors consider the SAT to be a redundant source of information as it does not provide additional, significant information than what HSGPA/HSR already provides (Crouse & Trusheim, 1988).

Waugh and Micceri (1994) examined the academic records of University of South Florida (USF) students to determine the correlation between high school academic performance and graduation and/or retention in college. The authors used a measure called graduation/retention that examined if students either graduated or were still enrolled at USF after four years. When correlations were run, the authors determined that student ACT or SAT scores did not significantly predict four year graduation/retention, while HSGPA could predict graduation/retention. In the defense of both the ACT and SAT, those organizations do not overtly claim to predict retention or graduation, though some of their more recent research does show that positive correlation (Stumpf & Stanley, 2002).

Other studies have also shown little to no utility when using the ACT or SAT to predict college success. For example, in one study of a large Midwestern university, the researchers found that the ACT composite score did not significantly correlate to first-year GPA in White students, Black students, or the entire population as a whole (Bryson et al., 2002). In a study of at-risk students, Matteson (2007) found that the SAT composite scores did not significantly correlate to either first semester or first year GPA and questioned the use of the SAT as an admission tool at the university studied, at least for at-risk students. Lastly, a small study of Latino/Latina students in a college in the

southwest U.S., SAT scores were not associated to persistence, nor likelihood of graduation at the university (Bordes-Edgar et al., 2011).

ACT and SAT exams were designed to predict FGPA of college students and the bulk of the research strongly corroborates this assumption (Crouse & Trusheim, 1988; Noble, 1991; Noble et al., 1999; Noble & Sawyer, 2002; Zwick, 2007). Further, the ACT and SAT exams were originally created to supplant HSGPA as an admission tool, which was considered an inconsistent predictor of college success. However, reams of evidence now suggest that HSGPA actually provides a more reliable method of predicting future success.

The ACT, SAT, and Gender

ACT and SAT composite scores are, on average, higher for males than in females (ACT, 2012; SAT, 2012). For the SAT combined scores (reading + writing + math), males averaged 1512 and females averaged 1486 for the school year ending in June 2013 (SAT, 2012). Also, scores in the SAT-math are consistently higher in males than females, with males averaging 33 to 36 points above their female counterparts of the last 10 years. Males also perform slightly better than females in the SAT-reading section, but only 3 to 9 points higher on average. Interestingly, females perform better on the SAT-writing section than their male counterparts by averaging 9 to 14 points higher in the last 10 years.

ACT shows a similar trend in its data (ACT, 2012). In 2012, males averaged a slightly higher ACT-composite score than females (21.2 to 21.0) with males performing

better in math and science and females doing better in reading and English. So, the two admission exams seem to be generally consistent in their evaluation of students by gender. Both exams predict that males will do better in math (about 5 to 6% better on average), while females seem to do better in English/writing (about 2 to 3.5% better on average). The only seemingly contradictory evaluation is on reading, where the SAT indicates that males are slightly more advanced in the reading ability, while the ACT indicates that females generally are more proficient.

If males are regularly scoring higher on ACT/SAT composite scores, then males should also be averaging higher FGPA than their female counterparts. At least this is what the College Board and ACT, Inc. would claim as both exams are used to predict FGPA. However, the evidence suggests otherwise. Generally speaking, females do better than males at all levels of the U.S. educational system, but certainly in high school and college (DeBerard et al., 2004; Voyer & Voyer, 2014). As stated by Voyer and Voyer (2014), "Although gender differences follow essentially stereotypical patterns on achievement tests, for whatever reasons, females generally have the advantage on school marks [GPA] regardless of the material" (p. 1). The largest difference between males and female GPA was in high school, but remained large and significant during postsecondary undergraduate education. The exact causes of these seemingly contradictory academic performances are only speculative (Biamonte, 2013), but clearly they exist as the trend has been consistent for a number of decades (Voyer & Voyer, 2014).

Despite the evidence that females academically outperform males in college (Voyer & Voyer, 2014), and yet males generally outperform females on both the ACT and SAT, is it possible that admission tests can still be used to predict FGPA for both genders accurately? ACT (Sanchez, 2013) has indicated that there are significant differences in the predictive ability of its test between males and females. As discussed before, the ACT score is more accurate when scores are higher; however, the ACT is also more accurate at predicting FGPA for females than it is for males at all levels of ACT scoring. For example, a 24 ACT composite score will accurately predict FGPA around 80% of the time for females, but only around 70% for males (Sanchez, 2013). The ACT model that does not account for race or gender (called the “total” model) falls squarely in-between the male and female prediction; therefore, the “total” model underestimates female FGPA and overestimates male FGPA. To be fair, this same trend is reflected when using HSGPA too where models over-predict male FGPA and underestimate female FGPA. A combined model using HSGPA and ACT scores only slightly improves the predictive ability of FGPA when gender is not accounted for (see Table 4).

Table 4: *Success Rates of HSGPA, ACT and ACT Combined With HSGPA in Predicting FGPA*

		SUCCESS RATE FOR HSGPA	SUCCESS RATE FOR ACT	SUCCESS FOR HSGPA & ACT (COMBINED MODEL)
Predicted a 2.5 or higher FGPA	Females	75%	75%	76%
	Males	66%	62%	66%
Predicted a 3.0 or higher FGPA	Females	68%	74%	73%
	Males	60%	58%	62%

Others have confirmed that the SAT scores of females are more strongly correlated to college GPA than male scores. In a study by Hu (2002), he found that female SAT combined scores were correlated more strongly to second semester college GPA than their male counterparts ($r = 0.322$ and $r = 0.256$, respectively). This correlation was so consistent that math and verbal sub-score correlations were also larger for females. It is even suggested by the researcher that the admission criteria for males and females be adjusted where male admission be more weighted toward their HSGPA than females, while female admittance be more strongly governed by their SAT scores (Hu, 2002).

The ACT, SAT, and Ethnicity

It has been a popular belief that admission high stakes tests, like the ACT or SAT, will underestimate the capabilities of minority groups (Crouse & Trusheim, 1988). During the early 20th century, as American society became more ethnically diverse and as high school became increasingly available to all peoples, some argued that the college examination process was more than just a way to screen out those students that were not academically prepared for college, but the exams were also used to screen out students that did not fit the typical socioeconomic mold of people that normally attend college (ACT, 2009). This perception of bias in admission exams continues to this day (Biamonte, 2013). Are ACT/SAT scores significantly different between races? Is the ACT/SAT racially biased? Can the tests be used to predict college success in minority groups?

Both the ACT and the SAT organizations show differences among ethnic group mean scores on their exams (ACT, 2012; SAT, 2012). Asian students significantly outperform other racial groups, including White students (ACT, 2012; see Table 5).

Table 5: ACT Average Composite Scores Ranked by Racial Group

	ASIAN	WHITE	HISPANIC/ LATINO	AMERICAN INDIAN	BLACK/AFRICAN AMERICAN
ACT composite score	23.6	22.4	18.9	18.4	17.0
Rank (1 = highest score)	1	2	3	4	5

(ACT, 2012)

The difference between White students and Black students is, on average, a 5.4 point difference. To put it another way, White students are typically “college ready” while Black students are not. These rankings are also consistent across all of the ACT subtest scores of English, math, reading, and science. In other words, Asian students are ranked number one in English, math, reading, and science scores, just above White students, who rank second.

The SAT has similar ethnic distributions for their test scores (SAT, 2012). The SAT organization uses different ethnic categories than the ACT, so it is not possible to do an exact comparison to ACT scores by ethnicity. However, the general trends do remain (some ethnic categories were removed for comparison) (see Table 6).

Table 6: SAT Average Sub-scores Ranked by Racial Group

	ASIAN	WHITE	HISPANIC/ LATINO	AMERICAN INDIAN	BLACK/AFRICAN AMERICAN
Reading	521	527	450	480	431
Reading Rank	2	1	4	3	5
Math	597	534	486	461	429
Math Rank	1	2	3	4	5
Writing	527	515	461	443	418
Writing Rank	1	2	3	4	5
Average Rank (1 = highest score)	1.3	1.7	3.3	3.7	5

(SAT, 2012)

It is beyond argument that ACT/SAT scores are different among racial groups, as decades' worth of data collected by ACT and the College Board have confirmed this trend. But those organizations have historically claimed that their admission exams are not racially biased (Jaschik, 2010). Both organizations argue that the ACT/SAT is designed to be indicative of college academic readiness; the differences in scores by race just indicates poorer academic preparedness by certain racial groups. Others disagree with this sentiment and show evidence that even when academic preparedness is accounted for, the tests are still racially biased (Jaschik, 2010). However, the College Board recently indicated that while they do not consider the test to be racially biased, poor access to preparation material by low income and Black/Hispanic students may contribute somewhat to earning lower scores (Hunt, 2014). It is almost certain that these millions of dollars spent annually on ACT/SAT preparation

give an advantage to high- or middle-class families, where Hispanic and Black students are proportionally more absent (Biamonte, 2013).

There is evidence that suggests that the ACT and SAT are inconsistent predictors across racial groups. Sanchez (2013), for example, found that the ability to accurately predict FGPA when using HSGPA and ACT were significantly and consistently lower for both Hispanic and African American students compared to White students (Table 7). Both Bryson et al. (2002) and Myers and Pyles (1992) found similar results where ACT scores were much more predictive of future college success in White students than Black students. Hu (2002) found no correlation between college GPA and SAT scores in Native American students, though one did exist in African-American students.

Table 7: *Success Rates of HSGPA, ACT, and ACT Combined With HSGPA in Predicting FGPA by Racial Category*

		SUCCESS RATE FOR HSGPA ONLY	SUCCESS RATE FOR ACT ONLY	SUCCESS FOR HSGPA & ACT (COMBINED MODEL)
Predicted a 2.5 or higher FGPA	Whites	74%	72%	75%
	Blacks	51%	52%	55%
	Hispanics	62%	59%	62%
Predicted a 3.0 or higher FGPA	Whites	68%	68%	70%
	Blacks	37%	46%	48%
	Hispanics	52%	53%	55%

(Sanchez, 2013)

Admission exams seem to be better predictors of college success when a student does not experience a cultural upset. Hoffman and Lowitzki (2005) concluded that if students are facing great “cultural shock because of race or religion” (p. 467) then their SAT scores became weaker predictors of academic achievement. Other studies by Fleming (2002) and Fleming and Garcia (1998) seem to verify this hypothesis as they found that scores of Black students, especially males, did not as accurately predict academic success at college and universities where the majority of students were White.

Generally speaking, ACT/SAT scores often correlate to college academic achievement including FGPA, cumulative GPA, and even the probability of graduation. However, some still contend that the exams are racially biased (Biamonte, 2013) and inconsistent predictors of college success, especially for minorities, (Fleming, 2002; Fleming & Garcia, 1998; Hoffman & Lowitzki, 2005; Sanchez, 2013). Hoffman and Lowitzki (2005) indicate that postsecondary institutions should use ACT/SAT scores cautiously when making admission and academic decisions:

Colleges and universities may need to do a better job of educating constituents about the multiple sets of factors that must be balanced in determining merit and shaping student bodies. Indeed, such inquiry may become a core component of the road map to more effective use of affirmative action or comprehensive review programs. (p. 468)

There is no doubt that Hispanics and Black students, on average, perform noticeably worse than White and Asian students on admission exams. Data from the College Board and ACT show this to be fact with no room for argument. However, both organizations claim that their exams are not racially or culturally biased and take great pains in order to increase their cultural reliability. *If* the exams are not culturally biased,

this would mean that the academic aptitudes of Hispanic and Black students are being measured accurately and fewer Hispanic and Black students should be admitted, on merit alone, into selective universities and colleges across the country. Therefore, some would say that academic excellence and diversity are incompatible at an institution of higher learning (Rowe, 2005); however, accrediting agencies often insist that higher education institutions address diversity and incorporate it into their mission or strategic planning (HLC, 2014). For example, the Higher Learning Commission (HLC), one of six regional institutional accreditors in the United States and accreditor to 1,000 institutions of higher education, submit that their institutions address the following criterion in order to apply for and attain accreditation.

Criterion 1. C. The institution understands the relationship between its mission and the diversity of society.

1. The institution addresses its role in a multicultural society.
2. The institution's processes and activities reflect attention to human diversity as appropriate within its mission and for the constituencies it serves.

So, pressures on higher education institutions seem to be in opposite directions.

Accrediting agencies expect institutions to stress the importance of diversity of an ever growing global society while others would say that maintaining high academic standards is not congruent with that insistence.

The Effect of Parents' Educational Level on Admission Exam Scores

There is an argument that students who have parents with college degrees will do better on standardized admission exams than students that do not have parents with advanced degrees or lack a high school education altogether. Research support has been mixed.

In the ACT Report Series (Noble et al., 1999), the research scientists found no significant relationship between ACT composite scores and family level of education, where each level of parents' education increase accounted for only 0.2 to 0.28 units on the ACT composite score. So, for example, if a student was raised by a parent with a master's degree, the expected increase in that student's ACT composite score would only be about 0.2 units higher than a student with a parent with a bachelor's degree. Even at the educational extremes, according to this study, the difference in the ACT composite scores would represent only about 1 unit. In contrast, the high school that a student attended was a more important variable when predicting ACT scores. And of course, HSGPA was, by far, the most important variable when it came to predicting ACT scores.

In a large study of University of California students, the researchers found that parents' education level did positively correlate to the prediction of SAT scores and parents' income. As has been discussed before, the SAT organization has admitted that some affluent, high school students are receiving more opportunities to prepare for the SAT while low-income students tend to receive little or no preparation (College Board, 2014).

The Effect of Family Income on Admission Exam Scores

Family income and level of education are strongly linked. Generally speaking, those that earn a college or professional degree will make more money than those that do not (Bureau of Labor Statistics, 2014). Therefore, it is often difficult to differentiate the effect of family income and parents' educational level on ACT/SAT scores. With this said, there is little doubt that family income plays some role in the prediction of ACT/SAT scores. The College Board has recently indicated that some students received additional test preparation before they take their SAT and this may provide an unfair advantage to some students, most likely those students that are not impoverished (College Board, 2014).

The Educational Testing Service (ETS) and ACT, Inc. have long claimed that their admission exams have opened more doors to higher education for low-income students than if the test did not exist (ACT, 2009; Educational Testing Service, 1980). In 1980, to support that contention, ETS (1980) wrote in a report the following statement:

History indicates, in fact, that selective admission to higher education was far more a matter of class and economic status prior to the use of national admissions tests than it has been since. The tests provided low-income students with the opportunity to prove that they could succeed in the demanding academic programs of the most selective institutions. (p. 4)

The authors of *The Case Against the SAT* strongly reject the ETS hypothesis and state, "ETS has never tried to determine whether students from secondary schools 'without reputations for educational excellence' are at less of a disadvantage with the SAT than they are with traditional achievement tests" (Crouse & Trusheim, 1988,

p. 123). According to these same authors, ETS has never even tried to collect the data to support their own contention.

In the publication *Summary of the Reign of ETS: The Corporation That Makes Up Minds*, authors Nairn and Nader (1980) determined that SAT scores were strongly correlated to family income. Therefore, the authors indicated, the SAT is really not a way to rank scholastic merit, but social class instead. ETS vehemently denied this assertion, indicating that the correlation between SAT scores and family income was paltry ($r = 0.30$ approximately) (Educational Testing Service, 1980). However, the correlation factor between SAT scores and total family income is four times larger than the average improvement in the prediction of FGPA when using the SAT, which, unsurprisingly, the ETS claims as significant. More damning, at the time of the published report, ETS's own data clearly showed that students in the highest income bracket are more than 24 times more likely to have a top SAT score than the lowest income bracket (Educational Testing Service, 1980). Further, data indicate that the SAT is much more strongly associated with total family income than HSR or other socioeconomic factors (see Table 8) (Crouse & Trusheim, 1988). This suggests that HSR is less influenced by socioeconomic factors than the SAT and therefore HSR is a more reliable predictor of college success when socioeconomic status is not accounted for.

Table 8: Correlation r Values Between Socioeconomic and Academic Scores

	TOTAL FAMILY INCOME	FATHER'S OCCUPATIONAL INCOME	FATHER'S EDUCATIONAL LEVEL	MOTHER'S EDUCATIONAL LEVEL
SAT Score	0.286	0.238	0.296	0.269
High School Rank	0.029	0.043	0.085	0.067

(Data from Crouse & Trusheim, 1988)

Additional evidence that admission exam scores were influenced by family income is mixed. Crouse and Trusheim (1988) found that SAT scores were higher in students with high family incomes. They assert that family income must be a part of any FGPA predictive model that includes the SAT or the model will over-predict FGPA of low-income students. Sanchez (2013) found that the ACT was a more reliable predictor of FGPA for high income students than low income students; however, the effect was moderate. Geiser and Santelices (2007) found in their study of University of California students that parents' level of income did positively correlate, albeit weakly, to SAT scores. But in an ACT report (Noble et al., 1999), the authors of the report found no correlation with family income and ACT scores. So, while there seems to be some evidence that ACT/SAT scores are linked to family income, the effect is marginal at best.

Using Admission Exams to Predict Student Success: Conclusion

The admission test may be dying; it is certainly becoming less important today than any time in the recent past. Today, 24 of the top 100 liberal arts colleges, as ranked by *U.S. News & World Report*, are SAT- and ACT-optional (Bruno, 2006; McDermott, 2008). The number of four-year colleges that do not require the ACT or SAT in order for

a potential student to be admitted exceeds 850, and while many of these colleges are technical or religious in nature, the number that are using admission exams continue to decrease annually (*SAT/ACT Optional 4-Year Universities*, n.d.), possibly without any real harm to admission standards and student success.

In a study conducted by Bates College (Bates News, 2005), researchers found statistically little difference in academic performance between those students that submitted their SAT scores for admission and those that did not. Since the college does not require SAT score submission, about one third of the students that were admitted to the college do not have an SAT score. When the “submitters” and “non-submitters” were compared, the researchers found:

- The graduation rates between groups were statistically the same.
- The final GPAs of both groups were within 0.05 units of each other.

Considering the Bates College study, does this mean that the SAT is inconsequential? Certainly the pool of applicants that did not submit their SAT scores could be as or more academically capable as those that did submit their SAT scores. There is just no way to determine the academic qualifications of students based on the study as written as both groups of students may have similar HSGPAs. Regardless, the point is taken that dropping the SAT for admission will undoubtedly increase the applicant pool and possibly increase the number of students of color that enter higher education.

DePaul University also went “test optional” for the 2012 freshman class. Results have been encouraging as retention rates for students who took the ACT or SAT were

nearly identical to those students who did not take the admission exams, and in two of the university's colleges, the GPA of non-takers was actually higher than takers of the exams (Hoover, 2013).

Does the ACT or SAT provide additional, useful information to colleges for predicting college success? The abundance of evidence suggests that when used with HSGPA or HSR, the SAT or ACT may moderately increase the prediction of student's FGPA (2 to 6%). Also, the evidence suggests that while high stakes testing may be more closely tied to income or educational level than HSR or HSGPA, it may actually overestimate the FGPA of minority or low income groups. But in the end, the authors of *The Case Against the SAT* believe that the SAT could be dropped by both large and small selective colleges and universities without negative consequence (Crouse & Trusheim, 1988). Adelman's (2006) analysis concurs with that assertion stating that the high stakes admissions tests are better predictors of which students actually enroll in college but are less capable at predicting future academic success.

The College Board also recognizes the challenges of standardized college entrance exams. In 2005, the SAT went through a major renovation. Recently, the College Board announced that the SAT would be changing once again in 2016 (Gumbrecht, 2014). College Board CEO David Coleman indicated during a press release that standardized tests have become "far too disconnected from the work of our high schools" (Coleman, n.d.). He indicated a concern that many students have the financial resources necessary to prepare for the exam, while some financially disadvantaged students may not be able to afford that same test preparation. Plans to provide free SAT

preparation with the Khan Academy has already been established to alleviate this concern.

But to be fair, while the evidence is generally more inconclusive than HSGPA or HSR, the ACT and SAT are generally correlated to FGPA and in some cases to retention/persistence and graduation rates. Noble and Sawyer (2002) believe that achievement tests and HSGPA are really different measures of academic performance, where the ACT (and hence the SAT) are measures of academic achievement in college preparatory courses while HSGPA may measure more intangible student attributes including motivation and effort. However, achievement tests may be better at predicting FGPA when (1) the FGPA of the student is high (3.75 or higher), and (2) when the ACT/SAT score is above average. The predictive ability of the admission exams seems to deteriorate when the composite scores or FGPA is lower than average. Further, Matteson (2007) found the SAT was not accurate at predicting the FGPA of at-risk students.

If the ACT/SAT is unreliable at predicting FGPA of at-risk students, are there other student populations that the tests produce unreliable predictions? While males, on average, generally do better than females on the ACT/SAT (composite), the GPA that males earn in college is generally lower than females. As stated above, achievement tests may not be good at measuring effort and motivation, but young women are more likely than men to aspire and to graduate from college (Gonzalez, 2012). The evidence is strong that achievement tests tend to overestimate the FGPA of males and

underestimate the FGPA of females if a combined male/female model is used to make the FGPA prediction (Sanchez, 2013).

Certainly the ACT/SAT have been at the forefront of controversy of racial bias. While both organizations claim that their exams are not biased, the trend is strong that Asians/Whites will significantly outperform Hispanic and African American students on admission exams. For example, ACT's own data indicate that Asians will earn a composite score of 6.6 points higher than African American students (ACT, 2012).

Studies have found that:

- The ACT predicts FGPA more accurately for White students than Black or Hispanic students.
- SAT scores for Black students are much more reliable at predicting FGPA when those students attend Historically Black Colleges and Universities (HBCU), especially for male students. Cultural disruption seems to be real and Black students do worse academically at predominantly White institutions.

The effect of a parents' level of education on ACT/SAT scores seems moderate at best. Noble et al. (1999) and Geiser and Santelices (2007) confirm that students who have parents with higher education degrees tend to do slightly better on these admission exams than students whose parents do not have these degrees. But again the effect is moderate where a student that has a parent with a doctorate will only, on average, earn a composite ACT score one point higher than a student whose parents

have only a high school education. Parents' educational level is not strongly correlated to FGPA either.

There seems to be a stronger link between ACT/SAT scores and family income (Nairn & Nader, 1980). Crouse and Trusheim (1988) showed some compelling evidence that suggests that SAT scores are closely linked to "total family income" and "father's occupational income." Just as important, their research showed that there was only a weak correlation with those same two income variables and HSR, indicating that HSR is potentially a better predictor of college success than the SAT because it is nearly independent of both family educational level and family income. Crouse and Trusheim conclude that using the SAT scores alone to predict FGPA will over-predict FGPA of low income students; however, including HSR in the predictive model alleviates these same concerns. A study by Sanchez (2013) found that both ACT and HSGPA were moderately more reliable at predicting FGPA for high income students than low income students as well.

USING HIGH SCHOOL GPA AND ACADEMIC RANK TO PREDICT COLLEGE SUCCESS

Introduction

Using HSGPA or HSR as a way to predict college success has been studied extensively. The hypothesis goes like this. If students have excellent HSGPA or high HSR, then the students would be predicted to attain higher college GPA, have higher college persistence/retention rates, and higher graduation rates than students with lower

HSGPA and HSR. Many academic studies have strongly supported this contention including data analyzed by ACT and the College Board.

Many four-year colleges and universities use a number of ways to evaluate students for admission into their institution due to the limited number of seats that they have for freshman. Even though colleges have used high stakes entrance exams since 1901 to evaluate potential students (ACT, 2009), colleges have continued to also use HSGPA as one of their favorite, if not the favorite, criterion for admitting students (Peterson's Staff, 2015) Highly selective universities may use HSGPA as a way to select students by taking only the very top performing high school students with average HSGPA being 3.5 or higher (Armstrong & Carty, 2003). For less selective colleges and universities, a "B average" in high school is still critical to college admission (Peterson's Staff, 2015).

Regardless of the academic studies showing that HSGPA was still an effective predictor of college success, and in most cases a better predictor than the SAT or ACT exams, many universities use the ACT/SAT as another way to gauge student academic aptitude. The supporters of using the ACT/SAT entrance exams claim that HSGPA can be unreliable as an entrance tool because high schools don't necessarily use the same measuring scale, use different methods to calculate their GPA, high schools have immense variation in academic rigor and expectations (Ramist, Lewis, & McCamley-Jenkins, 1994) and that HSGPA is experiencing consistent grade inflation (e.g., from 1982 to 2004 HSGPA went from an average of 2.62 to 2.86; Posselt, Jaquette, Bielby, & Bastedo, 2012). Therefore, it is assumed that a standard and "reliable" method (i.e., SAT

or ACT tests) of comparing students is necessary when judging students for college entrance. But how true is that contention?

HSGPA is a predictably flawed measure of a student's academic competence when comparing large groups of students because of the amount of variation in student academic history. For example, students will form their final HSGPA by taking different courses, being taught by different teachers, being found in different high schools and being evaluated using different grading techniques (NACAC, 2008). Even the way HSGPA is calculated will vary from high school to high school where some students receive additional grade-points for completing "college preparedness" or weighted classes. Interestingly, Geiser and Santelices (2007) found that unweighted HSGPA is a consistently better predictor of college performance than weighted HSGPA. Additionally, students who are "college bound" may have more academically rigorous courses that impact their HSGPA, possibly in a negative way, even though they may be better prepared for college. Considering the number of factors that could potentially influence a student's HSGPA, it is amazing to find that any correlation, yet alone a strong correlation, still exists between HSGPA and college performance.

Why does a correlation exist between HSGPA and college performance, most notably FGPA? While there is no definitive answer, some hypotheses do exist. Zahner, Ramsaran, and Steedle (2012) proposed that repeated sampling of high school academic performance over time and across many different academic skills is a good predictor of future academic success in college. Another explanation is that both HSGPA and college GPA are based on similar forms of academic evaluations. In other words, since high

school and college evaluations (tests, papers, etc.) are similar (“method covariance”) in both academic situations, if students perform well in one setting (i.e., high school) then they would do well in another similar setting (i.e., college) (Geiser & Santelices, 2007).

It is easy to find academic studies examining HSGPA and college success even 45 years ago. In 1968, Hopper compared high school GPA to college success. He measured college success in four ways by evaluating college English grades, biology grades, math grades, and overall cumulative college GPA. He found a very strong positive correlation existed between all variables and HSGPA, but found the strongest association between HSGPA and cumulative college GPA ($r = 0.58$). He therefore concluded that college GPA can be reliably predicted using HSGPA (Hopper, 1968). However, do contemporary studies show the same correlation?

There are a number of contemporary studies that have shown that HSGPA and HSR are strong predictors of college success. The evidence is quite overwhelming and indisputable that HSGPA can and is used to predict (1) grades in individual college courses (Belfield & Crosta, 2012; Hopper, 1968; Maryland Higher Education Commission [MHEC], 2011); (2) college freshman and sophomore GPA (ACT, 2010a; Armstrong & Carty, 2003; Beecher & Fischer, 1999; Bryson et al., 2002; Chase & Jacobs, 1989; Cimetta & D’Agostino, 2010; Geiser & Santelices, 2007; Hoffman & Lowitzki, 2005; Krockover, Mortlock, & Johnson, 1987; MHEC, 2011; Myers & Pyles, 1992; Olani, 2009; Robbins et al., 2004; Zahner et al., 2012); and (3) the GPA of graduating seniors (Belfield & Crosta, 2012; Cimetta & D’Agostino, 2010; Geiser & Santelices, 2007; Zahner et al., 2012). Further, HSGPA and HSR are correlated to other measures of college success, though

often less strongly, including (1) momentum (the speed of earning college credits) (Adelman, 2006; Beecher & Fischer, 1999; Belfield & Crosta, 2012; Micceri, Brigman, & Spatig, 2009); (2) semester to semester retention (Clements, 1969; Hoffman & Lowitzki, 2005, Robbins et al., 2004); and (3) attainment of a college degree (Adelman, 2006; Geiser & Santelices, 2007). HSGPA and HSR have consistently shown their utilitarian nature when predicting college success.

Using HSGPA and HSR to Predict College GPA

Plain and simple, HSR and especially HSGPA are correlated to college GPA. Research has shown this correlation in a number of instances, across a number of U.S. colleges and universities, for over six decades. Studies simplistic in design and scope (Krockover et al., 1987) to those that are incredibly detailed and include thousands of data points (Adelman, 2006) show this positive relationship between HSR/HSGPA and FGPA.

In a study that was developed to research if the SAT II was a better predictor of college success than the SAT I, Armstrong and Carty (2003) evaluated 18,000 freshman student records of a large public institution from 1996 to 2001. HSGPA was also evaluated. FGPA was the dependent variable that the SAT I composite scores, SAT II scores, and HSGPA were regressed against. While not strongly correlated ($r = 0.34$), HSGPA was more strongly related to FGPA than either SAT I or SAT II composite scores. This public university is highly selective, as indicated by the HSGPA averaging approximately 3.7 units. It is therefore possible that the regression is weak in this study

due to the HSGPA being skewed toward higher GPAs (>3.7 GPA). Interestingly, when the authors separated first generation students from non-first generation students, HSGPA was not as strongly associated to FGPA for first generation students ($r = 0.253$ for 1st generation and $r = 0.307$ for non-1st generation). So, it seems, based off this study, that HSGPA may be a slightly better predictor of FGPA for non-first generation students.

In a small scale study, designed specifically to test non-cognitive attributes of students against FGPA and retention, the authors also included SAT scores and HSGPA in their analysis (DeBerard et al., 2004). In this study they found that HSGPA was by far the strongest predictor of FGPA and nearly twice as strongly correlated as the SAT composite score.

In a comprehensive study of 80,000 students admitted in the University of California system, the researchers concluded that HSGPA is the strongest predictor of future college GPA at all academic levels when compared to SAT scores and HSR (Geiser & Santelices, 2007). Traditionally, HSGPA and ACT/SAT scores have been used as a way to predict FGPA. In this study, HSGPA predicted cumulative GPA for freshman, sophomore, junior, and senior levels ($r =$ approximately 0.33 for all levels). The correlation rates of SAT scores and college GPA were significantly less robust. If HSGPA is used to predict non-cumulative GPA for each level, HSGPA is somewhat less predictive as r values decrease from 0.31 for FGPA and 0.25 for senior GPA. Regardless, the strength of the prediction when using HSGPA is only slightly diminished and is still much more powerful than using SAT scores alone for the predictions. Another interesting note to this study is that the researchers compared the HSGPA to senior GPA in different

majors and while there were small differences in correlation values, FGPA still attained r values of 0.31 to 0.36 indicating that FGPA can reliably predict GPA for even the most challenging majors.

Chase and Jacobs (1989) devised a study to compare the predictive natures of cumulative high school GPA using all classes and just the HSGPA using only “academic” core classes (e.g., English, math, science, etc.). The assumption was that when less rigorous, non-college preparatory courses were dropped from the analysis (like vocational and physical education classes) that the new, academic core HSGPA would provide a stronger, more robust predictive tool for college success. While cumulative HSGPA was a significant and strong predictor of college FGPA ($r = 0.52$), academic core GPA was even better suited for predicting college FGPA ($r = 0.57$) supporting their hypothesis.

In another contemporary study, Belfield and Crosta (2012) analyzed a number of early academic variables as a way to predict college success, including HSGPA. The authors analyzed a large sample of community college students and found strong correlations with HSGPA and college success. In their statistical model, they found that HSGPA was the strongest predictor of future college GPA and explained over 21% of the variance of their model and was a better predictor of college success than all of the other factors they examined combined. Because regression models can be used to make predictions, the authors concluded that, on average, students enrolled in their community college system will attain a college GPA about 0.6 points less than their high school GPA (on a 4.0 scale). So, in other words, if a student is a 3.0 student in high

school, expect that student to attain about a 2.4 GPA in the community college system. This contention was supported by an ACT study of Illinois high school students where college grades were about 0.4 units lower than high school grades (ACT, 2010a).

A study of Utah Valley State students indicated a significant association between HSGPA and FGPA ($r = 0.46$) (Beecher & Fischer, 1999). Interestingly, and contradictory to the studies indicated above, FGPA (mean = 2.39) was somewhat higher than the HSGPA (mean = 2.32) on average for the students in this study group. ACT scores were also significantly related to FGPA but only explained an additional 5% of the variance and, therefore, HSGPA in this study was over four times more powerful at predicting FGPA than using ACT scores alone.

There is a strong belief that using high school academic data (e.g., HSGPA and ACT/SAT scores) should only be one part of any decision to admit students into four-year institutions of higher education. Using a meta-analysis of the most current literature of the time, Robbins et al. (2004) examined the data from 408 studies in order to examine academic and nonacademic variables that could be used to predict FGPA and freshmen retention rates. The meta-analysis focused on only studies that had previously examined students attending four-year institutions within the United States. This study confirmed that HSGPA was the strongest predictor of FGPA though self-efficacy and achievement motivation supplied “incremental contributions” above and beyond what HSGPA and achievement tests could predict. Surprisingly, the variable categories of “academic related skills” and “academic self-efficacy” were more strongly

correlated to retention of these same students than either HSGPA or academic achievement test scores.

Some researchers have shown that using only cognitive measures of students for determining admission into universities provides only one aspect of a student's ability to do well in college (Robbins et al., 2004). A more complete picture would include cognitive measures (HSGPA and/or ACT/SAT scores) and non-cognitive measures (e.g., academic self-efficacy and achievement motivation) together. In a study of over 3,300 university students, Olani (2009) hypothesized that HSGPA's ability to predict FGPA in university students would be negated when other variables (e.g., demographic data and psychological data) were included in the analysis. This particular study focused on the measuring of non-cognitive measures of students as a way to predict future university success. However, HSGPA accounted for 17% of the variance when predicting FGPA and was the only significant cognitive predictor for both sexes. Achievement motivation and academic self-efficacy accounted for only 4% of the predictive ability for FGPA. Once again, HSGPA was determined to be the strongest predictor of FGPA.

In the analysis of data collected from a five-year longitudinal study of over 50 colleges or universities, Zahner et al. (2012) concluded that HSGPA was the strongest predictor of both college sophomore and college senior GPA, accounting for approximately 21 to 24% of the variance of the model. The authors also analyzed scores by high school and there was considerable effect on the variance accounted for. In some high schools, HSGPA accounted for 44% of the variance in college sophomore grades and 67% in college senior grades. These are very high values. Conversely, in some high

schools, HSGPA accounted for only 1% of the variance predicting sophomore and senior college grades. This is an exceptionally low number and seems to be an outlier to the rest of the data set, but shows the potential impact of a high school's curriculum and faculty on college readiness. ACT/SAT scores accounted for around 15 to 18% of the variance on average when predicting college GPA. As discussed previously, the student body at an institution changes over time (students drop out of college or transfer, for example) creating a statistical "history effect" (Vogt, 2007) that should make statistical models less reliable with time. In this study, both HSGPA and the ACT/SAT could more accurately predict college sophomore grades than senior grades as would be predicted.

The *High School to College Success Report* for Illinois, published by ACT (2010a), documents the academic performance of ACT-tested public high school students who later attended a public postsecondary institution (including Sauk Valley Community College) in the fall of 2008 through the fall of 2010 in the state of Illinois. This study excluded those students who were in private high schools or those students who attended private postsecondary institutions. ACT did not do any comprehensive statistical analysis of any of the data, but just conducted a cursory analysis showing means and using graphs without using much of a written narrative. Due to this lackluster statistical analysis, the reader should be somewhat skeptical of the results reported in the next three paragraphs. However, many of the results found in this analysis mimic the results found in a highly regarded U.S. Department of Education study (Adelman, 2006).

On average, in the state of Illinois, students earned a 3.09 GPA in high school. This translated into a GPA of 2.69 for those same students during their postsecondary education—about a 0.4 unit difference. At Sauk, the trend was similar where local students earned a 3.02 HSGPA and a 2.32 GPA in college—a difference of 0.70 units. There is no explanation given for why the differential between HSGPA and college GPA at Sauk is nearly double the state average.

This type of GPA analysis was also conducted on students entering college, but needing developmental education. This analysis indicates that students who need developmental education in college have a HSGPA of 2.82 or only 0.27 grade units less than those who do not require developmental education. In other words, students earning a C+ average in high school are often testing into some form of developmental education in college (ACT, 2010a). Not surprisingly, students needing developmental education are also performing at a lower level in college than students who do not need developmental education (see Table 9).

The report also analyzed students who enrolled in year one of college and reenrolled in year two (the “persisters”) compared to students who enrolled in year one who did not return to college the following year (the “non-persisters”). As expected, persisters had a higher HSGPA, a higher first year college GPA, and a smaller differential between their HSGPA and college GPA (Table 9).

Table 9: *HSGPA and College GPA by Type of Student*

	STUDENT TYPE	HIGH SCHOOL GPA	COLLEGE GPA	DIFFERENCE (HS-COLLEGE)
Illinois Students	All	3.09	2.69	0.4
SVCC Students	All	3.02	2.32	0.7
Illinois Students	Needing developmental	2.82	2.47	0.35
SVCC Students	Needing developmental	2.82	2.19	0.63
Illinois Students	Persisters	3.12	2.8	0.32
Illinois Students	Non-persisters	2.73	2.03	0.7
SVCC Students	Persisters	3.10	2.5	0.6
SVCC Students	Non-persisters	2.83	1.87	0.96

In 1988, the Maryland Higher Education Commission (MHEC) responded to the General Assembly’s 1988 charge to “improve information to high schools and local school systems concerning the performance of their graduates at the college level” by producing the Student Outcome and Achievement Report (SOAR) (MHEC, 2011, p. 1). This report was published for 13 consecutive years until 2011. The report conducts a statistical analysis of former Maryland high school students’ high school and college academic records. Of particular interest to this dissertation is that ACT/SAT scores and HSGPA were correlated to the grades in the first college English and college math courses and to cumulative GPA after one year in college.

For 11 consecutive years, HSGPA was the best predictor of first college English grade and first-year grade point average. HSGPA has also been the best predictor of first math grade in 10 of the 11 SOAR studies. HSGPA was particularly strong in predicting

FGPA ($r = 0.48$) compared to other variables. SAT scores, for instance, only added approximately 3% to the predictive model. While HSGPA was less powerful in predicting first English course grades ($r = 0.37$) or first college math courses ($r = 0.36$), it still outperformed the SAT considerably in its predictive ability.

The conclusions of the study are quite powerful but do have limits. The report only contains information about Maryland high school graduates who (1) completed either the SAT or ACT, and (2) enrolled at Maryland colleges or universities. It excludes all Maryland high school graduates who enrolled in higher education institutions in other states. Regardless of its limitations, the consistency of the data over 13 years is an outstanding testament to the power of HSGPA in predicting college achievement.

Some universities have tweaked their admissions policies as an experiment. At Southern Illinois University, admission officials allowed prospective students without the requisite ACT scores to be admitted in the university (Bryson et al., 2002). This conditional admission experiment allowed the university to determine if other factors, some academic and some not, could be used as a way to accurately gauge which students could succeed at their university even when prospective students failed to reach that requisite ACT composite score usually needed for admittance. The statistical analysis showed that HSR and HSGPA were the two factors most highly correlated with first year college GPA ($r = 0.36$ and $r = 0.49$, respectively) (Bryson et al., 2002). Once again, HSGPA was the most significant factor when predicting college grades and was nearly twice as strong as the most significant ACT predictor (ACT English with an $r = 0.35$) (Bryson et al., 2002).

In Arizona, the authors of a study wanted to determine if the Arizona achievement test, called AIM, could be used as an admissions test instead of the ACT/SAT (Cimetta & D'Agostino, 2010). The authors compared HSGPA, SAT scores, and AIM scores with first year college GPA and students' GPA after attending the university for four years. The statistical analysis indicated that HSGPA was by far the most significant contributor to the model that predicts both FGPA and the fourth year college GPA ($r = 0.58$ and $r = 0.56$, respectively). The SAT and AIMs test were also correlated to both GPA measures; however, these accounted for only about a 4% increase in predictive value.

Hoffman and Lowitzki (2005) studied students that attended a small Lutheran university. They determined that HSGPA was a good predictor of FGPA in these students. Of particular interest to these researchers was if HSGPA would be as strong of a predictor for White and Latino students that attended the university. Interestingly, White student ($r = 0.34$) and Latino student ($r = 0.33$) correlations to FGPA were nearly identical.

After a couple studies indicated that the Compass test was performing poorly when placing students into college-level classes, Westrick and Allen (2014) conducted an in-depth study of the effectiveness of Compass and HSGPA in predicting college grades in first year classes for the ACT organization. The authors looked at grades in English composition, Speech, American History, Psychology, Sociology, Biology, Algebra, and other classes. What they found was not terribly surprising as HSGPA tended to, on average, outperform the Compass test when predicting grades in these individual

classes. The analysis showed that HSGPA was a better predictor of college class grades in 11 of 12 instances. Interestingly though, the authors noted that HSGPA's predictive ability decayed with the age of the student. So the HSGPA of students that have been out of high school for longer periods of time will be less able to predict grades. In an analysis of "traditional" (19 years or younger) and "nontraditional" (20 years or older), they found that HSGPA outperformed the Compass test in only 4 of 12 classes.

Using HSGPA to Predict College Momentum

A number of organizations and researchers have indicated that academic momentum is a key factor in attaining a college degree (Achieving the Dream, 2014; Adelman, 2006). Certainly a full-time student is much more likely to graduate than a part-time student (College Board Advocacy and Policy Center, 2012) as full-time students accrue college credits much faster than part-time. Part-time students will more likely encounter barriers to their completion (attainment of a full-time job, family commitments, moving out of the area, etc.) as their classwork may take at least twice as long as full-time students. Is it possible to predict which students will maintain greater academic momentum toward their degree using high school academic information?

Studies have shown that HSGPA is a strong predictor of academic momentum (the number of college credits earned during their first two years of college) (Belfield & Crosta, 2012). Students with an "A" average in high school attained an average of 44 credit hours compared to only 18 credit hours for "C" students. On average, students

with higher high school letter grades accumulated four credit hours more college credit *per semester* than a student one letter grade below them (Belfied & Crosta, 2012).

In a study by Micceri, Brigman, and Spatig (2009), their objective was to increase the quality of students that were being admitted into the University of South Florida.

Their goals were to determine

- those students who would most likely succeed at USF and therefore be automatic admits;
- those students who will likely not perform adequately at USF and would therefore be automatic denials;
- those students that may do well, but would require more intensive evaluation before an admission's decision could be made.

In order to better evaluate student applicant quality, a statistical analysis was conducted on 4,190 students that matriculated in either the summer or fall semester of 2007. High school transcript data were correlated to (1) first year USF GPA, (2) the number of credit hours completed in one academic year, and (3) a composite score that included students' GPA and credit hours earned hours (GPA/hours). HSGPA most strongly correlated to USF GPA and GPA/hours. In other words, students with higher HSGPAs were more likely to attain higher USF GPAs and attain more USF credit hours than those students with lower HSGPAs.

In a study of 409 Utah Valley State students, researchers found a weak but statistically significant correlation between HSGPA and momentum (Beecher & Fischer, 1999). In this study, students were considered "successful" if they completed 24 or

more credit hours during their freshman year (a full load) and “not successful” if they did not complete 24 or more hours. HSGPA accounted for 9% of the variance around this momentum score while other academic variables (e.g., ACT scores) were not significant. Since Utah Valley State is a four-year institution, it is assumed that students were mostly full-time and if they were not successful in completing 24 or more credit hours, the students would have withdrawn or failed from some or all of their academic credits. Regression analysis allowed the researchers to calculate a “hit rate”—how successful was their model in predicting their momentum score? HSGPA alone was successful at predicting if a student completed 24 or more credit hours 65% of the time. Adding the ACT to the model increased the hit rate by only an additional 1%.

Using HSGPA to Predict Semester to Semester Retention

Within the last few decades community colleges have become less focused on enrollment and more focused on retention. The cost of recruiting a new student is much higher than retaining a student that is already enrolled at the institution. Further, increased accountability by governing bodies (e.g., accrediting agencies and state governments) have led to increased scrutiny with a particular focus on retention. Certainly college GPA or success in early college gatekeeper courses has been used as a way to successfully predict retention (Leppel, 2002; Mikiko, Myron, & Mossler, 2012; Musoba & Krichevskiy, 2014); students that are performing at a high level academically are more likely to be retained the following semester. Internal studies at Sauk Valley Community College (SVCC) have shown a statistically significant relationship with a

student's First Year Experience (FYE) class grade during only the first four weeks of class and student retention the following semester (Wirgau, Nunez, & Mandrell, 2014).

Collegiate data are much more indicative of students' current motivation and academic skill level, but is it possible to use high school academic data also as a way to predict a student's retention rate?

In 1969, William Clements studied over 2,000 students entering Wisconsin State University. What he showed was that HSR was correlated to dropout rate at the university. For example, students in the top 10% of their high school class dropped out of the university at only a 1.4% rate. However, students in the 50th percentile of their high school class dropped out at an astounding 20% rate.

Waugh and Micceri (1994) studied University of South Florida students' four-year retention rates. HSGPA was a moderate predictor of four-year retention rates, but outcompeted both the ACT and SAT as predictors. When controlled for, the ACT/SAT scores had no real predictive ability. Since some students would have graduated before four years, the authors grouped four-year retention and graduation data together. This strengthened the relationship between HSGPA and "retention" rates. Students who had earned a 2.5 HSGPA had less than a 40% probability of being retained at USF. However, students with a 3.5 GPA had over a 60% probability of retention. The authors also found that there were interesting differences between White and Black students in retention rates. If a student had a low GPA, then the student was twice as likely to be retained by the university if the student was White.

Other studies have shown only a weak relationship between HSGPA and retention. Hoffman and Lowitzki (2005) conducted a small study of 500 mostly White students at a Lutheran university. When the student population was examined as a whole, there was no statistically significant relationship between HSGPA and fall-to-spring retention rates. Interestingly, when White students and Latino students were separated into their own student groups, HSGPA did relate to retention rates for Latinos, but not for White students.

Laskey and Hetzel (2011) studied 115 at-risk students at a midsized, Midwestern university. An at-risk student was defined as a student who did not reach the normal admission standards of the university (2.0 HSGPA and 20 ACT score). These students are co-admitted into a tutoring program and into a normal class schedule to increase their persistence. For this small group of at-risk students, neither HSGPA nor ACT scores were good indicators of retention. With this in mind, the range of student HSGPA and ACT scores were certainly limited as all at-risk students had very low HSGPAs and ACT scores; this may have impacted the statistical computations.

In a study of students in a community college in California, Mikiko, Myron, and Mossler (2012) evaluated a number of cognitive and non-cognitive variables and their relationship to semester-to-semester retention. In this study of 427 students, the stated HSGPA of persisters was actually lower than non-persisters (2.34 to 2.50, respectively); however, the values were not statistically different. Of value however was the finding that cumulative college GPA was a significant and robust predictor of student retention. This has been verified by others as well (Leppel, 2002). Considering that HSGPA is often

a strong predictor of college GPA, HSGPA may be still be a leading measure of semester-to-semester retention.

As mentioned above, the ACT organization has shown that HSGPA is a predictor of retention (ACT, 2010a; ACT, 2010b). Adelman (2006) and *Achieving the Dream* (2014) both indicate that both academic momentum and semester to semester retention are leading indicators of attainment of graduation. Therefore, can HSGPA be used to predict the likelihood of college graduation?

Using HSGPA to Predict Graduation from College

There is strong evidence that admission examinations, when used with HSGPA, can reliably predict FGPA (Crouse & Trusheim, 1988; Noble, 1991; Noble et al., 1999; Noble & Sawyer, 2002; Zwick, 2007). Other studies have shown that there is a rather strong correlation between FGPA and senior year GPA (Geiser & Santelices, 2007). It could be assumed that if ACT/SAT scores along with HSGPA could predict FGPA, then senior GPA could therefore predict completion of a degree. Studies like *The Toolbox Revisited* (Adelman, 2006) have supported this contention (see below for a thorough examination of this study). Have other academic studies supported this hypothesis?

In a study of over 79,000 entering freshman into the University of California over a four-year period, a significant correlation existed between HSGPA and four-year graduation rates (Geiser & Santelices, 2007). Since graduation could occur at any time during a student's stay at the university, the authors used four-year graduation rates in their statistical model. Only 40% of freshmen graduate within four years, which may be

one of the reasons that HSGPA explained only about 7% of the variance in this study. The authors did note that the HSGPA predictive model produced the highest percent concordance between predicted and actual outcomes at 63.5%, indicating that HSGPA may be a moderate predictor of bachelor's degree completion for these students. Adding SAT scores to the model added a very small increase in the predictive power.

In a study of 1,429 four-year postsecondary institutions (Stumpf & Stanley, 2002), the authors studied the utility of using HSGPA as a way to predict graduation. The authors grouped student GPAs into two main categories, those students with GPAs of 3.0 or higher and those students that had GPAs 2.0-2.9. Correlation values against graduation rates were +0.49 for students with a 3.0 and higher HSGPA and -0.46 for HSGPAs of 2.0 to 2.9. Simply, those students with higher HSGPAs tend to graduate more frequently than those with lower HSGPAs. When HSGPA was added to a regression model with ACT or SAT, HSGPA explained only about 5% of the variance while the ACT and SAT performed more robustly.

Waugh and Micceri (1994) found in their study of University of South Florida students that HSGPA was an effective predictor of both graduation and four-year retention rates. When compared to the ACT or SAT, HSGPA was substantially more correlated to graduation or four year retention rates.

Researchers studied student data from 2005 to 2010 at a Hispanic-serving university in a large urban area in the southeastern United States (Musoba & Krichevskiy, 2014). Their student data included 3,304 Latino students, 522 White students, and 771 Black students. In this study, the authors found that HSGPA was an

effective predictor of graduation for Hispanic student, but surprisingly not for White or Black students on campus. SAT scores were not a significant predictor for any group of students.

HSGPA as a Predictor of Future College Success: Conclusion

Using HSGPA to predict college success has been studied extensively. With rare exceptions, HSGPA and HSR can be used to accurately predict FGPA of students at many colleges and universities, despite gender and ethnic differences. Generally speaking, the evidence suggests that FGPA will be about 0.4 to 0.7 units lower than HSGPA. Also, HSGPA often outperforms the ACT and SAT when used in predictive models forecasting FGPA. Certainly, the ACT and SAT can add some additional power to these predictive models.

Despite statistical “history effects,” HSGPA seems also to be correlated to cumulative college GPA of sophomores, juniors, and seniors. Since college GPA, momentum, retention, and graduation are correlated to some degree, one would surmise that HSGPA, momentum, retention, and graduation are also linked. Certainly the preponderance of evidence suggests that HSGPA, momentum, retention, and graduation rates are correlated, but generally more weakly than is HSGPA and FGPA.

In conclusion, HSGPA is a significant, robust predictor of many facets of college success. First, it can successfully predict college GPA from freshman to senior years. Second, it can predict a number of other facets of college success including momentum retention and graduation rates. Third, HSGPA consistently outperforms all other

academic and non-academic variables when used to predict college success, especially FGPA. Fourth, despite grade inflation and regular change in high school curricula and rigor (e.g., No Child Left Behind), HSGPA is as a reliable and consistent predictor today as it was 50 years ago. Fifth, HSGPA can effectively predict future success as well in private or public or four-year or two-year higher education institutions. Sixth, HSGPA is a widely accepted way of predicting college success. ACT and the College Board and most university admission counselors agree that HSGPA can be effective at predicting college success, especially FGPA.

What many researchers do not include in their statistical models is the effect of a student's age. However, Westrick and Allen (2014) found that for students above the age of 20, the predictive ability of HSGPA may fade. This is tremendously important when predicting college success at a community college where the average student will be in their mid-20s.

While HSGPA is a well-established tool to predict college success, it probably should not be used alone when evaluating student transcripts. Many studies show an increased statistical robustness when ACT/SAT scores are used in conjunction with HSGPA. Other factors, like an evaluation of high school academic rigor may also supply effective information for college admission and placement.

HIGH SCHOOL ACADEMIC RIGOR

The Illinois Common Core Standards (Illinois State Board of Education, n.d.), Bill and Melinda Gates Foundation (2014), and the U.S. Department of Education (Adelman,

2006) all indicate that an academically rigorous high school curriculum is the best way to produce “college ready” high school students. Many states, including Illinois, have responded by altering the high school curriculum. In April 2014, the Illinois State Board of Education released a summary of a transition plan that incorporated the Common Core standards to prepare high school students for “an increasingly complex world” (Illinois State Board of Education [ISBE], 2014). By the 2013-2014 school year, all high schools are now in alignment with those standards in Illinois.

How is high school rigor measured? In the reviewed research, there is no standard method of evaluation. In a paper called *Is High School Tough Enough: At a Glance* (Center for Public Education, 2012), the author recaps the multitude of ways in which high school rigor can be measured. Probably the most popular strategy, according to the authors, is to count the number of AP courses that a student passed in high school. Simply, if a student took an AP course, he or she was often more likely to perform better and graduate from college than those students that did not take AP classes. Further, students taking rigorous math courses were more likely to attend and complete college. Additional ways of measuring rigor, in ways that positively correlated to college success, include being involved in dual enrollment (dual credit), early college high school programs, and upper level classes like calculus (Adelman, 2006; Klepfer & Hull, 2012). However, high school curriculum across the U.S. is tremendously varied. For example, some high schools don’t even offer calculus. Therefore, any definition of “rigor” is not a “one size fits all” situation.

A study of high school curriculum has shown that academic rigor has intensified over the last few decades (if rigor is measured strictly by the number of advanced classes taken by high school students) (Posselt et al., 2012). For example, when comparing the academic rigor of a typical high school student in 1972 to 2004, both the number of classes a typical high school student takes in math (1972 = 2.16, 2004 = 3.74) and science (1972 = 3.28, 2004 = 4.1) has increased despite a decrease in average SAT scores during that same time period (scores declined from 1051 to 1004 from 1972 to 2004) (Posselt et al., 2012). This decrease in the average SAT score is most often explained by additional students, not all of which are college bound, taking the SAT; non-college ready students are lowering the average (Posselt et al., 2012).

Is measuring the number of “rigorous” courses a high school students take an accurate way to measure academic intensity? Some would say that it clearly is (Adelman, 2006; Noble et al., 1999). Noble et al. (1999) correlated academic rigor (as defined by the type and number of college preparatory classes a student had taken) to the average increase in ACT scores. They concluded that taking advanced math classes in high school would dramatically improve the ACT scores of a student, even in the subtest scores. For example, when compared to a high school student who did not complete calculus, a high school student who passed calculus would average a 2.04 higher score in ACT-English, 3.48 points higher on ACT-mathematics, 2.27 points higher on ACT-reading, 1.77 points higher in ACT-science, and 2.39 points higher in the ACT-composite. Noting that correlation is not causation, there does seem to be a link between higher ACT scores and completing more advanced high school classes.

In a study of over 4,000 University of South Florida students, Micceri, Brigman, and Spatig (2009) studied the predictive ability of HSGPA and HS rigor on college success. As mentioned before, HSGPA was a strong predictor of academic success at the university. However, high school academic rigor and USF student success were also correlated. For the purposes of this study, HS academic rigor was deemed greater (1) if the HS student took an AP course, (2) if the HS student was dual enrolled, (3) if he/she earned more than 6 STEM units, and (4) if he/she earned at least 6 language units (English and foreign language) than those students that did not complete those standards. Each of these academic predictors was moderately good at predicting college success when used alone, but was more robust when used together. For example, if a student was dual enrolled in high school *and* had taken 6 units of STEM, then the student was more likely to be successful at USF than if he/she had taken only 6 units of STEM.

The authors of this same study (Micceri et al., 2009) also created a matrix that references both HS academic rigor and HS GPA and the likelihood of success at USF (success is defined as 3.0 college GPA) and proposed using this matrix as a way of selecting students for admittance into USF. Those students with higher HSGPA and more academic rigor (as described above) would be more likely to be admitted. If, for example, a HS student has a 3.5 or higher GPA and two of the “academic rigor” indicators, then he or she has an 87% chance of making a 3.0 or higher at USF. Those students with a lower GPA and less academic rigor would not be admitted or admitted with reservations.

In a study of 9,000 students who enrolled in two- or four-year colleges or universities, high school academic rigor was an important facet linked to college retention (persistence) (Klepfer & Hull, 2012). In this study, retention was defined as reenrolling at some college or university one year after initial enrollment. Their findings indicated that retention was correlated directly to the level of math that the student completed in high school. The authors ranked the rigor of high school math classes in this manner: Calculus > Trigonometry, Algebra 3 or Statistics > Algebra 2 > Algebra 1 or Geometry. Students that completed calculus in high school and then enrolled in just four-year colleges or universities were retained at an 88 to 94% rate. Those that had completed only Algebra 1 or Geometry persisted in college from 61 to 78%. Socioeconomic status and other academic indicators influenced the model to some degree, but the overall trends were similar. The data analysis also indicated that the trends found for students in four-year universities/colleges were also found for students enrolled in two-year colleges. Overall, students had lower retention rates in two-year colleges than four-year colleges.

Klepfer and Hull (2012) also examined the number of Advanced Placement courses that students completed in high school and then looked for associations with one year college retention. Again controlling for socioeconomic level and prior academic achievement, students that took an AP course were more likely to persist for at least one year at a college or university than students that did not complete any AP courses. The effect was most dramatic in the lowest academic groups or those of minority status. These students, if they completed an AP course and enrolled in a university, persisted at

an 87% rate compared to only 74% rate for those that did not take an AP course.

Though the effect was lessened at the highest academic levels or non-minority groups, those that completed AP courses were still 6% more likely to persist. At two-year colleges, the effect of an AP class was even more magnified.

The authors of the previous study (Klepfer & Hull, 2012) indicated that their data set included all students that took the final AP exam and not just students that passed the final AP exam. In order to investigate if passing an AP exam improved persistence over those students that did not, they reran the analysis, but the results were nearly identical to their first. It didn't seem to affect persistence in a negative manner if a student did not pass the final AP exam. "This suggests that it is the rigor of the AP curriculum that improves student persistence in college rather than simply mastering the content" (Klepfer & Hull, 2012, p. 10).

SAT analyzes their student data annually in a report called the *Total Group Profile Report* (SAT, 2012). Their data show that student SAT scores are generally positively associated with academic rigor of their high school program (i.e., more rigor = higher SAT scores). In this case, rigor is defined as the number of courses a student completed in high school in English/language arts and mathematics. Interestingly, academic rigor was not always perfectly associated with higher SAT scores, even in the same subject area. For example, students completing two years of English/language arts generally scored *higher* on their SAT than students that completed three years of English/language arts (Figure 1). Similar trends are found in math as well, where students with two years of math tend to do better on the SAT-math than students that

have had three years of math (Figure 2). Since the number of years of academic study can be misleading in these associations, SAT also correlates SAT scores with the highest level of math completed. Here the results were more consistent; those students who completed calculus had higher SAT scores in every subject area than those that had pre-calculus, etc.

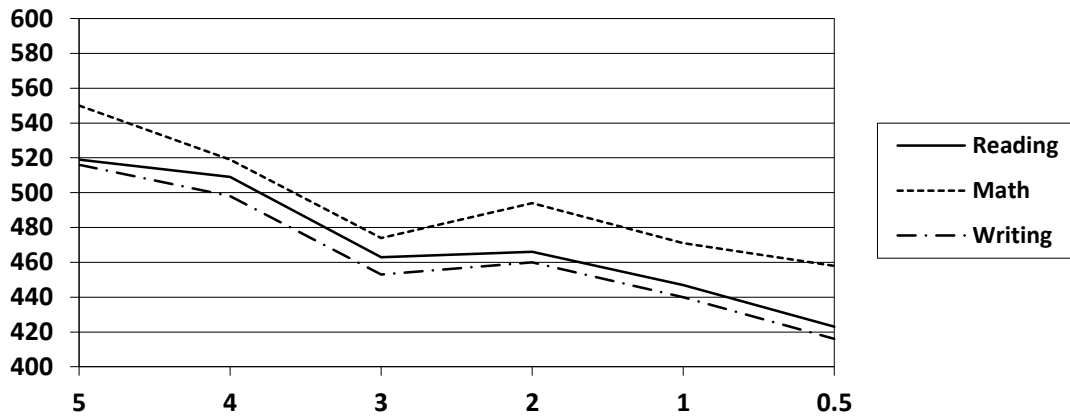


Figure 1. SAT scores in reading, math, and writing compared the number of years of English/language arts studied.

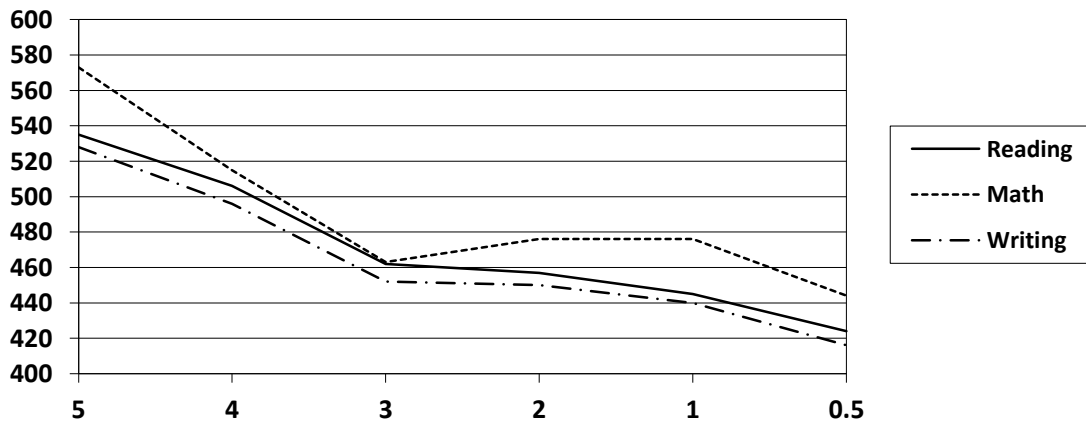


Figure 2. SAT scores in reading, math, and writing compared to the number of years of math studied.

The Center for Public Education (2012) suggested in a paper that students who complete AP courses are nearly twice as likely to complete a college degree within five years.

High School Academic Rigor: Conclusion

Without a doubt, a more rigorous high school curriculum better prepares high school students for the trials of earning a college degree. Students who take more math, English, dual credit and AP courses are generally better prepared for college-level work. Studies generally show that HSGPA and academic rigor are the top two factors when predicting future college success. Adelman (2006) shows that academic rigor is the number one factor for predicting attainment of a bachelor's degree. The ACT/SAT scores tend to be a distant third at making college success predictions.

While the impact of high school academic rigor on college preparation cannot be discounted, increasing the number of prescribed college-readiness courses a student takes is not always the answer, especially in high schools with low academic standards (Conley, 2007). The number of science and math courses taken by high school students has dramatically increased since 1972 indicating an increased level of academic rigor; but HSGPA has also increased during that same time span. Not accurately measured until 1982, the average HSGPA has increased from 2.62 to 2.86 in 2004, indicating high school grade inflation despite supposedly tougher academic standards. Conley (2007) has indicated that ultimately the "quality" of the courses a student takes is really what

matters, but this is very difficult to quantify across all of the more than 18,000 high schools in the United States.

U.S. DEPARTMENT OF EDUCATION STUDY: THE TOOLBOX REVISITED

Some studies are so comprehensive that they cannot be effectively characterized or summarized in the sections above. The U.S. Department of Education Study called *The Toolbox Revisited* (Adelman, 2006) is one such study.

In 2006, the U.S. Department of Education released a comprehensive 200-page report that summarized what attributes of a high school education fostered attainment of a bachelor's degree up to 8.5 years after graduating from high school (Adelman, 2006). The study tracked over one million high school students from 1992-2000 and conducted regular interviews with them and correlated high school and college transcript data with attainment of a bachelor's degree (p. xv). Therefore, the study captured data from students that entered a four-year college and graduated there, or a student that entered a community college and then transferred to a four-year college and graduated there, or a student that meandered from one postsecondary school to another and another until he or she attained a bachelor's degree. Success, in this study, is defined clearly as attainment of a bachelor's degree. The study does halt after 8.5 years after high school graduation; and therefore any student who attained a bachelor's degree afterward is not counted (p. xvi). Further, students that did not graduate high school, attained a GED instead of a high school diploma, or did not enroll into a four-year institution by age 26 were also not studied (p. xvi).

One of the issues discussed in this study is the complexity of degree attainment (Adelman, 2006, p. xvi). More than 60% of successful students will attend more than one higher education institution before they attain a bachelor's degree. A significant number of successful students (13%) will attend community college to "fill gaps" in their education, most often completing community college classes in the summer while they are briefly away from their four-year institutions. Another 8% of students will "swirl" from one school to another before they eventually complete a degree. As the editor of this study indicated, we see students enter the community college system and leave and we assume they drop out, but in reality many of them are "swirling" and therefore are difficult to track (p. xx). The addition of dual-credit courses has complicated the picture to even a greater degree.

The high school factor that most strongly contributes to attainment of a bachelor's degree is academic intensity (rigor). For example, if students completed the course work (listed below) successfully in high school, then students had a 95% chance of earning a bachelor's degree and 41% chance of earning a master's degree or a Ph.D. by the age of 26 (Adelman, 2006, p. xviii). A Carnegie unit is one academic year of instruction in the high schools (about 120 hours of instruction). The courses and corresponding Carnegie units are as follows:

- 3.75 or more Carnegie units of English
- 3.75 or more Carnegie units of mathematics
- 2.5 or more Carnegie units of science or 2.0 Carnegie units of lab science
- more than 2.0 Carnegie units of foreign languages

- more than 2.0 Carnegie units of history and social studies
- 1.0 or more Carnegie units of computer science
- more than one Advanced Placement course

In other words, if students prepare for college by successfully completing academically rigorous coursework, then they are much more likely to attain a bachelor's degree.

The study also confirms that the attainment of high-level math (Algebra 2 or higher) is crucial to sustaining "academic momentum" in college (Adelman, 2006, p. xix). Those students armed with more math academic intensity when they graduated high school were more likely to attain a bachelor's degree and earn more credits per semester than those that were not as academically prepared in math (p. 60). This association was measured precisely. For example, a student that passes calculus is twice as likely (with an 83% probability) of attaining a bachelor's degree compared to a student who passes only Algebra II (with only a 39% probability) (p. 31). Therefore, the high school curriculum for college bound students must be mathematically rigorous. Unfortunately, not all high schools actually offer the highest-level math courses (e.g., calculus) and fewer schools do so that serve mostly minority students creating a potential racial disparity in educational attainment (p. 32).

The study also looked at high school academic performance as an indicator of bachelor's degree attainment. HSR and HSGPA were the second strongest predictors of college GPA and academic momentum toward a bachelor's degree (Adelman, 2006, p. xxii). The correlation was staggering with a student in the highest quintile in GPA/class rank 10 times more likely to attain a bachelor's degree compared to a student in the

lowest quintile (p. 36). When a multivariate analysis was used to correlate high school academic information to attainment of a bachelor's degree, academic intensity ranked first accounting for a 0.42 predictive weight, GPA/Rank accounting for 0.33 of the predictive weight, and high stakes tests (like the ACT or SAT) accounting for only 0.25 of the predictive weight (p. 37). Interestingly, high stakes tests were a more meaningful predictor of which students will *enter* college as compared to HSGPA/HSR (p. 39). So HSGPA/HSR can more accurately predict college *success* while high stakes tests can more accurately predict *entrance* into higher education.

Surprisingly, student demographic information did not strongly correlate with college success after HSGPA/HSR and academic rigor were accounted for. Only economic status was significantly, but weakly, correlated to attainment of a bachelor's degree (Adelman, 2006, p. xxiii). Other factors like race and gender were never significant (p. xxiii). This study conclusively shows that attaining an academic rigorous education is the most important factor for higher education success. It is important to note that students that did not graduate high school, attained a GED, or never attended a four-year college were not sampled, therefore slightly skewing the data toward nonminority students (p. xvi). And certainly, attainment of an academic rigorous high school education is strongly linked to a higher socioeconomic status.

THE USE OF PLACEMENT TESTS TO PREDICT COLLEGE SUCCESS AND DETERMINE CLASS PLACEMENT

ACCUPLACER and Compass are standardized placement exams that allow higher education institutions to assess the reading, writing, and math abilities of incoming

students. Many institutions use only ACCUPLACER or Compass as their way to assess college readiness even though research has shown that using more than one technique is a much more reliable method for measuring readiness (Noble et al., 2004). How accurate are ACCUPLACER and Compass at evaluating incoming student ability? Can these tests also be used to predict future college success?

Scott-Clayton (2012) looked at the accuracy of both the Compass test and HSGPA as placement tools. HSGPA was found to be better than the Compass test when placing students into correct English or math classes. The author suggested that if a student has an "A" or "B" HSGPA that they should not be enrolled into developmental classes. However, if the student had a "C" or "D" average in high school, the student should take the Compass test to acquire additional information about a student's placement. If the highest placement data are then used (either HSGPA or the Compass) to place students, then remediation rates would drop 8 to 12%.

In another 2012 study of data of a statewide community college system, Belfield and Crosta (2012) studied the utility of using high school transcript data and the placement tests Compass and ACCUPLACER to determine future college success. This study strongly corroborated the results of Scott-Clayton (2012), and the authors suggested that placing all incoming students into either developmental classes or into all college-level classes would be a more effective placement policy than using either Compass or ACCUPLACER alone. HSGPA had half the error rate of both placement tests and the authors suggested that incoming students with a C+ HSGPA should be allowed to enter college-level classes as was similarly suggested by Scott-Clayton.

Since placement tests are designed to place students into classes that students can succeed in at the college, it would seem logical that placement test scores might be effective at predicting college success. Belfield and Crosta (2012) examined this issue and found that when HSGPA and placement tests were added to the same predictive model, Compass and ACCUPLACER scores became insignificant in predicting college GPA or grades in gate-keeper courses. Further, Compass and ACCUPLACER became nearly insignificant in predicting the number of credits earned (momentum) by students. As stated by the authors, "To predict college GPA, all that is needed is HSGPA. To predict college credits earned, both the placement test and HSGPA are valuable, but HSGPA is more valuable than the placement test" (Belfield & Crosta, 2012, p. 19).

Partly in reaction to the skepticism to the ability of Compass to accurately place students into classes, Westrick and Allen (2014) conducted a large-scale analysis of ACT's Compass score data and compared it to grades in 12 college classes (e.g., English Composition, Biology, Sociology, Algebra, etc.). As was discussed before, HSGPA outperformed Compass in predicting grades in those classes in 11 of 12 cases. However, when students were separated into two age categories, the researchers found that HSGPA's ability to predict grades degraded as the student got older. However, HSGPA also tended to be more accurate in predicting correct class placement (either correctly placing a student into developmental education classes or college level classes).

With a number of studies claiming that placement exams were poor predictors of college success and had high fail rates when predicting correct placement, Mattern and Packman (2009) analyzed placement and grade data from 17 institutions, 14 that

were community colleges. They found a moderate to strong correlation between ACCUPLACER test results and college course success, where success was either a C or higher or a B or higher. When two ACCUPLACER subtests were used together to make predictions (e.g., elementary algebra and arithmetic), the combined scores performed even better than when using only a single test to make a prediction. The authors did not look at the predictive ability of HSGPA.

In summary, placement exams like Compass and ACCUPLACER provide some ability to predict college success (e.g., Mattern and Packman, 2009). However, as was seen with the ACT/SAT, HSGPA seems to still be a better predictor of college success, even when predicting grades in certain gateway classes. Also, as was seen with the ACT/SAT, when used in conjunction with HSGPA there is an increase in the predictive power. Predictive models should most likely include both HSGPA and the Compass or ACCUPLACER score when determining placement into developmental/college level classes and when predicting college success.

OTHER STUDENT DATA AS PREDICTORS OF COLLEGE SUCCESS

While high school rigor, HSGPA, HSR, and ACT/SAT scores can be very strong predictors of college success, those variables do not exist in a vacuum. One of the tenets of corollary statistics is “correlation is not causation” and so one must be careful to make assumptions of the actual meaning of the data. When examining college success, many studies have examined multiple facets of students besides academic data to find if other data may also provide a significant predictor of college success. The College and

Career Readiness and Success Center at American Institutes of Research (CCRSC, 2013) wrote a summary report of factors that are associated with postsecondary success. In this report, the Center found that students who were present at high school 90% of the time and had no more than one failure in 9th grade classes were predicted to be more successful in college. Armstrong and Carty (2003) found some evidence to suggest that being a “first generation” student has some influence on college success. Certainly, as has already been discussed, gender, income level, parents’ educational level, and ethnicity have influence on the predictive ability of statistical models and should be accounted for in the model.

There are many other factors that researchers have looked at extensively in order to predict college success. Examples include looking at students’ alcohol drinking and smoking habits and physical and mental health (DeBerard et al., 2004). Wolfe and Johnson (1995) found that “self-control” was a significant predictor of college success. Intrinsic motivation may be correlated to retention and graduation (Prospero, Russell, & Vohra-Gupta, 2012; Vansteenkiste, Lens, & Deci, 2006). The number of factors linked to college success are numerous, but this dissertation focused on creating a statistical model that uses easily gathered high school transcript data. Other factors that require additional testing and surveying were not part of this research.

CONCLUSION

It is possible to use student high school data to accurately predict college success. According to Adelman (2006), academic preparation and intensity are the keys

to the attainment of a bachelor's degree despite the influence of other demographic data like race or parent income level. Students that attain a strong academic core of four years of English and math, 2-3 years of science, 2 years of foreign language, 2 years of history/social studies, and 1 year of computer science in high school who also attain an above average HSGPA are essentially assured of earning a bachelor's degree or higher 8.5 years after graduation from high school. While racial and economic road blocks to receiving a higher education degree are real, Adelman (2006) has shown that these barriers can be overcome with academic preparation.

HSGPA is also a better predictor of college success, on average, than high stakes exams like the SAT or ACT, and course placement tools such as ACCUPLACER and Compass. In all of the categories of predicting college success (college GPA, placement accuracy, momentum, retention, and graduation rates), HSGPA generally outperforms standardized tests regularly and convincingly. Of particular importance is that students that have higher HSGPAs will not only have higher grades in college, but attain their degree faster than those students with lower grades (Belfield & Crosta, 2012). And while HSGPA does not exist within a vacuum, higher education institutions should be more cognizant of the statistical predictive power of the readily available HSGPA while taking into account gender and ethnicity into their predictive models. HSGPA should also be utilized more often as a way to admit and place students into the correct college classes. It is the hope that by using HSGPA more appropriately, higher education institutions will also increase retention, persistence, and graduation rates which is the ultimate goal of this dissertation.

CHAPTER THREE: METHODOLOGY

INTRODUCTION

This study used statistical techniques to determine if high school demographic and academic information could be used to predict the academic success of students who enrolled at SVCC during the fall semester immediately following their high school graduation. The students chosen for this research project attended one of five local feeder high schools and Sauk Valley Community College (SVCC) in years 2011-2013. High school names were not used in this project to maintain anonymity. All data were found on either the students' high school transcripts or from the SVCC student records. The researcher was given IRB approval to conduct this research on September 24, 2014 (Appendix A).

RESEARCH QUESTIONS

This research project was designed to answer the following two questions.

1. Could high school student academic data be used to predict academic success at SVCC?
 - a. What variables were most important in the prediction of college success?
 - b. What variables were insignificant to the prediction of college success?

2. What role will demographic data have on the robustness and reliability of the statistical models created? Can a “one size fits all” model be created for all genders, races and income levels, or will separate models need to be created? In order to answer this question thoroughly, a multiple linear regression will be conducted on each college success variable. This technique should highlight the most important academic and demographic predictor variables found in the data set.

STUDY POPULATION

Data from recently graduated high school students attending SVCC were used in this research analysis. These students all graduated from high school in years 2011-2013 and enrolled immediately at SVCC in the following fall semester (Table 10). This method allowed the researcher access to the students’ fall semester academic information at SVCC.

Table 10: *Number of Students Used in Study by Year and High School*

HIGH SCHOOL	2011	2012	2013	TOTALS
1	64	75	70	209
2	12	24	19	55
3	19	22	13	54
4	52	47	61	160
5	68	82	71	221
Totals	215	250	234	699

Having access to high school transcript information provided a rich source of information for study. Some of the information was strictly academic in nature, while some provided information about demography. Unfortunately, in some cases, not all data variables were collected from each student. For example, not all students completed a Free Application for Federal Student Aid (FAFSA); therefore, it was not possible to get family and individual income data for all students.

Most of the student data was already stored within SVCC's data warehouse. A request for the data was sent to the Information Services Department at SVCC and an Excel data file was created and sent to the researcher on a secure internal connection. However, in some cases, individual transcripts had to be analyzed by the researcher and additional data manually merged onto a single Excel data file. Student name and identification number were scrubbed from the data set as soon as all information was merged; only academic and relevant demographic information remained. Student age was not included in this analysis because all students included in this data set were 17-18 years of age. The data file was kept on a password protected computer at SVCC that can only be accessed by the researcher. A backup copy of the data was placed on an external drive which was locked within the desk of the researcher's office.

INDEPENDENT VARIABLES (POSSIBLE PREDICTORS OF COLLEGE SUCCESS)

Demographic Data

Student demographic data could be as important to predicting college success as student academic data. Previous research has shown that race/ethnicity, high school

attended, gender, and family income (see Chapter Two) are all important possible correlates to college success (Table 11). For example, it is possible that the high school attended may play a dramatic role in the statistical model as some high schools may better prepare their students for college. Demography may play a critical role in creating a robust, predictive model of college success and must be accounted for.

Table 11: *Five Student Demographic Variables Analyzed Within This Study*

PREDICTORS OF COLLEGE SUCCESS: DEMOGRAPHIC VARIABLES	TYPE OF DATA	VALUES WITHIN THE DATA SET
Race	Nominal	White Black Hispanic Asian Native American
Gender	Nominal	Male Female
Total income	Ratio	\$361–220,476
High school attended	Nominal	1–5
College program declaration	Nominal	Career Transfer

The academic goals of community college students are incredibly heterogeneous. For example, some students have the academic goal of attaining a two-year A.A. or A.S. degree and then transferring to earn a four-year degree (the “transfer” student). Other students are satisfied with attaining a two-year career degree (A.A.S.) or a shorter certificate (the “career-technical” student) and quickly entering the workforce. Little is known about the possible effects of program/degree selection on predictive modeling (CCRSC, 2013), but it is possible that two predictive models would be needed

in order to increase accuracy; therefore, college program declaration data were also incorporated into the analysis.

Student Academic Data

There are many possible academic predictors of college success. Table 12 summarizes the academic variables collected and analyzed in this study. HSGPA was recorded on a scale of 0.0 – 4.0 or as an “unweighted” grade point average. In other words, HSGPA is capped at 4.0 and calculated without adding additional grade-points for college-preparatory, Advanced Placement (AP) or honors-level courses. Geiser and Santelices (2007) have found that unweighted HSGPA is consistently a better predictor of college performance than weighted HSGPA. One of the reasons for this may be that high schools weight their college-preparatory classes differently. For example, one high school added 0.5 units to the final class grade of a weighted class. However, at another high school, the final class grade was weighted an additional 1.0 units. So a student making a “B” in a biology class would get a 3.0 in an unweighted class, a 3.5 in a weighted class at high school 1 compared to a 4.0 at high school 2. This clearly would create problems with statistical reliability as the same grade is recorded in three different manners.

Table 12: *Sixteen Student Academic Variables Analyzed Within This Study*

PREDICTORS OF COLLEGE SUCCESS: ACADEMIC VARIABLES	TYPE OF DATA	VALUES WITHIN THE DATA S
HSGPA (unweighted)	Interval	1.26-4.00
High School Percentile	Interval	34.6-100%
Number of HS math classes completed	Ratio	0-6
Number of HS science classes completed	Ratio	0-5.5
Number of dual credit classes completed	Ratio	0-13
Number of weighted classes completed	Ratio	0-22
ACT composite score	Interval	10-33
ACT reading score	Interval	8-36
ACT English score	Interval	6-35
ACT math score	Interval	12-34
ACT science score	Interval	9-35
Compass score: Reading	Interval	34-99
Compass score: Writing	Interval	1-99
Compass score: Algebra	Interval	15-98
Compass score: College Algebra	Interval	18-90
Credits Enrolled (control variable)	Ratio	3-19

High school transcripts specify students' high school academic rank. The student with the highest HSGPA in the graduating high school class is ranked number 1 and the student ranked with the second highest HSGPA is ranked 2 and so forth. Some high schools calculated academic rank based on weighted HSGPA and other high schools used unweighted HSGPA. Since it is not possible for the researcher to access the high school records of students that did not attend SVCC, it is not possible for the researcher to adjust the ranking manually so that all high schools are ranking students in exactly

the same manner. Therefore, the data set, for this variable, loses some reliability, but the researcher believed the data were valuable and they were not discarded. High school academic rank data were converted into a percentile score. This reconfigured the data so that the highest ranked student in a high school class was ranked as the 100th percentile and the lowest HSGPA was ranked in the 1st percentile category. High school percentile was used in the statistical analysis and not rank. High school percentile (HSP) was calculated for each student using this formula:

$$HSP = \frac{\# \text{ students in HS class} - \text{student rank} \times 100\%}{\# \text{ students in HS class}}$$

There is no true measure of high school academic rigor. Most commonly, academic rigor has been measured by researchers by recording the number of science, math, AP, weighted, or dual-credit classes that students pass during their high school tenure (Adelman, 2006). The SVCC Admission Office staff evaluated transcripts of all entering high school students and entered, into the SVCC's database, the number of science and math classes a student completed. High school students that have completed one semester of a math or science class, while earning a grade of A-C, received a score of 0.5 units. Only Algebra 1, Algebra 2, Geometry, Calculus and Trigonometry classes counted toward the high school math category. Only Biology, Physics and Chemistry classes counted toward the high school science category. Weighted high school classes were counted by the researcher from each HS transcript. Only weighted classes where students earned a D+ or higher were counted in this category. Each weighted high school class was assigned a value of 1.0. The number and

types of weighted courses varied considerably among high schools. Lastly, dual-credit classes were SVCC classes that high school students completed before graduating high school. Each dual-credit class was assigned a value of 1.0.

High school students in Illinois were mandated by the state government to take the ACT during their junior high school year. Therefore, ACT scores were readily available for students attending SVCC. The ACT composite, science, math, English, and reading scores were all collected from student high school transcripts and entered into the SVCC data warehouse.

The college staff utilized Compass academic placement exams as a way to evaluate many students who enrolled in the college. Compass placement exams were administered by SVCC to place students in the proper English and math classes at the college. Nearly 54.2% of SVCC's students required academic remediation during 2011-2013 (SVCC internal data). For Compass math scores, the Compass exams indicated which level of math incoming students are proficient in and the numerical score they achieved in the proficiency. For example, student 1 might earn a 78 on the college algebra section and therefore tests into college algebra. Student 2 might earn an 84 on the pre-algebra section and therefore tests into pre-algebra (a developmental math course).

Lastly, the number of credits that a student enrolled in during the fall semester at SVCC were included in this analysis. It is possible that this variable may be interacting with some of other dependent and independent variables listed in this statistical study.

Class credits were not counted unless the student was enrolled in that credit bearing class on the 10th day of the fall semester.

DEPENDENT VARIABLES (MEASURES OF COLLEGE SUCCESS)

College success can be defined in a number of ways. FGPA is by far the most common “success” variable seen in the literature, especially from those researchers who conduct correlational and regression analyses. Considering the large number of ways that college success can be measured, this research focused on the following five college success variables (Table 13).

1. *FGPA*. FGPA was defined as the grade point average (GPA) of students after the first fall semester at SVCC is completed. GPA was calculated using standard methodology. Developmental courses were counted within the FGPA calculation. Students with a higher FGPA were considered more successful. Students who withdrew from 100% of their classes were considered a missing data point for FGPA.

Some high school students have taken classes at SVCC as dual credit students before enrolling at the college in the fall semester following high school graduation. Technically these dual credit courses have been used to calculate the cumulative college GPA of SVCC students. However, dual credit grades were not included within the calculation of FGPA used in this analysis, only SVCC classes taken during the fall semester were used in the calculation. Conversely, dual credit grades were used to calculate HSGPA by high school administration.

2. *Momentum*. Momentum was defined as the total number of class credit hours earned in the fall semester at SVCC. Students with higher momentum scores (i.e., more college credits) were considered more successful than students who earned fewer credits in the fall semester. Students who enrolled in only one or two credit hours at SVCC were dropped from the analysis; this accounted for only seven students or less than 1% of the data and left 699 student data points remaining. This was conducted because these students could only be enrolled in 1-credit classes which are limited to only P.E. classes on campus.

3. *Grade Points (Momentum*FGPA)*. This metric was a measure of both momentum and FGPA and was calculated by multiplying the FGPA of a student with the number of credit hours successfully completed (momentum) by that same student. For example, a student who earned a 3.0 GPA and successfully completed 10 credit hours would be awarded 30 grade points in this metric. It could be argued that a student with a 2.7 FGPA and who earned 15 credit hours would be more successful than the previous student because they have earned 40.5 grade points.

4. *Class persistence*. This metric measured the percentage of credits successfully completed in the first fall semester for each student. Success for this metric was defined as “passing” a course. In developmental classes, success was defined as a “C” grade or higher. In college-level classes, success is defined as “D” or higher. All other grades, including classes that students withdraw from (“W” grades), counted as an unsuccessful credit completion. For example, if a student successfully completed seven credit hours and withdrew from or failed three credit hours, then this metric would be reported as

70% class persistence rate (7/10 credits successfully completed). It is debatable as to whether classes that students withdrew from should count against this metric.

However, Adelman (2006) indicated that momentum is an incredibly important predictor of completion and so it was decided to have withdrawals count against persistence rates. Students who completed a larger percentage of their classes were considered more successful.

Of course many students change their academic course schedule early in the semester. Therefore, a course was only counted toward a student's persistence rate calculation if the student was still registered for the course on the 10th day of class in the fall semester. (This is the last day to receive 100% refund and is also consistent with the Illinois Community College Board reporting format.)

5. *Fall semester to spring semester retention.* If a student was registered for the fall semester on the 10th day of classes and reenrolled the following spring semester, then the student was considered retained. Spring semester enrollment was determined by 10th day class rosters. For this metric, students who transferred to another postsecondary institution or completed a certificate and did not return to SVCC, were counted as "retained." This determination was standard practice for calculating retention rates as it does not penalize a student nor the institution when students have completed their academic goal (some certificates require only the completion of three credits for example) or if the student transferred to another institution to continue their college degree.

Table 13: *Five College Success Variables (Dependent Variables) Examined in This Study*

DESCRIPTION OF METRIC	LEVEL OF MEASURE	UNITS
FGPA	Interval	0-4
Momentum	Ratio	0-19
Grade Points (FGPA*Momentum)	Ratio	0-76
Persistence	Interval	0-100%
Fall semester to spring semester retention	Nominal	Not retained=0 Retained=1

QUANTITATIVE RESEARCH DESIGN

These statistical analyses had two main goals. First, statistical tests were utilized to determine whether or not the means or medians (i.e., the “central tendency”) of several groups (e.g., males vs. females) were equal or significantly different. Second, regression analyses used predictor variables to create statistical models that forecast college success.

The central tendency of a dataset can be defined in a number of ways, but the two most common measures are the mean and median. The mean of a data set was calculated just as an average is normally calculated. A median was calculated by determining the middle data point of an ordered data set. Both are accepted ways of measuring central tendency (Stephens, 2004). Two statistical tests, ANOVA and Kruskal-Wallis, were used to determine if two or more mean or median values from two or more groups were statistically different from one another. ANOVA is the preferred statistical test as it is more robust than Kruskal-Wallis, but ANOVA can only be used when the data have met certain specifications (Stephens, 2004).

Predictive models were also created using linear regression techniques (e.g., Stepwise or Binary Logistic Regression). Linear regression is a statistical tool used to model a single dependent (“college success”) variable, like FGPA, against one or more independent (“predictor”) variables, like HSGPA or ACT composite scores. The technique creates a linear relationship between the dependent and independent variables and must be statistically significant ($p \leq 0.05$) in order to be relevant to this study. As seen in the simple hypothetical example below (Figure 3), it might be possible to use HSGPA (“the predictor” variable) as a way to forecast FGPA (“the college success” variable) using data collected from SVCC students. Based on the graph below, a student earning a 2.5 HSGPA would be expected to earn a 2.0 FGPA at SVCC.

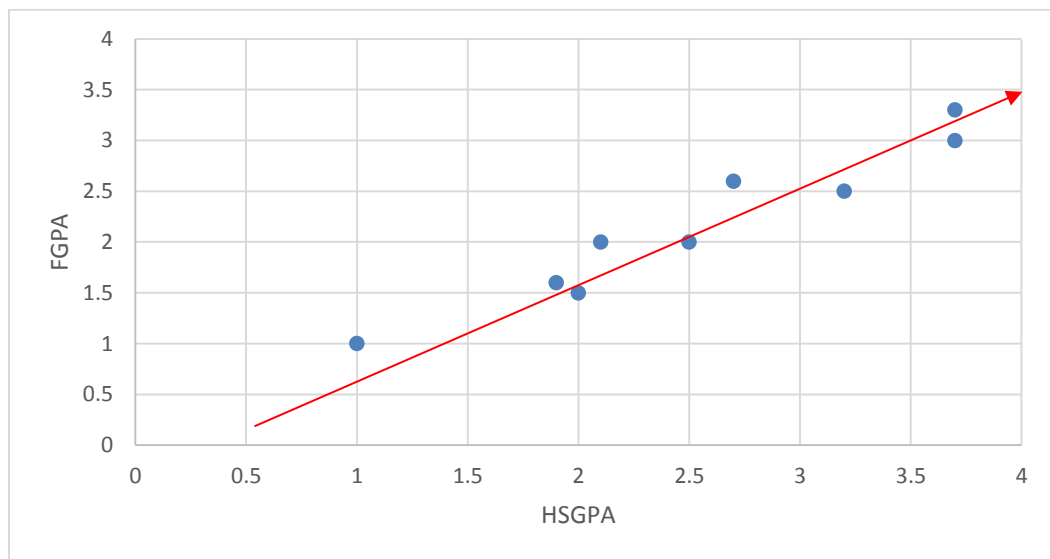


Figure 3. Hypothetical linear regression model showing the relationship between HSGPA and FGPA. (This relationship, when significant, can be used to predict FGPA for future SVCC students.)

IDENTIFYING DIFFERENCES IN CENTRAL TENDENCY

ANOVA and Kruskal-Wallis

There were statistical assumptions that had to be met in order to utilize ANOVA (Stephens, 2004), the preferred method of determining differences in central tendency.

In order to meet the assumptions of ANOVA, the following steps were conducted:

1. A Bartlett's test for equal variances was conducted on the all of the analyzed variables. For example, the Bartlett's test was conducted to determine if the variance of HSGPA for both males and females was equal. The variances of the variables were considered equal if the calculated probability (p) > 0.05 .
2. An Anderson-Darling normality test was conducted to determine if the variables were normally distributed. For example, the normality test was conducted on HSGPA on both males and females. The datasets were considered normally distributed if the calculated probability (p) > 0.01 .
3. If the variables were determined to have equal variances *and* if all of the variables were determined to have normal distributions, then an ANOVA statistical test was used to determine if there were any significant differences between the means of the variables. If $p \leq 0.05$, then some of the mean values of the variables were considered significantly different from one another. If $p > 0.05$, then the mean values of all of the variables were considered equal.
4. If the variables were determined not to have equal variances *or* if all of the variables were determined not to have normal distributions, then a Kruskal-

Wallis, a nonparametric statistical test, was used to determine if there were any significant differences between the median values of the variables. If $p \leq 0.05$, then some of the median values of the variables were considered significantly different from one another. If $p > 0.05$, then the median values were considered equal.

5. If a $p \leq 0.05$ was calculated for either the ANOVA or Kruskal-Wallis tests and only two groups were being compared (e.g., male HSPGA vs. female HSGPA), then it can be logically deduced that the two groups had different mean or median values. However, if two or more groups were being compared (e.g., HSGPA by race), then ANOVA or Kruskal-Wallis tests would only indicate that at least two of the groups had different mean or median values; some of the variables may have had the same mean or median as another group. This was a limitation of both of these statistical tests. Therefore, additional testing was required to determine which groups actually had different means or medians.
 - a. If an ANOVA test was used and if three or more variables were being compared, then a Tukey's test (at a 95% confidence) was utilized to determine which variables had different mean values.
 - b. If a Kruskal-Wallis test was used and if three or more variables were being compared, then a Sign test (at a 95% confidence) was used to determine which datasets had different median values.

Chi Square

The chi-square test was used to test whether there are significant differences between the expected frequencies and the observed frequencies of one or more categories (nominal data) (Rumsey, 2009). For example, chi square was used to determine if retention (categories of yes, no) distributions were significantly different between male and female students. If $p \leq 0.05$, then the chi-square test indicated that the actual distribution was not due to chance alone.

Regression Analysis

The complete dataset contained variables that were ratio, interval, and nominal level. Ratio and interval level variables can be easily utilized within a typical regression analysis. However, nominal variables must be recoded into interval data in order to be used. Gender, high school attended, race, and retention variables were all recoded into interval data (Table 14). Race and high school were recoded using dummy coding.

Table 14: *Five Nominal Variables Recoded Into Interval Data*

NOMINAL VARIABLE	RECODED AS A NUMERICAL VARIABLE
Gender	Male = 0 Female = 1
High school attended	Dummy coded into 0 and 1 where HS1 was the reference
Race	Dummy coded into 0 and 1 where "White" was the reference
College program declaration	0 = Career 1 = Transfer
Retention	0 = not retained 1 = retained

A regression analysis is a mathematical way to determine a linear relationship between two or more variables (Rumsey, 2009). The dependent variable is sometimes known as the response variable. For this study, the dependent variables were “college success” variables of FGPA, Momentum, Persistence, Grade Points, and Retention (Table 14). The independent variables are the inputs or possible predictors of the dependent variables. The independent variables in this study included student academic and demographic data (Table 15). To accommodate the five college success dependent variables, five separate regression analyses were conducted. All regression analyses were conducted using the statistical software SPSS.

Table 15: *All Independent Variables Used in Statistical Analyses With Number of Data Points for Each Variable*

INDEPENDENT VARIABLES (THE “COLLEGE SUCCESS PREDICTORS”)	INDEPENDENT VARIABLES SAMPLE SIZE (MISSING)	DEPENDENT VARIABLES (“COLLEGE SUCCESS VARIABLES”)	DEPENDENT VARIABLE SAMPLE SIZE (MISSING)
Gender	699 (0)	FGPA	681 (18)
Race	679 (20)	Momentum	699 (0)
High school attended	699 (0)	Grade Points	699 (0)
Total income	333 (364)	Persistence	699 (0)
College program declaration	699 (0)	Retention	699 (0)
Credits Enrolled	699		
HSGPA (unweighted)	680 (19)		
High school percentile	678 (21)		
Total number of math classes	682 (17)		
Total number of science classes	682 (17)		
Total number of weighted classes	676 (23)		
Total number of dual credit classes	699 (0)		
ACT composite score	675 (24)		
ACT reading score	677 (22)		
ACT English score	677 (22)		
ACT math score	677 (22)		
ACT science score	677 (22)		
Compass score: Reading	510 (189)		
Compass score: Writing	383 (316)		
Compass score: Algebra	236 (461)		
Compass score: College Algebra	74 (602)		

Note. The number in parentheses were the number of missing data points.

There are a number of assumptions that should be met when multiple linear regression statistical techniques are being used (Nau, 2015). If the assumptions are not

met, the predictions made by the equation formed from the model may not be as accurate. The assumptions are:

1. There should be at least five data points for each independent variable used in the multiple regression model. Twenty or more data points per independent variable is optimal. The largest statistical model that was conducted in this study contained 16 independent variables, and therefore, 320 observations were needed to create optimal statistical conditions. For this study, 637 students were used in the most complex models satisfying these conditions.
2. Normality of error distribution. An error is determined by taking the predicted value from the linear equation and subtracting the value of the actual data point. For example, if the predicted value is 1 and the actual value is 0, then the error is 1. These errors (called residuals) should be normally distributed. Some statisticians have indicated that a violation of this assumption weakens the predictive ability of the statistical model (Nau, 2015). However, Frost (2014) indicated that statistical studies conducted by Minitab, Inc. have indicated that regression “test results are reliable even when the residuals depart substantially from the normal distribution” (n.p.) as long as the sample size is greater than 15. While histograms of residuals indicate a distribution nearly normal, the sample size of all models conducted in this analysis were substantially larger than 15. This assumption was considered met.

3. The relationship of the expected value of dependent variable is a straight-line function of the independent variable. Evaluation of scatter plots of dependent and independent variables indicate that the relationship is generally linear.
4. Statistical independence of errors. This assumption was satisfied because all data points for the same variable were from separate students; there were no cases where the same student was used twice for the same variable.
5. Homoscedasticity (constant variance) of the errors. Following the methodology of Nau (2015), scatter plots of errors (residuals) versus predicted values were generated for each model. Residual distribution was evaluated to be uniform across predicted values indicating good evidence that homoscedasticity occurred in all models. This assumption was assumed to be met.

Once the assumptions of linear regression were determined to be met, a stepwise linear regression procedure was used to reduce the number of independent variables down to only the most significant predictors (Stephens, 2004). Stepwise techniques removed independent variables from the model one at a time if the independent variable's $p > 0.05$. This creates the most parsimonious model where only significant independent variables will remain.

It is important to be cautious when interpreting the results of a stepwise linear regression as the results may not be representative of reality. According to Nau (2015), the results of a stepwise regression may be *questionable* if:

1. The results are illogical. For example, as discussed in Chapter Two, HSGPA is likely to be the best predictors of college success. If HSGPA was not a significant predictor of college success in a model or if HSGPA actually lowered the predictive ability of the model instead of increasing it, then concern should be noted. However, as will be noted in Chapter Four, HSGPA was consistently the best or second best predictor of college success in all five models, thus alleviating this concern.
2. When more than one significant independent variable is added to the predictive model, the R^2 values decrease. Adding more than one independent variable to the model should always increase the predictive ability of the model (i.e., the R^2), not decrease it. In every model conducted for this project and when more than one independent variable was significant, the R^2 value increased. Therefore, this caveat was not a concern.
3. Rerunning a statistical model with only the significant variables gives dramatically different results than the original stepwise procedure when all of the predictor variables were used together. For example, if HSGPA, ACT composite scores, and gender were found to be the only significant predictors of FGPA when conducting a stepwise regression analysis with 13 other predictor variables, then HSGPA, ACT composite scores, and gender should remain statistically significant if the analysis was conducted again with only those three variables. When every model was rerun (where necessary)

using only significant independent variables, the results were always consistent with the original evaluation.

A multitude of data were collected from each regression analysis (see Table 16 for an example). Because more than one independent variable may predict a single dependent variable, multiple statistically significant models may be generated from a single data set. In the example provided in Table 16, there are two models presented including Model A and Model B. The variables were only included within the table if they were statistically significant with $p \leq 0.05$. Actual significance can be found under the column labeled Model *P*.

Table 16: *Example of Two Regression Models and Associated Statistics*

MODEL	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Model A							
Constant	-0.053	0.347	0.214	--	43.5	<0.001	1.0
HSGPA	0.824	0.125					
Model B							
Constant	-0.277	0.355	0.231	0.027	25.2	<0.001	--
HSGPA	0.755	0.127					0.948
Compass Writing	0.006	0.003					0.948

Note. This model explains FGPA using HSGPA and Compass Writing scores.

The R^2 value indicates the amount of statistical variance accounted for in each model. For example, Model A explained 0.214 or 21.4% of the variance found in FGPA. For Model B, an additional independent variable was added and found to be significant

(Compass Writing), but its inclusion only explained an additional 0.027 or 2.7% of the variance when it was included in a new model along with HSGPA. While Model B is more complex, it does not increase the predictive abilities of the model to any great degree.

It is possible for two or more independent variables to statistically interact which may negatively affect the statistical reliability of the model. A measure of this interaction is referred to as “tolerance” and is measured statistically to determine any adverse interactions (Table 16). Tolerance values 0.1 or less would be of a concern statistically (IDRE, 2015). If this occurs, then some of the independent variables may need to be dropped from the analysis to alleviate this concern. You will notice in Table 16 that tolerance values are 0.948 between HSGPA and Compass writing. There is no interaction between these two variables.

Linear regression also calculates the “best fitted” line for the data. Lines are constructed using this formula: $\text{Dependent Variable} = \text{Constant} + \text{Independent Variable} * \text{IV Coefficient}$. Using the information from Table 15, Model A, the formula to predict FGPA was $\text{FGPA} = -0.053 + 0.824 * \text{HSGPA}$.

When an additional significant independent variable is placed into the model (Like Model B, Table 16), then the formula would be created in the following manner: $\text{FGPA} = -0.277 + 0.755 * \text{HSGPA} + 0.006 * \text{Compass Writing Score}$. Notice the coefficients are likely to change with each new model. These equations can now, with an expected amount of error, be used to predict FGPA.

Binary logistic regression was used on the dependent variable Retention. Binary logistic regression analysis is a statistical technique used when the predictor variables

are a mix of categorical and continuous variables and the dependent variable is coded as a binary variable (e.g., yes, no or retained, not retained) (Wuensch, 2014). However, interpreting the results of a binary logistic regression analysis is quite different than a typical regression analysis. Following Wuensch (2014), an example will be used to illustrate the results of an analysis conducted for Chapter Four.

In the following example, Compass scores (algebra, writing, reading), HSGPA and the control variables high school attended, gender, race, and program of study were used to predict fall to spring retention (0 = not retained, 1 = retained) using a stepwise binary logistic regression. As shown in Table 17, the significant predictor variables were indicated. Significance was determined by a p value of 0.05 or lower. In this case, the significance value (p) for HSGPA was 0.002 and is much lower than the 0.05 threshold. All other predictor variables were found to be insignificant ($p > 0.05$) and were not shown in the results table. If an additional predictor variable was found to be significant, it would have been included as a “step 2.” This is very similar to the stepwise multiple linear regression analysis already described.

Table 17: *Example of an SPSS Output for Binary Logistic Regression That Shows Significance Values and Exp(B)*

		VARIABLES IN THE EQUATION					
		B	S.E.	WALD	df	SIG.	EXP(B)
Step 1 ^a	HSGPA	1.371	.433	10.021	1	.002	3.939
	Constant	-1.904	1.090	3.051	1	.081	.149

^a Variable(s) entered on step 1: HSGPA.

The Exp(B) statistic indicates the odds that an event will occur. To convert this to a probability, the following formula is utilized: $\text{Probability} = \text{Exp}(B) - 1.0 \times 100\%$. In this example, $3.939 - 1.0 \times 100\% = 293.9\%$. In other words, for each increase in one full unit of HSGPA, there is a 293.9% increase in the probability that a student will be retained. Students with 4.0 are much more likely to be retained than students with 1.0 HSGPAs.

The Cox & Snell R Square and Nagelkerke R Square can be interpreted as an R^2 in multiple regression (Table 18). For consistency, only Nagelkerke R Square is reported in Chapter Four. In this example, the Nagelkerke R square is only 0.112, which is rather low. This can be interpreted that only 11.2% of the variance in retention was predicted by HSGPA.

Table 18: *Example of an SPSS Output for Binary Logistic Regression That Shows the -2 Log Likelihood and R^2 Values*

STEP	-2 LOG LIKELIHOOD	COX & SNELL R SQUARE	NAGELKERKE R SQUARE
1	136.068	.066	.112

RELIABILITY AND VALIDITY

The reliability of the measures was of paramount concern in this study. First and foremost, the measure of any student's academic knowledge is always an inexact science. For example, one teacher may deem a student to earn an "A" grade while another teacher might think the same student earned a "B" grade in the same class. Therefore, the unreliability of the measure of academic knowledge will affect some predictor and college success variables including FGPA, HSGPA, high school percentile

and other measures associated with them. Also, students will have taken different high school and college classes. Therefore, FGPA and other measures of success from one student to another were not always reliable. Despite this limitation, a very large number of academic studies (see Chapter Two) have found correlations between these same predictor and college success variables that were studied in this project (see Chapter Two). Certainly this loss of reliability statistically interfered with explaining a large amount of variance in the data set.

It is not possible to address the reliability concerns mentioned above as students were taught by different teachers using different techniques while using different evaluation tools for assessment. However, in order to increase the reliability of the sample, only students who enrolled at SVCC during the fall semester following their spring high school graduation were utilized in this analysis and only the fall semester grades were used within the analysis. Lastly, some high schools used weighted GPAs and others used unweighted GPAs to calculate their final academic ranking for graduating students. It is not possible for the researcher to correct this discrepancy; however, the researcher believed that not using these data could be detrimental to the study, therefore, the researcher accepted the loss of reliability with the HSR variable.

The reliability of the Compass and ACT tests were not in question. ACT, Inc. regularly tested reliability coefficients and scores range from 0.85 – 0.92 on the subtests to 0.96 on the ACT composite score (Jones & Glockner, 2004). The Compass test exhibited somewhat lower values of reliability (0.73 – 0.90), but they were still

acceptable (Mellard & Anderson, 2007). Vogt (2007) indicated that only if reliability coefficients fall below 0.70 that data reliability may be of a concern.

This analysis included all available students to make the predictive model as robust as possible; a random sample was not used. External validity is therefore compromised and the analysis cannot be extrapolated to other college populations. However, this project was intentionally designed to focus on the students of SVCC and was not meant to be used to predict college success at any other community college and so the loss of external validity was accepted by the researcher.

The methods should help reduce internal validity effects. History and maturation validity effects were minimized by using only students who graduate from high school in the spring and then enroll at SVCC in the following fall semester. GED students were not used in this analysis. College success was only measured from data in that fall semester. This reduces history effects because as students advance through college, the cohort loses cohesion as some students drop out and new students enroll into that same cohort class (Vogt, 2007). Also, since the cohort was comprised of only recently graduated high school students, the analysis removed any confounding maturation effects of an older “nontraditional” group that may have behaved statistically different than recently graduated high school students. Previous research has shown that some predictive variables of college success attenuate with time away from high school (Mattern & Packman, 2009), but since all data are derived from students that are 17–18 years of age, this attenuation effect is negated.

SUMMARY

This study has examined academic and demographic data from recently graduated high school students. These students graduated high school in years 2011-2013 from five high schools found within the SVCC district and matriculated to SVCC during the following fall semester after their high school graduation.

The first section of this study examined how different demographic groups performed academically at SVCC. For example, do females outperform males at the college? Do White students have a better chance at succeeding in college compared to other racial categories? Will students that have more dual credit or more weighted high school classes attain higher grades when they matriculate to SVCC?

The second section of this study used linear regression techniques to develop predictive models that can be used to forecast college success for future SVCC students. It is hoped that this modeling can be used by academic advisors to make data-driven decisions when enrolling new students into college classes or that it can be used by college staff to predict which students need remediation before they ever step foot on campus.

The very large sample size of 699 students has allowed for a robust statistical analysis to be generated. These students represented five high schools, five racial groups, and two genders. Two programs of study were also examined including the transfer student and the career-technical student.

CHAPTER FOUR: RESULTS

INTRODUCTION

These results are divided into three distinctive sections. The first section is used to compare the means or medians of academic preparedness data and college success data by groups (gender, high school, etc.). Section 2 displays the results of the five regression models, one for each college success variable mentioned within the methodology. Section 3 uses the linear regression formulas generated in section 2 as a way to predict future success of students at SVCC.

SECTION 1: ANALYSIS OF CENTRAL TENDENCY

Presented throughout section 1 are both mean and median values for all demographic groups where ANOVA or Kruskal-Wallis were utilized. It is important to realize that the mean and median values may be dramatically different even though they both represent the “central tendency” of a variable for a certain population. For example, as discussed in this section, the mean, or average, number of weighted classes per student in this population is 2.3. However, the median number of weighted classes is zero; in other words, the typical student completed zero weighted classes. Having both the mean and median values gives the reader a better understanding of the central tendency of the population.

Additionally, some statistical values were presented to give a fuller explanation of the results of statistical tests. For Kruskal-Wallis, ANOVA and chi-square tests, the p value and relevant test values were presented for each test. In the case of Kruskal-Wallis and ANOVA, the p value indicated the probability that the mean/median values of groups were the same. For example, if $p = 0.01$, then there is only a 1% chance that the mean/median values of the groups were the same. The H (Kruskal-Wallis), F (ANOVA) and Chi Square statistics are the outcomes of the statistical calculations. H , F , and chi-square values are used to produce the p values; larger H , F , and chi-square values will result in smaller p values, which indicate a higher probability of significant differences between the groupings.

This data set contains 699 recently graduated high school students who attended Sauk Valley Community College the first fall semester after their high school graduation. Student data were analyzed from three distinct high school graduation years including 2011, 2012, and 2013. Each year accounts for approximately one-third of the students analyzed in this data set (Table 19). Five high schools were represented in the population with the largest high school accounting for 31.6% of the sample and the smallest high school accounting for just 7.7% of the sample. These were the five largest feeder high schools for SVCC.

Table 19: *Number and Percentage of Students Representing Each High School by Year of Graduation*

	2011	2012	2013	TOTALS
High School #1	64 30.6%	75 35.9%	70 33.5%	209 29.9%
High School #2	12 21.8%	24 43.6%	19 34.5%	55 7.9%
High School #3	19 35.2%	22 40.7%	13 24.1%	54 7.7%
High School #4	52 32.1%	47 29.6%	61 38.4%	160 22.9%
High School #5	68 30.8%	82 37.1%	71 32.1%	221 31.6%
Totals	215 30.7%	250 35.8%	234 33.5%	699 100%

Community colleges are committed to open access and allow most applicants to enroll despite any academic deficiencies the students may have. SVCC is no different. Any students that have high school degrees or the equivalent can enroll at the college in a degree seeking program or certificate; therefore, there is wide dispersion in students' academic ability (Table 20). The study population has, on average, a B- HSGPA and below average ACT composite scores. Further, the average high school percentile is ordinary at 56% indicating the typical SVCC student is an average high school academic achiever.

Table 20: *Academic Preparedness Descriptive Statistics for 699 Students Represented in This Study*

	HSGPA	HS PERCENTILE	ACT COMPOSITE	NUMBER OF DC CLASSES	NUMBER OF WT. CLASSES	NUMBER OF SCIENCE CLASSES	NUMBER OF MATH CLASSES
Minimum	1.26	3%	10.0	0	0	0	0
Mean	2.90	56.0%	20.3	1.8	2.3	2.3	2.8
Median	2.93	57.5%	20.0	1.0	0.0	2.0	3.0
Maximum	4.0	100.0%	33.0	13	22	5.5	6.0

A closer look at ACT scores revealed that the mean and median scores for the composite, English, math, reading, and science were all very similar with an average of approximately 20 (Table 21). The maximum student scores approached or equaled 36 (the best score possible) for a few students; however, some students also attained single digit scores on some sections.

Table 21: *ACT Descriptive Statistics for 699 Students Represented in This Sample*

	ACT ENGLISH SCORE	ACT MATH SCORE	ACT READING SCORE	ACT SCIENCE SCORE	ACT COMPOSITE SCORE
Maximum	35	34	36	35	33
Mean	20.0	20.2	20.3	20.0	20.3
Median	20.0	20.0	20.0	20.0	20.0
Minimum	6	12	8	9	10

The typical student enrolled in 13.7 credit hours during their first fall semester at SVCC. However, there was considerable variance in the number of credits enrolled. Some students enrolled in as few as three credits while one student enrolled in 19 credit

hours (see Figure 4). As stated in Chapter Three, any student who enrolled in just one or two credits were removed from this analysis.

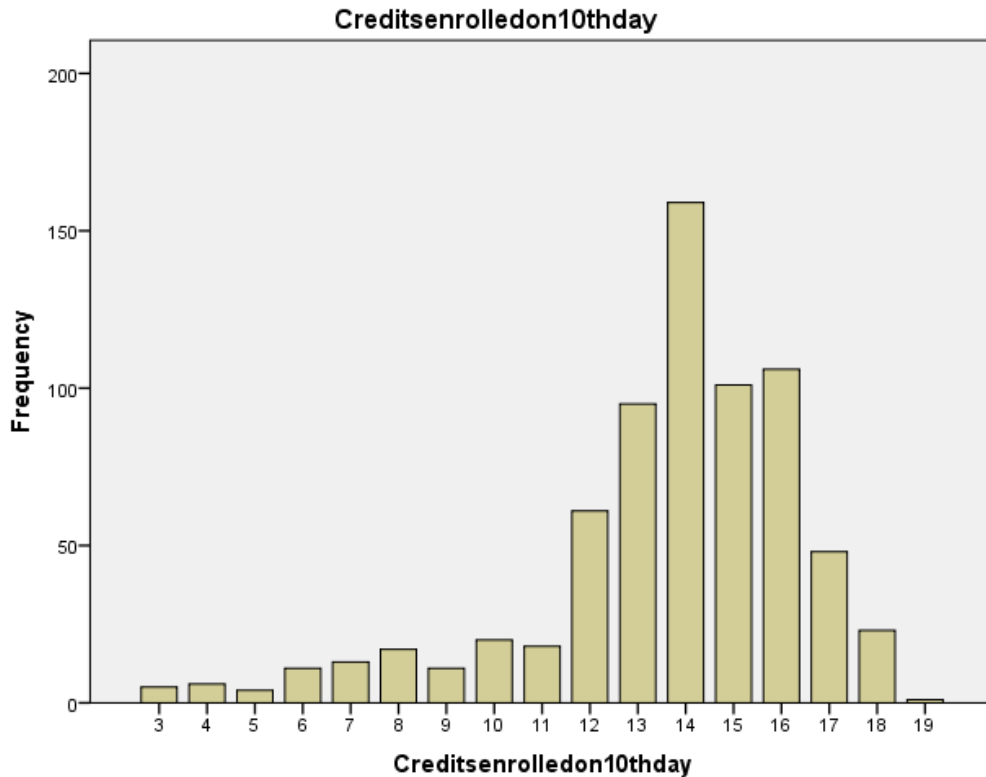


Figure 4. Histogram of the number of credits students enrolled in during the fall semester.

These same students averaged a C to C+ GPA during their first semester at SVCC averaging about 0.51 grade points less on FGPA than their HSGPA (Table 22). Students typically earned 10.2 credit hours their first college semester, which is considered less than fulltime (12 credits). Students failed or withdrew from 25.8% of the class credits which helps explain the low momentum rate (Table 22). However, these same students generally returned to Sauk the very next semester with an impressive 83.8% of the students returning.

Table 22: *College Success Descriptive Statistics for 699 Students Within the Sample*

	FGPA	MOMENTUM	PERSISTENCE RATE (%)	GRADE POINTS	SPRING SEMESTER RETENTION RATE (%)
Maximum	4.0	19.0	100.0%	72.0	n/a
Mean	2.39	10.2	74.2%	27.8	83.8%
Median	2.50	11.0	90.9%	28.9	n/a
Minimum	0.00	0.0	0.0%	0.0	n/a

Analysis of Central Tendency by High School

The data analyzed in this study were not normally distributed; therefore, most of the group comparisons required the use of the Kruskal-Wallis test. If the data were parametric and the data sets had equal variances, ANOVA tests were used instead. In order to be concise, not all statistical information is presented directly in this results section; however, additional information on all statistical tests can be found in Appendix B.

Academic Preparedness

The analysis indicated that students from some high schools were better prepared academically than students from other high schools (Table 23). For example, Kruskal-Wallis tests found significant differences in the number of dual credit ($p < 0.001$; $H = 23.92$), weighted ($p < 0.001$, $H = 48.67$), science ($p < 0.001$; $H = 48.67$), and math ($p < 0.001$; $H = 27.95$) classes that students completed at the different high schools. Statistical testing (Sign tests at 95% confidence) indicated that HS1 and HS2 produced students with less weighted course experience than the other three high schools. HS2

and HS3 were producing students with less dual credit classes passed than the other schools. HS4 produced students with the fewest science classes while HS3 produced students with the fewest math classes.

Table 23: Mean or Median Academic Preparedness Values by High School

	MEAN & MEDIAN HSGPA	MEAN & MEDIAN HS PERCENTILE ^a	MEAN & MEDIAN ACT COMPOSITE	MEAN & MEDIAN NUMBER OF DUAL CREDIT CLASSES ^a	MEAN & MEDIAN NUMBER OF WEIGHTED CLASSES ^a	MEAN & MEDIAN NUMBER OF SCIENCE CLASSES ^a	MEAN & MEDIAN NUMBER OF MATH CLASSES ^a
HS 1	2.82 2.84	57.4% 60.0%	20.6 21.0	1.8 1.0	0.6 0.0	2.5 2.5	2.7 3.0
HS 2	3.00 3.1	52.0% 52.0%	20.0 20.0	1.1 0.0	0.4 0.0	2.8 3.0	2.5 2.5
HS 3	2.97 3.00	38.3% 32.5%	20.8 20.8	1.1 0.0	4.3 4.0	2.5 2.6	2.5 2.2
HS 4	2.92 2.95	65.0% 67.3%	19.9 20.0	1.7 1.0	4.0 1.0	2.0 2.0	2.7 3.0
HS 5	2.91 2.94	53.7% 53.4%	20.1 20.0	2.3 1.0	2.5 0.0	2.0 2.2	3.5 3.1

^a Significant differences in median values between high schools ($p \leq 0.05$) using Kruskal-Wallis. Sign Tests were used to confirm which high schools were significantly different from one another.

The analysis also confirmed that students from some high schools may be more academically underprepared than other high schools due to significantly lower high school percentiles. A Kruskal-Wallis test found a statistically significant difference between high school percentiles ($p < 0.001$, $H = 48.5$). Students from HS3 averaged only the 33rd percentile in their high school graduation class and were ranked significantly lower than students from the other high schools.

Not all academic preparedness variables were significantly different. The HSGPA between high schools only varied by 0.08 points and an ANOVA confirmed that no difference existed between HSGPAs ($p = 0.21$, $F = 1.47$). The average ACT composite scores between students of the five high schools also did not significantly differ (ANOVA, $p = 0.14$, $F = 2.19$).

Enrollment Data

There were no significant difference in the number of credit hours enrolled by high school (ANOVA: $p = 0.122$, $F = 1.83$). There was only a 0.9 credit hour difference between the high schools with the highest average credit hour enrollment and with the lowest average credit hour enrollment.

College Success

All five college success variables were analyzed to determine if some high schools were producing more successful students at SVCC than other high schools (Table 24). FGPA ($p = 0.019$, $H=11.7$), grade points ($p = 0.017$, $H=11.99$) and retention rates ($p = 0.007$, Chi-square value = 14.1) were all significantly different between high schools. HS3 had students with the lowest median FGPA (2.31) while HS2 had students with the highest median FGPA (2.78). HS1 has the highest median number of grade points at 33.0 units while HS4 and HS5 students had the lowest median values. There was also a dramatic difference in retention rates. Students from HS3 were retained at a 92.6% retention rate while HS4 students were only retained at a 75.5% rate.

Not all college success variables were significantly different between high schools. Kruskal-Wallis tests found no significant differences between the median values for momentum ($p = 0.138$, $H = 6.97$) and persistence rate ($p = 0.233$, $H = 5.57$) by high school. Therefore students from each high school were accumulating about the same number of credits at the end of their first semester at SVCC (approximately 10–12 credit hours).

Table 24: Mean or Median College Success Values by High School

	MEAN & MEDIAN FGPA*	MEAN & MEDIAN MOMENTUM	MEAN & MEDIAN PERSISTENCE RATE (%)	MEAN & MEDIAN GRADE POINTS ^a	SPRING SEMESTER RETENTION RATE (%) ^b
HS 1	2.53 2.66	10.8 12.0	77.1% 100.0%	30.6 33.0	85.2%
HS 2	2.59 2.78	10.7 11.0	77.2% 100.0%	31.4 30.0	80.0%
HS 3	2.20 2.31	10.3 12.0	71.3% 88.1%	26.5 27.5	92.6%
HS 4	2.29 2.50	9.3 10.0	68.3% 76.9%	25.0 24.9	75.5%
HS 5	2.33 2.38	10.2 11.0	75.5% 81.3%	26.3 25.9	87.3%

^a Significant differences in median values between high schools ($p \leq 0.05$) using Kruskal-Wallis. Sign Tests were used to confirm which high schools were significantly different from one another.

^b Significant differences in mean values between high schools ($p \leq 0.05$) using chi square.

The high school attended seems to play a role in both academic preparation for college and for college success at SVCC. The high school variable will be controlled for in the multiple linear regression model in section 2.

Analysis of Central Tendency by Gender

Academic Preparedness

Females made up a significant proportion of the students in this study. In total, 412 students were female (58.9%) and only 287 (41.1%) were male.

Kruskal-Wallis tests indicated that females entered SVCC better prepared than males (Table 25). First, females had a higher HSGPA than males, outpacing males by 0.16 units ($p = 0.001$, $H = 11.52$). Second, females had a higher high school percentile ($p < 0.001$, $H = 10.6$). Third, females often came to SVCC armed with more dual credit ($p < 0.001$; $H = 59.04$) and weighted ($p < 0.03$, $H = 4.7$) classes earned in high school.

Not all of the academic preparedness data supported the contention that females were better prepared academically. Males and females had similar ACT composite scores ($p = 0.296$, $H = 1.09$) and a similar number of science ($p = 0.074$, $H = 3.18$) and math classes ($p = 0.204$, $H = 1.62$).

Table 25: *Academic Preparedness Mean and Median Values by Gender*

	MEAN & MEDIAN HSGPA ^a	MEAN & MEDIAN HS PERCENTILE ^a	MEAN & MEDIAN ACT COMPOSITE	MEAN & MEDIAN NUMBER OF DUAL CREDIT CLASSES ^a	MEAN & MEDIAN NUMBER OF WEIGHTED CLASSES ^a	MEAN & MEDIAN NUMBER OF SCIENCE CLASSES	MEAN & MEDIAN NUMBER OF MATH CLASSES
Female	2.96 2.98	58.5% 61.9%	20.1 20.0	2.3 2.0	2.6 0.0	2.4 2.3	2.9 3.0
Male	2.81 2.82	52.4% 50.7%	20.5 20.0	1.1 0.0	1.9 0.0	2.2 2.0	2.7 3.0

^a Significant differences in mean values between genders ($p \leq 0.05$) using Kruskal-Wallis.

Enrollment Data

There was no significant differences between the numbers of credit hours a male or female student enrolled in during their first fall semester at SVCC (ANOVA, $p = 0.495$, $F = 0.465$). Males enrolled in 13.7 credit hours on average while females enrolled in 13.5 credit hours.

College Success

While females were coming to SVCC better prepared academically (at least by the measures of this study), females surprisingly only outperformed males in one of five college success variables (Table 26). Kruskal-Wallis tests indicated that females have a slight, but significant advantage in FGPA ($p = 0.038$, $H = 3.18$). However, other college success variables were not significantly different (Momentum, $p = 0.153$, $H = 2.04$; Persistence, $p = 0.107$, $H = 2.6$; GPA \times Momentum, $p = 0.052$, $H = 3.79$, and retention rates ($p = 0.17$, Pearson chi-Square value = 1.9) even though female mean and median scores were higher in every category.

Table 26: *College Success Mean and Median Values by Gender*

	MEAN & MEDIAN FGPA ^a	MEAN & MEDIAN MOMENTUM	MEAN & MEDIAN PERSISTENCE RATE (%)	MEAN & MEDIAN GRADE POINTS	SPRING SEMESTER RETENTION RATE (%)
Female	2.46 2.61	10.5 12.0	76.1% 100.0%	28.8 30.0	85.4%
Male	2.29 2.38	9.9 11.0	71.3% 80.0%	26.1 25.0	81.5%

^a Significant differences in mean values between genders ($p \leq 0.05$) using Kruskal-Wallis.

Analysis of Central Tendency by Race

Academic Preparedness

SVCC collected racial/ethnicity data on its students. SVCC uses six racial types for its data base: White (W), Black (B), Hispanic (H), Asian (A), Native American (NA), and Unknown (U). White students make up the majority of the student population accounting for 580 of 683 students (of known racial classifications) or 84.9% of the student population (Table 27).

Table 27: *Number and Percentage of Students of Different Racial Classifications*

	NUMBER OF STUDENTS	PERCENTAGE OF STUDENTS
Asian	4	0.6%
Black	23	3.4%
Hispanic	73	10.7%
Native American	3	0.4%
White	580	84.9%
Unknown	16	n/a

Since Asian and Native American students accounted for 1% of the study population combined (or 7 students), those data were also not analyzed as part of this section. The unknown race category (16 students) was not relevant and was also not analyzed in this section.

White students significantly outperformed minority students in nearly every academic preparedness indicator examined (Table 28). White students had significantly higher HSGPAs ($p < 0.001$, $H = 19.78$), HS percentiles ($p < 0.001$, $H = 20.49$), and ACT composite scores ($p < 0.001$, $H = 26.71$) than both Black and Hispanic students. White

students were more likely to accumulate more dual credit classes than Black and Hispanic students ($p = 0.008$, $H = 9.77$). White students were also more likely to accumulate more science ($p < 0.001$, $H = 25.99$) and math ($p = 0.007$, $H = 9.84$) classes than Hispanic students, but not Black students. Black and Hispanic students did not significantly differ in any academic preparedness measurements listed above. White, Black, and Hispanic students accumulated the same number of weighted classes ($p = 0.136$; $H = 3.99$).

Table 28: *Academic Preparedness Mean and Median Values by Race*

	MEAN & MEDIAN HSGPA*	MEAN & MEDIAN HS PERCENTILE*	MEAN & MEDIAN ACT COMPOSITE SCORE ^a	MEAN & MEDIAN NUMBER OF DUAL CREDIT CLASSES ^a	MEAN & MEDIAN NUMBER OF WEIGHTED CLASSES	MEAN & MEDIAN NUMBER OF SCIENCE CLASSES ^a	MEAN & MEDIAN NUMBER OF MATH CLASSES ^a
Black	2.71 2.65	46.7% 47.4%	18.5 18.0	0.8 0.0	0.7 0.0	1.9 2.0	2.8 3.0
Hispanic	2.63 2.64	44.9% 44.2%	18.1 18.0	1.6 0.0	1.9 0.0	1.6 1.5	2.4 2.5
White	2.94 2.97	57.8% 60.4%	20.5 20.0	1.9 1.0	2.4 0.0	2.4 2.0	2.9 3.0

^a Significant differences in median values between racial classifications ($p \leq 0.05$) using Kruskal-Wallis. Sign Tests were used to confirm which racial classifications were significantly different from one another.

Enrollment Data

There was no significant difference in the number of credits White, Black, and Hispanic students enrolled in during their first fall semester at SVCC (ANOVA, $p = 0.284$, $F = 1.26$). On average, Black students enrolled in 14.5 credit hours, White students in 13.6 credit hours, and Hispanic students in 13.4 credit hours.

College Success

There was a significant difference in high school academic preparation between racial groups who attended SVCC; therefore, it is not surprising that there were some significant differences in academic success at SVCC as well (Table 29). Kruskal-Wallis tests showed significant differences in two of the five college success variables including FGPA's ($p < 0.001$; $H = 17.5$) and grade points accumulated ($p = 0.003$; $H = 11.8$). White students outperformed both Hispanic and Black students in these categories, but there were no significant differences between Hispanic and Black students in these same categories. Momentum ($p = 0.095$, $H = 4.7$), persistence rates ($p = 0.176$; $F = 3.5$), and retention rates ($p = 0.86$, chi-square value = 0.293) were not significantly different among racial groups.

Table 29: College Success Mean and Median Values by Race

	MEAN & MEDIAN FGPA ^a	MEAN & MEDIAN MOMENTUM	MEAN & MEDIAN PERSISTENCE RATE (%)	MEAN & MEDIAN GRADE POINTS ^a	SPRING SEMESTER RETENTION RATE (%)
Black	1.95 2.00	9.6 10.0	66.5% 78.6%	23.4 22.0	87.0%
Hispanic	2.02 2.00	8.9 10.0	66.4% 73.3%	21.5 18.4	82.2%
White	2.45 2.61	10.4 12.0	75.3% 93.5%	28.6 30.0	83.6%

^a Significant differences in median values between racial classifications ($p \leq 0.05$) using Kruskal-Wallis. Sign Tests were used to confirm which racial classifications were significantly different from one another.

Racial classification seems to play a role in both academic preparation for college and for college success at SVCC. The racial classification variable will be controlled for in the multiple linear regression model in section 2.

Analysis of Central Tendency by Program Declaration

Academic Preparedness

SVCC has allowed students to categorize themselves into two academic groups when they registered for classes. One academic classification is the “transfer” student. These students were, when they registered, interested in attaining an associate degree (A.A. or A.S. degrees) that would transfer to a four-year institution. The other students classified themselves as “career-technical education” (CTE) students who were interested in attaining a terminal certificate or associate degree (A.A.S.) that translated quickly into employment opportunities.

Transfer students were academically better prepared for college than CTE students according to this analysis (Table 30). Transfer students had higher HSGPA ($p < 0.001$; $H = 14.27$), higher HS percentiles ($p = 0.011$; $H = 6.54$), higher ACT composite scores ($p < 0.001$; $H = 22.62$), more science ($p < 0.001$; $H = 13.95$) more math ($p < 0.001$; $H = 19.04$), and more weighted classes ($p < 0.001$; $H = 15.61$) than CTE students.

Conversely, CTE students completed significantly more dual credit courses (approximately 2.2) than transfer students (approximately 1.7) ($p = 0.041$, $H = 4.19$).

Table 30: Academic Preparedness Mean and Median Values by Program of Study

	MEAN & MEDIAN HSGPA ^a	MEAN & MEDIAN HS PERCENTILE ^a	MEAN & MEDIAN ACT COMPOSITE ^a	MEAN & MEDIAN NUMBER OF DUAL CREDIT CLASSES ^a	MEAN & MEDIAN NUMBER OF WEIGHTED CLASSES ^a	MEAN & MEDIAN NUMBER OF SCIENCE CLASSES ^a	MEAN & MEDIAN NUMBER OF MATH CLASSES ^a
CTE	2.76	51.9%	18.8	2.2	1.4	2.0	2.4
	2.66	47.8%	19.0	1.0	0.0	2.0	2.5
Transfer	2.95	57.4%	20.7	1.7	2.6	2.4	2.9
	2.97	59.4%	21.0	1.0	0.0	2.5	3.0

^a Significant differences in median values between program declarations ($p \leq 0.05$) using Kruskal-Wallis.

Enrollment Data

Significant differences in the mean number of credit hours enrolled in by CTE and transfer students was found ($p < 0.001$, $F = 56.9$). Transfer students enrolled in an average of 14.1 credit hours will CTE students enrolled in 12.3 credit hours.

College Success

It would be expected, based on high school academic performance alone, that transfer students should outperform career-technical students in their first semester at SVCC. However, this analysis indicated mixed results supporting that particular hypothesis (Table 31). For example, transfer students had significantly higher momentum ($p < 0.001$, $H = 15.96$), grade points ($p = 0.004$, $H = 8.46$), and retention rates ($p = 0.004$, chi-square = 8.3). However, FGPA ($p = 0.857$, $H = 0.03$) and class persistence rates ($p = 0.993$, $H = 0.00$) were not significantly different.

Table 31: College Success Mean and Median Values by Program of Study

	MEAN & MEDIAN FGPA	MEAN & MEDIAN MOMENTUM ^a	MEAN & MEDIAN PERSISTENCE RATE (%)	MEAN & MEDIAN GRADE POINTS ^a	SPRING SEMESTER RETENTION RATE (%) ^b
CTE	2.40 2.50	9.1 10.0	73.6% 100.0%	24.2 24.0	77.3%
Transfer	2.38 2.53	10.6 12.0	74.3% 82.4%	28.9 30.7	86.1%

^a Significant differences in median values between program declarations ($p \leq 0.05$) using Kruskal-Wallis.

^b Significant differences in retention rates between program declarations ($p \leq 0.05$) using chi square.

Academic classification seems to play a role in both academic preparation for college and for college success at SVCC. The academic classification variable will be controlled for in the multiple linear regression model in section 2.

Analysis of Central Tendency by FAFSA Completion

An analysis was also conducted on the academic preparedness and the fall semester academic outcomes for those students who had completed their FAFSA compared to those students that did not complete their FAFSA. Statistical analyses like the ones conducted above indicated that there were no significant differences in any of the variables analyzed ($p > 0.19$). Therefore, those two groups of students have statistically similar median values for all measured variables.

SECTION 2. REGRESSION ANALYSIS: CAN COLLEGE SUCCESS BE PREDICTED?

Introduction

College success was defined in five manners for this research project and included FGPA, persistence, momentum, grade points, and retention. There were 20 independent variables, but the sample size for all of these variables was not uniform and some independent variables had very small sample sizes. For example, the Compass scores for college algebra consisted of only 74 students. However, sample sizes for most of the other predictor variables approached the maximum of 699.

When using the stepwise regression analysis, if all 21 independent variables were included within a single model to determine which variables were the most important predictors, then this single statistical model would have included data from only 15 students because only 15 students would have had a data point for all 20 variables. This is an unacceptable loss of statistical power (Rumsey, 2009) and would have included only 2.1% of the students found in this study. Therefore, multiple models were conducted for the same college success variable (dependent variable) and careful thought was placed into making appropriate comparative selections (see hypothesis testing below). The author recognizes that there are multiple ways in which this analysis could have been conducted, but the aim of this methodology was to maximize the student sample size, and therefore, maximize statistical power when finding the most important predictor variable(s) of college success.

Hypothesis Testing

In total, there were 21 independent variables and five college success variables. Multiple linear regression techniques were used to determine which predictor variables would best predict: FGPA (Model 1), Momentum (Model 2), Persistence (Model 3), Grade Points (Model 4), and Retention (Model 5). For Models 1-4 a stepwise multiple linear regression technique was used to determine the most parsimonious predictive model. For Model 5, a stepwise binary logistic regression analysis was used to determine the best predictive model for fall semester to spring semester retention. For each of the five models, three hypotheses were tested.

- Hypothesis A: HSGPA is a better predictor of college success than Compass scores.
- Hypothesis B: HSGPA is a better predictor of college success than Total Income.
- Hypothesis C: HSGPA is the best predictor of all the remaining predictor variables.

Hypothesis A: HSGPA Is a Better Predictor of College Success Than Compass Scores

The Compass test is a high stakes placement device used by SVCC as a way to determine if students should be allowed to enroll in college-level English and math courses. At SVCC, for this student population being studied, students were only required to take the Compass test if they did not meet the ACT “cut scores” or did not complete their high school prerequisite courses. For example, in order for high school students to enter college-level English courses they must have earned an ACT English score of 21 or

higher. Otherwise, the student was required to complete the Compass test to determine their correct English class placement; most students who failed to meet the ACT cut score were placed within remedial English classes because the Compass test validated the ACT result (SVCC internal data). For math placement, if students did not earn an ACT math score of 23 or higher or did not complete the required prerequisite high school courses, they were also required to complete the Compass test in order to determine class placement for math. Therefore, the Compass test is strongly affiliated with either developmental students or with students that are on the cusp of being declared a developmental student. This “Compass required” subset of the student population is therefore not even truly representative of the entire studied population.

Previous research has shown a relationship with Compass scores and college success variables (Belfield & Crosta, 2012). However, Compass scores are rarely the most important predictor of college success, especially if HSGPA is also being utilized in a predictor variable (Belfield & Crosta, 2012). Additionally, correlation tables indicate a significant relationship between Compass scores and many other variables within this study (Appendix C, Table C-1), and therefore, it’s possible that other predictor variables are better predictors of college success.

In order to determine if Compass scores were significantly related to the five college success variables, five multiple regression models were generated that included HSGPA, Compass reading, Compass writing, and Compass algebra predictor variables. Compass college algebra was dropped from the analysis due to a very small sample size because including it would have dramatically reduced the statistical power of this

model. HSGPA was included within this model because the educational literature strongly suggests that HSGPA will likely be the most important predictor variable of college success and Compass scores will become irrelevant (see Chapter Two). Race, gender, program declaration, and high school attended were used as controls in each model. It was hypothesized that HSGPA would be the most significant predictor of college success in each of the five statistical models and Compass scores will be insignificant or unimportant.

Hypothesis B: HSGPA Is a Better Predictor of College Success Than Total Income

Total student income was not available for each student. In total only 333 students (less than half of the student population) completed their FAFSA forms which was the source of information for this “income” variable. Some researchers have found that income may be a predictor of high school rank/GPA or scores on achievement tests, and hence, may be connected to college success as well (Crouse & Trusheim, 1988). However, a significant number of studies indicate that HSGPA is the most important predictor of college success (see Chapter Two). Certainly some correlation exists between HSGPA, Total Income, and the five college success variables (Appendix C, Table C-2).

In order to determine if Total Income was significantly related to the five college success variables, five multiple regression models (one for each college success variable) were generated that included HSGPA and Total Income. Race, gender, program declaration, and high school attended were used as control variables. It is hypothesized

that HSGPA will be the most significant predictor of all five college success variables and Total Income will become insignificant to the predictive models.

Hypothesis C: HSGPA Is the Best Predictor of All the Remaining Predictor Variables

Certainly there is strong evidence to suggest that HSGPA would be the most significant predictor of college success in this study; however, a number of other studies have indicated that high school rigor, ACT scores, and other academic variables were also important in predicting college success (see Chapter Two). Significant correlations exist between some of these predictor variables (Appendix C, Table C-3). Model C was used to determine which of the remaining predictor variables, including HSGPA, were the most important in predicting college success. It is hypothesized that HSGPA will be the most significant predictor of college success for all five models.

Note that during the following sections, it is possible that the same predictor variable, like HSGPA, was the most significant predictor for hypothesis A, hypothesis B, and hypothesis C. However, since each hypothesis is examining a particular subset of the 699 students and not the entire student population, the calculated R^2 values were different from one another.

There was amazing consistency in the results for all five models and for each of the three hypotheses within each model. For hypotheses A and B, Compass scores and Total Income were either statistically insignificant or the variables were found to supply little additional variance to the predictive equations; therefore, Compass scores and Total Income were dropped from the overall analysis (hypothesis C) for all five models. See below for complete details.

Model 1: Using Stepwise Regression as a Way to Predict FGPA

Model 1A. Using Compass Scores and HSGPA to Predict FGPA

As discussed above, Compass algebra, Compass reading, Compass writing and HSGPA were used in a linear regression model to predict FGPA. Race, gender, program declaration, and high school were used as controls in the model. The calculations of the stepwise regression model (1A) indicated that HSGPA was the most robust predictor of FGPA and accounted for 21.4% of the variance (Table 32). Compass writing was another variable that also contributed to the prediction of FGPA, but it only accounted for 2.7% additional variance to this model. Compass reading and algebra were not found to be significant predictors of FGPA.

Table 32: *Model 1A – Significant Predictors of FGPA and Related Regression Statistics*

MODEL 1A	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-0.053	0.347	0.214	--	43.5	<0.001	1.0
HSGPA	0.824	0.125					
Constant	-0.277	0.355	0.231	0.027	25.2	<0.001	--
HSGPA	0.755	0.127					0.948
Compass Writing	0.006	0.003					0.948

Note. Sample size was 169 students.

In trying to determine the most important factors for predicting FGPA, Compass scores were not considered important enough to remain in the overall predictive model for FGPA (see 1C below), because (1) Compass scores were not taken by all of the

student population leading to a very low sample size; (2) Compass scores were taken only by students that are either in need of academic remediation or on the cusp of needing remediation, therefore, Compass scores do not represent the entire population; and (3) when included with HSGPA, the three Compass scores were either not statistically significant or only contributed a minuscule amount to the predicted variance of the overall model.

Model 1B. Using Total Income and HSGPA to Predict FGPA

A regression analysis was utilized where HSGPA and Total Income were used to predict FGPA. Race, gender, program declaration, and high school were used as controls in the model. These calculations for this regression analysis indicated that total income was not a viable factor for predicting FGPA (Table 33), leaving HSGPA as the only predictor remaining in this model. Since total income was not collected for every student, it could be suggested that this analysis is biased toward FAFSA completers and is not indicative of the entire student population. While this may be true, a previous analysis (see above) on FAFSA completers and non-completers indicated no significant difference in any predictor or college success variable. In this regression model, Total Income was statistically insignificant when paired with HSGPA, and was therefore, not considered important enough to remain in the overall predictive model of FGPA.

Table 33: *Model 1B – Significant Predictors of FGPA and Related Regression Statistics*

MODEL 1B	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-0.113	0.234	0.286	--	127.0	<0.001	1.0
HSGPA	0.886	0.079					

Note. Sample size was 319 students.

Model 1C. Predicting FGPA Using the Remaining Fifteen Predictor Variables

The sample sizes of the remaining 16 predictor variables were substantial. Therefore all of the remaining variables (Table 34) were included in Model 1C to determine which variables, if any, were significantly related to FGPA. Stepwise linear regression was used to make this determination.

Table 34: *Remaining Predictor Variables and Related Sample Size Used in Model 1C*

INDEPENDENT VARIABLES (THE "COLLEGE SUCCESS PREDICTORS")	INDEPENDENT VARIABLES SAMPLE SIZE
Gender	699
Race	679
High school attended	699
College program declaration	699
Credits enrolled	699
HSGPA	680
High school percentile	678
Total number of math classes	682
Total number of science classes	682
Total number of weighted classes	676
Total number of dual credit classes	699
ACT composite score	675
ACT reading score	677
ACT English score	677
ACT math score	677
ACT science score	677

According to the calculations of this stepwise regression analysis, HSGPA was the most robust predictor of FGPA (Table 35). When used alone, HSGPA accounted for 28.1% of the variance when predicting FGPA. In total, seven significant equations were produced by the stepwise regression process, only the first four equations were shown in Table 35. The three equations not listed below included the predictor variables high school percentile, program of study, and the number of weighted classes. These three

variables, while statistically significant, only increased the R^2 by 1.8% combined, and therefore, were considered inconsequential.

Table 35: *Model 1C – Significant Predictors of FGPA and Related Regression Statistics*

MODEL 1C	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-0.137	0.166	0.281	----	247.9	<0.001	1.0
HSGPA	0.882	0.056					
Constant	-0.373	0.186	0.289	0.009	129.1	<0.001	0.746
HSGPA	0.792	0.065					0.746
ACT Science	0.025	0.009					
Constant	-0.302	0.188	0.295	0.006	88.4	<0.001	0.744
HSGPA	0.799	0.064					0.739
ACT Science	0.023	0.009					0.990
HS # 5	-0.163	0.071					
Constant	-0.241	0.188	0.303	0.008	68.8	<0.001	0.742
HSGPA	0.807	0.064					0.738
ACT Science	0.022	0.009					0.854
HS # 5	-0.238	0.076					0.861
HS # 4	-0.225	0.084					

Note. Sample size was 637 students.

A number of predictor variables were not significant in model 1C. These variables included gender, HS #2, HS #3, race, the number of dual credit classes, the number of science classes, the number of math classes, ACT English score, ACT math score, ACT Reading score, ACT composite score, and number of credits enrolled.

Only the first two equations were calculated below. The first linear equation for 1C uses only HSGPA as a way to predict FGPA. The scatterplot below (Figure 5) indicated a weak relationship between the two factors as there is considerable variance around the “best fit” line. This is not surprising as only 28.1% of the variance is accounted for by HSGPA.

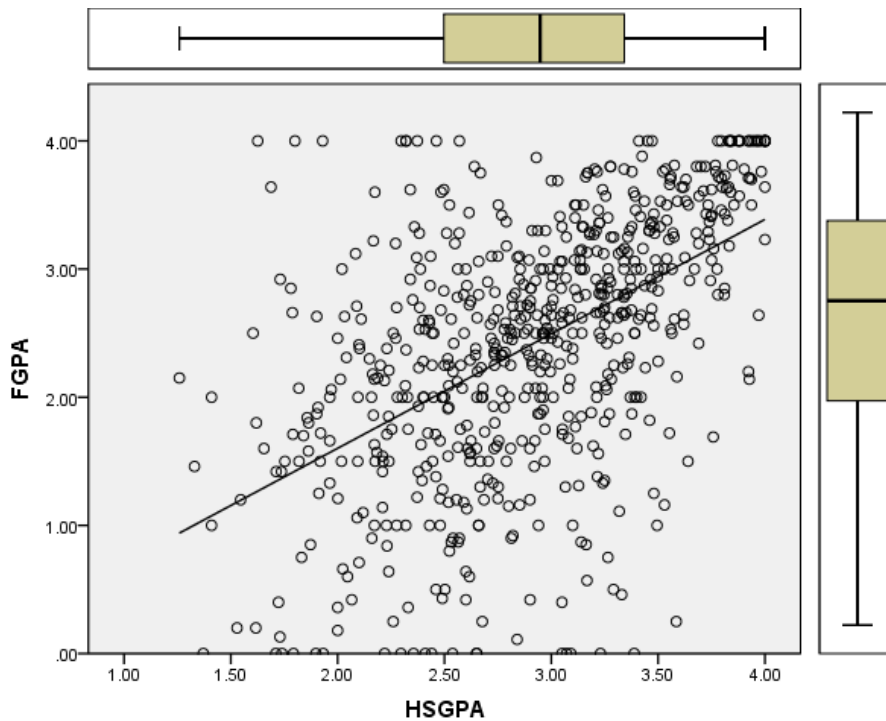


Figure 5. Scatterplot of FGPA against HSGPA.

The first predictive equation for Model 1C is calculated to be: $FGPA = -0.137 + 0.882 \cdot HSGPA$. Table 36 illustrates a simple conversion from HSGPA to FGPA using this formula.

Table 36: HSGPA Predicts FGPA

HSGPA	FGPA (PREDICTED)
1	0.75
2	1.63
3	2.51
4	3.39

Histograms of predicted FGPA and actual FGPA (Figure 6) indicated that this formula, which only explains 28.1% of the variance, underestimated the number of students with FGPA above 3.5 and the number of students with FGPA below 1.0. This phenomenon is likely due to the fact that both the dependent and independent variable are categorical variables and are constrained between 0 and 4. This is a limitation of this predictive model.

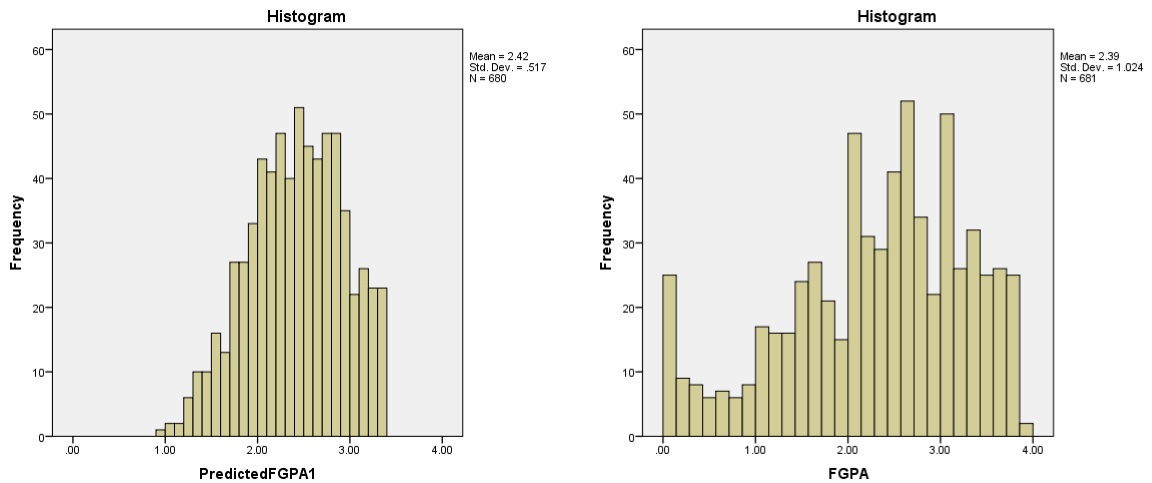


Figure 6. Histogram of actual FGPA and predicted FGPA using only HSGPA.

The second equation to predict FGPA included both HSGPA and ACT science scores. The equation is: $FGPA = -0.373 + 0.792 * HSGPA + 0.025 * ACT \text{ science score}$. The resultant histograms (Figure 7) indicated that once again, this model underestimated the number of FGPA's above 3.5 and the number of FGPA's less than 1.0.

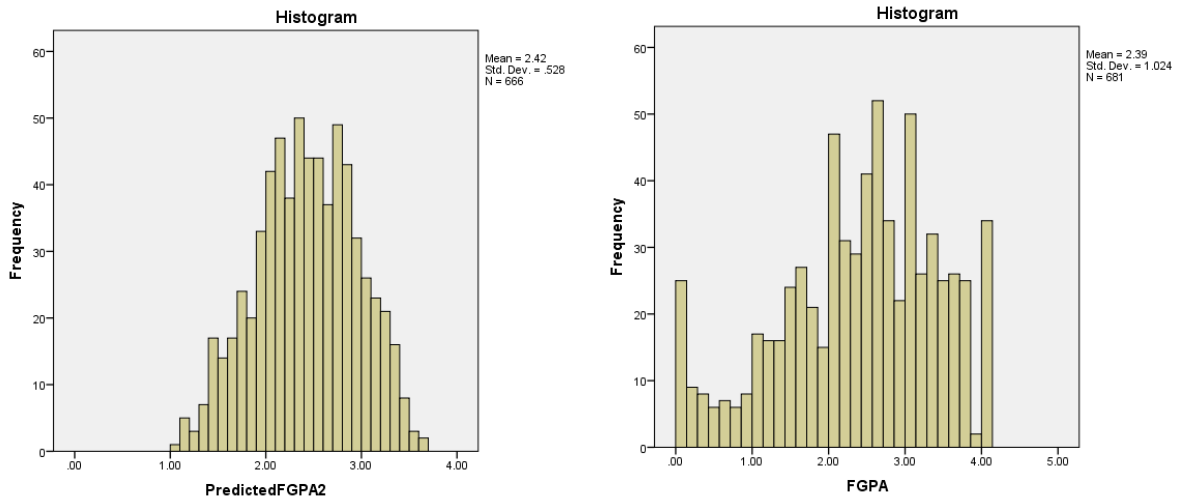


Figure 7. Histogram of actual FGPA and predicted FGPA using HSGPA and ACT science scores.

Model 2: Using Stepwise Regression as a Way to Predict Momentum

Model 2A: Using Compass Scores, HSGPA, and Number of Credit Hours Enrolled to Predict Momentum

As was discussed in Model 1, the small number of Compass scores available could dramatically reduce the statistical power of the stepwise regression analysis. Therefore, as in Model 1, Compass scores will be combined with HSGPA, and additionally, the number of credits enrolled in the fall to see if Compass scores are a predictor of momentum. FGPA was placed within the model because of its known

association to college success. The number of credits enrolled was included as a variable as it was strongly suspected that momentum was related to the number of credit hours a student originally enrolled within at the college. College algebra Compass scores were not used due to its small sample size. Race, gender, program declaration, and high school were used as controls in the model.

The statistical calculations indicated that Credits Enrolled for this subset of students was the most robust predictor of momentum (Table 37). HSGPA increased the models predictive ability by nearly 10% when added to the second equation. All Compass scores were insignificant and therefore were not considered as important factors for predicting momentum in this study.

Table 37: *Model 2A – Significant Predictors of Momentum and Related Regression Statistics*

MODEL 2A	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-1.061	1.719	0.192	---	38.9	<0.001	1.0
Credits Enrolled	0.773	0.124					
Constant	-7.929	2.187	0.287	0.095	32.9	<0.001	
Credits Enrolled	0.714	0.117					0.989
HSGPA	2.82	0.604					0.989

Note. Sample size was 166 students.

Model 2B. Using Total Income and HSGPA to Predict Momentum

Total income, HSGPA, and Credits Enrolled were used in a stepwise regression model to predict Momentum. Race, gender, program declaration, and high school were

used as controls in the model. Credits Enrolled and HSGPA were the only significant predictors of Momentum; Total Income was not significant (Table 38). Total income was not used in Model 2C to predict Momentum.

Table 38: *Model 2B – Significant Predictors of Momentum and Related Regression Statistics*

MODEL 2B	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-2.141	1.121	0.283	--	127.5	<0.001	1.0
Credits Enrolled	0.919	0.081					
Constant	-8.439	1.249	0.417	0.134	115.2	<0.001	
Credits Enrolled	0.726	0.077					0.915
HSGPA	3.069	0.357					0.915

Note. Sample size was 327 students.

Model 2C. Predicting Momentum Using the Remaining Fifteen Predictor Variables

The sample sizes of the remaining 16 predictor variables (Table 34 above) were all above 675, creating a robust sample size. The stepwise linear regression process generated four significant equations (Table 39). The first equation uses only Credits Enrolled to predict Momentum. When HSGPA was included in the second equation, it increases the amount of variance explained by nearly 13%. Equations three and four only increased the explained variance by 1.3% combined.

Table 39: *Model 2C – Significant Predictors of Momentum and Related Regression Statistics*

MODEL 2C	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R ²	MODEL R ² CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-2.421	0.793	0.297	--	274.4	<0.001	1.0
Credits Enrolled	0.941	0.057					
Constant	-8.906	0.899	0.424	0.128	239.3	<0.001	0.923
Credits Enrolled	0.763	0.054					0.923
HSGPA	3.079	0.257					
Constant	-7.797	0.968	0.432	0.008	164.4	<0.001	0.892
Credits Enrolled	0.733	0.054					0.892
HSGPA	2.467	0.327					0.561
# Science Classes	0.459	0.154					0.547
Constant	-7.761	0.965	0.437	0.005	125.5	<0.001	0.892
Credits Enrolled	0.732	0.054					0.892
HSGPA	2.587	0.330					0.547
# Science Classes	0.386	0.157					0.525
HS #4	-0.804	0.347					0.957

Note. Sample size was 653 students.

The second equation used Credits Enrolled and HSGPA, but the equation explained a large amount of variance (42.4%) around the Momentum success variable. The formula for this model was: Momentum = -8.906 + 0.763*Credits Enrolled + 3.079*HSGPA. However, the formula dramatically underestimated Momentum scores less than two credits (Figure 8).

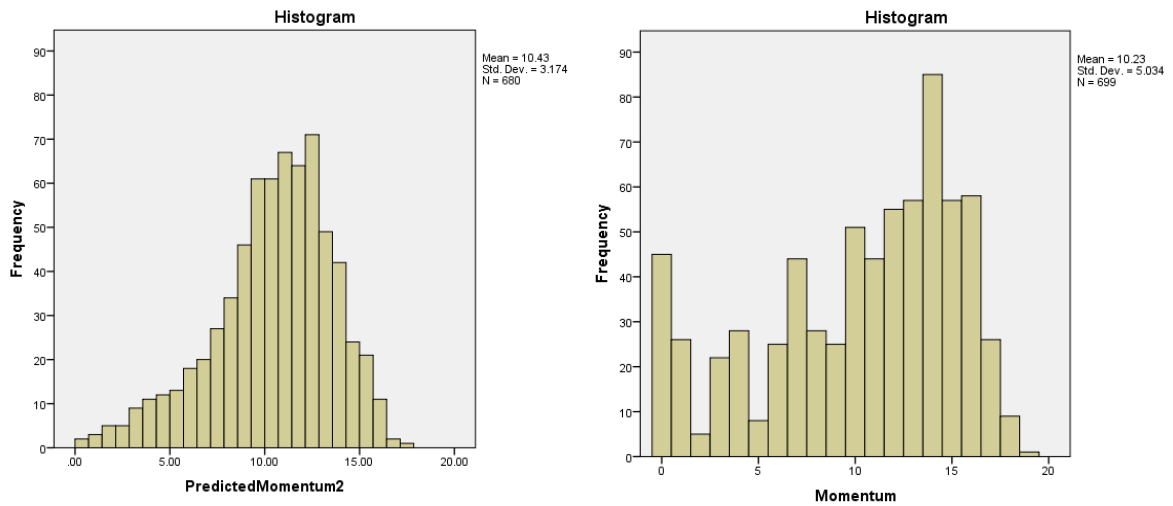


Figure 8. Histograms of actual Momentum scores and predicted Momentum scores using HSGPA and Credits Enrolled.

The following predictor variables were not significantly related to Momentum:

Gender, HS Percentile, # of Dual Credit classes, # of weighted classes, # of math classes, all ACT scores, program of study, HS #2, HS #3, HS #5 and race.

Model 3: Using Stepwise Regression as a Way to Predict Persistence

Model 3A: Using Compass Scores and HSGPA to Predict Persistence

Following the same procedure as in Models 1 and 2, Compass scores were used along with HSGPA to determine if Compass scores could predict Persistence. Compass scores for college algebra were not included due to its small sample size. Race, gender, program declaration, and high school were used as controls in the model. The calculations of this model indicated that HSGPA was the only significant predictor of Persistence and that Compass scores in math, writing, and reading were insignificant

(Table 40). Due to the insignificance of Compass scores, they were not utilized in any other models to predict Persistence.

Table 40: *Model 3A – Significant Predictors of Persistence and Related Regression Statistics*

MODEL 3A	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	0.117	0.125	0.118	--	22.0	<0.001	1.0
HSGPA	0.211	0.045					

Note. Sample size was 166 students.

Model 3B. Using Total Income and HSGPA to predict Persistence

HSGPA and total income were utilized to predict Persistence (Table 41). Race, gender, program declaration, and high school were used as controls in the model.

HSGPA was the only significant predictor of Persistence; Total Income was not a significant predictor of Persistence. Total income was not be used as a variable in any additional model to predict Persistence.

Table 41: *Model 3B – Significant Predictors of Persistence and Related Regression Statistics*

MODEL 2B	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	0.119	0.077	0.180	--	70.8	<0.001	1.0
HSGPA	0.219	0.026					

Note. Sample size was 327 students.

Model 3C. Predicting Persistence Using the Remaining Fifteen Predictor Variables

Using the remaining 16 predictor variables, a stepwise multiple linear regression analysis generated three significant equations that can be used to predict Persistence (Table 42). However, the models were not robust and explained only 18% – 19.7% of the variance. The second and third equations only increased the variance explained by 1.7% and were not examined further.

Table 42: *Model 3C – Significant Predictors of Persistence and Related Regression Statistics*

MODEL 3C	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	0.105	0.055	0.180	--	143.2	<0.001	1.0
HSGPA	0.224	0.019					
Constant	0.119	0.055	0.190	0.010	76.4	<0.001	0.999
HSGPA	0.225	0.019					
HS #4	-0.073	0.026					0.999
Constant	0.165	0.059	0.197	0.007	53.0	<0.001	0.552
HSGPA	0.187	0.025					
HS #4	-0.061	0.026					0.957
# Science Classes	0.027	0.012					0.542

Note. Sample size was 653 students.

The first equation listed above, which used only HSGPA, explained only 18.0% of the variance in Persistence. The formula for this model is: Persistence = 0.105 + 0.224*HSGPA. A scatterplot shows the loose relationship between HSGPA and Persistence (Figure 9). Notice the number of students that attained 100% persistence (completed all of their credits) or withdrew or failed all of the credits (0%).

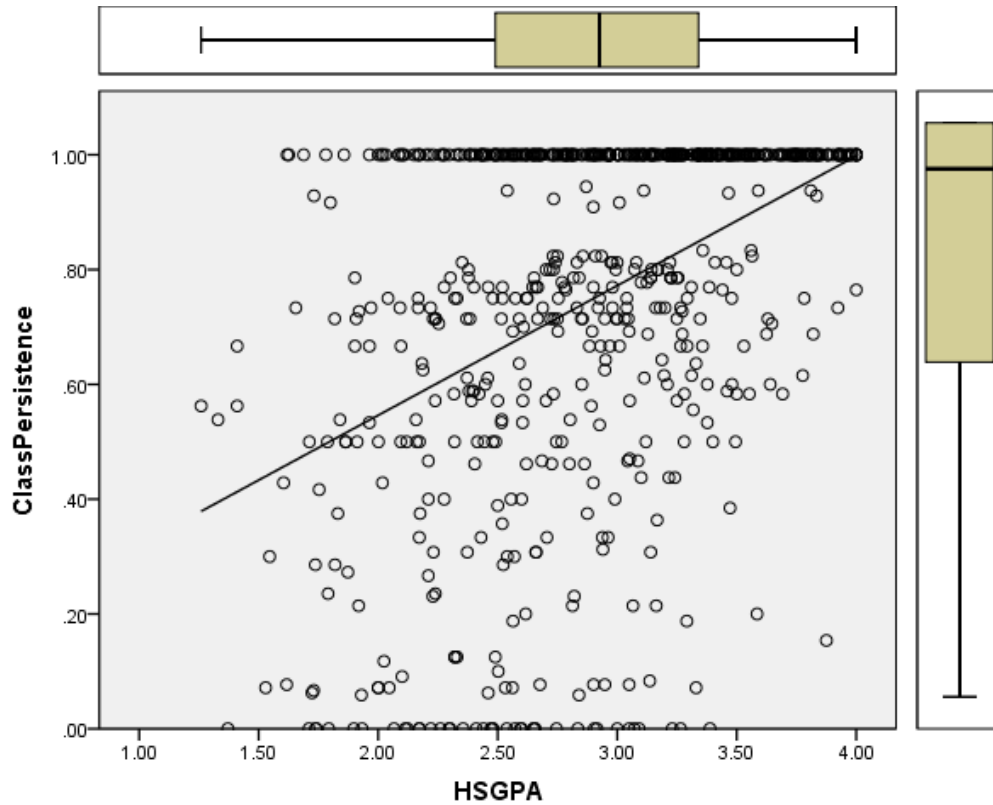


Figure 9. A scatterplot of HSGPA and Persistence.

The equation for predicting persistence is imprecise (Figure 10). Actual class persistence is weighted toward either end of the spectrum, with most of the students reaching 100% persistence rate (completing 100% of their credits). However, the next most frequent group of students earned 0% persistence rate.

Most predictor variables were insignificant when explaining Persistence. Insignificant variables included gender, HS percentile, # of dual credit classes, # of weighted classes, # of math classes, all ACT scores, program of study, enrolled credits, race, HS #2, #3, and #5.

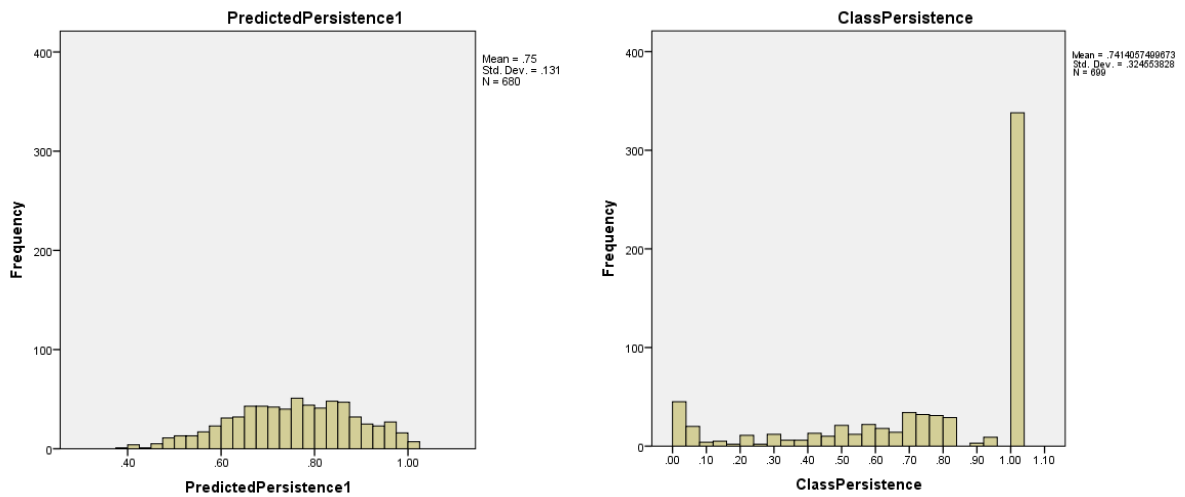


Figure 10. Histograms of actual Persistence and predicted Persistence using HSGPA and Credits Enrolled as predictor variables.

Model 4: Using Stepwise Regression as a Way to Predict Grade Points

Model 4A: Using Compass Scores and HSGPA to Predict Grade Points

HSGPA, Credits Enrolled, and Compass scores (except college algebra Compass scores) were used to determine if they could predict Grade Points (defined as Momentum \times FGPA). Credits Enrolled were used in this calculation as it was strongest predictor of Momentum in Model 2. Race, gender, program declaration, and high school were used as controls in the model. Three equations were generated from this analysis (Table 43). In the first equation, HSGPA was the only significant predictor of Grade Points explaining 21.4% of the variance of Grade Points. The second equation included Credits Enrolled, but model three included Compass Algebra scores which added 3.6% of explained variance to the third model. Compass reading and writing were not significant. Due to the small amount of variance that Compass Algebra supplied to the

model and that all other Compass scores were insignificant, all Compass scores were not be included in any further analysis of Grade Points.

Table 43: *Model 4A – Significant Predictors of Grade Points and Related Regression Statistics*

MODEL 4A	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-13.622	5.674	0.214	--	44.7	<0.001	1.0
HSGPA	13.670	2.046					
Constant	-33.996	7.060	0.299	0.085	34.8	<0.001	0.989
HSGPA	12.743	1.949					
Credits Enrolled	1.686	0.379					0.989
Constant	-33.499	6.899	0.335	0.036	27.2	<0.001	0.845
HSGPA	10.417	2.059					
Credits Enrolled	1.528	0.374					0.969
Compass Algebra	0.209	0.070					0.829

Note. Sample size was 166 students.

Model 4B. Using Total Income and HSGPA to predict Grade Points

HSGPA, Credits Enrolled, and Total Income were used to predict Grade Points.

Race, gender, program declaration, and high school were used as controls in the model.

The statistics generated showed that only HSGPA and Credits Enrolled were significant (Table 44). Total income was not be utilized in the rest of this analysis when predicting Grade Points.

Table 44: *Model 4B – Significant Predictors of Grade Points and Related Regression Statistics*

MODEL 4B	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R^2	MODEL R^2 CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	-25.194	3.833	0.385	--	201.9	<0.001	1.0
HSGPA	18.382	1.294					
Constant	-41.908	4.473	0.450	0.069	133.5	<0.001	0.915
HSGPA	16.013	1.277					
Credits Enrolled	1.749	0.275					

Note. Sample size was 327 students.

Model 4C. Predicting Grade Points Using the Remaining Fifteen Predictor Variables

The remaining 16 predictor variables were used to predict Grade Points. The calculations from the stepwise regression analysis indicated that nine statistically significant equations were generated (Table 45). The first model used only HSGPA as a way to predict Grade Points. This model explained 36.4% of the variance around Grade Points. Adding Credits Enrolled increased the predictive ability by 8.3% to 44.5% total. Equations three and four only raised the variance explained by 1.3%. Equations five through nine added an additional 2.5% predictive ability combined and were not listed below.

Table 45: Model 4C – Significant Predictors of Grade Points and Related Regression Statistics

MODEL 3C	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	MODEL R ²	MODEL R ² CHANGE	MODEL F STATISTIC	MODEL P	TOLERANCE
Constant	25.017	2.820	0.364	--	372.1	<0.001	1.0
HSGPA	18.390	0.953					
Constant	-43.718	3.244	0.445	0.083	262.1	<0.001	0.923
HSGPA	15.852	0.926					0.923
Enrolled Credits	1.907	0.193					0.923
Constant	-39.012	3.484	0.454	0.010	181.9	<0.001	0.561
HSGPA	13.259	1.178					0.892
Enrolled Credits	1.782	0.195					0.547
# Science Courses	1.948	0.554					
Constant	-36.926	3.623	0.457	0.003	138.2	<0.001	0.516
HSGPA	12.552	1.225					0.888
Enrolled Credits	1.754	0.195					0.536
# Science Courses	1.786	0.559					0.756
# Weighted	0.311	0.153					

Note. Sample size was 653 students.

The equation generated, using only HSGPA and Enrolled Credits, explained 44.5% of the variance in the college success variable Grade Points. The formula for this model is: Grade Points = -43.718 + 15.852*HSGPA + 1.907*Enrolled Credits.

As was the case in models 1, 2, and 3, this formula under-predicts very low scores on Grade Points, especially those that received zero grade points (Figure 11). Students achieved zero grade points by either withdrawing from all of their classes

(persistence = 0%) or by failing all of their classes. These data indicate that a substantial portion of SVCC students are either withdrawing or failing their classes (>11%).

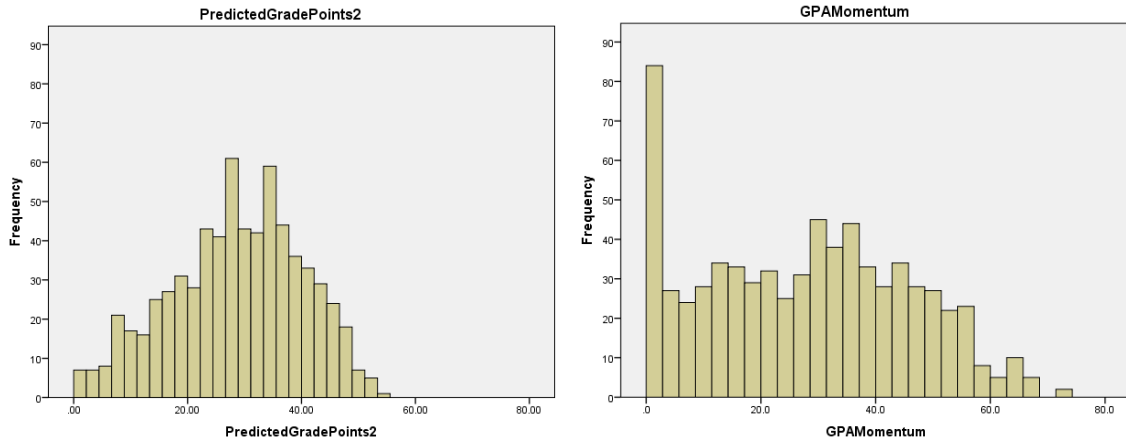


Figure 11. Histograms of actual Grade Points and predicted Grade Points using HSGPA and Credits Enrolled as predictor variables.

Not all predictor variables were utilized in the model to predict Grade Points. Excluded from this analysis were gender, HS percentile, # of dual credit classes, # of science classes, # of math classes, all ACT scores, program of study, all high schools, and race.

Model 5: Using Binary Logistic Regression as a Way to Predict Retention

A stepwise, binary logistic regression analysis was conducted to determine which predictor variables could successfully predict the retention of students. The methodology will be similar to Models 1-4 where Compass scores (hypothesis A) and Total Income (hypothesis B) will be analyzed first. Hypothesis C used the remaining 16 independent variables to predict retention.

Model 5A: Using Compass Scores and HSGPA to Predict Retention

HSGPA and Compass scores (except college algebra Compass scores) were used to determine if they could predict retention. Race, gender, program declaration, and high school were used as controls in the model. HSGPA was the only significant predictor of retention explaining 11.2% of the variance (Table 46). Compass reading, writing, and algebra scores were not significant. Considering that Compass scores were insignificant in predicting retention when used with HSGPA, all Compass scores were not included in any further analysis of retention.

Table 46: *Model 5A – Significant Predictors of Retention and Related Regression Statistics*

MODEL 5A	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	NAGELKERKE R^2	MODEL R^2 CHANGE	CHI-SQUARE STATISTIC	MODEL P	EXP(B)
Constant	-1.904	0.433	0.112	--	136.1	0.001	0.149
HSGPA	1.371	1.090					3.939

Note. Sample size was 166 students.

Model 5B. Using Total Income and HSGPA to predict Retention

HSGPA and Total Income were used to predict retention. Race, gender, program declaration, and high school were used as controls in the model. The statistics generated showed that only HSGPA was significant in predicting retention (Table 47); therefore, Total Income was not utilized in the rest of this analysis when predicting Retention.

Table 47: *Model 5B – Significant Predictors of Retention and Related Regression Statistics*

MODEL 5B	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	NAGELKERKE R^2	MODEL R^2 CHANGE	CHI-SQUARE STATISTIC	MODEL P	EXP(B)
Constant	-1.128	0.713	0.077	--	15.3	<0.001	0.324
HSGPA	0.985	0.260					2.677

Note. Sample size was 325 students.

Model 5C. Predicting Retention Using the Remaining Fifteen Predictor Variables

Using the remaining 16 independent variables to predict retention using stepwise binary logistic regression, the calculations indicated that five equations were generated. The first equation used only Credits Enrolled as a way to predict Retention and accounted for 12.8% of the variance (Table 48). The second equation used both Credits Enrolled and HSGPA to predict Retention and accounted for 18.9% of the variance. The addition of high school #4, number of weighted courses and ACT reading added an additional 5.3% to the predictive ability of the model.

Table 48: Model 5C – Significant Predictors of Retention and Related Regression Statistics

MODEL 5C	UNSTANDARDIZED COEFFICIENTS	STD. ERROR OF COEFFICIENTS	NAGELKERKE R^2	MODEL R^2 CHANGE	CHI-SQUARE STATISTIC	MODEL P	EXP(B)
Constant	-1.502	0.458	0.128	--	49.8	<0.001	0.233
Credits Enrolled	0.247	0.036					1.280
Constant	-3.791	0.670	0.189	0.061	75.3	<0.001	0.023
Credits Enrolled	0.203	0.037					1.225
HSGPA	1.040	0.211					2.829
Constant	-3.708	0.681	0.207	0.018	82.8	<0.001	0.025
Credits Enrolled	0.202	0.037					1.224
HSGPA	1.085	0.214					2.960
HS #4	-0.715	-0.715					0.489
Constant	-3.001	0.729	0.223	0.016	89.7	<0.001	0.050
Credits Enrolled	0.190	0.037					1.209
HSGPA	0.830	0.233					2.292
HS #4	-0.848	0.264					0.428
# Weighted Classes	0.140	0.061					1.151
Constant	-2.240	0.772	0.242	0.009	98.0	<0.001	0.106
Credits Enrolled	0.208	0.038					1.231
HSGPA	1.060	0.251					2.887
HS #4	-0.955	-0.955					0.385
# Weighted Classes	0.174	0.063					1.190
ACT Reading	-0.083	0.029					0.921

Note. Sample size was 653 students.

For the second equation where only Credits Enrolled and HSGPA were used to predict retention rates, the following probabilities were produced:

- For every additional credit a student enrolled within in the fall semester, there was a 22.5% increased probability of retention.
- For every additional increase in one unit of HSGPA, there was a 182.9% increased probability of retention.

As an interesting note, the third equation includes HS #4 and if as student graduated from this high school they have a 51.1% decreased probability of being retained.

Not all predictor variables significantly predicted retention. Excluded from this analysis were gender, HS percentile, # of dual credit classes, # of science classes, # of math classes, all ACT scores except ACT reading, program of study, high school #1, #2, #3, #5, and race.

Regression Models Summary

The regression models generated by this analysis predicted between 19.7% and 48.5% of variance around the five college success variables (Table 49). The use of the models to predict future student success should be used with caution as they are generally poor predictors of success of students at either extreme—those students who do exceptionally well or those who do exceptionally poorly.

Table 49: *Five College Success Models, Their R² and the Number of Variables Required to Produce the Result*

	FGPA	MOMENTUM	CLASS PERSISTENCE	GRADE POINTS	RETENTION
Model with largest R ²	0.314	0.437	0.197	0.485	0.242
# predictor variables needed to attain R ²	7	4	3	8	5
Equation used in analysis (R ²)	0.287	0.424	0.180	0.446	0.207
# predictor variables used in equation	2	2	1	2	2

Interestingly, only nine of the original 21 predictors of college success were found to be significant predictors of college success (Table 50). HSGPA was utilized in all five college success models and was utilized as either the most important or the second most important predictor in every model. The number of credits enrolled was also utilized in three of five models and was the most important predictor in two of those three models. High school attended was found to be significant in all five models, but the additional variance accounted for by high school was negligible. The number of science and weighted classes were also found to be significant, but generally unimportant in three of five models.

Table 50: *College Success Predictor Variables and Their Use in Five College Success Models*

INDEPENDENT VARIABLES ("COLLEGE SUCCESS PREDICTORS")	FGPA	MOMENTUM	PERSISTENCE	GRADE POINTS	RETENTION	# OF TIMES REPRESENTED IN MODELS
Gender	No	No	No	No	No	0/5
Race	No	No	No	No	No	0/5
High school attended	Yes (3 & 4)	Yes (4)	Yes (2)	Yes (5, 6, 8)	Yes (3)	5/5
Total income ^a	No	No	No	No	No	0/5
Program of Study	Yes (6)	No	No	No	No	1/5
Credits Enrolled	No	Yes (1)	No	Yes (2)	Yes (1)	3/5
HSGPA	Yes (1)	Yes (2)	Yes (1)	Yes (1)	Yes (2)	5/5
High school percentile	Yes (5)	No	No	No	No	1/5
# Math classes	No	No	No	No	No	0/5
# Science classes	No	Yes (3)	Yes (3)	Yes (3)	No	3/5
# Weighted classes	Yes (7)	No	No	Yes (4)	Yes (4)	3/5
# Dual credit classes	No	No	No	No	No	0/5
ACT composite score	No	No	No	No	No	0/5
ACT reading score	No	No	No	No	Yes (5)	1/5
ACT English score	No	No	No	No	No	0/5
ACT math score	No	No	No	No	No	0/5
ACT science score	Yes (2)	No	No	No	No	1/5
Compass: Reading ^a	No	No	No	No	No	0/5
Compass: Writing ^a	No	No	No	No	No	0/5
Compass: Algebra ^a	No	No	No	No	No	0/5
Compass: College Algebra ^a	n/a	n/a	n/a	n/a	n/a	n/a

Note. Numbers indicate where they were first entered into the predictive model where 1 equals the most important factor.

^a After hypothesis testing (A & B), these variables were removed from the analysis due to their low predictive power. Compass College Algebra scores were not included within the analysis because of its very low sample size.

Models A & B: Hypothesis Testing

HSGPA was conclusively a better predictor of Compass scores and Total Income in all five models where HSGPA was the most important predictor variable in 8 of 10 hypotheses tested. Compass scores generally did not contribute or did not significantly contribute to the predictive abilities of any of the five college success models (Hypothesis A). Total Income was never found to be significant in any of the predictive models run with HSGPA (Model B).

CHAPTER FIVE: FINDINGS, RECOMMENDATIONS FOR SVCC, AND RECOMMENDATIONS FOR FUTURE RESEARCH

INTRODUCTION

This study was used to determine which academic and demographic factors of recently graduated high school students were significantly related to academic success during the students' first fall semester at Sauk Valley Community College. In total, data from 699 students were analyzed including data from 21 potential college success predictor variables. Success at SVCC was defined in five ways including fall grade point average (FGPA), momentum, grade points, class persistence, and fall-to-spring retention.

Chapter Five reveals the major findings of this research project, provides practical recommendations, gives suggestions for additional research, and discusses its limitations. These recommendations can be utilized by college personnel as a way to increase the success of SVCC's students as freshmen, and ultimately to increase completion rates.

STUDY LIMITATIONS

This was a comprehensive study of 699 recently graduated high school students who enrolled at SVCC during the fall semesters of years 2011-2013. While this research

was intended to create a model to predict success of future students, some limitations exist.

- This study evaluated college success only during the students' first semester at SVCC. It is not presumed that these models can be used to predict college success past the first fall semester.
- The age of the student was not evaluated as the study population was composed of all recently graduated high school seniors, and therefore, it was assumed that the ages of the students were between 17–18 years of age. These models created in this research may not accurately predict the success of “non-traditional” students who are much older and who are returning to college after a significant break from high school.
- While this research evaluated data from three consecutive years (2011-2013), the population of students entering SVCC will certainly vary from year to year. For example, the number of students who enrolled at SVCC with 3.5 HSGPAs has increased this last year to much higher levels than average. Therefore, the models generated from this research may not accurately predict academic outcomes for future populations of students as population dynamics shift at the college.
- This study was purposely focused on the students of SVCC. These college success models, while providing a possible framework for research for other post-secondary institutions, are likely not to accurately predict success at other institutions, especially four-year bachelor's degree universities.

THE FINDINGS

What Does It Mean To Be Successful in College?

There is just no standard way to define college “success.” Some researchers have defined college success simply as completing a degree or credential (Adelman, 2006; Geiser & Santelices, 2007; Mattern et al., 2013). Certainly this is logical as most students attend a postsecondary institution to attain an academic credential of some kind. But trying to relate the college graduation rates of students to high school academic variables could dramatically reduce the reliability of the statistics used to make any predictions (Vogt, 2007). Despite this concern, some studies have successfully correlated high school academic variables to college graduation (Adelman, 2006; Stumpf & Stanley, 2002; Waugh & Micceri, 1994). However, trying to conduct the same types of statistical studies on community college students could provide frustratingly poor results because nationally only 12.9% of community college students will graduate with an associate degree in two years and only 28% will graduate in four years (Offenstein & Shulock, 2009). The sample size of this study would have been dramatically reduced if “success” was determined as only graduation. So the focus of this research was to discover ways of measuring college success when students were freshmen. It is hoped that these freshmen success variables could be used as a way to identify which students, without ever having set foot on campus, would be considered “at-risk.” Identification and intrusive remediation of these “at-risk” students may dramatically increase the rates of future credential completion.

For freshmen, measuring the completion of a credential is not possible, so other success variables were identified as candidates early in this research process. FGPA is the most commonly used college success variable because it is assumed that FGPA is also predictive of a college student's future academic success in college (Belfield & Crosta, 2012; Geiser & Santelices, 2007). This theorem is so strongly embedded within the culture of higher academics that the two most commonly used standardized entrance exams (e.g., ACT and SAT) are designed to do just that, to predict the FGPA of students (Crouse & Trusheim, 1988; Noble, 1991; Noble et al., 1999; Noble & Sawyer, 2002; Zwick, 2007). The assumption is that high ACT or SAT scores will strongly relate to high FGPA which will relate to future retention and graduation of those same students (Adelman, 2006; Clements, 1969).

Certainly FGPA seems to be an important predictor of future success, but other researchers (Adelman, 2006; Achieve the Dream, 2014) have indicated that credit accumulation (momentum) is also a powerful predictor of future credential attainment. Essentially, those students who can accumulate credits more quickly have a higher likelihood of graduating. For example, previous research suggests that a part-time community college student has little hope of ever completing an associate degree while full-time students are much more likely to complete their credentials (College Board Advocacy and Policy Center, 2012).

This research study also evaluated the grade points accumulated during a student's first fall semester as a potential success variable. Some would argue that this variable may be a significant predictor of future graduation as the variable is a

combination of credit accumulation and FGPA, but independently important in predicting future retention and graduation of students (Micceri et al., 2009). It could be suggested that students with high FGPA's and credit accumulation would be much more likely to graduate in the future than a student who simultaneously had a low FGPA and had earned only a few credits in the first semester.

Could classroom persistence in a student's first semester be predictive of future college success? Are students who persist, or pass, their college classes at a high rate more likely to be retained semester to semester and to graduate with a degree than a student that has low persistence?

Certainly retaining students from semester to semester is incredibly important. Even the best students can't graduate if they don't remain enrolled. Personnel at postsecondary institutions must believe retention is important as significant resources are spent by colleges each year to retain students (Cuseo, 2003), and statistical models like the ones discovered in this research may create an "early warning" system for at-risk students who are more likely to dropout or stop out.

Recently Graduated High School Students Attending SVCC Are Not Prepared for College

Recently graduated high school students attending SVCC are, on average, not prepared for college-level work. SVCC admits about one-third of all graduating students from high schools in its district each fall semester (internal SVCC data), but the researcher did not have access to data from all high school students in the five high schools studied. Therefore, it is not possible for the researcher to compare students

who attended SVCC to those students who immediately matriculated to a four-year university following their high school graduation. But because most universities are selective in the types of students they admit, with strong academic records often being of paramount importance to acceptance (NACAC, 2008, 2015), it is therefore likely that community college students are, on average, less college-ready than students attending most four-year universities. SVCC students in this study population have slightly lower mean ACT composite, math, reading, English, and science scores than the national average (Table 51). According to these results, ACT would not consider an average SVCC student to be college-ready (ACT, 2012). The average SVCC student also earned a B–HSGPA (2.90), which is below national averages (3.0) (National Center for Education Statistics, 2009). Further, the high school percentile for SVCC students is very ordinary at 56% indicating that the most academically prepared high school students are not enrolling at SVCC right after graduation. The large proportion (54%) of SVCC students who require remediation is another strong indicator that new students are not strongly prepared for college-level work (internal SVCC data).

Table 51: *ACT Scores for SVCC Students Compared to National Averages of All Students Taking the ACT*

	ACT ENGLISH SCORE	ACT MATH SCORE	ACT READING SCORE	ACT SCIENCE SCORE	ACT COMPOSITE SCORE
SVCC Mean	20.0	20.2	20.3	20.0	20.3
National Mean	20.2	20.9	21.1	20.7	20.9
ACT College Readiness Benchmarks	18	22	22	23	n/a

(National data from ACT, 2012)

An academically rigorous high school education is often considered one of the most important factors for college readiness (Adelman, 2006). While academic rigor is difficult to define, students who take more math, science, weighted or dual-credit classes are often considered to be better prepared academically (Adelman, 2006). What this research project revealed is that there is a wide variance in college-readiness in recently graduated high school students who attend SVCC. While the average student completed 1.8 dual credit classes, the maximum number of classes completed was 13, but many students completed zero. The median number of weighted high school classes was ZERO for new SVCC students, but the maximum was 22 weighted classes. There was even wide dispersion in the number of math and science classes that students completed, which is surprising since many of these classes are required for graduation by the local high schools. As noted in Chapter Two, Adelman (2006) determined that a student would have a 95% chance of attaining a bachelor's degree if the high school student completed all of the following:

- 3.75 or more Carnegie units of English
- 3.75 or more Carnegie units of mathematics
- 2.5 or more Carnegie units of science or 2.0 Carnegie units of lab science
- more than 2.0 Carnegie units of foreign languages
- more than 2.0 Carnegie units of history and social studies
- 1.0 or more Carnegie units of computer science
- more than one Advanced Placement (weighted) course

It may be unfair to compare these academic rigor expectations set by Adelman (2006) to the community college students in this study, but the comparison does indicate that the typical high school student in this research project was deficient in the number of weighted (AP) classes, math classes, and advanced science classes that were strongly predictive of bachelor's degree attainment. It would seem that the majority of high school students who later attended SVCC were not completing an academically rigorous education at their high schools which is not at all surprising because the average student ranked only at the 56th percentile in their graduating classes.

Freshmen Were Only Moderately Successful at SVCC

This research has indicated that SVCC freshmen were poorly prepared for the rigors of a college education, and therefore, it is no surprise that these same students are only moderately successful at SVCC. Freshman FGPA was only 2.39 units and was significantly lower than HSGPA (2.90); this is congruent with national and Illinois data that showed FGPA to be significantly lower than HSGPA (ACT, 2010). Further, while the average student enrolled in 13.6 credit hours (Figure 12), they completed just over 10 credits (just below full-time) and were persisting at only a 74% rate in their first semester (Figure 12). Unfortunately, 6.4% of freshman students did not complete any credits at the college during their first semester (Figure 12). At this rate of credit accumulation it will take an average student three or more years to complete a degree at SVCC.

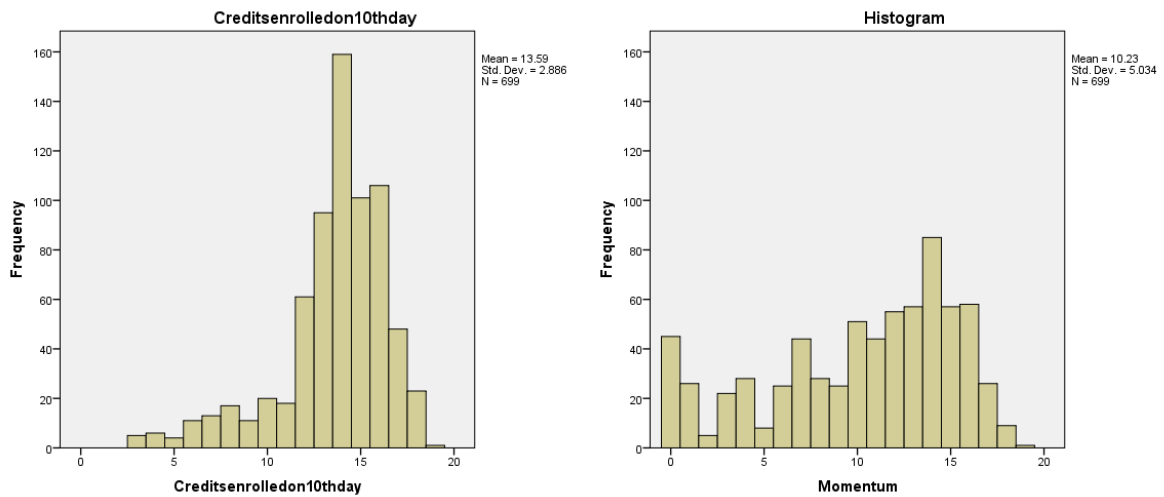


Figure 12. Histogram of number of students and number of credits enrolled and completed.

SVCC has historically recorded an excellent fall to spring retention rate and this cohort follows that trend. These cohorts of students were retained at an impressive 83.8% rate from the fall to spring semesters. Unfortunately, the low momentum (10 credits) and FGPA (2.39 points) is indicative of a poor future completion rate for this group of students. While SVCC is better than average in Illinois for completion rates, history shows that only 18% of first-time, full-time students completed their certificate or degree in 100% time and 35% completed within 200% time (2009 cohort data from IPEDS).

The Effect of High School Attended and Academic Preparation on College Success

Comparing student academic preparedness from the five high schools is difficult and probably prejudicial. For example, this project compared only students that have matriculated to SVCC, and therefore, it is impossible for the researcher to compare how

individual high schools prepare *all* of their students for college because this dissertation focuses on only a subset of their former students. Another possible confounding factor is that some high schools are matriculating some of their best students to SVCC (e.g., HS #4's students average a percentile of 65%) while other high schools are matriculating some of their lower-ranking students (e.g., HS #3's average percentile is 38.3%). With these caveats in mind, the high schools seem to have their own strengths and challenges when preparing students for college. For example, the students of HS #4 completed more weighted classes than HS #2, but the students of HS #2 completed more science classes than students of HS #4. Both of these academic factors have been determined by other researchers to be important in creating the "rigor" necessary for college success (Adelman, 2006; Center for Public Education, 2012). Interestingly, despite the variance in academic preparation from each high school, the students' ACT scores were not statistically different between high schools. This is truly the only standard academic measurement between high schools and it shows no difference in student academic readiness for college in this group of students.

Significant differences were found in the academic preparedness of students from the five high schools studied. In fact, five of the seven college preparedness variables were significantly different among high schools (Table 52). When these academic preparedness variables were ranked from best (1) to worst (5), HS #1 provided the most robust educational preparation overall (average rank of 2.4) by sending some of their best students (determined by percentile) to SVCC who had also earned a large array of dual credit courses (Table 52). HS #4 and #5 were not far behind, averaging a

rank of 2.6 each. Interestingly, high schools seem to be preparing their students for college in different ways as every school studied was ranked first in one of the preparedness categories (Table 52).

Table 52: *Academic Preparedness Variables Ranked From Highest (1) to Lowest (5) by High School*

	HSGPA	HS PERCENTILE	ACT COMPOSITE	NUMBER OF DUAL CREDIT CLASSES	NUMBER OF WEIGHTED CLASSES	NUMBER OF SCIENCE CLASSES	NUMBER OF MATH CLASSES
HS 1	No statistical difference	2 nd	No statistical difference	1 st	4 th	3 rd	2 nd (tied)
HS 2		4 th		4 th (tied)	5 th	1 st	4 th
HS 3		5 th		4 th (tied)	1 st	2 nd	5 th
HS 4		1 st		3 rd	2 nd	5 th	2 nd (tied)
HS 5		3 rd		2 nd	3 rd	4 th	1 st

Because students were matriculating to SVCC from different high schools and those students were being prepared for college in a variety of ways, it was important to control for all of these factors in a single model. As described in Section 2 of Chapter Four, a stepwise regression analysis allowed multiple academic variables to be placed within the same predictive model. An analysis of the five college success models indicated:

- The number of dual credit classes a student attained was not an important predictor in any of the five college success models.
- The number of math classes a student attained was not an important predictor in any of the five college success models.

- The number of science classes a student completed was moderately important in three of five college success models, specifically models predicting momentum, persistence, and grade points.
- The number of weighted classes a student completed was minimally important in three of the five college success models, specifically models predicting FGPA, grade points, and retention.
- The number of science courses and the number of dual credit courses were predictors of different college success variables except for grade points. Therefore, the two predictors have different utility in predicting college success.

It is surprising that the number of upper-level math courses and dual credit courses did not correlate to college success. This is contradictory to evidence presented by Adelman (2006), Noble et al. (1999), Klepfer and Hull (2012) and Micceri et al. (2009) that showed dual enrolled students or students who earned more high-level math courses would perform better in college. Additionally, common sense would seem to dictate that students who complete dual-credit courses should be more likely to be successful at SVCC. Dual-credit courses are “college-level” classes that matriculate to SVCC as college credit and are supposedly held to the same standards as on-campus courses. However, when other academic and demographic variables were controlled for, these two predictors were not significant.

The number of science classes and the number of weighted classes (which may include some AP courses) a high school student completed certainly seems to

moderately predict college success in this study. This supports the claims of Micceri et al. (2009) who found that the number of science classes (all STEM classes in particular) a high school student completed increased the probability of attaining a high FGPA. The Center for Public Education (2012) showed evidence that the more AP (weighted) courses a high school student completed, the more likely that student would do well in and graduate from college.

When college success variables (e.g., FGPA, persistence, etc.) were ranked by high school and summed into an average college success ranking, the average ranking is similar to the average ranking for the number of science classes a student takes at each high school (Table 53). Additionally, the regression findings indicated that the number of science classes was the third most important predictor variable for college success. These two findings would seem to indicate that the local high school administration should mandate that high school students complete additional science courses before they can graduate.

Table 53: *College Success Variables and the Number of Science Classes Ranked by High School*

	FGPA	MOMENTUM	PERSISTENCE RATE	GRADE POINTS	SPRING SEMESTER RETENTION RATE	AVERAGE COLLEGE SUCCESS RANKS	AVERAGE # SCIENCE CLASSES RANKS
HS 1	2 nd	No Statistical Difference	No Statistical Difference	2 nd	3 rd	2.3 (2 nd)	3 rd
HS 2	1 st			1 st	4 th	2.0 (1 st)	1 st
HS 3	5 th			3 rd	1 st	3.0 (3 rd)	2 nd
HS 4	3 rd			5 th	5 th	4.3 (5 th)	5 th
HS 5	4 th			4 th	2 nd	3.3 (4 th)	4 th

Females Were Better Prepared for College, but Were Not the Clear Academic Winners at SVCC

Are male or female high school students generally better prepared for college?

National data is generally ambiguous on deciding that point. As noted in Chapter Two, females consistently earn higher GPAs throughout their K-12 education, especially in high school, and that same trend continued through their postsecondary education (Voyer & Voyer, 2014). However, data collected by the ACT and College Board indicate that males generally outperform females on the ACT and SAT composite scores, though that trend is not nearly as consistent when examining subtest scores (ACT, 2012; SAT, 2012). For example, males generally outperform females in the math subtests, but females tend to outperform males in English/writing skills subtests (ACT, 2012; SAT, 2012).

According to the findings of this research, female students attending SVCC for the first time are better prepared for college than their male counterparts. Females have higher mean HSGPAs, have higher HS percentiles, and completed more dual-credit and weighted classes than males on average. There was no significant difference in any of the other potential predictor variables. In other words, males did not outperform females on ANY of the predictor metrics measured for this study. Paradoxically, all of this additional academic preparation by females in high school did not produce higher ACT composite scores. This trend has been found nationally as well and ACT considers this nothing more than an artifact of “self-selection” as more females attend college than males, and hence, more females are taking the ACT (ACT, 2005). However, this

does not seem to explain the findings here as the average female has higher HSGPA, but lower ACT scores than males.

Considering that females are better prepared for college based on their high school academic record, the assumption would be that females should outperform males at SVCC. Surprisingly, the evidence that females outperform males at SVCC is sparse. The only significant difference between the two groups was found in FGPA where females attained a 2.46 FGPA and males attained a 2.29 FGPA. It is possible that more females are enrolled in more academically challenging classes and programs at SVCC, but this research did not evaluate that possibility. But regardless of their program of study, both males and females were generally performing poorly by only averaging C to C+ in their classes. There were no significant differences in momentum, persistence, grade points, or retention rates.

Adelman (2006) and others (Center for Public Education, 2012) have indicated that an academically rigorous high school education is critical to a student's success in college. This study, however, has shown that only the number of science courses and the number of weighted courses are moderately related to college success. While female students in this study completed significantly more weighted classes than males, they did not complete more science classes than males. However, while a significant predictor, the number of weighted classes a student completes is only weakly related to their future college success, so this may explain why females do not have a larger success advantage over males in college.

The College Success Gap for Blacks and Hispanics Is Real

The data are overwhelming nationally that Black and Hispanic students are less academically prepared, on average, for college than their White counterparts. For example, White students typically outperformed Blacks and Hispanics on all categories of the ACT (ACT, 2012) and the SAT (SAT, 2012). These results indicate that the average White student is college ready while the average Black or Hispanic student is not.

The data analyzed for this study support that contention that White students matriculating to SVCC are better prepared for college-level work than their Black or Hispanic counterparts. White students significantly outperformed Black and Hispanic students in six of seven high school academic categories including HSGPA, HS percentile, ACT composite scores, number of dual credit classes, the number of science classes, and the number of math classes. Only for the number of weighted classes was parity achieved.

This study found moderate differences in academic performance at SVCC between the races. White students outperformed both other races in FGPA and grade points, but not momentum, persistence, and retention. There was no significant difference found between Black and Hispanic students in any of the college success variables.

Race was controlled for during the regression analysis found in Section 2 of Chapter Four. As expected, the actual race of an individual was not a factor when predicting college success, but academic preparation was a factor. On average, White students have significantly higher HSGPAs and earn more science classes than either

Black or Hispanic students. Both of these factors have been determined to relate to success at SVCC, especially HSGPA, and so it is not surprising that White students were performing at a higher academic level during their first semester at SVCC than either racial group.

It is satisfying and unsurprising to note that race is a nonfactor when it comes to a student's potential achievement in college. But the academic achievement gap between races is real and it is essential to find a way to close the academic gap between the races.

Career-Technical Students Are Less Prepared for College

Evaluating the academic motivations of SVCC's students yielded some interesting findings. As a community college, SVCC offers "transfer" programs and "career-technical education" (CTE) programs for its students. Transfer students are those students who intend to attain either an Associate in Art (A.A.) or an Associate in Science (A.S.) degree and then transfer to a four-year bachelor's degree granting institution. Typically, CTE students intend to attain an Associate in Applied Science (A.A.S.) degree or a certificate and then immediately enter the workforce. These groups of students vary considerably in their academic preparation for college and their college success while at SVCC.

Students with the goal of transferring to a four-year postsecondary institution have higher HSGPAs, HS percentiles, and ACT composite scores and have earned more dual credit, weighted, science, and math classes than CTE students. This additional preparation seems to pay off for the transfer students as they outperform CTE students

in momentum, grade points, and retention. Interestingly, there is no significant difference in FGPA or persistence rates. Could it be that once CTE students find a true academic interest that their focus on classroom success increases? It would seem so. Unfortunately, it seems as if many of these same students are leaving college after one semester as their retention rates are significantly lower than transfer students. Are CTE students leaving college to take employment opportunities?

In Section 2 of Chapter Four, program of study (i.e., CTE or transfer) was utilized as a control variable for all five models of college success. For four of five models, program of study was not found to be a significant predictor of college success. It was determined to be the sixth strongest predictor for FGPA, but only accounted for less than 1% of the explained variance. It is safe to say that program of study is inconsequential in predicting college success in the first semester of college. Once again it is the difference in the academic preparation, specifically HSGPA, the number of science classes and the number of weighted classes, that is the determining factor for college success in transfer students. CTE students have graduated high school more underprepared than their “transfer” counterparts.

Predicting FGPA to Forecast the Need for Early Academic Intervention

At SVCC any student who earns less than a 2.0 GPA will be placed on academic probation. Using the predictive analytics generated by this research can help determine which students may be at-risk of academic probation before they ever set foot on campus. As a simple example, FGPA can be predicted from a student’s HSGPA using this

formula: $FGPA = -0.137 + 0.882 * HSGPA$ (see Chapter Four). If FGPA is considered to be 1.99 (academic probation), then HSGPA can be calculated.

$$1.99 = -0.137 + 0.882 * HSGPA$$

$$1.99 + 0.137 = 0.882 * HSGPA$$

$$2.127 / 0.882 = HSGPA$$

$$HSGPA = 2.41$$

Therefore, recently graduated HS students with a 2.41 HSGPA or less are predicted to be on probation after their first semester at SVCC. This predictive modeling will allow college personnel to intervene early in the semester and help students with study skills, time management, life skills, and other key factors students need to master in order to succeed in college. For this group of students, this early intervention may be critical to their semester-to-semester retention and ultimate graduation.

Students with a Good HSGPA Should Be Encouraged To Enroll In More Classes

Momentum is key to completing a college degree (Achieving the Dream, 2014; Adelman 2006). Adelman (2006) indicates that students who earn “less than 20 credits by the end of the first calendar year of enrollment [have] a serious drag on degree completion” (p. xx). Unfortunately, too many community college students take classes at a piecemeal rate. Community colleges want to be there for students who can only afford to take a few classes at a time or just don’t have the time nor the energy to take more than one or two classes a semester. This is part of the culture of a community college, to be flexible and affordable to part-time students; “we” want to see ourselves

as understanding to our student base. But the reality is, these part-time students will likely never graduate from college as national statistics indicate that only 8% will graduate within six years of their enrollment (College Board Advocacy and Policy Center, 2012). Is it ethical to passively watch a student enroll into college classes knowing that the likelihood of that student reaching commencement is nearly a zero probability?

There is an ongoing campus debate at SVCC on whether it should be strongly encouraged for students to take additional credits if they are a part-time student, even when the national data clearly show that part-time students are likely to never graduate. The argument is that some students will be overwhelmed by taking too many classes and their GPA and financial aid eligibility will be compromised. This research gives academic advisors a baseline to gauge how many credit hours a student should enroll in based off their HSGPA.

The best predictor of momentum, by far, was the number of credits a student originally enrolled in during the fall semester. A student cannot be expected to complete 12 credit hours of college classes if they only enroll in six! However, HSGPA was also a strong co-predictor of momentum and the two predictor variables can be used to make a robust prediction of student success. Table 54 illustrates an example of four hypothetical situations where students have varying HSGPAs. Essentially the model predicts that if a student enrolled in 15 credit hours of coursework, that a student with a 3.0 HSGPA would still likely complete 12 credit hours of instruction. It is likely that this student may withdraw or fail a class; however, he or she has now accumulated 12 full-time credit hours of college work and is well on his/her way to completing a degree.

Table 54: *Predicted Momentum for New SVCC Students Based on HSGPA*

HYPOTHETICAL HSGPA	CREDITS ENROLLED	PREDICTED MOMENTUM (CREDITS ACCUMULATED)
4.0	15	14.9
3.5	15	13.3
3.0	15	11.8
2.5	15	10.2

Students that enroll at SVCC with very excellent HSGPAs should always be encouraged to take a “full load” of 15 or more credit hours in order to complete their degree within two years. Certainly college academic advisors should encourage these students to not only complete their degree, but to complete their degree as quickly as possible. As the saying goes, “time is money.”

What about the student with a poor HSGPA? Certainly a thoughtful approach must be taken by SVCC academic advisors when counseling these students. But the model predicts difficulties for these students even when they enroll in just a few classes. According to this research, 6.4% of students will completely fail or withdraw from their classes at SVCC and the momentum model clearly predicts that students with low HSGPAs will be the likely culprits. If a part-time student with a 2.0 HSGPA enrolled in two three-credit classes, he or she would likely complete only one of those classes. A part-time student with an even lower HSGPA would be predicted to not complete a single course. Students with very low HSGPAs will require strong intervention tactics in order for them to have any chance of success. However, this momentum model can

predict who these students are likely to be allowing them to be identified and remediated before they have a chance to fail or withdraw from their classes.

When It Comes to Predicting College Success, HSGPA Is King, but Credits Enrolled Is No Slouch

The literature review found HSGPA to be the most consistent predictor of college success. Certainly this research only strengthens the argument that HSGPA is a useful predictor of college success. Despite the persistent evidence found in the educational research literature, the predictive ability of HSGPA is not a valued commodity at SVCC and has not recently been used for *any* purpose at the college in the last 20 years or more. The researcher believes there are three reasons for this. First, SVCC is only now truly focusing on retaining students; the college administration and the Board of Trustees have been historically fixated on new enrollment. This focus on enrollment did not require a complex statistical analysis to be conducted to predict college success at the college; it only required the college to recruit harder and market better. Second, HSGPA still has a stigma of being an unreliable predictor of any student success measurement. The researcher has experienced a strong disrespect for the predictive abilities of HSGPA by college personnel. Third, the college has historically not employed an institutional researcher that could conduct high-level statistics.

As somewhat of a surprise, the number of credits a student enrolled in was also a strong predictor in three of the five success models, specifically for momentum, grade points, and retention. Certainly it is logical that the number of credits a student enrolled in should be strongly related to momentum (number of credits earned) and grade points

(momentum*FGPA). However the number of credits enrolled was also positively related to fall to spring retention. Can the number of credits a student enrolls in the fall semester be predictive of a student's motivation to return the following semester and complete a degree? This research indicates that it may.

Surprise! Some Expected Predictors Were Not Related to College Success

This research study was designed to be a comprehensive analysis of both academic and demographic factors of students and determine which factors were the most important in predicting future success. As stated before, HSGPA and credits enrolled were two of the strongest predictors of future success at SVCC. However, the identification of factors that were not significant is nearly as interesting. This research has determined that gender, race, the total income of a student and their family, the number of math and dual credit classes and ACT composite scores were not significant short term predictors of success at SVCC. Gender, race and the number of math and dual-credit classes have already been discussed elsewhere in Chapter Five.

High school percentile was only weakly significant when predicting FGPA (5th most important variable); it was not significant in any of the other four success models utilized in this study. While HSGPA and high school percentile are somewhat interrelated and redundant, this analysis indicated that HSGPA obviously outweighed high school percentile in its predictive power.

As stated in Chapter Two, the income of students or of their families has been positively correlated to academic success, especially on admission exams (Crouse &

Trusheim, 1988; Educational Testing Service, 1980; Nairn & Nader, 1980). For example, a student from a family making \$100,000 or more each year is much more likely to do well academically than a student who comes from a family who makes \$50,000. This research, however, which controlled for a number of demographic and academic factors, found that the total income of a student (and their family) to be irrelevant to the predictions of short-term academic success at SVCC. As indicated in Chapter Four, when paired with HSGPA, total income becomes an insignificant predictor and was dropped from the analysis. Once again, academic preparation trumps most other so-called predictive factors.

The Compass tests are designed to provide information on whether a student should be placed within college-level math and English classes or placed within developmental education classes. Unlike the ACT and SAT, Compass tests are not designed to predict success at the college; they are for course placement only. This research has corroborated that point. When utilized along with HSGPA, Compass scores were not important predictors of college success.

One of the most important findings in this research is that ACT composite scores were not significant predictors in any college success model. Generally, the educational literature has found HSGPA to be the most important predictor of college success, but ACT or SAT scores to be secondary co-predictors (Chapter Two). These current research findings indicated that ACT composite scores were not significant predictors of future college success when paired with other predictor variables (e.g., HSGPA). Additionally, ACT English and ACT math scores were not found to be significant in any success model.

Only ACT reading (retention) and ACT science (FGPA) were found to be significant predictors. Matteson (2007) and others (Bryson et al., 2002; Myers & Pyles, 1992) found that ACT and SAT scores were not accurate at predicting success of “at-risk” students or students of color. The College Board has recognized this discrepancy and believe an underlying cause is that those students with fewer financial resources, which includes a significant number of students of color, cannot afford the same SAT test preparation as those students with families in a better financial footing. Considering that a large proportion of the students studied for this research could be considered “at-risk,” the researcher speculates if the ACT scores are not reliable predictors for “at-risk” students as well.

Academic preparation is critical to future college success. This research has shown the strong relationship between students’ high school academic preparation (e.g., HSGPA, number of science and weighted courses) and their short-term success at SVCC. However, high stakes exams (e.g., ACT or Compass) and demographic variables add little, if any, predictive ability to the short-term academic success of freshmen at SVCC.

RECOMMENDATIONS FOR SAUK VALLEY COMMUNITY COLLEGE

1. Student interventions for at-risk students should be proactive instead of reactive.

The model to predict FGPA can be used to predict which freshmen will likely be placed on academic probation in their first semester at SVCC. This model should allow the Student Success Committee and academic advisors to intervene before a

- student is on academic probation, and not after. The nature of these interventions is unclear, but certainly identifying these at-risk students earlier would be beneficial to the college and to its students. Considering that many of these “at-risk” students are also minority students, programs could be designed specifically for the large Hispanic population attending SVCC. Additionally, programs specifically targeting male achievement may be beneficial to the college’s retention and graduation rates.
2. Freshmen with HSGPA of 3.0 or higher should be strongly counseled to take a full credit load (12–15 credit hours). It is time for SVCC to break away from the culture of allowing strong students to take classes in a piecemeal fashion. Academic advisors should sell the value of an education to students, discuss with them the poor probability of ever completing a degree while being part-time, and tell them to sacrifice now so they don’t have to later. Students with HSGPA of 3.0 can graduate from college on-time if given the right encouragement.
 3. SVCC administration should strongly recommend to local high school superintendents and principals that their students should take more science classes in order to be college-ready. This study considered a number of demographic and academic factors that were related to college success, but only a few of those were ever related to success—the number of science courses being one of them. Students with a good HSGPA and a strong background in science are likely to do very well at SVCC.
 4. At SVCC, objectives of the strategic plan include increasing persistence, retention and graduation rates. Attracting “better” students to the halls of SVCC would only

benefit progress toward those goals, and possibly even enhance the performance of less college-ready students. SVCC should focus recruiting efforts on high school students with HSGPAs of 3.0 or better. The model generated during this research shows that students with a HSGPA of 3.0 or better and taking a full academic load will likely maintain a FGPA of 2.50 or higher and complete at least 12 college credits during their first fall semester at SVCC.

5. The rigor of the dual credit program should be investigated. There is considerable debate on whether a high school student, being taught on their high school campus by a high school teacher, is receiving a similar college education and experience when compared to a student that comes to SVCC to take classes. This is a highly volatile discussion as on-campus faculty feel as if they have lost control of “their” classes and high school faculty, who are equally qualified as on-campus faculty, feel attacked that their rigor is not up to par. Certainly the Illinois Community College Board and the Higher Learning Commission believe that dual-credit classes should provide a similar educational experience for students, but does it? This research has indicated that the number of dual credit courses that a student completes does not correlate to success at SVCC. Internal SVCC data also indicated that more than 90% of dual-credit students are earning an “A” average, which is strong evidence that the classroom experience and expectation may not be the same. Using the guidelines established by the Higher Learning Commission and the National Alliance of Concurrent Enrollment Partnerships, college personnel should investigate the rigor and utility of the dual-credit program at SVCC. Students completing these courses,

especially with grades of A, should be highly successful when taking classes at the College, but this research has indicated that dual credit attainment is not adding to students' academic "tool kit" for college preparation during their first semester as a full-time student at SVCC.

6. The researcher is a strong proponent of maintaining the "open door" to higher education. Community colleges provide the last, best hope for a higher education for many and it is vital that access is maintained. However, having an "open door," but also recruiting the best and brightest students, should not be mutually exclusive functions. What many four-year institutions do very well is to recruit students with excellent academic records to their institutions; they understand the strong connection between high school academic record and success. This research project supports the contention that SVCC should also focus on recruiting talented high school seniors who will do exceptionally well at SVCC, increasing retention and completion rates at the college.

FUTURE RESEARCH

1. This same cohort of students should be followed for four additional years after enrolling in their first fall semester at SVCC to track their graduation rates. Research should focus on which of the five college success variables (e.g., FGPA, retention, persistence, etc.), if any, are most useful in predicting future graduation? If a single freshmen college success variable can be identified, it can be monitored closely by college personnel during a student's inaugural semester.

2. While females were generally more academically prepared than their male counterparts, females were only outperforming males in college success variable (FGPA) in their first semester at SVCC. This analysis has created more questions than it answered unfortunately.
 - a. If females were more academically prepared than males in high school, why do females not enjoy higher ACT scores when compared to males?
 - b. Females have statistically significant advantages in HSGPA and the number of weighted classes earned, so why do females not enjoy a larger academic advantage at SVCC especially in college success variables like class persistence, fall-to-spring retention, grade points and momentum (credit accumulation)? A possibility is that one of the genders may enroll in more academic rigorous programs and classes than the other.
 - c. Does the significant difference in FGPA between males and females magnify from semester to semester leading to significant and perceptible differences in academic achievement between genders with time? Are females completing their credentials at higher rates?
 - d. If an attainment gap truly exists with males, what college interventions and new strategies may help males make up that difference?
3. Future research could focus on the high school academic preparation of students, especially those students who will be entering the “trades” (CTE programs). Are CTE students unsure if they will be enrolling in college, and therefore, not focused on their academics? Is there disconnect with high school academic achievement and

the future goals of CTE students? Understanding the mentality and motivation of students who are opting to enter the trades may allow for early intervention tactics by college and high school staff. It is the researcher's belief that those students who plan on entering the CTE programs do not feel as if their high school education is as meaningful or applicable to "their" college focus on the trade programs. However, the opposite is true, their high school education is as important to their academic future as it is to "transfer" students.

4. Future research should investigate the ability of ACT scores to predict success in college-level English or math courses. Currently, SVCC uses ACT cut scores as a way to place students into either developmental or college-level math or English courses. If a student is below the ACT cut score, he/she has the option of taking a Compass test that would allow them to test into the college-level class. But these research findings support the research of Scott-Clayton (2012) and indicate that HSGPA may be the only necessary factor when determining placement of students. Scott-Clayton's (2012) recommendation was to place students with an "A or B" HSGPA directly into college-level classes and those with HSGPAs of "C" or lower should be placed within developmental classes. The utility of such a design should be investigated, and if true, would dramatically reduce the amount of bureaucracy at the college.
5. Lastly, it is hoped that this research has provided a foundation for creating additional predictive analytics that can forecast grades in classes at SVCC. The researcher calls this "academic forecasting" and would help determine a student's

academic course placement (development or college-level) and the likelihood of passing other classes the student is eligible for as a freshman. Table 55 provides an example of a data sheet that an academic advisor and student may have access to if using academic forecasting. Having access to this information could allow the student and advisor to make better academic choices based on data and not just on intuition and experience. It is hoped that this additional information would increase persistence and retention rates, and ultimately completion rates of these students.

Table 55: *A Hypothetical Example of “Academic Forecasting” for a Newly Enrolled Freshman Student at SVCC*

JOHN SMITH HSGPA: 3.23 MAJOR: CRIMINAL JUSTICE		ROCK FALLS HIGH SCHOOL CLASS OF 2015	IS INTERVENTION RECOMMENDED? YES, THE STUDENT SUCCESS COORDINATOR SHOULD FOLLOW- UP WITH THIS STUDENT.
Category	Recommendation	Suggested Classes	
English Placement	College Level	English 101	
Math Placement	Developmental	Math 075	
Suggested freshmen major courses	Probability of success (A-C)	Probability of Passing (A-D)	
CJS 101	73-77%	78-81%	
CJS 103	74-78%	79-83%	
CJS 120	56-66%	70-74%	
Suggested freshmen Gen Ed courses	Probability of success (A-C)	Probability of Passing (A-D)	
FYE 101	94-96%	97-99%	
HUM 101	72-81%	82-84%	
GOV 163	82-85%	86-91%	
PED 101	94-96%	97-99%	

CONCLUSION

This research study has reinforced some of the current findings found within the educational literature and has uncovered some novel findings on the ability to predict college success in a student's first semester in college. First, HSGPA, despite all of its presumed flaws, was still the best predictor of college success. HSGPA was either the first or second most important predictor of college success in all five college success models studied in this dissertation. HSGPA seems to measure a student's motivation and grit as much as academic ability. Unexpectedly, scores on the ACT were not important predictors of college success in this population of community college students.

The number of credits a student enrolls in during their first semester as a freshmen also played a role in the prediction of college success. Can this variable be indicative of a student's motivation to be successful in college? The researcher thinks so. Certainly students with higher HSGPAs should always be encouraged to take a full load of college classes during their first year at SVCC as this may lead to increased completion rates.

Certainly, the amount of academic rigor a student is exposed to in high school played a role in how well students performed at SVCC. Interestingly, the number of dual-credit classes and math classes a student completed in high school was really unimportant in making predictions on this population of students. The number of weighted classes and the number of science classes, especially, were moderately important in predicting a student's success at SVCC. It is suggested that local high school

principals and superintendents should explore increasing the number of required course offerings that fit these two academic categories.

Ultimately, the average student who enrolled at SVCC straight out of high school was academically “at-risk.” There may be many reasons for this including poor academic preparation in high school or just poor motivation by the student. Additionally, many of the students in this population are first generation, so they do not have a strong understanding of what a postsecondary education is like and the academic rigor they will face in college. Postsecondary institutions, especially community colleges that have high proportions of at-risk students, need to leverage every available resource to help students become more successful. If colleges spend millions of dollars each year purchasing retention software or hiring retention personnel, why shouldn’t community colleges spend similar resources to invest in research that will allow for academic forecasting to improve student placement and persistence? A new college student that gets off to a great start academically is more likely to accumulate college credits, be retained, and complete a credential.

Maintaining the “open door” is key to the mission of a community college, and therefore, it is imperative to be innovative when helping students succeed in college. Academic forecasting has the potential to provide an immediate return on investment.

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APPENDIX A: FERRIS STATE UNIVERSITY IRB APPROVAL

To: Dr. Robbie Teahen, Dr. Sandra Balkema and Mr. Steve Nunez
From: Dr. Stephanie Thomson, IRB Chair
Re: IRB Application #140804 (Title: *Using high school student academic and demographic data to predict success at Sauk Valley Community College*)
Date: September 24, 2014

The Ferris State University Institutional Review Board (IRB) has reviewed your application for using human subjects in the study, "*Using high school student academic and demographic data to predict success at Sauk Valley Community College*" (#140804) and has determined that it meets Federal Regulation category, *Expedited –2E*. This approval has an expiration date of one year from the date of this letter. **As such, you may collect data according to procedures in your application until September 24, 2015.** It is your obligation to inform the IRB of any changes in your research protocol that would substantially alter the methods and procedures reviewed and approved by the IRB in this application. Your application has been assigned a project number (#140804), which you should refer to in future correspondence involving the same research procedure.

We also wish to inform researchers that the IRB requires follow-up reports for all research protocols as mandated by Title 45 Code of Federal Regulations, Part 46 (45 CFR 46) for using human subjects in research. We will send a reminder to complete either the Final Report Form or the Extension Request Form to apply for a study continuation. Both forms are available on the [IRB homepage](#). Thank you for your compliance with these guidelines and best wishes for a successful research endeavor. Please let us know if the IRB can be of any future assistance.

Regards,



Ferris State University Institutional Review Board
Office of Academic Research, Academic Affairs

APPENDIX B: ASSUMPTIONS FOR TESTING CENTRAL TENDENCY

Introduction

Chapter Three describes the procedure for determining differences in central tendency of variables. In order to choose the best statistical test to identify the differences in central tendency, the Anderson-Darling normality test and the Bartlett's test for equal variances were used first. This information was not included in Chapter 4, but instead is included here as an appendix.

For the Bartlett's test for equal variances, the variables are considered to have equal variances if $p > 0.05$. For the Anderson-Darling normality test, the datasets were considered normally distributed if $p > 0.01$. If the variables were determined to have equal variances AND if all of the variables were determined to have normal distributions, then an ANOVA statistical test was used to determine if there were any significant differences between the means of the variables. If the assumptions for ANOVA were not met, then the Kruskal-Wallis statistical test was used instead.

Both the ANOVA and Kruskal-Wallis tests only indicate if there are significant differences between two or more populations; they do not indicate which populations have different mean or median values. Additional testing was required to determine which populations actually have different means or medians.

1. If an ANOVA test was used and if three or more variables were being compared, then a Tukey's test (at a 95% confidence) was utilized to determine which variables had different mean values.

2. If a Kruskal-Wallis test was used and if three or more variables were being compared, then a Sign test (at a 95% confidence) was used to determine which datasets had different median values.

Differences in Central Tendency between High Schools

Question: Do the students from the five district high schools have different HSGPAs?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p = 0.413$	Normal
#2	$p = 0.156$	Normal
#3	$p = 0.325$	Normal
#4	$p = 0.230$	Normal
#5	$p = 0.076$	Normal

Bartlett test for equal variances: $p = 0.512$. Variances equal.

ANOVA was used: $p = 0.21$, $F = 1.47$. No differences between high schools.

Question: Do the students from the five district high schools have different HS percentiles?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p = 0.090$	Normal
#3	$p < 0.005$	Not Normal
#4	$p < 0.005$	Not Normal
#5	$p = 0.022$	Normal

Bartlett test for equal variances: $p = 0.372$. Variances equal.

Kruskal-Wallis: $p < 0.001$, $H = 48.5$. Differences between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	53.4%	59.7%	65.4%
#2	37.2%	52.0%	60.8%
#3	22.9%	32.5%	44.8%
#4	62.8%	67.3%	72.2%
#5	49.6%	53.4%	58.8%

Question: Do the students from the five district high schools have different ACT composite scores?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p = 0.125$	Normal
#2	$p = 0.090$	Normal
#3	$p = 0.643$	Normal
#4	$p = 0.044$	Normal
#5	$p = 0.016$	Normal

Bartlett test for equal variances: $p = 0.49$ Variances equal.

ANOVA: $p = 0.140$. No differences in mean values.

Question: Do the students from the five district high schools earn the same number of dual credit classes while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$P < 0.005$	Not Normal
#2	$P < 0.005$	Not Normal
#3	$P < 0.005$	Not Normal
#4	$P < 0.005$	Not Normal
#5	$P < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.023$. Variances not equal.

Kruskal-Wallis Test $p < 0.001$, $H = 23.92$. Differences between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	1	1	2
#2	0	0	0
#3	0	0	1
#4	0	1	1
#5	1	1	2

Question: Do the students from the five district high schools earn the same number of weighted classes while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	P<0.005	Not Normal
#2	P<0.005	Not Normal
#3	P<0.005	Not Normal
#4	P<0.005	Not Normal
#5	P<0.005	Not Normal

Bartlett test for equal variances: $p < 0.001$. Variances not equal.

Kruskal-Wallis Test $p < 0.001$, $H = 48.67$. Differences between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	0	0	0
#2	0	0	0
#3	2	4	6
#4	0	1	2
#5	0	0	1

Question: Do the students from the five district high schools earn the same number of science classes while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	P<0.005	Not Normal
#2	P<0.005	Not Normal
#3	P<0.005	Not Normal
#4	P<0.005	Not Normal
#5	P<0.005	Not Normal

Bartlett test for equal variances: $p = 0.221$. Variances are equal.

Kruskal-Wallis Test $p < 0.001$, $H = 48.67$. Differences between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	2.0	2.5	3.0
#2	2.7	3.0	3.0
#3	2.3	2.5	3.0
#4	1.5	2.0	2.0
#5	2.0	2.0	2.5

Question: Do the students from the five district high schools earn the same number of math classes while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p < 0.005$	Not Normal
#3	$p = 0.012$	Not Normal
#4	$p < 0.005$	Not Normal
#5	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.007$. Variances are not equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 27.95$. Differences between high schools found.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	2.5	3.0	3.0
#2	2.0	2.5	3.0
#3	1.5	2.5	3.0
#4	3.0	3.0	3.0
#5	3.0	3.5	3.5

Question: Do the students from the five district high schools earn the same FGPA's while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p < 0.005$	Not Normal
#3	$p = 0.075$	Normal
#4	$p < 0.005$	Not Normal
#5	$p = 0.085$	Normal

Bartlett test for equal variances: $p = 0.008$. Variances are not equal.

Kruskal-Wallis Test $p = 0.019$, $H = 11.7$. Differences found between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	2.50	2.66	2.84
#2	2.46	2.78	3.02
#3	2.02	2.31	2.58
#4	2.25	2.5	2.64
#5	2.14	2.38	2.60

Question: Do the students from the five district high schools earn the same number of credits their first semester at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p < 0.005$	Not Normal
#3	$p < 0.005$	Not Normal
#4	$p < 0.005$	Not Normal
#5	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.109$ Variances equal.

Kruskal-Wallis Test: $p = 0.138$, $H=6.97$. No differences between high schools.

Question: Do the students from the five district high schools have the same class persistence rate while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p < 0.005$	Not Normal
#3	$p < 0.005$	Not Normal
#4	$p < 0.005$	Not Normal
#5	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.027$ Variances equal.

Kruskal-Wallis Test $p = 0.233$, $H=5.57$. No differences between high schools.

Question: Do the students from the five district high schools have the same class grade points while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
#1	$p < 0.005$	Not Normal
#2	$p = 0.374$	Normal
#3	$p = 0.045$	Normal
#4	$p < 0.005$	Not Normal
#5	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.008$. Variances are not equal.

Kruskal-Wallis Test $p = 0.019$, $H=11.7$. Differences found between high schools.

Sign confidence intervals

High School	Lower CI	Median	Upper CI
#1	28.99	33.00	35.89
#2	24.77	30.00	34.61
#3	18.81	27.50	35.62
#4	19.65	24.91	29.88
#5	21.00	25.92	28.98

Differences in Central Tendency between Genders

Question: Do males and females have the same HSGPA?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	$P = 0.248$	Normal
Female	$P = 0.006$	Not normal

Bartlett test for equal variances: $p = 0.425$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 11.52$. Differences found between genders.

Question: Do males and females have the same High School Percentile?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	$P < 0.005$	Not normal
Female	$P < 0.005$	Not normal

Bartlett test for equal variances: $p = 0.934$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 10.6$ Differences found between genders.

Question: Do males and females have the same ACT composite score?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	$P < 0.005$	Not normal
Female	$P < 0.005$	Not normal

Bartlett test for equal variances: $p = 0.276$. Variances equal.

Kruskal-Wallis Test: $p = 0.296$, $H = 1.09$. No differences found between genders.

Question: Do males and females earn the same number of dual credit classes while in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p < 0.001$ Variances not equal.

Kruskal-Wallis Test: $p < 0.001$ $H = 59.04$. Differences found between genders.

Question: Do males and females earn the same number of weighted classes while in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.086$ Variances equal.

Kruskal-Wallis Test: $p = 0.03$ $H = 4.70$. Differences found between genders.

Question: Do males and females earn the same number of science classes while in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.271$ Variances equal.

Kruskal-Wallis Test: $p = 0.074$, $H = 3.18$. No differences found between genders.

Question: Do males and females earn the same number of math classes while in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.096$. Variances equal.

Kruskal-Wallis Test: $p = 0.204$, $H = 1.62$. No differences found between genders.

Question: Do males and females earn the same FGPA while at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.168$. Variances equal.

Kruskal-Wallis Test: $p = 0.038$, $H=3.18$. Differences were found between genders.

Question: Do males and females earn the same number credits while at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.318$. Variances equal.

Kruskal-Wallis Test: $p = 0.153$, $H=2.04$. No differences were found between genders.

Question: Do males and females have the same persistence rate while at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.096$. Variances equal.

Kruskal-Wallis Test $p = 0.107$, $H=2.6$. No differences were found between genders.

Question: Do males and females earn the same number of grade points while at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
Male	P<0.005	Not normal
Female	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.971$. Variances equal.

Kruskal-Wallis Test $p = 0.052$, $H=3.79$. No differences were found between genders.

Differences in Central Tendency between Races

Question: Do White, Black, and Hispanic students attain the same HSGPA while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$p < 0.005$	Not Normal
Black	$p = 0.072$	Normal
Hispanic	$p = 0.89$	Normal

Bartlett test for equal variances: $p = 0.779$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 19.78$ Differences were found between races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	2.47	2.65	2.76
Hispanic	2.43	2.64	2.84
White	2.90	2.97	3.04

Question: Do White, Black, and Hispanic students attain the same HS percentile while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$P < 0.005$	Not Normal
Black	$P = 0.407$	Normal
Hispanic	$P = 0.122$	Normal

Bartlett test for equal variances: $p = 0.322$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 20.49$ Differences

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	35.8%	47.4%	51.7%
Hispanic	36.8%	44.2%	49.9%
White	56.9%	60.4%	63.3%

Question: Do White, Black, and Hispanic students attain the same ACT composite score while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$P < 0.005$	Not Normal
Hispanic	$P = 0.269$	Normal
Black	$P = 0.010$	Not Normal

Bartlett test for equal variances: $p = 0.621$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 26.71$ Differences between races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	17	18	19
Hispanic	17	18	19
White	20	20	21

Question: Do White, Black, and Hispanic students attain the same number of dual credit courses while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$P < 0.005$	Not Normal
Black	$P < 0.005$	Not Normal
Hispanic	$P < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.581$. Variances equal.

Kruskal-Wallis Test: $p = 0.008$ $H = 9.77$. Differences found between the races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	0	0	0
Hispanic	0	0	1
White	1	1	1

Question: Do White, Black, and Hispanic students attain the same number of weighted courses while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	P<0.005	Not Normal
Black	P<0.005	Not Normal
Hispanic	P<0.005	Not Normal

Bartlett test for equal variances: $p = 0.833$ Variances equal.

Kruskal-Wallis Test: $p = 0.136$ H=3.99. No differences between races.

Question: Do White, Black, and Hispanic students attain the same number of science courses while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	P<0.005	Not Normal
Black	$P = 0.210$	Normal
Hispanic	P<0.005	Not Normal

Bartlett test for equal variances: $p = 0.889$ Variances equal.

Kruskal-Wallis Test: $p < 0.001$, H=25.99 Differences found between the races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	1.2	2.0	2.3
Hispanic	1.0	1.5	2.0
White	2.0	2.0	2.5

Question: Do White, Black, and Hispanic students attain the same number of math courses while in high school?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	P<0.005	Not Normal
Black	$P = 0.125$	Normal
Hispanic	P<0.005	Not Normal

Bartlett test for equal variances: $p = 0.651$ Variances equal.

Kruskal-Wallis Test: $p = 0.007$, H=9.84 Differences found between races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	2.0	3.0	4.0
Hispanic	2.2	2.5	2.5
White	3.0	3.0	3.0

Question: Do White, Black, and Hispanic students attain the same FGPA while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$P < 0.005$	Not Normal
Black	$P = 0.888$	Normal
Hispanic	$P = 0.249$	Normal

Bartlett test for equal variances: $p = 0.856$ Variances equal.

Kruskal-Wallis Test $p < 0.001$, $H = 17.48$. Differences were found between races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	1.39	2.00	2.37
Hispanic	1.66	2.00	2.45
White	2.55	2.61	2.67

Question: Do White, Black, and Hispanic students attain the same number of credits while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$p < 0.005$	Not Normal
Black	$p = 0.42$	Normal
Hispanic	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.313$. Variances equal.

Kruskal-Wallis Test $p = 0.95$, $H = 4.7$ No differences between races.

Question: Do White, Black, and Hispanic students have the same class persistence while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$p < 0.005$	Not Normal
Black	$p = 0.005$	Not Normal
Hispanic	$p < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.17$. Variances equal.

Kruskal-Wallis Test $p = 0.176$, $H=3.47$ No differences between races.

Question: Do White, Black, and Hispanic students have the grade points while at SVCC?

Anderson-Darling Normality Tests

High School	p value	Distribution
White	$P < 0.005$	Not Normal
Black	$P = 0.051$	Normal
Hispanic	$P < 0.005$	Not Normal

Bartlett test for equal variances: $p = 0.383$ Variances equal.

Kruskal-Wallis Test: $p = 0.003$, $H=11.78$. Differences found between races.

Sign confidence intervals

Race	Lower CI	Median	Upper CI
Black	8.4	22.0	28.0
Hispanic	12.0	18.4	24.7
White	28.0	30.0	31.9

Differences in Central Tendency between Program Declaration

Question: Do transfer students and CTE students have the same HSGPA when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	$P < 0.005$	Not normal
Transfer	$P < 0.005$	Not normal

Bartlett test for equal variances: $p = 0.627$. Variances equal.

Kruskal-Wallis Test $p < 0.001$, $H = 14.27$. Differences found between program types.

Question: Do transfer students and CTE students have the same HS percentile when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	$P = 0.075$	Normal
Transfer	$P = .005$	Not normal

Bartlett test for equal variances: $p = 0.149$. Variances equal.

Kruskal-Wallis Test $p = 0.011$, $H = 6.54$. Differences found between program types.

Question: Do transfer students and CTE students earn the same ACT composite score when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	$P = 0.051$	Normal
Transfer	$P < 0.005$	Not normal

Bartlett test for equal variances: $p = 0.489$. Variances equal.

Kruskal-Wallis Test $p < 0.001$, $H = 22.62$. Differences found between program types.

Question: Do transfer students and CTE students earn the same number of dual credit courses when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.082$. Variances equal.

Kruskal-Wallis Test: $p = 0.041$, $H=4.19$. Differences found between program types.

Question: Do transfer students and CTE students earn the same number of weighted courses when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.063$. Variances equal.

Kruskal-Wallis Test $p<0.001$, $H=15.61$. Differences found between program types.

Question: Do transfer students and CTE students earn the same number of science courses when in high school?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.586$. Variances equal.

Kruskal-Wallis Test: $p<0.001$, $H=13.95$. Differences found between program types.

Question: Do transfer students and CTE students earn the same number of math courses when in high school?

Variable: # of Math classes

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.821$. Variances equal.

Kruskal-Wallis Test $p < 0.001$, $H = 19.04$. Differences found between program types.

Question: Do transfer students and CTE students earn the same FGPA when at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.974$. Variances equal.

Kruskal-Wallis Test: $p = 0.857$, $H = 0.03$. No differences found between program types.

Question: Do transfer students and CTE students earn the same number of credits when at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.416$. Variances equal.

Kruskal-Wallis Test: $p < 0.001$, $H = 15.96$. Differences found between program types.

Question: Do transfer students and CTE students have the same class persistence when at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.661$. Variances equal.

Kruskal-Wallis Test $p = 0.993$, $H=0.00$. No differences between program types.

Question: Do transfer students and CTE students earn the same number of grade points when at SVCC?

Anderson-Darling Normality Tests

Gender	p Value	Distribution
CTE	P<0.005	Not normal
Transfer	P<0.005	Not normal

Bartlett test for equal variances: $p = 0.024$. Variances not equal.

Kruskal-Wallis Test $p = 0.004$, $H=8.46$. Differences found between program types.

APPENDIX C: SPEARMAN CORRELATION TABLES FOR PREDICTOR
AND COLLEGE SUCCESS VARIABLES

Table C-1. Spearman Correlations Between Compass Scores, HSGPA and the Five College Success Variables

			Correlations									
			CompassAlgebra	CompassReading	CompassWriting	HSGPA	FGPA	Creditsenrolledon10thday	Momentum	ClassPersistence	GPAMomentum	Retained
Spearman's rho	CompassAlgebra	Correlation Coefficient	1.000	.342**	.374**	.348**	.267**	.171**	.297**	.239**	.325**	.197**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.008	.000	.000	.000	.002
			N	236	208	183	227	232	236	236	236	236
	CompassReading	Correlation Coefficient	.342**	1.000	.577**	.369**	.329**	.177**	.249**	.201**	.308**	.128**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.004
			N	208	510	351	494	498	510	510	510	510
	CompassWriting	Correlation Coefficient	.374**	.577**	1.000	.296**	.280**	.160**	.253**	.206**	.275**	.141**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.002	.000	.000	.000	.006
			N	183	351	383	373	375	383	383	383	383
	HSGPA	Correlation Coefficient	.348**	.369**	.296**	1.000	.545**	.261**	.489**	.419**	.593**	.248**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
			N	227	494	373	680	663	680	680	680	680
	FGPA	Correlation Coefficient	.267**	.329**	.280**	.545**	1.000	.140**	.600**	.668**	.847**	.322**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
			N	232	498	375	663	681	681	681	681	681
	Creditsenrolledon10thday	Correlation Coefficient	.171**	.177**	.160**	.261**	.140**	1.000	.574**	.136**	.435**	.275**
		Sig. (2-tailed)	.008	.000	.002	.000	.000	.000	.000	.000	.000	.000
			N	236	510	383	680	681	699	699	699	699
	Momentum	Correlation Coefficient	.297**	.249**	.253**	.489**	.600**	.574**	1.000	.828**	.916**	.501**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
			N	236	510	383	680	681	699	699	699	699
	ClassPersistence	Correlation Coefficient	.239**	.201**	.206**	.419**	.668**	.136**	.828**	1.000	.828**	.470**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
			N	236	510	383	680	681	699	699	699	699
	GPAMomentum	Correlation Coefficient	.325**	.308**	.275**	.593**	.847**	.435**	.916**	.828**	1.000	.487**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
			N	236	510	383	680	681	699	699	699	699
	Retained	Correlation Coefficient	.197**	.128**	.141**	.248**	.322**	.275**	.501**	.470**	.487**	1.000
		Sig. (2-tailed)	.002	.004	.006	.000	.000	.000	.000	.000	.000	.000
			N	236	510	383	680	681	699	699	699	699

** Correlation is significant at the 0.01 level (2-tailed).

Table C-2. Spearman Correlations Between Total Income, HSGPA and the Five College Success Variables

			Correlations							
			TotalIncome	HSGPA	FGPA	Creditsenrolledon10thday	Momentum	ClassPersistence	GPAMomentum	Retained
Spearman's rho	TotalIncome	Correlation Coefficient	1.000	.229**	.111*	.204**	.179**	.117*	.168**	.058
		Sig. (2-tailed)		.000	.046	.000	.001	.033	.002	.295
			N	333	327	325	333	333	333	333
	HSGPA	Correlation Coefficient	.229**	1.000	.545**	.261**	.489**	.419**	.593**	.248**
		Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000
			N	327	680	663	680	680	680	680
	FGPA	Correlation Coefficient	.111*	.545**	1.000	.140**	.600**	.668**	.847**	.322**
		Sig. (2-tailed)	.046	.000		.000	.000	.000	.000	.000
			N	325	663	681	681	681	681	681
	Creditsenrolledon10thday	Correlation Coefficient	.204**	.261**	.140**	1.000	.574**	.136**	.435**	.275**
		Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000
			N	333	680	681	699	699	699	699
	Momentum	Correlation Coefficient	.179**	.489**	.600**	.574**	1.000	.828**	.916**	.501**
		Sig. (2-tailed)	.001	.000	.000	.000		.000	.000	.000
			N	333	680	681	699	699	699	699
	ClassPersistence	Correlation Coefficient	.117*	.419**	.668**	.136**	.828**	1.000	.828**	.470**
		Sig. (2-tailed)	.033	.000	.000	.000	.000		.000	.000
			N	333	680	681	699	699	699	699
	GPAMomentum	Correlation Coefficient	.168**	.593**	.847**	.435**	.916**	.828**	1.000	.487**
		Sig. (2-tailed)	.002	.000	.000	.000	.000	.000		.000
			N	333	680	681	699	699	699	699
	Retained	Correlation Coefficient	.058	.248**	.322**	.275**	.501**	.470**	.487**	1.000
		Sig. (2-tailed)	.295	.000	.000	.000	.000	.000	.000	
			N	333	680	681	699	699	699	699

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Table C-3. Spearman Correlations Between Academic Predictor Variables and the Five College Success Variables

		Correlations															
		HSGPA	HSPercentile	ACTEnglish	ACTReading	ACTMath	ACTScience	ACTComposite	DualCreditClasses	WeightedClasses	TotalScience	TotalMath	FGPA	Momentum	ClassPersistence	GPAMomentum	Retained
HSGPA	Correlation Coefficient	1.000	.914**	.571**	.434**	.580**	.516**	.597**	.356**	.531**	.653**	.702**	.545**	.489**	.419**	.593**	.248**
	Sig. (2-tailed)	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	680	676	666	666	666	666	665	680	675	680	680	663	680	680	680	680
HSPercentile	Correlation Coefficient	.914**	1.000	.525**	.414**	.536**	.485**	.555**	.360**	.484**	.582**	.680**	.524**	.444**	.373**	.550**	.213**
	Sig. (2-tailed)	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	676	678	664	664	664	664	662	678	672	676	676	661	678	678	678	678
ACTEnglish	Correlation Coefficient	.571**	.525**	1.000	.748**	.699**	.702**	.905**	.296**	.494**	.586**	.561**	.394**	.341**	.232**	.412**	.139**
	Sig. (2-tailed)	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	666	664	677	677	677	677	675	677	662	668	668	660	677	677	677	677
ACTReading	Correlation Coefficient	.434**	.414**	.748**	1.000	.574**	.654**	.854**	.220**	.403**	.471**	.460**	.278**	.247**	.155**	.303**	.082**
	Sig. (2-tailed)	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.034**
	N	666	664	677	677	677	677	675	677	662	668	668	660	677	677	677	677
ACTMath	Correlation Coefficient	.580**	.536**	.699**	.574**	1.000	.725**	.843**	.252**	.437**	.592**	.688**	.378**	.406**	.291**	.443**	.178**
	Sig. (2-tailed)	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	666	664	677	677	677	677	675	677	662	668	668	660	677	677	677	677
ACTScience	Correlation Coefficient	.516**	.485**	.702**	.654**	.725**	1.000	.866**	.256**	.447**	.550**	.559**	.370**	.349**	.263**	.408**	.156**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	666	664	677	677	677	677	675	677	662	668	668	660	677	677	677	677
ACTComposite	Correlation Coefficient	.597**	.555**	.905**	.854**	.843**	.866**	1.000	.287**	.506**	.621**	.640**	.401**	.375**	.265**	.440**	.154**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	665	662	675	675	675	675	675	675	660	667	667	658	675	675	675	675
DualCreditClasses	Correlation Coefficient	.356**	.360**	.296**	.220**	.252**	.256**	.287**	1.000	.221**	.283**	.286**	.209**	.139**	.133**	.181**	.086**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000	.023**
	N	680	678	677	677	677	677	675	699	676	682	682	681	699	699	699	699
WeightedClasses	Correlation Coefficient	.531**	.484**	.494**	.403**	.437**	.447**	.506**	.221**	1.000	.476**	.484**	.292**	.356**	.253**	.370**	.180**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000	.000
	N	675	672	662	662	662	662	660	676	676	675	675	659	676	676	676	676
TotalScience	Correlation Coefficient	.653**	.582**	.586**	.471**	.592**	.550**	.621**	.283**	.476**	1.000	.656**	.427**	.469**	.372**	.516**	.266**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000	.000
	N	680	676	668	668	668	668	667	682	675	682	682	665	682	682	682	682
TotalMath	Correlation Coefficient	.702**	.680**	.561**	.460**	.688**	.559**	.640**	.286**	.484**	.656**	1.000	.416**	.452**	.357**	.497**	.233**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000	.000
	N	680	676	668	668	668	668	667	682	675	682	682	665	682	682	682	682
FGPA	Correlation Coefficient	.545**	.524**	.394**	.278**	.378**	.370**	.401**	.209**	.292**	.427**	.416**	1.000	.600**	.668**	.847**	.322**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000	.000
	N	663	661	660	660	660	660	660	681	659	665	665	681	681	681	681	681
Momentum	Correlation Coefficient	.489**	.444**	.341**	.247**	.406**	.349**	.375**	.139**	.356**	.469**	.452**	.600**	1.000	.828**	.916**	.501**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000
	N	680	678	677	677	677	677	675	699	676	682	682	681	699	699	699	699
ClassPersistence	Correlation Coefficient	.419**	.373**	.232**	.155**	.291**	.263**	.265**	.133**	.253**	.372**	.357**	.668**	.828**	1.000	.828**	.470**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000
	N	680	678	677	677	677	677	675	699	676	682	682	681	699	699	699	699
GPAMomentum	Correlation Coefficient	.593**	.550**	.412**	.303**	.443**	.408**	.440**	.181**	.370**	.516**	.497**	.847**	.916**	.828**	1.000	.487**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.	.000
	N	680	678	677	677	677	677	675	699	676	682	682	681	699	699	699	699
Retained	Correlation Coefficient	.248**	.213**	.139**	.082**	.178**	.156**	.154**	.086**	.180**	.266**	.233**	.322**	.501**	.470**	.487**	1.000
	Sig. (2-tailed)	.000	.000	.000	.034**	.000	.000	.000	.023**	.000	.000	.000	.000	.000	.000	.000	.
	N	680	678	677	677	677	677	675	699	676	682	682	681	699	699	699	699

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).