PREPPED FOR SUCCESS: IDENTIFYING THE FACTORS THAT LEAD TO STUDENT SUCCESS IN ECONOMICS PRINCIPLES COURSES PRIOR TO COURSE ENROLLMENT

by

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"Essentially, all models are wrong, but some are useful."

-George E.P. Box

ABSTRACT

The United States is challenged with drastically improving student completion rates in higher education, especially community colleges, without sacrificing quality or access. Decades of research have examined factors that lead students to be successful in college, yet completion rates remain persistently low. This paper argues that the problem is not with understanding student success at the macroscale (i.e., student success in general), but a lack of understanding at the microscale (i.e., at individual course level). Predictive analytics could help educational researchers uncover answers at this scale. This study examined the surveys and records of students enrolled in Economics Principles courses at one community college during one academic year to discover what factors are related to their success in the course (i.e., earning a grade of "C" or better).

Four research questions were proposed to develop an understanding of the relation between these factors and student success. The fourth research question developed binary logistic regression models to predict students' success in their course, for the current sample of students and a subsequent cohort. Results show that 16 factors were related to students' success in the course, including GPA, the instructor, if they had completed an economics course in a prior term, and the number of withdrawals they had in the prior semester. Results indicate that these factors differ depending on the Economics Principles course students complete (Microeconomics vs. Macroeconomics). Evidence also suggests these factors could predict student success in the course better than the course overall pass rate.

These findings could inform prospective students, instructors, and academic advisors on factors that students can develop prior to course enrollment to maximize their likelihood of passing the course, and therefore improving their chances of completing their degree program. Discussion includes expanding this study model to other disciplines to further understand student completion outcomes.

DEDICATION

In dedication to my mother, Linda Thor, my father, Bob Huntsinger, and grandmother, Mildred Thor, who made sure I always did my homework and showed me that the world was full of endless possibilities.

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CHAPTER 1: INTRODUCTION TO THE STUDY

Introduction

The community college has experienced a dramatic shift in focus from student "access" to student "success" over the previous six years with the introduction of the Completion Agenda. Soon after taking office, President Barack Obama (2009) set an ambitious goal for college and university educators, administrators, state legislators, and policymakers to help America once again have the highest proportion of college graduate in the world by 2020. The stakes could not be higher for the future of the nation, noting that a good education is a prerequisite to the pathway of opportunity and every American will need education above a high school diploma (2009). Obama has aligned this goal with financial resources by proposing "incentive grants" in his 2015 budget awarded to colleges based on the number of on-time Pell graduates (Field, 2014).

Once the leader of the world in degree attainment, the United States now lags behind other countries in degree earned among the young adult workforce (Bolden, 2009). Though currently fifth in the world in terms of its adult population (25-64) holding a college degree, this ranking drops to fourteenth when just considering young adults (25-34) (Hull, 2012). Indeed, there is much room for improvement as only 30% of first-time community college students graduate within three years, and only 18% earn a bachelor's degree within eight years of high school graduation (Integrated Postsecondary Education Data System (IPEDS), 2003). The cost of so many students not completing college is not just realized in lost future productivity, household incomes, and tax revenue; over a five-year period, federal, state, and local government agencies spent approximately $4 billion on community college students who began as first-time, full-time, degree-seeking students but did not return for a second year of school (Schneider & Yin, 2011).

In order to improve these graduation rates, community colleges need to find new ways to help students succeed and complete their degrees on time. In order to expedite the discovery of solutions, community college leaders need to have a working knowledge of the answer to the question, “which factors contribute to student success in higher education?” Although much research has been done to address this issue at a macroscale (i.e., what predicts student success in general), there has been scant research on predictors of students’ success at the microscale (i.e., at the individual course level). Understanding predictors of success for individual courses is key to providing data-informed advisement to students so that they have the best chance possible of passing any given class required for a degree plan. Improving completion rates for individual courses should lead to faster program completion, and at a lower average cost per student (through reduced time, tuition, and fees associated with retaking unsuccessful courses). This benefits students, community colleges, and taxpayers.

This study will focus on two particular common general education courses at colleges and universities across the United States, Macroeconomic Principles and Microeconomic Principles, and will discover which factors students bring to the course prior to the beginning of formal coursework that predict their success in the courses. With this crucial information in hand, prospective students can be better advised by advisers, faculty, and other college personnel as to what they could do prior to enrollment to maximize their chances of successfully completing the course. Through demonstration of the efficacy of this approach, similar studies could be conducted for other high enrollment college courses, thereby improving completion rates for students at the course and ultimately the program level.

Background on the Problem

Chapter 2 will review the literature of what is known about the factors that predict student success in higher education, with a particular focus on community colleges. To facilitate comprehension, these factors have been sorted into discrete but somewhat overlapping categories, including “demographic/social predictors,” “academic predictors,” “personal/cognitive predictors,” and “institutional predictors,” in which the latter suggest best practices implemented by higher education institutions to boost course and degree program completion among the student population that they serve. Separate from these four distinct categories is a review of a new tool available to colleges and universities referred to as analytics (usually with a precursory adjective commonly including “learning,” “data,” “insight,” “predictive” or “prescriptive”). This tool is used to analyze student-generated data points to understand and predict future student outcomes. In turn, that information is used to intervene with students to yield better outcomes. Although the combination of past research and new tools has generated greater understanding as to why some students are more successful in college than others, there is a glaring dearth of research on student success predictors at the individual course level. Student success variables can and likely will differ depending on if a student is a taking, for example, a Biology Principles course, Healthy Living course, or Introduction to Philosophy course. Understanding these differences in the factors that predict student success in these unique courses can create opportunities to custom tailor advice and intervention for students to improve success rates and reduce time and cost to degree completion.

There are multiple demographic/social characteristics of students that predict their success in college and university courses. Students that come from families of higher socioeconomic status are more likely to complete college (Napoli & Wortman, 1996), particularly because these households have greater economic resources that they can impart to their children-students, such as rigorous academic preparation, high educational aspirations, and general family support (Kuh, G., Kinzie, J., Buckley, J., Bridges, B., & Hayek, J. C. 2008). On the contrary, students who are unmarried parents experience lower completion rates, often due to financial constraints that force them to stop their education so that they can increase the number of hours worked and corresponding immediate income (Goldrick-Rab & Sorensen, 2010).

African-American and Hispanic students tend to complete at lower rates than Caucasian and Asian students (Murtaugh, Burns, Schuster, 1999). One explanation for this is that these lower completing ethnic groups come to college less prepared for college-level math, writing, and reading classes, as measured by college entrance placement exams (Grimes, 1997).

Women tend to outperform men in college, both in terms of average semester grade point average (GPA) (Graunke and Woosley, 2005) and, since 2001, in bachelor's degree completion. This is at least partially due to the fact that women come to college better prepared to succeed than men do as measured by high school grades, college placement test scores, and college preparatory coursework (Kuh et al., 2008).

Traditional aged students (young adults, typically measured between the ages of 18 and the mid-20s) are more likely to persist (Crosta, 2013a) and complete college (Shapiro et al., 2012; Bahr, 2012a) at a higher rate than non-traditional aged students (those older than their mid-20s). A significant reason for this is that external life demands on non-traditional students, from work and family expectations, negatively correlate with GPA (Sarason, Johnson, and Siegel, 1978), persistence (Mulligan & Hennessey, 1990; Bers & Smith, 1991; Axelson & Torres, 1995; Napoli and Wortman, 1998), and retention (Carter, 1982).

First-generation college students complete at a lower rate than those students who have had at least one parent go to college (Burns, 2010), and take longer to graduate when they do graduate (Sparkman, Maulding, and Roberts, 2012). Likely related to this phenomenon is the structure of the household students come from (e.g., the need to care for children at home), the family's attitude towards education (the amount of value perceived in obtaining a higher education credential), the student's social connections in college, and the student's social capital (how well they understand how the college process works) are all related to the success rates of students (Burns, 2010; American College Testing Program, 2007; Karp, O'Gara & Hughes, 2008; Kuh et al., 2009).

However, there is scant evidence in the literature about how demographic/social factors relate to student success in individual courses. Although the main purpose of this study is to uncover variables that students can change in order to better succeed in individual courses, it is important to understand the factors they cannot change in order to understand how these variables relate to each other.

The prior academic background of students and their academic performance while in college both strongly relate to the success they experience in college in many important ways. Simply put, those students with better academic preparedness show higher initial goal completion (Napoli & Wortman, 1998). Students' high school GPAs and standardized test scores predict their college GPA (Astin, 1993). Students who complete a rigorous core college preparatory curriculum in high school are more likely to stay in high school, go to and stay in college, and ultimately earn a college degree (American College Testing Program, 2007; Burns, 2010). The quality of the K-12 schools students attend, independent of the communities they are located in or the student populations that they serve, also predict student success (Black, Lincove, Cullinane, & Vernon, 2014).

Student behaviors that demonstrate a strong commitment to achieving academic goals predict their success. The act of declaring academic goals is associated with higher course and degree completion (Bahr, 2012a; Harackiewicz, Barron, Tauer, Carter, & Elliot, 2000). Attending college immediately after high school and attending uninterrupted full-time are indicators of student success in college (Burns, 2010; Bahr, 2012a). Persistent enrollment in consecutive courses, particular in a course sequence, greatly improves a student's chances of passing the course (Bahr, 2012b; Shapiro et al., 2014). It seems that the first year, even the first semester, of college for students is extremely important in determining their ultimate success (Predictive Analytics Reporting (PAR) Framework, n.d.; Crosta, 2013a). Full-time students, and those students that take more credits per semester (and pass the courses), are more likely to persist and find greater success (Fike & Fike, 2008; Bahr, 2012; Crosta, 2013a; Crosta, 2013b; Shapiro et al., 2014).

The type of courses taken in college, particularly emphasizing mathematics, can indicate the chances of student success later on in their college careers (Bahr, 2012a; Burns, 2010). Taking developmental education courses, or the need for students to take these courses, is disastrous for students seeking to complete a degree program as less than 10% of these students graduate from community college in less than three years (Complete College America, 2012), and each additional developmental course taken reduces a student's chance of passing a course by 34% (Predictive Analytics Reporting (PAR) Framework, n.d.).

Although we know much about the academic predictors of student success for degree completion, there remains a gap in the knowledge as to what academic predictors are associated with success for particular courses.

There are personal or cognitive factors of individual students that predict their success in college, outside of their socioeconomic background or academic history. Students with positive psychological health (e.g., positive self-concept, psychological independence) have better outcomes than those displaying traits of psychological maladjustment (depression, loneliness) (Baker & Siryk, 1989). Life stressors, including outside stressors (Metzner, 1984) as well as academic issues (Tobey, 1997), impact students' adjustment to college and their rate of attrition. Students who are more conscientious tend to have better academic outcomes (Saklofske et al., 2012; Burns, 2010). Students with good motivation and self-regulation are more likely to persist and complete (American College Testing Program, 2007). Students who demonstrate academic self-efficacy and optimism are strong predictors of academic performance (Chemers, Hu, & Garcia, 2001). Those students who believe that they are the ones in control of their destiny, or that have an internal locus of control, tend to acquire and use academic information more readily and therefore tend to have better academic outcomes (Gifford, Briceno-Perriott, Mianzo, 2006). Demonstrated commitment to an academic goal or institution are strong predictors of first semester GPA and degree completion (Kuh et al., 2009). However, little research has been conducted on students' personal attributes in terms of their success in individual courses.

The higher education institution that students attend also influences their academic success. Some of these factors are generally outside of the control of college and university leaders to influence, such as the type of institution they are (four-year college and universities have significantly higher success rates than community colleges (Shapiro et al., 2012)), the size of the institution they lead (larger institutions tend to have worse student outcomes (Astin, 1993; Bailey et al., 2005a; Pascarella & Terenzini, 2005)), and the state they are located in (Bailey et al., 2005a). However, a growing body of evidence shows that motivated college and university leaders can instill institutional practices and procedures that can help more students succeed. Practices that influence student success span nearly every corner of the institution, including registration rules and procedures (Safer, 2009; Smith, Street, Olivarez, 2002), promoting student engagement through involvement outside of class (Graunke & Woosley, 2005), the quality of library services (Soria, Fransen, and Nackerud, 2014), and counseling services (Scoggin & Styron, 2006). The type of faculty at colleges and universities, and how they perform their work, are integral to student success. This includes the percentage of full-time faculty employed (Bailey et al., 2005a; Jacoby, 2006), the prevalence of learning communities (Pascarella & Terenzini, 2005; Scrivener et al., 2008), the use of active and collaborative learning techniques in instruction (Pascarella & Terenzini, 2005; Tinto & Love, 1995; Zhao & Kuh, 2004), faculty commitment to uncovering student success strategies (Mellow and Heelan, 2008), and perceived support of faculty by the student body (Shelton, 2003). Helping new students adjust to higher education through the use of new student seminars or courses can lead to higher degree completion (Murtaugh, Burns, Schuster, 1999). Also, helping students establish appropriate academic and career goals is linked to better outcomes (Burns, 2010). Increasingly, new strategies are being tested and put into place to get more students to complete developmental education courses or to avoid them altogether (Edgecombe, 2010), such as better alignment of curriculum between high schools and community colleges (Fain, 2013). However, there is a lack of research showing how institutional leaders can impact student success rates at the individual course level.

Most of the preceding research discussed uncovered factors of student success in higher education through the use of traditional academic research studies and methodologies. There are, however, new tools available to colleges and universities focused on understanding student success factors in real time, referred to as learning analytics (occasionally the adjective “learning” is substituted with the adjectives “data,” “insight,” “predictive,” or “prescriptive,” as will be the case in this paper). Only recently available due to the necessity of sufficiently powerful information technology resources, data storage systems, and the ability to collect large amount of “digital footprints” (markers of student behavior stored in an information technology system), data scientist professionals (either internal or external to the higher education institution) are able to sift through the mountain of data to uncover hitherto unknown patterns of student success. These new processes are in alignment with national movements focused on improving student success in higher education through better use of data, such as Achieving the Dream (2006). Predictive analytics has already demonstrated its use in areas outside of academia, from predicting presidential and senate races (Bartlett, 2012) to creating successful online dating matches or suggesting products one might be interested in purchasing based on one's prior purchases (Parry, 2012). Data analytics has so far proven useful in academia as well, although its impact is surely in its infancy. It has been used to predict and reduce the dropout rate at the American Public University System (Schaffhauser, 2013), helping students choose courses that are both challenging and critical to their degree program while improving course completion rates (The Economist, 2013), and even helping students improve their time management and study skills (Vendituoli, 2014). However, like the preceding type of research discussed, there are few published findings of what factors predict student success in individual courses using learning analytics.

Although the literature on student success is extensive, far too many students are not completing their degree programs. It may be the case that there are certain factors that would prohibit some students from completing a degree regardless of the academic environment they are in, but it is likely that institutions could do more to increase their completion rates through a better understanding of factors that help students succeed in particular courses.

Statement of the Problem

The literature is rich with studies dating back decades that strive to illuminate the factors that drive student success. However, nearly all of these studies focus on student success at the macroscale, meaning applying student success factors across the students' entire tenure at the higher education institution, or factors for success for any given developmental or college-level course attempted, regardless of the specific skills, abilities, or knowledge needed for success in that course. However, it is unlikely that the factors that lead to student success are identical between college courses. There may, in fact, be key differences that predict student success in, say, Introduction to Algebra from Organic Chemistry or Introduction to Cinema. This leaves a gap in the knowledge in which learning analytics strategies may help. These methods and tools use student data, collected during regularly scheduled courses, using data from students who self-selectively enroll, to find new factors that predict student outcomes. Learning analytics techniques provides a basis for effective interventions to help improve student outcomes and find key differences between courses that could make course-specific customized recommendations possible. Higher education leaders need to understand the factors that predict student success in individual courses, not only while the students are taking the course but also before they even register for them. Knowledge of these factors will help guide students to the resources they need to succeed and help them decide when they are best prepared to take a challenging course needed for their degree so that they can ultimately succeed, faster and at a lower overall cost.

Purpose of the Study

The purpose of this study was to address research questions to help understand what factors predict student success before enrollment in the economics principles courses. This was accomplished through a quantitative study of all participating adult economics students at one mid-sized, suburban community college over one academic year. The study was designed to find the factors that the students' possess prior to course enrollment that are predictive of successful course completion. Although factors outside the students' control (e.g., race, high school achievement) were analyzed in order to account for confounding factors, the real purpose of the study was to uncover the factors that students can change through their deliberate actions so that future students can increase their probability of passing the courses through appropriate preparation.

By combining student survey responses with their pertinent student information system (SIS) data, a wide range of information about the students' demographic/social, academic, and personal background was compiled to create a large set of independent variables (IVs). Through a combination of descriptive statistics and the building of a predictive algorithm, through the use of binary logistic regression, this study focused on how these IVs relate to the dependent variable (DV), whether the student was successful in the course (i.e., received a grade of A, B, C, or P) or not (i.e., received a grade of W, Y, I, D, or F). Relating the IVs to the DV will give researchers and practitioners focused on college student success more information about what it takes for students to succeed in college, particularly in economics.

Like most learning analytics studies, this was an observational study. It does not attempt to randomly sample from a broader student population and place some students in a treatment group and others in a control group, such as would be found in an experimentally designed study. On the contrary, the study's participants have self-selected to enroll in the course prior to commencement of the study; only then were factors analyzed to differentiate successful students from non-successful ones. One major difference between this study and many learning analytics studies is that this study does not use real-time data to analyze student behavior while the student is enrolled in the class, but only analyzes student patterns of success after the completion of the course. Only after understanding which factors lead student to success in economics principles courses prior to their enrollment in them can practitioners attempt to influence students' decisions on when to enroll in the courses and how to best prepare for the courses prior to enrollment.

Significance of the Study

Researchers and practitioners interested in improving student success rates need to understand the factors that predict student success in particular college courses, not just in college courses in general. This study focuses on understanding the factors that predict student success in two courses, Macroeconomic Principles and Microeconomic Principles, which has not been studied in the literature. With this knowledge in hand, higher education institutions can better guide prospective students into when to take these courses and what to do beforehand to maximize their chances of passing the course on their first attempt. Academic advisors, economics instructors, and others who work directly with students in choosing their course schedule will move from a "bowling in the dark" strategy of class recommendation to one based on data, with the corresponding expectation that this will improve student performance in these two specific courses and reduce attrition rates.

However, if this study proves useful in improving student performance in the economics principles courses, this same pattern of analysis can be scaled up to many others, if not all other courses within the institution. Not only would similar gains in student performance be expected to occur at the course level, but even more useful information could be generated by knowing the specific factors of student success within an entire degree program through the understanding of the links between courses. This research could ultimately lead researchers and practitioners to create a web, or network, of interlocking courses to create individualized pathways that the data show would maximize a particular student's chances of earning a college degree in a chosen field, based on their own particular background, abilities, and interests. In addition to increasing the chances of earning a degree, a student would do so in less time and at a lower cost because the need to retake courses will be reduced. It is useful to note that academic practitioners have for decades structured degree pathways through an interlocking system of prerequisite courses, based on professional judgment. What is different now is the scale of this potential endeavor, and replacing subjective (though expert) judgment with objective observation. Although the scale of this particular research is small relative the potential ends, it nonetheless provides an integral step, a proof of concept, of the power that individualized, predictive course selection could have on the higher education landscape for decades to come and serve as an important tool in achieving the goal of drastically increasing the number of college graduates in this country.

Primary Research Questions and Hypotheses

Research Question I is "*which factors in the study (independent variables) significantly relate to student success (dependent variable?"* The null hypothesis is "there are no factors that are significantly related to student success," and the alternative hypothesis is "there is at least one factor significant related to the dependent variable."

Research Question II is "*Of the factors related to student success (independent variables), are any significantly related to each other?"* In this case, the null hypothesis is "there are no significant relations between the independent variables related to student success," and the alternative hypothesis is "there is at least one significant relation between two or more independent variables related to student success."

The third research question is *"are there different relations between the factors (independent variables) and student success (dependent variable) depending on which course is taken (Macroeconomic Principles vs. Microeconomic Principles)?"* In this case the null hypothesis is "the factors associated with student success are the same between the Macroeconomic Principles and Microeconomic Principles courses," and the alternative hypothesis is "there are one or more variables associated with student success that differ between the Macroeconomic Principles and Microeconomic Principles courses."

Research Question IV is "*what factors, in combination, best predict student success before enrollment in the economics principles courses?*" The null hypothesis is "knowing two or more independent variables does not lead to a more accurate understanding of a students' likelihood of success in economics courses than only knowing one independent variable," and the alternative hypothesis is that "knowing two or more independent variables can significantly improve predictions of student success in the economics principles courses."

Research Design

In order to find answers to the research questions, the faculty-researcher and faculty-facilitators recruited adult student volunteers enrolled in Macroeconomic Principles (ECN211) or Microeconomic Principles (ECN212) during the 2013-2014 academic year (fall or spring semester) at one mid-sized, suburban community college in the Southwest United States. This is an observational study; no attempt was made to randomly sample from a broader student population or to sort them into treatment or control groups as would be the case in an experimental design. On the contrary, the student-participants in the study enrolled in the course prior to understanding that a research study would be conducted, and therefore represent a composite of students as would enroll in a non-laboratory or field setting. This increases the external validity of the study (and reduces internal validity), although it is limited in scope by only looking at students at one community college and in one academic year.

Survey questions were created based on the literature review of what previous studies have shown are related to student success (e.g., Grimes, 1997; Burns, 2010), as well as the professional judgments (based on many years of experience in classroom instruction) held by the economics faculty members who helped craft the instrument as to what factors tend to promote student success in their courses, enhancing internal criteria validity of the instrument. The survey questions were piloted during the academic year prior to the research study to make any adjustments needed before the actual research study. The research was extended to one academic semester after the main study was conducted in order to collect student data used to test the robustness of predictive algorithms used in testing Research Question IV.

Before the beginning of each semester of data collection, the researcher made copies of the two-page survey (Appendix A) and informed consent form (Appendix B), sorted them into envelopes by course section numbers, and distributed them to instructor-facilitators during the bi-annual pre-semester economics instructors' meeting. Surveys and informed consent forms were then administered by the economics instructors teaching their respective classes during the research period. Within the first two weeks of the semester (the particular day within that period was at the instructor's discretion), all students attending the course that day were read a script (Appendix D) describing the nature and purpose of the study, as well as informing them that participation was completely voluntary and that participation or nonparticipation would neither yield academic nor nonacademic rewards or punishments. Furthermore, students who were younger than 18 years of age were not included in the study. At this point, all the students who attended class on the day of the study (as determined by their instructor) were administered a student survey along with the informed consent form that they signed if they volunteered to be part of the study, which gave the researcher permission to access their college records via the college's Student Information System (SIS) to collect supplemental data, including their final grade (the dependent variable of the study) at the conclusion of the course. There were 23 separate sections (when the honors cohort sub-sections were merged with the standard section of the course), ranging from 5-36 students ($M = 24.04$, $SD = 7.55$).

Once all surveys and informed consent forms were returned to the researcher, the researcher submitted them to the college's institutional research office, which digitized the responses. This data was then merged with information pulled from the students' SIS records, including their final course grades (dependent variable), to create the data set used for analysis in this study.

During the first part of the analysis phase, descriptive and inferential statistics explored the relation between the independent variables and the dependent variable (Research Questions I and III) as well as between the independent variables (Research Question II). During the second part, focused on answering Research Question IV, binary logistic regression models were built using a five step process in order to uncover which factors, in combination, are most influential to student success in ECN211, ECN212, and both courses together. The binary logistic regression models were then applied to both the sample used to build the models as well as a new cohort of students (enrolled in the Fall 2014 semester) to test the predictive power of the model on student-participants' not used in the creation of the statistical model. Data collection and analysis procedures were nearly identical for this last cohort as for the previous ones.

Assumptions, Limitations, and Scope (Delimitations)

There are multiple assumptions made in this study. It is assumed that student-participants will be truthful and accurate in self-reporting information on the survey, that student records will be free of errors and up-to-date, and that instructor-facilitators and institutional researchers will not manipulate or otherwise compromise the data. It is assumed that students' final grades in their courses are a result of their performance in the class and that they have earned the grade that they received through their individual actions. There is an assumption that there is adequate and approximately equal amount of academic rigor across all sections and instructors of the courses; this assumption is supported by the ongoing collaborative relationships between the full-time and part-time economics faculty members, who frequently discuss and share pedagogical techniques, assignments, the commonly adopted textbook, and the discipline's common final exam.

There are also multiple limitations to this study. Although there were significant efforts to understand the literature on student success variables for inclusion of this study, not all variables were included in either the survey or information pulled from the SIS. Instructor and researcher beliefs may bias the type of questions asked on the survey. The survey questions may be limited in their capacity to fully collect data relevant to understanding student success in the course. The type of questions found in the SIS may not be perfectly suited for research studies as the nature of the data collected may reflect more of the institution's need to generate reports for accountability than for research purposes.

In addition to the limitations of the study, there are also delimitations of the study that have been deliberately introduced in order to reduce the scope of the study. The study only includes students 18 years of age or older, in order to avoid the necessity of acquiring parental consent for participation in the study; this means a subset of minors enrolled in the course were omitted. The study only looks at one institution, which may and probably will differ substantially from other community colleges across the country. It only examines a cohort in one academic year, which may be substantially different from cohorts in other years, particularly over longer time frames. At this community college, economics is only taught in an in-person course modality, and the student success factors could be different for students who take these courses in a hybrid (blended) or online-only course modalities. The surveys were only conducted on one day of class (to minimize disruption to the course), so students who were absent that day were not included in the study; indeed, it may be that students who miss a day early in the semester (first two weeks of course) may tend to share a common characteristic important to understanding student success in the course. It is also important to consider that this is a voluntary study for participants (not mandatory), and there may be key characteristics of those choosing to not participate that would have helped the researcher understand student success.

Definition of Terms

College Placement Tests (College Entrance Placement Exams): Assessments administered to students by college officials upon admission to the institution to determine their academic preparedness for college mathematics, English, and reading courses. Students who score low in specific areas (e.g., English) are advised or mandated to complete developmental education courses in those areas, or seek other academic assistance, before enrolling in college-level classes in those areas. These students are also mandated to take strategies for college success as part of mandated Student Success Initiative (SSI) process.

Course Success/Passing: A student completing a course with a letter grade of A, B, C; a student receives a passing grade such that it could be used towards completion of a degree program or as transfer credit to another higher education institution. Letter grades of D, F, W, or Y are considered unsuccessful attempts.

Learning/predictive analytics: A field of educational research focused on using students' data to understand and predict students' academic success, with an emphasis on using that information to improve student outcomes through data-informed student interventions and changes in classroom practices and college policies and procedures.

Program Completion: the conferral of a certificate, associate degree, or equivalent at the institution of study.

Student Information System (SIS) Record: Specific information about a student, such as their demographic and academic information, collected routinely by college officials about students and stored in the SIS.

Student Information System (SIS): The data system used at the community college to house student records.

Student Success: Depending on the context, may refer to a student completing a course with a passing grade (i.e., A, B, C, or P) or reaching a successful exit point from the institution (i.e., completing a degree program or transferring to four-year institution).

Student Success Survey ("Survey"): The instrument used by the researcher to collect information about the student-participants that was not collected in (or provides a complement to) their SIS Record.

Summary

The United States was at one time the global leader in the share of the adult population with higher education credentials. This is no longer the case for young adults, and in a world that increasingly places a premium on skilled and educated workers in labor markets, a reversal of this trend requires swift and meaningful action if the United

States wishes to maintain its economic superpower status and relatively high standard of living.

To address the stagnating higher education completion rates, researchers must understand why some students succeed in achieving higher education credentials while others do not. This knowledge is necessary so that practitioners at colleges and universities can convert these findings into practices and procedures that improve student success rates. Researchers have been studying student success related to socio/demographic, academic, personal/cognitive, and institutional factors for decades; yet, the stagnation in success rates continues. What has been missing from the research is a focus on understanding student success not just on the macroscale, which is important, but also on the microscale, or how student success factors differ between individual courses. Armed with this knowledge, practitioners can create customized, data-informed recommendations for students as to how best to prepare for individual courses before taking them in order to maximize their chances of passing them. Increased success at the course level should ultimately lead to increased success at the degree level. The new methods of learning analytics have been focusing on understanding these issues, but results are not widely shared in the research literature at this time.

This study uses the tools and framework of learning analytics to understand the factors that predict student success for two economics courses at one community college in one academic year. Despite the modest scope of the project, the research aims to show "proof of concept" of how applying similar tools across the curricula at colleges and universities around the nation could yield amazingly powerful results for improving student success. With these tools in hand and the will to use them, the United States could once again become the leader in the world in higher education credentials among young adults.

However, before the presentation of the methodology of the study is shown and its corresponding findings, a detailed understanding of what is known about student success over the multiple decades of research must be reviewed. This research played an integral role in the development of the current study.

CHAPTER 2: LITERATURE REVIEW

Introduction

The academic literature is rich in studies that have reviewed facets of the question “which factors contribute to student success in higher education?” Yet gaps remain, specifically when addressing this question in the context of individual course completion. However, having a solid foundation of what we do know about what predicts student success will inform the approach and data collection for this study. In this literature review, the known answers to the question “which factors contribute to student success in higher education?” have been categorized by demographic/social predictors (relating to students’ social and economic status within the broader society), academic predictors (prior performance in high school and college behavior), personal/cognitive predictors (of or relating to the students themselves, outside of the other two categories), and institutional predictors (how the institution of higher learning that students attend can impact their success, both through actions institutional leaders can take as well as factors seemingly outside of their control). In addition to these broad categories, readers will be introduced to a relatively new and particularly relevant method for ascertaining these relations known as “learning analytics,” and what this nascent field has uncovered about student success. To be clear, there are unavoidable overlaps between categorical distinctions, as factors in one category can influence factors in other categories (e.g., those students from higher socioeconomic backgrounds may tend to have better academic preparation in high school) and factors in one category can influence factors within the same category (for example, minority students may disproportionately come from lower income households). Nevertheless, the author believes that the categories provide a comprehensible framework to facilitate the understanding of the findings. Chapter 2 concludes by comprehensively analyzing what is known about student success in college and what gaps in the literature remain, particularly in the context of individual course completion, that this study intends to address.

Demographic/Social Predictors

The students' relative or absolute economic status, as measured by the amount of income that their household receives or the neighborhood they live in, is a significant predictor of college success. Students of higher socioeconomic status are more likely to complete their initial college goal (Napoli & Wortman, 1998), yet community colleges disproportionately serve students struggling with financial independence and that come from low-income families (Burns, 2010). Only a small proportion of low-income household students achieve college-level reading skills, because when a family has more economic resources, they have a greater ability to provide their children wtih rigorous academic preparation, high educational aspirations, and family support (Kuh, G., Kinzie, J., Buckley, J., Bridges, B., & Hayek, J. C. 2008). Poropat (2009) found in a meta-analysis of related research studies that the correlation between socioeconomic status and student success was .32, suggesting approximately 10% of a students' success can be attributed to a student's socioeconomic status (R^2=.102).

An important way that household income impacts student success is manifested by the number of hours that students work per week, and need to work, during college. Working is negatively associated with college success. Scoggin and Styron (2006) found that financial reasons and work (which are closely related) are the leading causes for withdrawal. Most college students work to support themselves and go to school at the same time, leading to high stress. These job-related stresses eventually lead many to drop out (work being the top reason given by students for not returning to school once they leave). Young people who fail to finish college are often essentially putting themselves through school, with little outside financial help (Johnson, Rochkind, Ott, & DuPont, 2010). This is especially true of unmarried parents, whose rates of college attendance has substantially increased over time but experience low completion rates, often due to financial constraints that force them to stop their education to increase the number of hours worked (Goldrick-Rab & Sorensen, 2010). However, students employed in Federal Work-Study programs who planned to work anyway, particularly low income ones, are more likely to graduate as a result (Scott-Clayton & Minaya, 2014).

African-American and Hispanic students tend to complete at lower rates than Caucasian and Asian students (Murtaugh, Burns, Schuster, 1999). In Bahr's study (2012a), a disproportionately large share of Asian and Filipino students were identified as most-likely-to-succeed and disproportionately few African-Americans and Native Americans were expected to succeed, given their overall enrollment as first-time students. One explanation of this racial/ethnic difference is that different groups come to college with differing levels of preparation for college-level work. According to college placement test scores, African-American students placed into college-level math, writing, and reading classes (ranging from 59-62%) at a lower rate than their Caucasian counterparts (ranging from 81-88%) (Grimes, 1997). These numbers make sense in the context that there are large differences in college readiness between Whites and minorities (African-Americans and Latinos) at every grade level, with a small percentage of minorities and low income household students achieving college-level reading skills (Kuh et al., 2008). Only 14% of black students and 30% of Latinos meet college-readiness standards in mathematics, while 53% of white students meet the standards (Center for Community College Student Engagement, 2014). According to Wood & William (2013), "Black men in community colleges are more likely to be older, be classified as low-income, have dependents (e.g., children), be married, and have delayed their enrollment in higher education" (p. 3). Graunke and Woosley (2005) showed that being non-Caucasian is significantly negatively correlated with both fall and spring semester GPA, while Napoli and Wortman (1998) found that being a non-minority was predictive of initial college goal completion. The preceding research gives context for understanding why at both the two-year and four-year institutional levels, African-American and Latino students, particularly males, are less likely to complete a college credential on-time, despite having higher aspirations (U.S. Department of Education, 2012a; U.S. Department of Education, 2012b; Center for Community College Student Engagement, 2014). African-American, Hispanic, and multi-racial students younger than 26 years of age who have had a withdrawal in the previous term are at greatest risks for failing a course (Predictive Analytics Reporting (PAR) Framework, n.d.). Despite the lack of academic preparation and academic success, evidence shows a minimal difference in self-reported reasons for withdrawal by students based on ethnicity (Scoggin & Styron, 2006). Research shows that the lower success rates for minority students is not exclusively present at the student-level; institutions with a higher percentage of minority students have lower graduation rates, even after accounting for the race of individual students. In other words, these institutions have a lower graduation rate than would be predicted solely by the demographic makeup of the student population (Bailey, Calcagno, Jenkins, Kienzi & Leinbach 2005a, 2005b).

Women have the edge over men in college completion. In the Sparkman, Maulding, and Roberts' (2012) study, white women were among the demographic profiles most likely to complete college. Graunke and Woosley (2005) found that women had a higher fall and spring semester GPA than men. Since 2001, women have completed more bachelor's degrees than men, and at an increasing margin, due in part to women outperforming men on other predictors of college achievement—high school grades, college placement test scores, and college preparatory coursework (Kuh et al., 2008). Grimes (1997) showed that women are higher in other factors believed to be related to college success, such time management skills and interest in attending college. Another explanation of these results is that women have a greater initial institutional commitment (Napoli & Wortman, 1998).

In light of the previous findings, a clear understanding of the retention patterns between males and females is not as straight forward. Alarcon and Edwards (2013) found that females were 1.59 times more likely to leave the university than males. Other studies have found that there is not a statistically different student gender gap in withdrawing between the fall and spring semester, after controlling for covariates (Fike and Fike, 2008), or for one, two, or four years after starting at the institution (Murtaugh, Burns, Schuster, 1999).

Age plays some role in student success, though in a more nuanced way than income, race/ethnicity, or sex. Most research suggests that younger students have a better chance of completing their degree programs. Shapiro et al. (2012) found that students starting college younger than 24 years of age showed a total completion rate of 56.8% at either their initial or another institution, higher than students starting 24 years of age or older who had a completion rate of only 42.1% (however, the authors note that age and enrollment intensity may be significantly correlated and thus skew the results; enrollment intensity will be discussed later). Crosta (2013a) found that students 19 or younger were more likely to be early persisters whereas those older than 20 were more likely to be early dropouts. In Bahr's study (2012), 83% of students identified as most-likely-to-complete were between the ages of 17-19. Students 20 and younger had better than 50:50 odds of still being enrolled four years after starting college, whereas those older than 20 had less than 50:50 odds (Murtaugh, Burns, Schuster, 1999). However, other studies found that older students are more likely to return between the fall-to-spring semester, and older students are less likely to drop courses during their first semester (Fike & Fike, 2008). Older students have a greater initial institutional commitment (Napoli & Wortman, 1998). With age comes experience and life context, but also marriage, children, and work obligations, and thus older students tend to have tighter time and financial constraints (Crosta, 2013a). Sarason, Johnson, and Siegel (1978) found that life demands/life stress is negatively related to GPA, and Carter (1982) found that family responsibilities were among the top 5 most prevalent reasons for attrition by older students. External demands, such as from work or family, have a negative impact on persistence (Mulligan & Hennessey, 1990; Bers & Smith, 1991; Axelson & Torres, 1995; Napoli and Wortman, 1998).

Predictors of student success at the degree level may not be the same for the course level (particularly for online courses). Counter-intuitively from the preceding findings, researchers studying online students in the American Public University System (APUS) found neither ethnicity nor gender were significant predictors of whether a student would drop out (Schaffhauser, 2013). Phil Ice, APUS' vice-president of research and development, explained that the reason for this is that “online learning is totally color-blind” (p. 2). Findings from the Predictive Analytics Reporting (PAR) Framework (n.d.) corroborate these results, finding that “in the presence of behavioral data, demographic variables (race, gender, age) tend to lose significance” (p. 4).

First-generation college students’ face more challenges to college completion than those students who had at least one parent go to college (Burns, 2010). First-generation students earn fewer credits in their first year, take more remedial courses, and are more likely to repeat courses; this is at least partly a result of first generation students being less likely to have taken advanced math and advanced placement classes, demonstrated less knowledgeable about how to apply for college and financial aid before college, have lower high school grades, and were less engaged overall in high school (Kuh et al., 2008). Sparkman, Maulding, and Roberts (2012) found that first generation students took longer to graduate, reflecting perhaps lower parental financial support and the need to work. However, another study found that the parents’ education level is not consistently associated with student retention (Fike & Fike, 2008).

Perhaps related to first generation student status, the structure and attitudes of the household that students come from (apart from socio-economic status) seems to matter in predicting student success. Households that require the student to care for children at home, where the student is a single parent, or lack social capital (such as having family members who have attended college) are negatively related to student success (Burns, 2010). A family's attitude towards education and their involvement in a student's school activities predict academic success (American College Testing Program, 2007). Fike and Fike (2008) found that having a father who has had some college education increased the odds of fall-to-spring retention (though paradoxically, if the mother had some college, it is negatively related).

Students who lack the social connections, or social capital, are missing an important complementary asset to their college preparation (Karp, O'Gara & Hughes, 2008). Burns (2010) identifies the sources of social capital development from "parents with college degrees, having a high school diploma as opposed to a GED, having a sibling or other relative who attended college, and having employers or other outside networks who provide information on college" (p. 5). Without social capital, students may not have adequate information about higher education, struggle navigating the college application process, or accessing student support services like tutoring and advising (Johnson, Rochkind, Ott & DuPont, n.d.; Karp, O'Gara & Hughes, 2008). When students come from families who have few or no members with college experience, there could be an insufficient level of emotional support or a lack of awareness of commitment necessary in order to complete college (Sparkman, Maulding, Roberts, 2012). Crosta (2013a) found that early dropouts were 40% less likely to receive financial aid or a Pell

Grant in their first term of college, suggesting a lack of social capital led students to insufficient financial resources to stay in college to completion.

Beyond social capital, social support predicts student achievement. College aspirations, both by the student and their parents, are strong predictors of first semester GPA and ultimate college success (Kuh et al., 2009). Social support also improves student success through reducing the performance-sapping effects of test anxiety (Sarason, 1981) and promoting higher GPAs (Napoli and Wortman, 1998). Astin (1984) suggests that the most important factor for student success and retention in the first year is student involvement. Social support may be particularly important for minority groups; building a social support network was associated with increased student success of Native American nursing students (Metz, Cech, Babcock, & Smith, 2011) and Black nursing students (Dapremont, 2011). Family social support played an "integral role" in academic success of Black males attending a historically Black college and university (Palmer, Davis, & Maramba, 2011).

Academic Predictors

The academic performance of students, both during high school and early on in their college career, is very important to predicting student success. Simply put, those with better academic preparedness show higher initial goal completion (Napoli & Wortman, 1998). Academic preparation may indeed be even more important than the student's socioeconomic or demographic background. A study completed by the Los Angeles Community College District found that academic preparation, not gender or race, was the most powerful predictor of college success (Perrakis, 2008). Indeed, prior academic preparation and cognitive ability (discussed later) "surpass all other factors in the determination of student performance and persistence in college" (American College Testing Program, 2007, p. 1). Likewise, Conley (2005) believes that academic preparedness is the single most important factor that determines college success. These are heartening results for those that aspire to close the performance gap between demographic groups, suggesting improving early academic programs could overcome structural barriers to student achievement from differences in household income, race, sex, and first-generation college student status.

Students who complete a rigorous core college preparatory curriculum in high school are more likely to stay in high school, go to and stay in college, and ultimately earn a college degree (American College Testing Program, 2007; Burns, 2010). Conversely, academically low-performing high school students who entered college were unlikely to remain in college for more than a year (Jacobson & Mokher, 2009). Interestingly, nonacademic factors are more important in determining high school academic performance, while high school GPA and ACT scores are stronger at predicting college success (American College Testing Program, 2007). Indeed, higher high school GPAs and first year college GPAs both predict college student retention four years after initial enrollment (Murtaugh, Burns, Schuster, 1999). However, Schuh (1999) found that high school GPA was not predictive of college graduation rates. Characteristics negatively associated with educational attainment include delaying enrollment after high school graduation and lacking a high school diploma (Burns, 2010; Crosta, 2013a).

It is not just the curriculum attempted or completed in high school that matters, but the quality of the high school attended as well. Independent of the student's own household income, those who come from low-income communities often attend schools lacking the resources needed to provide college-ready education (Wimberly & Noeth, 2005). When controlling for socioeconomic status, sex, and race, researchers Black, Lincove, Cullinane, & Vernon (2014) found that students coming from high quality high schools are expected to earn nearly a full grade percentage point higher than those from low quality high schools, and that this difference persists for years after the student's freshman year in college.

Overall, the data indicate that college readiness assessments do predict student success in college. Astin (1993) found that among the admissions data available, a high school student's GPA and standardized test scores were the best predictors of a student's college GPA. The American College Test (ACT) predicts retention among first-year college students (Alarcon & Edwards, 2013). The Scholastic Aptitude Test (SAT) predicted university students' retention after four years at the institution (Murtaugh, Burns, Schuster, 1999). However, Schuh (1999) found that a student's ACT score was unrelated to predictions of college graduation.

Declaring college goals is important to student success. Bahr (2012a) found common characteristics in community college students identified as most likely to succeed. Of these, 73% indicated an intention to transfer and only 6% were pursuing a non-career and non-transfer education associate's degree, whereas students less likely to succeed had more varied college goals. Harackiewicz, Barron, Tauer, Carter, & Elliot (2000) found that students who had high achievement goals had greater success in both their current courses as well as courses attempted in the future. However, Bressler, Bressler, and Bressler (2010) found no relationship between goal setting and academic performance in an online accounting course.

Attending college immediately after high school and attending uninterrupted full-time are indicators of student success in college (Burns, 2010; Bahr, 2012a). Likewise, students who were unlikely to complete tended to enroll part-time, intermittently, and yielded a low student success rate of 26% (Bahr, 2012a) and had lower graduation rates (Bailey et al., 2005a). Indeed, Shapiro et al. (2012) found that six years after beginning college, those students who attended college exclusively full-time had a completion rate of 76.2%, while only 20.1% of exclusively part-time students completed a degree and 68% were not enrolled anymore (although 11.4% were still enrolled, suggesting a longer time horizon may be appropriate for these students). Mixed enrollment students (sometimes full-time, sometimes part-time) showed a completion rate of 40.9%, a rate that falls between full-time and part-time completers.

Completing the first semester and first year of college is especially important; new students are significantly more likely to drop out or fail than continuing students, but once they have some success, they tend to persist (Predictive Analytics Reporting (PAR) Framework, n.d.). Crosta (2013a) observes that the highest dropout rate for students is after the first term, and the majority of these students will never return to a higher education institution again. Unsurprisingly, early dropouts performed much worse academically, receiving failing, incomplete, or withdrawal grades in their first term courses at a 30 to 40 percentage points higher rate relative to early persisters (Crosta, 2013a).

The number of credit hours taken is a factor in student success. Full-time students tend to complete at a higher rate than part-time students. Although there is a strikingly wide array of patterns that students take from initial enrollment to terminus (either completion or non-completion), those students that tend to enroll full-time as opposed to part-time as well as enroll term after term with few breaks have the highest probability of degree completion (Crosta, 2013b; Shapiro et al., 2014). Students who take a greater number of semester hours are more likely to persist from the fall to spring semester (Bahr, 2012a; Crosta, 2013a), although only if they end up completing them (Fike & Fike, 2008); however, another study found that the more online courses a new student takes, the more they struggle (Predictive Analytics Reporting (PAR) Framework, n.d.).

Persistent, consecutive enrollment, particularly in a sequence of courses, is a key to success. For developmental students, those who do succeed in a developmental education course but delay enrollment in the next sequence are both less likely to ever take the next course and are less likely to pass it if they do eventually attempt it; the longer the delay, the worse the results (Bahr, 2012b). Indeed, of the student population that has had some college but no degree, nearly a third dropped out of higher education after having enrolled in just a single semester and never returned (Shapiro et al., 2014). However, researchers studying online students in the American Public University System found that students who had transferred at least one credit hour to the institution were more than four times as likely than students who had no transfer credits (Schaffhauser, 2013).

Perhaps unsurprisingly, the duration of a student's tenure at the institution predicts student success. In Bahr's study (2012a), the defining difference between the most-likely-to-complete cluster and the somewhat-likely-to-complete one was the duration of their stay at the community college (an average of 6 years for most-likely, 4 years for somewhat-likely).

The course modality chosen by students could impact their success. Crosta (2013a) found that early persisters had the lowest failure rates in hybrid courses (25%), followed by face-to-face (traditional) courses (29%), and online courses (37%). Course modality seemed to matter less for early dropouts, however, who failed about 50% of their classes regardless of course modality (Crosta, 2013a). However, Jaggars' (2011) review of the post-secondary literature on online learning finds that online courses, at least as "currently and typically implemented," hinders progression for low-income and underprepared students.

The type of courses taken and the field of study impacts students' success. In one study, students identified as most likely to succeed took many credits of humanities, math, and social/behavioral sciences, taking on average 18 units of basic skills math and English courses (Bahr, 2012a). Mathematics preparation is one of the most predictive indicators of success in college (Burns, 2010); indeed, students who complete high level mathematics courses in high school are more than twice as likely to graduate from college as their peers who have taken lower level mathematics courses (Conley, 2005). Bahr (2012a) found that students more likely to succeed in college took more math courses and were more likely to succeed in them, as well as more courses in physical and life sciences; on the contrary, students who were identified as unlikely to succeed had less than a 1% pass rate in college-level math courses. By far the biggest predictor of a student's GPA is the academic field they choose, more than all other nonacademic factors combined (American College Testing Program, 2007).

Developmental education (or the student's need to develop pre-college skills) is a major barrier to student completion, though there is debate as to why that is. The traditional rationale is that many students never learned college-ready skills in high school, or that non-traditional college age students have forgotten these skills over time, and therefore must be taught them before attempting college-level courses. Deficiencies in skills are assumed to be accurately measured by placement exam scores that show which students need remediation by taking developmental education courses. In recent years, this traditional narrative has been questioned by research, one by a meta-analysis showing weak evidence for the effectiveness of placement exams in predicting college-level course completion (Hughes & Scott-Clayton, 2010), and two quantitative analyses showing that placement exams are relatively weak predictors of college success (Belfield & Crosta, 2012; Scott-Clayton, 2012). These analyses showed that the use of high school grades alone would reduce the number of "under-placed" errors and increase the success rate of those going directly to college-level courses, and that combining placement test scores with high school GPA has an even greater power in predicting success in college-level courses. Perin and Charron (2006) go one step further, calling for institutions to explore other models to support underprepared students than traditional developmental education, such as accelerated or self-paced remediation instruction and immersion programs.

Regardless of the reason why students are placed into developmental education, the chances of degree completion for those in developmental education are not bright, either at the course level or program level (Bailey & Morest, 2006). Complete College America (2012), calling developmental or remediation education as it currently exist today the "bridge to nowhere," found that more than half of students entering two-year colleges are placed into remediation courses, where less than 10% of those students graduate from community colleges in 3 years or less. Each additional developmental education course a student is enrolled in reduces her chance of passing a course by 34% (Predictive Analytics Reporting (PAR) Framework, n.d.). Students in developmental education courses experience a higher withdrawal rate (32%) and are at greater risk of withdrawing from non-developmental education courses as well (18%) (Predictive Analytics Reporting (PAR) Framework, n.d.). Crosta (2013a) found that early dropouts were five percentage points more likely to be in developmental reading, writing, or math, and more likely to be placed two or three levels below college-level in all three areas. The inverse is true too, that those students who successfully complete developmental education tend to have better outcomes. The students who are able to successfully complete a developmental reading course, and to a lesser extent a developmental mathematics course, are much more likely to persist between the fall and spring semesters (Fike & Fike, 2008). For those students finding themselves taking developmental education, and those institutions wanting to help them, completion of developmental education courses is a key milestone to college completion.

Students who place into developmental courses several levels below college-level have worse outcomes than those who place closer to college-level coursework, despite the observation that each groups' tenure at the institution is about the same (Bahr, 2010). Students who score lower on placement exams tend to have more classes to take than those who score higher. Bahr (2010) concludes that lower-level developmental education students barely have enough time to complete the developmental sequence before they depart the institution, whereas higher level developmental education students have more time to get to college-level coursework. Another reason low placed developmental education students have less success is that, regardless of the level of course a student is taking, they must decide at the end of the course whether to continue to the next course or not; having more courses in a sequence means there are simply more opportunities for students to decide to step off track (Bahr, 2009). Yet another explanation may be in course taking patterns between lower-skilled and higher-skilled developmental education students, such that lower-skilled students choose to delay enrollment in the subsequent course in the developmental education sequence (Hagedorn &Kress, 2008). The consequences of this means that there is less effective time to complete the developmental sequence before the average students leaves the institution (Bahr, 2010) and a higher probability of forgetting key content from the previous developmental course before the next, higher one is taken (Hagedorn, 2010).

It may be obvious that student completion of courses predicts program completion, but this does not simply occur through a greater rate of credit accumulation per semester, but also through a higher likelihood of enrollment in future courses. Students who withdrew from a class in the prior semester had a 45% lower chance of passing the class they are currently in; however, for each additional course a student completes, they are 12.5% (associate-level) or 23% (bachelors-level) more likely to continue to be enrolled (Predictive Analytics Reporting (PAR) Framework, n.d.). At least for developmental education students, those who do not succeed in a remedial course greatly reduce their chances of attempting the course a second time (Bahr, 2012b).

Personal/Cognitive Predictors

Multiple personal and cognitive factors related to individual student success go beyond demographic/social and academic predictors. As mentioned earlier, prior academic preparation and cognitive ability surpass all other factors in determination of students' performance and persistence in college (American College Testing Program, 2007).

Baker and Siryk (1989) found in a review of the literature that the psychological state of college students could relate to a student's adjustment and attachment to a college (though they did not link this directly to student success outcomes). Several measures of "psychological maladjustment," such as depression, loneliness, social avoidance, and psychological distress are negatively related to attachment with the institution, while measures of "positive psychological health," such as high self-esteem, psychological independence, and positive self-concept are positively associated with attachment to the institution (Baker & Siryk, 1989). As Napoli & Wortman (1998) put it, "students who are relatively free from anxiety and depression and who have a greater positive self-image are more adept in forming social relationships in college" (p. 22).

Potentially related to a student's psychological health as well as life circumstances, the level of stress and associated anxiety students undergo predicts their success. Stress varies at different times in the academic calendar (Friedlander, Reid, Shupak, Cribble, 2007). Brainard (1973), Martin (1974), as well as Hunter and Sheldon (1980) found that family pressure and obligations were negatively related to student completion. Metzner (1984) found that a measure of outside stress predicted attrition for students attending an urban commuter college. Anxiety levels relating to academic issues (Tobey, 1997) and daily hassles (Brooks & DuBois, 1995) impact students' adjustment to college and their likelihood of retention. Some studies find that life demands/life stress is negatively related to GPA (Sarason, Johnson, &Siegel, 1978; Pritchard & Wilson, 2003).

However, more recent studies have found no significant correlation between stress and academic performance (Saklofske, Austin, Mastoras, Beaton, and Osborne, 2012; Krumrei-Mancuso, Newton, Kim, & Wilcox, 2013).

Beyond straightforward cognitive abilities, a students' conscientiousness is important in predicting their academic success (Saklofske et al., 2012). The most important personality trait is a student's level of conscientiousness (as measured by the Big Five traits, which also include openness, extraversion, agreeableness, neuroticism, as described by Costa & McCrae, 1992), which actually predicts college success more than academic preparation (Burns, 2010). Conscientiousness has a positive impact on students' academic integration (i.e., attending class, studying, completing assignments) (Pascarella & Chapman, 1983a, b; Napoli & Wortman, 1998) and retention (Alarcon & Edwards, 2013). Indeed, Poropat (2009) found that when secondary academic performance was controlled for, conscientiousness added as much to the prediction of tertiary academic performance as intelligence did. Conrad (2006) showed positive bivariate correlations between conscientiousness and GPA as well as course performance, incrementally over academic ability and other traits (none of the other Big 5 traits were significantly associated with academic performance). Related to conscientiousness, attention to study was predictive of first semester GPA (Krumrei-Mancuso et al., 2013). Beyond association with academic performance, students with a high level of conscientiousness are more likely to attend class (Conrad, 2006) and establish commitment to an academic goal (Napoli & Wortman, 1998). It is important to note that conscientiousness is not randomly distributed among students, but is moderately consistent between 18–22 year olds and is higher in older adults (Conrad, 2006). It may be that conscientiousness even plays a role before the student arrives at college, as the selection process for students who do not graduate “is far more limited and often seems happenstance and uninformed” relative to those that do graduate (Johnson et al., 2010, p. 1). However, in Alarcon and Edwards’ (2013) study of retention in first-year college students, conscientiousness was no longer a significant predictor of student retention once a student’s affectivity was added to the model.

Likely related to a student’s conscientiousness, motivation, and self-regulation is the timing of registration for classes, which predicts the student’s success. Students with high levels of conscientiousness tend to register for classes earlier (Burns, 2010). This is important, as Ford, Stahl, Walker, and Ford (2008) found an inverse relationship between time of registration and course grades. Congruently, late registration for courses led to poorer course outcomes (Safer, 2009) as well as a reduced likelihood of persistence to future enrollment (Smith, Street, Olivarez, 2002).

Motivation and self-regulation, such as emotional control, academic self-confidence, and self-discipline are associated with persistence and completion (American College Testing Program, 2007). Students with higher self-esteem had a positive relation with commitment (Napoli & Wortman, 1998). Academic self-efficacy was predictive of students’ first semester grade point average (Krumrei-Mancuso et al., 2013). Outside (but perhaps related to) a student’s conscientiousness or goal setting is an intangible quality that could be defined as “work ethic” or “grit.” The degree to which a student works hard, as measured by the amount of quality time on task, is perhaps unsurprisingly related to actual academic achievement (Stern, 1970; Pace, 1980, 1984) and persistence (Pascarella and Chapman, 1983a).

A key difference found between underprepared and college-ready students is not a difference in learning strategies or self-esteem, but differences in their locus of control; students with a greater internal locus of control believe they can influence their environment, so they acquire and use academic information more effectively, resulting in higher academic achievement. (Grimes, 1997). At-risk students, on the other hand, are more likely to demonstrate a self-defense tendency to view positive outcomes as internal and negative outcomes as external. Interestingly, non-persisting students, both college-ready and underprepared, demonstrated a higher general self-esteem (Grimes, 1997). One may hypothesize that when students with an external locus of control faced challenging coursework, instead of doing all necessary preparation and risking failure and damage to their self-esteem, they simply refused to engage (either by withdrawing or not taking the necessary steps to achieve success) so as to provide them "an out" to maintaining their high self-esteem.

Personal interest, commitment, goal setting, and personal habits play significant roles in student success. As referenced earlier, college aspirations are strong predictors of first semester GPA and ultimate college success (Kuh et al., 2009). Tinto (1975) said that, "Once the individual's ability is taken into account, it is the student's commitment to the goal of completing college that is most influential in determining college persistence" (p. 102). Students committed to clear academic goals and to attending college, as well as indicating an interest in the subject matter itself, are all associated with persistence and completion (American College Testing Program, 2007). Graunke and Woosley (2005) found significant correlations between a commitment to a major and GPA for both the fall and spring semesters for sophomores. Nora and Cabrera (1993) have shown that demonstration of a particular type of commitment, institutional commitment (commitment to graduate from the particular institution enrolled in), is related to both the desire to persist and actual persistence behaviors.

Institutional Predictors/ Best Practices

The preceding research shows that many of the predictors of student success are determined by the students themselves and their circumstances, whether they be demographic/social, academic, or personal/cognitive in nature. Indeed, Bailey et al. (2005a) conclude that personal student characteristics appear to be more important to graduation rates than institutional variables; even the most engaging courses and college environment might not be enough to make the highest risk students successful (Community College Survey of Student Engagement, 2005). For this and other reasons, the first part of this section will discuss institutional predictors of student success that institutional leaders have little to no control over. However, thoughtful consideration of institutional characteristics could still be valuable in terms of improving student completion (Burns, 2010). The second part of this section will look at institutionally controllable factors that influence student success. Based on the previously discussed and other research, there are multiple implications for best practices that focused faculty and administrators can embrace to ensure a greater number of their incoming students leave the institution with a higher education credential. As Kuh et al. (2005) observe, there is not a single path for student success that institutions may follow; even institutions with similar policies and practices may differ in how they approach them, and that this is a good sign as it allows institutions to pursue innovative pathways to student success, aligned with the institution's unique mission.

Institutional Factors Beyond the Control of Institutions

The choice of higher education institution that the student decides to attend, or other factors present that frame or limit this decision for students, relates to student success. Shapiro et al. (2012) found that 71.5% of students who started at four-year private nonprofit institutions completed within 6 years, somewhat higher than the approximately 60% completion rate for those starting at four-year public and two-year private for-profit institutions. In stark contrast, just over one-third of students who started at two-year public institutions (such as community colleges) obtained a credential within six years. These differences seemed to be at least somewhat explained by the different admissions standards between the institutions (competitive enrollment process for the former institutions vs. open enrollment for two-year public institutions), and the corresponding differences in student demographic characteristics and academic preparation found in these different student populations. However, Pascarella and Terenzini (1991) found that two-year college students are less likely to persist than four-year college students even after holding constant a variety of relevant personal, aspirational, academic, socio-economic status, and family background characteristics. Napoli and Wortman (1998) speculate the difference in rates can be explained by the problems associated with commuter students needing to meet the demands from multiple communities (family, friends, work, as well as college) while students attending residential institutions are to a large degree insulated from these multiple demands.

The size and geographical location of the institution that students choose can also impact their chances of success. Institutions that serve a greater number of students tend to have worse student outcomes (Astin, 1993; Bailey et al., 2005a; Pascarella & Terenzini, 2005). Students who attend urban colleges can expect a 3.7% lower chance of graduation than their suburban college counterpart (Bailey et al., 2005c). Bailey et al. (2005b) postulate that this could be due to smaller institutions having a more personalized atmosphere and services that better serve traditional aged students. However, students from larger campuses have significantly higher social integration than students from smaller campuses (Napoli & Wortman, 1998); Tinto's (1993) model highlights larger institutions having a greater diversity of social and intellectual communities from students to choose from, increasing the likelihood of a good fit. Completion rates also differ among colleges of different states, due to different states policies and the impact these policies have at the community colleges in their state (Bailey et al., 2005a).

Institutional Factors Within the Control of Institutions

Student success starts as early as the registration process for students. This paper has previously reviewed the research showing an association between late registration and poor educational outcomes (Safer, 2009; Smith, Street, Olivarez, 2002). Smith, Street, and Olivarez (2002) point to this evidence for arguing that colleges should do away with late registration, although it may be unclear whether the act of missing classes early in the semester due to late registration itself negatively impacts students' outcomes or if students who register later already have characteristics associated with poor academic outcomes (e.g., having a low conscientiousness personality trait). Smith, Street, and Olivarez (2002) suggest possible policy changes to discourage or eliminate late registration, including encouraging early and regular registration with easier access to registration during this time, discouraging students on academic probation from registering late, providing more flexible payment options for those that register early, mandating group counseling (on time management, organizational skills, study skills, and test taking skills) for late registers, and offering more later start courses.

The type of faculty that students interact within their courses matter to student success. Colleges with a larger percentage of part-time faculty members correlate with lower student graduation rates (Bailey et al., 2005a; Jacoby, 2006), though this might be due to other factors related to both of these outcomes, such as a resource-poor community.

The employment status of the faculty members matter, but perhaps how they teach is even more important. Particularly, pedagogy practices that focus on active, collaborative, and cooperative learning that facilitates students' construction of knowledge rather than passively receiving it from the instructor is much more powerful in terms of learning acquisition and retention (Tinto & Love, 1995; Zhao & Kuh, 2004; Pascarella & Terenzini, 2005) while also tending to promote the success of college students (Mellow and Heelan, 2008). Beyond students being more successful in class and engaged in the college, research shows that when students work together more often on assignments and projects, it fosters the creation and maintenance of communication networks that they use to share institutional knowledge, procedures, and best practices that facilitates student success (Karp, Hughes, and O'Gara, 2008).

What faculty do outside the classroom matters too; Mellow and Heelan (2008) observe that faculty that are focused on student success are continuously developing a culture of evidence on what works with student learning. This requires assessment of student learning outcomes and the subsequent refining of pedagogical strategies to address areas of weakness based on their data findings. Faculty can do much to promote student success through providing social support. For example, nursing students who perceived greater faculty support were more likely to persist through a nursing program than those that perceived less faculty support (Shelton, 2003).

How institutions structure courses for faculty to teach matters as well. Learning communities (i.e., a cohort of student taking two or more courses together, taught by a collaborating pair or group of faculty) have been particularly successful. Engstrom and Tinto (2008) found that low income and underprepared students enrolled in learning communities were significantly more engaged academically and socially, perceived a greater amount of support, and were more likely to persist to the following year than their peers enrolled in non-learning community courses. Others studies have linked the learning community experience with improved educational outcomes (Pascarella & Terenzini, 2005; Scrivener et al., 2008).

Colleges can facilitate the development of a culture of student success by fostering greater interaction between students, both in and out of class. Tinto (1993) proposes that the students' social and academic integration into the college community is a key aspect of student persistence. This model has support in the research, showing that social and academic integration predicts both short-term (Bers and Smith, 1991; Napoli and Wortman, 1998) as well as long-term (Pascarella, Smart, and Ethington, 1986) persistence and graduation patterns among community college students (of which, social integration made a larger difference). Positive connections with peers can be a powerful vaccine against attrition: peer discouragement to leave college is positively related to persistence (Anderson, 1981; Metzner, 1984). Involvement in activities is significantly correlated with spring GPA (Graunke & Woosley, 2005), showing the important role that colleges' student life departments plays. These findings would suggest that community colleges are wise to support their student life departments and integrate students as quickly as possible into the college social environment.

Both the type of faculty and activeness of student life on campus points to a less tangible underlying issue: student engagement. Karp, Hughes and O'Gara (2008) found students who felt a sense of belonging at their community college persisted to their second year. Students' interactions with faculty and staff are significantly correlated with GPA (Graunke & Woosley, 2005). How well colleges score on the Community College Survey of Student Engagement (CCSSE) can predict student persistence and success (McClenney and Marti, 2006). Benchmarks of student engagement on the CCSSE include active and collaborative learning, student effort, academic challenge, student-faculty interaction, and support for learners.

Beyond the faculty and student life department, student support services are critical for student success. Fike and Fike (2008) found that the strongest positive predictor of fall-to-spring retention is the participation in student support services program. Burns (2010) observes that most students lack sufficient study skills, which community colleges have responded to with student success courses that address proper study skills such as note taking, time management, test taking skills, and information about learning styles. Soria, Fransen, and Nackerud (2014) found that the use of a college's library at least once during the first year was a significant predictor of retention for students between their first and second years, suggesting that instruction on how to use library services could be fruitful. The primary factor in students' self-reported reasons for withdrawal is personal reasons, not academic difficulty, suggesting that the counseling service at the college should play a key part in assisting students to manage or resolve their personal problems and avoid withdrawal from college (Scoggin & Styron, 2006). In addition, Scoggin and Styron (2006) observe that research consistently shows that academic advising plays a positive role in students' decisions to persist. A leading reason for withdrawal cited by females is health, suggesting a college nurse could help with some issues, conducting health fairs, and other health-promoting activities (Scoggin & Styron, 2006).

At many colleges and universities, students are recommended or required to take a student success seminar or course, and for good reason. Enrollment in freshmen orientation predicts student retention four years after enrollment in a university (Murtaugh, Burns, Schuster, 1999). Derby (2007) found that optional participation in a semester-long orientation course predicted program completion (though self-selection bias could at least partially explain this). Zeidenberg, Jenkins, & Calcagno (2007) found that students who completed student success courses were more likely to persist and reach educational attainments or transfer; they advocate for expanding requirements for students to participate in student success courses. Karp, Calcagno, Hughes, Jeong and Bailey (2007) found in their qualitative study of student success courses that students learned the majority of their college-related knowledge, and state that by not making these courses mandatory for all students (in particular part-time students) it creates inequitable opportunities for college success.

Evidence suggests that some students who begin to struggle in their coursework may be able to move back to the completion track if an adequate early alert system is in place. Administrators who set up a process to inform students of their absences can also address the potential result of their missing classes, and that faculty members need to be informed of the need for early intervention strategies for students and to encourage the communication of problems as they arise to avoid withdrawal (Scoggin & Styron, 2006). Educators, guidance counselors, students, and families should monitor students early in the semester, before they may get into academic trouble (American College Testing Program, 2007).

Beyond linking struggling students to academic support, early alert systems can help in linking distressed students to counseling services. As reported earlier, Baker and Siryk (1989) found that psychological maladjustment is linked to a lower attachment to the institution. Improving student's psychological health or mental health could therefore lead to greater positive self-image, integration into the institution, and ultimately successful outcomes. Counseling or workshops related to stress management and alcohol consumption for incoming freshmen could help improve student retention and success (Pritchard & Wilson, 2003).

Many students lack sufficient academic and career goals (Burns, 2010). A prominent myth in U.S. higher education is that students who decide to drop out fully understand the value of a college degree, whereas the reality is that students who leave college do realize that a degree is an asset, but may not fully recognize the impact that dropping out of school will have on their future (Johnson et al, 2010). Career planning should play a more prominent role early in students' tenure at the institution.

Receiving financial aid positively correlates with retention (Fike & Fike, 2008). Approximately eight out of ten dropouts reported that making it possible for part-time students to be eligible for more financial aid would "help a lot" (Johnson et al, 2010).

Colleges should take efforts to make sure that all students are aware of the financial aid options available to them. They should also consider adopting aid packages that more fully align with their student success initiatives, such as performance-based scholarship programs. For example, using scholarship funds supplemental to federal and state financial aid that are contingent on students enrolling in a minimum number of credits and making satisfactory progress toward their degree (MDRC, n.d.). In one study of performance-based scholarship programs, known as Open Doors Demonstration (sponsored by MDRC), randomly assigned students to the scholarship were 6.5 percentage points more likely to be registered through four semesters, as well as benefit from positive effects on credit accumulation, grade point averages, engagement, and perceived social support (Richburg-Hayes et al., 2009).

Although academic support services are clearly important, they must be well structured. By using programmatic approaches, colleges risk having an emphasis on "fixing" students; despite having relatively high levels of engagement in college services relative to whites, minorities have the lowest outcomes (Center for Community College Engagement, 2014). Social Psychologist Claude M. Steele in his book *Whistling Vivaldi: How Stereotypes Affect Us and What We Could Do About It* (2010) explains that people experience stereotype threat when they fear "confirming, or being seen to confirm, society's darker suspicions" (p. 178); this pressure causes those students under stereotype threat to significantly underperform, especially for those that care a great deal about their performance. To counteract stereotype threat, and therefore improve student success among this population, Shaun R. Harper, an associate professor and executive director of the Center for the Study of Race and Equity in Education at the University of

Pennsylvania, recommends focusing on students' assets, and not their deficits (Mangen, 2014).

As noted earlier, the majority of students who enroll in community colleges for the first time place into developmental (remedial) education. Placement into developmental courses significantly reduces their likelihood of completing degrees. Despite this significant barrier to college completion, this paper has referenced research earlier that placement exam scores were weak predictors of college success (Hughes & Scott-Clayton, 2010; Belfield & Crosta, 2012; Scott-Clayton, 2012). This has led some colleges to begin experimenting with changes in college policy and program design related to development education that could therefore lead to improved student success outcomes. A few colleges have begun focusing on reducing the number of students placing into developmental education by working with local feeder high schools. Innovative programs like Tennessee's Seamless Alignment and Integration Learning Support (SAILS) program has community colleges working with local high schools to identify students in need of math remediation and helps them through dual enrollment developmental education courses so that they are ready for college level math upon matriculation; Chattanooga State Community College has seen 83% of students complete all remediation competencies while 25% of the students completed college-credit math before graduating high school (Fain, 2013).

Some colleges are experimenting with alternatives to standard, mandatory placement into developmental education as a way of improving program outcomes, with some success. Research at the City University of New York, Chabot College, and Community College of Denver show that students who are placed into shorter remediation sequences (i.e., covering the same remedial course information as a traditional remediation course in a shorter period of time) are more likely to take and pass college level math and English courses. The suggested explanations for this include fewer opportunities for students to exit, exposure to more rigorous coursework that could help motivate students, and potential under-placement in courses allow college-ready students a faster opportunity to take challenging college-level coursework (Hodara & Jaggars, 2012; Jaggars, 2012). Another promising model is placing relatively high performing development education students into college-level courses with supplemental instruction, such as in the Accelerated Learning Program at the Community College of Baltimore County (Jenkins, Speroni, Belfield, Jaggars, & Edgecombe, 2010). Although results are still preliminary, and solutions for students with severe academic deficiencies are not adequately addressed by these new approaches, Edgecombe's (2010) recent review of the literature led her to conclude that there is sufficient evidence from a variety of models, from course redesign to mainstreaming students, that colleges can use to improve student outcomes.

A strategy that some higher education institutions are using to reduce the number of students placing into developmental education while simultaneously enhancing students' social capital regarding the college enrollment process and successful behaviors is through stronger partnerships with the elementary and secondary education sectors (PK-12). One survey of high school teachers found that two-thirds (65%) did not believe that most of their students were ready for college level work (Conley, n.d.). Although high school students and parents report familiarity with the college enrollment process, they are less familiar with what is needed to be successful in college (Conley, 2005).

Conley (2005) calls for closer alignment between high school and college curriculum to prepare students for college success. This means that high school and college faculty need to spend more time collaborating and sharing perspectives, ideas, and materials (Conley, n.d.). Other ways of bridging the secondary and higher education bridge have shown to be successful too, including dual enrollment programs; one study found a link between dual enrollment and better student outcomes, such as the likelihood of earning a high school diploma, enrolling in college, persisting to the second semester, remaining enrolled two years after high school graduation, college grade point average, and earning postsecondary credits (Karp et al., 2007).

Learning Analytics: A New Tool for an Old Problem

Colleges and universities are getting savvier with how they use the data they collect on students in order to help more students persist and successfully complete their courses and ultimately their degree programs. One example of this is the Achieving the Dream (2006) movement in which more than 200 institutions of higher education participate in and agree to a set of basic principles to change policies, practices, structures, and the institutional culture aimed at improving retention and student success through the use of data. This is a welcome development; as Crosta (2013a) argues "to reverse the trend of early dropout, colleges need to make greater effort to detect early failure and provide more meaningful academic support to students who are at risk of struggling in their first semester" (p. 3). By analyzing the rich datasets left by students in an online environment, practitioners can use analytics (usually with a precursory adjective commonly including "data," "insight," "learning," "predictive," or "prescriptive") to analyze student-created data points to understand and predict future student outcomes, and use that information to intervene with students to yield better outcomes.

Predictive analytics has already shown great promise in fields outside of academia. Predictive analytics practitioners Nate Silver, Sam Wang, and Simon Jackson all independently predicted the electoral-college outcomes of all 50 states in the 2012 United States Presidential election (Bartlett, 2012). The online dating site eHarmony uses data analytics to match people based on user-generated profiles, and online retailer Amazon uses data analytics to recommend books and other products that customers might like based on previous purchases and searches (Parry, 2012).

Although learning analytics is fairly new in the higher education landscape, there are already multiple examples of institutions using these tools to improve student outcomes. The American Public University System has begun applying predictive analytics techniques to the data generated from its online student population; by using 187 data points, and identifying students who were likely to drop out in the next 5 days (so as to intervene with the student), they were able to reduce the dropout rate by 17% (Schaffhauser, 2013).

Another example is the eAdvisor system used at Arizona State University. The system, in use since the 2008-09 academic year, creates a plan for when students should take key courses, marking the students as "off-track" if they fail to sign up for a key course or do well in it (Parry, 2012). By keeping track of a student's progress towards degree completion and making sure that courses that are difficult but critical to a student's degree are taken early, the university has seen its completion rate (among all races) increase from 77% to 84% (The Economist, 2013).

Degree Compass is another program used to help students succeed in college; the program ranks courses by their usefulness towards the student's indicated degree, and also predicts which courses the student is likely to get the best grade in based on historical factors. A large-scale trial of Degree Compass by Austin Peary State University found that while the average probability of a student earning an "A" or "B" in a class is 62%, when students take courses that Degree Compass predicts they will at least get a "B" in, the rate jumps to 90% (The Economist, 2013).

In yet another example of predicting student success, Adam Lange of Rio Salado College (a community college serving 43,000 online students) created a model that could predict with 70% certainty if a student was likely to earn a "C" or better in the class, and then alert professors so they could intervene with students unlikely to succeed (Parry, 2012). Indeed, the field of predictive analytics has exploded in the last few years, with firms and products such as PeopleSoft Campus Solutions, CourseSmart Analytics, Dell's Education Data Management, and Cengage Learning's MindTap promising to change the way students choose courses and programs and the way faculty use student data to improve instruction and student interventions (EDUCAUSE exhibitors respond to key campus IT trends, 2013).

These programs are helping real students succeed. At the University of Wisconsin at Oshkosh, first year students are taking surveys through a system called EBI MAP-Works, a system intended to identify and help at-risk students. As a first generation student there, Callie S. Blakey found that she was not studying as much as a typical first year college student. She changed her studying patterns, and is now a rising junior studying finance and is active in three honor societies (Vendituoli, 2014).

Perhaps one of the most useful aspects of these emerging tools is to help uncover previously misunderstood patterns of student retention. Although much of the academic research on retention has been focused on retention of students within the freshmen year or between the freshmen and sophomore year (Alarcon & Edwards, 2013), the Education Advisory Board (a research, technology, and consulting company) found that of all students who drop out of college, only about half do so before their junior year. Predictive analytics programs that help students pick the right classes for them or that could help find subtle cues that the student is in danger of withdrawal could dramatically help these upper-level students complete their degrees (Vendituoli, 2014).

Data analytics is not only the purview of the online environment. Although it is easier to scoop up and sift all those digital footprints left when students engage in online courses or learning management systems, some professors are using similar tools in the traditional lecture hall. Perry J. Samson, professor of atmospheric science at the University of Michigan, has invented a software platform called LectureTools. Students in large lecture halls can use LectureTools to follow along with the professor during lecture, take notes, ask questions or indicate when a topic is confusing, and answer questions posted by the professor. Although adoption by professors and students has been spotty, it does generate an after lecture report that professors can use to modify lesson plans in the future. According to Samson, the software may in the future be able to identify at-risk students more effectively than counting log-ins or assignment submissions (Kolowich, 2014).

The benefits of learning analytics on student success does not just give institutional leaders and faculty data they could use to improve student outcomes; it could also be used to foster student engagement with the institution and their peers. For example, the Arizona State University Facebook application uses student profiles to suggest friends among the student body (Parry, 2012).

There are, of course, concerns that must be addressed and safeguarded against whenever a new technology threatens to disrupt the status quo, particularly in a system as data-dependent as learning analytics. Some examples include privacy right concerns, such as if the data were to get into “the wrong hands.” Others are concerned about self-fulfilling prophecies, that “red flagging” certain students for additional support may have the unintended consequences of actually making them less likely to succeed since they know they have characteristics disadvantaged to their success. Others such as Vincent Tinto worry that models based on social class, gender, race, and other high level factors are aggregations on the average, whereas “the individual is not an average… an individual is an individual.” Another challenge institutions face is to identify resources to process this abundance of data into useful information and eventually wisdom, particularly in an era of constrained resources. Perhaps the starkest challenge is faculty resistance or disinterest in these systems; a 2014 EDUCAUSE survey found this as among the top concerns of learning analytics advocates (Vendituoli, 2014).

These concerns are well founded and need to be at the forefront of thinking as institutions continue to expand the use of learning analytics and change college policies in response to what they learn from these tools. However, a combination of common sense safeguards, technological advancements, and an emerging record of success should diminish these concerns over time. Institutions should mandate that, whenever possible, learning analytics programs anonymize the data to prevent misuse of personal student data. Data analytics programs themselves should be able to give guidance as to when interventions of at-risk students is leading to a greater negative outcome than the status quo, and be the first sign that practices need to change to prevent negative self-fulfilling prophecies from occurring. Individuals are indeed individuals, and the richer and more timely data that can be gathered on individual students, the more colleges can customize interventions and recommendations that honor this fact and leverages it to ever greater student success. Thanks to the power of Moore's Law (the historical observation and prediction that computers double in processing power per dollar expenditure approximately every 18 months), information technology is experiencing exponential growth in processing power and will continue to experience it for the foreseeable future (Brynjolfsson & McAfee, 2014); this will soundly address the question of limited resources available to process the massive amount of student data needed to power predictive analytics models. If faculty really care about the success of their students and see promoting their success as a primary function of their professional responsibilities, then the combination of an empirical track record of success combined with easier to use tools and interfaces with data should spark more and more faculty to drop resistance and become passionate advocates for using learning analytics tools to help more of their students succeed.

Through its short period of use, predictive analytics has shown both anecdotal as well as quantifiable successes for student outcomes. As computer processing power continues to improve in the decades to come, colleges and universities will find many opportunities to harness these tools to help more students persist unto completion. There is much room for expansion too, as only five% of several hundred institutions surveyed by EDUCAUSE in 2013 were using such analytical programs (compared to nearly half using some sort of early alert system) (Vendituoli, 2014).

Conclusion

This literature review reveals that there is much known about what it takes for students to persist and complete in higher education. Certainly, not every student begins on equal footing at the starting line. Many factors that are largely out of the control of students predict ultimate college success. Those students coming from households with higher incomes and therefore placing less need for them to work while attending school, are White or Asian, women, traditional aged (young adult), and have fewer out of college demands face a structural “leg up” on their lower income, African-American and Latino, male, non-traditional (older) aged counterparts who may face greater demands outside of college. There may be some doubt that a student’s cognitive abilities or level of conscientiousness can substantially change with any level of intervention. A student’s high school preparatory work is largely outside of the control of colleges and universities.

However, this hardly permits higher education leaders to throw up their hands and proclaim the goal of making the U.S. the leading nation in college completion unobtainable. On the contrary, the literature shows that college support services for students (academic advising, counseling, student life, etc.) play an important role in differentiating the completion rate of one institution from another, even given a similar student population in terms of demographic/social characteristics, academic preparation, and cognitive/personal abilities. Higher education institutions need to play a more pro-active role in reaching out to K-12 schools to align curricula and expectations. When the students reach their campuses, college leaders need to give their students every advantage available to help keep them there and provide them the help they need to persist and complete. Colleges need to treat students as individuals with a unique set of characteristics that require a unique set of support systems to help them succeed. The old paradigm of granting students the “right to fail” must be uprooted so the new paradigm of granting students the “right to succeed” can take its place.

A powerful new tool that higher education institutions are slowly embracing, that has already been embraced widely by private industry, is that of predictive analytics. As students leave their data footprints in college databases, not just in online-only courses, but in learning management system across course modalities, placement test scores, and a plethora of interactions with college staff, institutions can start putting the puzzle pieces together to better understand the profile of students who succeed and the ones who do not. Armed with that information, colleges can institute policies, practices, procedures, and interventions that can “tilt the playing field” so that significantly more students at their institution will succeed.

It is clear that there has been significant research into the factors that drive student success at the college level, some of which can be influenced by the institution’s leaders and some of which cannot, and that the tools these leaders can use to impact outcomes has never been greater. However, what the literature is lacking is an understanding of the factors that drive student success within particular classes. It is clear that student characteristics and the institutional support systems in place can significantly impact student degree programs in the aggregate, but individual students do not complete programs in the aggregate. They do so through the successful sequential completion of multiple college-level (and often developmental) courses. Are the factors that predict completion of an English Composition course perfectly overlapped with those that predict completion of College Algebra or Introduction to Sociology? They may not be. There is a gap in the literature to identify the factors that predict student success in individual courses; indeed, after an extensive search of the literature, remarkably little research has focused on predictors of success in individual courses. Understanding such factors could prove very fruitful as it could better help advisors and faculty assist students in planning appropriate course sequencing.

In order to reduce that gap in knowledge, the current study will focus on identifying the predictors of student success in two classes, the Macroeconomic Principles and Microeconomic Principles, for one community college. If successful, it could serve as a model for further research of predictors for other courses that could aid college leaders in developing data-driven course sequencing plans to share with prospective students. Empowering prospective students, academic advisors, and other stakeholders with this information could lead to better decision making, improved learning, and ultimately higher retention and success rates.

CHAPTER 3: METHODOLOGY

Introduction

The purpose of this study is to answer the four research questions related to what factors are related to student success in the two Economics Principles courses prior to course enrollment. The answer to this question has not been addressed in the literature, yet serves as a crucial foundational block for researchers that seek to understand how factors of student success vary between individual college courses, as well as aids practitioners (such as academic advisors and instructors) who can use this knowledge in order to help prospective economics students better prepare prior to enrollment so as to maximize their likelihood of passing the course on their first attempt. This study can be seen as a first step towards a complete analysis of pre-enrollment predictors for individual developmental and college-level courses across the curriculum. When this occurs, it will give students and their advisors a data-driven approach to mapping out their degree programs so as to maximize their chances of passing individual courses, minimize their time to degree completion, and therefore potentially drastically increase degree completion rates, all while reducing the cost of higher education due to limiting repeated course attempts.

In order to obtain the data used to find the answer to the four research questions, students enrolled in any Macroeconomic Principles (ECN211) and Microeconomic Principles (ECN212) (together, referred to as “economics” or “economics courses”) at a suburban community college over the course of the 2012-2013 academic year (pilot study), 2013-2014 academic year (research study), and Fall 2014 semester (new data to test models) were given a survey (Appendix A) along with an informed consent form (Appendix B) to complete within the first two weeks of class. If the students chose to complete the survey and sign the informed consent forms, this allowed the researcher to access the student-participant's SIS records, including the letter grade that the student received at the end of the course (dependent variable). All instructors and all sections of economics at the community college participated during the entire study. The two sets of data (survey data and SIS data) were then combined to create the research data set used for analysis. First descriptive (Research Questions I-III) and then inferential statistics (Research Question IV) will be used to find evidence to support the null hypotheses or alternative hypotheses.

Research Design and Justification of Research Design

This is an observational study, typical of learning analytics research studies. As is normal in courses with no prerequisites such as economics, neither the researcher nor any college official has the ability to prevent or mandate enrollment of students into the course who otherwise are allowed to enroll in college courses, thus eliminating the possibility of the researcher selecting a particular population to study. Although it would lead to higher internal validity and more certain causal results (by reducing confounding variables), it would nevertheless be impossible to conduct a true experiment in this setting. There are some variables, such as the socioeconomic status or race of the student, that are simply out of the control of any researcher, regardless of time and resources available. There are variables that theoretically could be manipulated, such as assigning students to take specific courses before enrolling in economics, but this generally would be considered unethical as well as impractical. In other words, the researcher, like the instructor, works with the students that happen to enroll in the courses that semester. These are the study participants, and they are not-randomly assigned to various treatment groups by the researcher.

Regardless, an observational research design is preferred for this study because the method takes the given environment under research “as is” and thus has a higher degree of external validity than an artificially manipulated experimental design would have. The observational research design was chosen as it was the most practical and has the most external validity related to the population of students under study: students who enroll in economics principles courses. By observing how each student completed the course (received a passing grade or not), and then finding what variables distinguished the passing students from those that did not, inferences can be made about the behaviors that students exhibit before enrolling in economics that are related to course completion.

Pilot Study

A pilot study was conducted during the Fall 2012 and Spring 2013 academic semesters. The main purpose of the pilot study was to refine the coordination process of distribution and collection of all survey instruments and informed consent forms between the economics faculty members and researcher, establishing the process for aggregating the data at the college’s institutional research office, and finding (and correcting) errors in the process and survey questions. The actions of the pilot study honed the communication strategy of the researcher with the economics faculty survey facilitators and their expectations of participation in the process during the actual study. It also confirmed that all questions and instruments were collecting data as was intended during the design of the study.

Setting and Participants

The location of this study was a community college in the southwest United States. This mid-sized community college serves roughly 15,000 students a year in a relatively fast growing portion of the county, and is categorized as a Hispanic-serving Institution according to Title V of the Higher Education Act of 1965, meaning that it serves at least 25% full-time student equivalent (U.S. Department of Education, 2011). It is about 20 miles away from the downtown of a major metropolitan city. This study is intended to include all adult (i.e., 18 years of age or older) students taking economics courses during the Fall 2013 and Spring 2014 semesters at this community college; however, participation is made optional through the signing of an informed consent form in compliance with Institutional Review Boards (IRBs) requirements of both Ferris State University (the researcher's home university of study) (Appendix E) and the community college at which the study took place (Appendix F).

It is important that the sample size of the study be large enough to have enough statistical power (i.e., the ability to detect that the null hypothesis of the study is false when it is, indeed, false), given the expected effect size (i.e., the difference between the treatment and control group means (in this case students passing or not passing the courses, divided by a pooled standard deviation) and alpha level (the probability of a type I error occurring when a researcher concludes that there is a difference between group means when, in fact, there is not). For example, if a researcher expects a small effect size between groups of 0.2 (i.e., a difference equal to 2/10 of a standard deviation), using a conventional decision rule to define statistical significance of alpha = 0.05 (i.e., if there were truly no difference between the treatment and control group, 0.05 or 5% of the time the test would erroneously conclude that there was), and a power level of 0.8 (i.e., if there was a difference between the groups of an effect size of 0.2, it would be detected 0.8 or 80% of the time), then the sample would need to be at least 776 participants (Weiner & Craighead, 2012). Through the pilot process, the researcher has acted to minimize the loss of sample size through errors due to miscommunication, distribution, or collection processes; however, the actual sample size will depend on multiple considerations largely outside the researchers' control, such as the overall enrollment level in economics courses during the timeframe of the research study, the number of students who are attending class during the day that the survey and informed consent form are filled out, and the percentage of students who will not participate in the study due to voluntary choice or disqualification due to age (participants must be 18 years of age or older).

Instrumentation

There were two ways of collecting relevant information about the student participants in this study. The first method is through a survey administered by all economics instructors during the first two weeks of the course (it was important to administer the surveys early in the semester in order to collect information prior to substantial student attrition). The purpose of the survey is to collect information hypothesized to be relevant to the research question, based on the literature review and commonly held judgments among the economics faculty at the institution as to what it takes for students to be successful in their courses. Survey questions reflected information collection attempts that were either impossible to get from the students' academic record or had a high chance of being outdated in the student record. Examples of questions asked on the survey include "how many hours a week do you read or study for all classes?," "how many hours a week do you work for an employer?," and Likert-type questions such as "my friends and family believe that I tend to make long-range goals, stay organized and plan routes to these goals." See Appendix A for the complete survey.

The second method for collecting data was through collection of certain pieces of information about the students through the college's Student Information System (SIS), the college's record of the students. As part of standard college procedures, the institution collects and maintains records on a wide range of data about its students, including age, demographic information, placement tests scores, zip code of residence, number of credits earned, etc. (for a complete list of variables collected about student participants and the type of variables they are, see Appendix C). As this information was collected after the completion of the course, the students' final grade in the class (i.e., if they passed or not) was included, which serves as the dependent variable in this study.

Procedure

Before the beginning of the Fall 2013 and Spring 2014 semester (the research period), the researcher made copies of the two-page survey and informed consent forms, sorted them into envelopes by course section number, and distributed them to instructor-facilitators during the bi-annual pre-semester economics instructors' meeting.

Instructor-facilitators determined which day within the first two weeks of their course they wished to distribute and collect the surveys and informed consent forms. They read consistent written explanatory materials, the "script" (Appendix D), to explain the study and recruit student participation. To gather the data, the economics full-time and adjunct faculty members at the community college administered informed consent forms and student surveys to all students attending on a particular regularly scheduled course day within the first two weeks of the new semester (although any student could take the survey, only adult students were included in the survey). Instructors reserved the last 10 minutes of a regularly scheduled class to inform the students of the purpose of the research, their rights in terms of participation or nonparticipation, and to allow them time to complete the survey. With students' informed consent, their corresponding student records were collected through the SIS to supplement this survey data. These methods are in compliance with both Ferris State University's (Appendix E) institutional research board (IRB) and the IRB of the community college where this study takes place (Appendix F).

To increase the reliability in collecting the survey data across instructors, the researcher met with the college's economics faculty-facilitators prior to each semester of the pilot and study period to train them on the methods and procedures of the study, including verbal scripts to students, and how to administer and collect the informed consent forms and surveys. To ensure that students had a minimum incentive to misrepresent information on the survey (jeopardizing internal validity), to not feel pressured to participate, or feel uneasy about revealing personal information, students were assured that their participation in the study would have no impact on their performance in the class, that confidentiality would be maintained, and that the records would be anonymized before publication.

After the surveys and informed consent forms were completed and signed by participating students, the instructors collected the documents from all students (including from any non-participating students), returned them to the envelopes they received them in, and returned them to the researcher.

To further reduce the risk of reliability and validity in data collection, a dedicated agent of the college's institutional research department gathered SIS-specific data for each voluntary participating student to ensure accurate, reliable, and confidential data gathering and security.

Data Processing and Analysis

After collecting all survey and informed consent packets, the researcher delivered the packets to the college's institutional research department to digitize the questions. This data set was then merged with information pulled from the students' college records, including their final course grades, to create the data set under analysis.

When coding the variables, the dependent variable (DV) relevant to the central research question is economics students' pass rates, represented as a binomial, nominal variable ("1" is passing with a grade of A, B, C, or P, and "0" is not-passing with any other letter grade). The independent variables (IVs) under consideration are the students' demographic/social, academic, and personal backgrounds (see Appendix C for a complete list and type of variables examined in the study).

To answer the Research Questions I-III (used to guide the process in building the models for Research Question IV), the first step in the analysis process was to perform descriptive statistics to explore the relation between the independent variables as well as individual IVs and the DVs. This is an important first step to look for likely candidates for inclusion in Research Question IV of the process (see next paragraph), as well as to observe any highly related independent variables that need to be considered (Research Question II). Due to the nature of the level of measurement of the variables in this model (nominal, ordinal, and ratio), statistical tests designed to work with these variables such as t-tests (for quantitative variables) and chi-square (χ^2) (for categorical variables) are appropriate to use.

To answer Research Question IV, a binary logistic regression model was built to uncover which factors are most influential to student success. Binary logistic regression is appropriate when the DV is categorical, and is considered more flexible and encountered more frequently in research reports than other methods such as log-linear methods (Vogt, 2007). Though the binary logistic regression model necessitates a categorical, binary dependent variable, the predictor variables used in the model may be categorical, continuous, or a mix. The binary logistic regression model was then applied to the current student data set (used to build the model) in step four as well as to those enrolled in the Fall 2014 cohort to test the predictive power of the model in step five (see Chapter 4 for a detailed description of the binary logistic regression model).

Ethical Considerations

The study is deemed to be one of minimal risk to participants and the probability and magnitude of harm or discomfort anticipated in the research was not greater than any ordinarily encountered in daily life, or during the performance of routine physical or psychological examinations or tests. The information collected as part of the survey is not outside the bounds of regular information that instructors may ask their students to voluntarily provide as part of a practice to better know their students or understand the strengths and weaknesses of the class as a whole.

During the entire research process, the only ones that had access to the survey information and its data were the student-participants completing the survey, the instructor-facilitators trained in the process, the researcher, and officials working in the college's institutional research office. After the surveys were collected by the instructor-facilitators, they were passed on to the researcher, who kept them in a locked office until they were hand delivered to the college's institutional research office for processing. At that point, the surveys were kept in a locked drawer until ready to process. After processing, the researcher was notified, picked up the packets, and returned back to his office where they are kept in a locked file. Therefore, the chances of the survey instruments falling into the hands of an unauthorized person are minimal. Two years after the publication of this research study, the surveys will be destroyed through shredding. The datasets are already anonymized.

After the survey information was digitized into a spreadsheet, it was combined with the students' SIS data and then stripped of personal identification numbers. This information was compiled by only one agent of the institutional research office. It was then emailed to the researcher for analysis. This means that there are three copies of the data set (on the institutional researcher's computer, the researcher's computer, and the email with the attachment), of which all are password protected by the user.

Internal and External Validity

According to Vogt (2007), internal validity "pertains to the accuracy of relevance of the study's results for the question being studied" (p 118). One measure of internal validity is content validity, "which gauges the degree to which the content of a test or survey matches the content it is intended to measure. Judgment is most often the only feasible way to assess content validity" (Vogt, 2007, p 118). The independent variables for this study came from two sources, from researcher-generated survey questions and from institutionally-established SIS variables. The survey questions were reviewed by instructor-facilitators who have many years of experience teaching economics and institutional researchers trained in research methodology; the phrasing of the questions were deemed clear and the multiple-choice answer format for the questions were found mutually exclusive and exhaustive. A pilot study was reviewed to observe how students responded to the survey questions and no concerns were found. Furthermore, the survey questions are of a factual basis and are more prone to error due to the student-participants' misperception of reality (e.g., they believe that they study more for their classes than they actually do) than to a misinterpretation of the question being asked.

As for the information collected from the SIS, the variables collected and how they are defined are determined through a complex, opaque system influenced by federal and state statutory requirements and reporting necessities, as well as criteria established at the district-level of the multi-college district some years ago. Like the survey data, however, these tend to be very objective questions that are less likely to be at risk of misinterpretation but still may lose reliability due to the imperfect memory or documentation methods of students or transcription errors of staff.

External validity, in contrast to internal validity, "refers to whether these results can be generalized beyond the subjects studied. In other terms, to what degree does information about your sample also provide information about your population?" (p.

118). To have the greatest external validity on a national level, a random sample of the population of all students taking Macroeconomic Principles or Microeconomic Principles at community colleges across the country would have to be surveyed and studied; due to prohibitive cost and the impractical logistical nature of this (and also that SIS information differs across community colleges), some external validity is compromised through examination of students at just one community college in a single year. The sample of this study will differ between similar cohorts of students at other community colleges during the same academic year and between cohorts of the same institution in different years, and thus reduces the generalizability of this study's findings to other economics student populations.

As noted earlier, the college is designated a Hispanic-serving Institution as defined by the Higher Education Act of 1965 (note later in the paper that a near majority of the students in this study sample identified as Hispanic). According to an internal analysis conducted by the author, using enrollment data provided on the college's website and the U.S. Census Bureau's 2008-2012 American Community Survey 5-Year Estimates (U.S. Census Bureau, n.d.), the median household income of the service area of the college is approximately 14% higher than the county as a whole. However, this study does have the external validity of examining the cohort as would naturally be occurring "in the field" (i.e., those that actually enrolled in these courses during the study period). This cohort is expected to share many of the same socio/demographic, educational, and personal attributes of other community college economics cohorts. The findings of this study should be seen as contributing evidence to the generalized research question of "*which factors predict student success in economics courses before enrollment?*" on the state or national level, and only replication of this study will determine the robustness of the study's findings to the general population.

Summary

This study addresses the four research questions focused on understanding the factors that relate to student success in the Economics Principles courses prior to course enrollment. The study does this by studying the data of all participating economics students at one community college in one academic year. Through the completion of student surveys and informed consent forms, most adult students in this cohort gave consent to participate in the study. By combining their survey responses with their pertinent SIS data, a wide range of data about the students' demographic/social, academic, and personal background was compiled to create a large set of IVs and the DV. Although the relationships between these IVs are of some interest in this study (as discussed in the next section), the real focus of this study is on how these IVs relate to the DV, whether the student passed the course (i.e., received a grade of A, B, C, or P) or not (i.e., received any other letter grade). By relating the IVs to the DV, it will give researchers focused on student success in higher education more information about what it takes to succeed in college, particularly in economics. The most immediate and practical application will be to empower academic advisors, economic instructors, and others who influence when a student takes economics to give students data-informed advice on how best to prepare for the rigors of the course so that they can maximize their chances of succeeding when they enroll in it. In the next chapter, the results of this study will be presented.

CHAPTER 4: RESULTS

Introduction

The purpose of this chapter is to present the results of the study. A description of all economics students based on retrieved information from SIS will be presented. These results in and of themselves could be of use to researchers and practitioners interested in better understanding who the students are that take economics principles courses at the community college, if only at one community college during one academic year. However, not all students enrolled in economics that year participated in the study. After discussion of how some students were excluded from the sample, a description of how the sample differed from the broader cohort will be discussed. Finally, evidence supporting or rejecting the hypotheses of the four research questions will be presented, including the creation of logistical regression models and the results of internal and external testing of their prediction's accuracy.

Description of All Students Enrolled in Economics

This section will describe all students enrolled in economics in the Fall 2013-Spring 2014 academic year at the community college, according to the college's official records, regardless of the students' age or agreement to be part of the formal study (the next section will discuss how the sample used in this study differs from this population). During this academic year, the college offered a total of 25 sections of the two economics courses, Macroeconomic Principles (ECN211) and Microeconomic Principles (ECN212), neither of which have prerequisites to enrollment. Most students who were enrolled in an economics course took ECN211 (55.7%), and most enrolled during the spring 2014 semester (55.52%). See Table 1 for the frequency of student enrollment by class and semester.

Table 1: All Economics Students, By Course and Semester

COURSE	FALL 2013	SPRING 2014	TOTAL (%)
ECN211	137	171	308 (55.70%)
ECN212	109	136	245 (44.30%)
Total (%)	246 (44.48%)	307 (55.52%)	553 (100.00%)

The 25 sections of the courses were taught by one full-time and seven part-time economics faculty members that academic year. Each faculty member taught between one to three sections per semester (two part-time faculty members taught only one course in one semester).

There were a total of 553 duplicated recorded cases of enrollment (i.e., individual students could be represented multiple times) in the fall and spring semesters of the 2013-2014 academic year at this community college. Of these, 480 (86.80%) were students who took only one economics course (either ECN211 or ECN212) during one of the semesters; the 73 remaining students took 2 or more economics courses during the academic year (most took 2, one student took 3). See Table 2 for how students took multiple courses during the academic year.

Table 2: Enrollment Pattern for Students Enrolled in Two or More ECN Classes

ENROLLMENT PATTERN	NUMBER OF STUDENTS (%)
ECN211 and ECN212 in the fall semester (16-week course)	6 (8.20%)
Took ECN211and ECN212 in the spring semester (16-week course)	9 (12.3%)
ECN211in fall and ECN212 in spring	34 (46.60%)
ECN212 in fall and ECN211in spring	6 (8.20%)
ECN211in both fall and spring	4 (5.50%)
ECN212 in both fall and spring	3 (4.10%)
ECN211and ECN212 in the fall (accelerated)	0 (0%)
Took 211 and 212 in the spring (accelerated)	11 (15.10%)
Total	73 (100%)

Most students who enrolled in an economics course registered for a course in the morning (57.3%). The rest either took their course in the evening (23.1%) or in the afternoon (19.2%). The average student attempted close to a full load (12 credit hours) of course credits (M = 11.84, SD=3.67), with credits enrolled in ranging from 3-22.

Socio/Demographic/Personal Factors

The average age (in years) for an economics student at this community college was early-20s (M = 23.61, S.D. = 7.68). The age range was 13-57 (though only students 18 or older were included in the sample, as discussed later). Most students enrolled in economics were male (55.70%). The plurality of students (48.5%) self-identified as Hispanic. The ethnic identity of the students is included in Table 3.

Table 3: Self-reported Ethnicity Description of All Economics Students[1]

ETHNICITY DESCRIPTION	NUMBER OF STUDENTS (%)
American Indian	6 (1.10%)
Asian	39 (7.10%)
Black	48 (8.70%)
Hawaiian	2 (0.40%)
Hispanic	268 (48.50%)
White	177 (32.00%)
Not Specified	13 (2.40%)
Total	553 (100%)

1. *There is no ability for students to identify multiple ethnicities in SIS*

Nearly two-thirds (63.47%) of the students were first generation students (i.e., neither of their parents attended college), compared to less than a third for the national undergraduate population (U.S. Department of Education, 2008). Forty-four students (7.96%) were veterans. Nine students (1.63%) were dependents of a person currently serving in the military.

The vast majority of students (90.05%) currently spoke English as their primary language, with other students primarily speaking Spanish (4.52%), Vietnamese (1.08%), or Arabic (0.18%), with the remainder either speaking another language or not answering the question. However, many more students spoke a language other than English as children. Growing up, nearly a quarter (22.78%) of the students spoke Spanish and an additional 4.16% spoke another foreign language (including Arabic, Chinese, French, Hungarian, Italian, Polish, Tagalog, Thai, Turkish, and, most frequently in this group, Vietnamese).

The majority of students who enrolled in economics worked while attending college, though the number of hours worked varied considerably (with the largest category being students who did not work). Figure 1 shows the distribution of hours worked for all economics students that year.

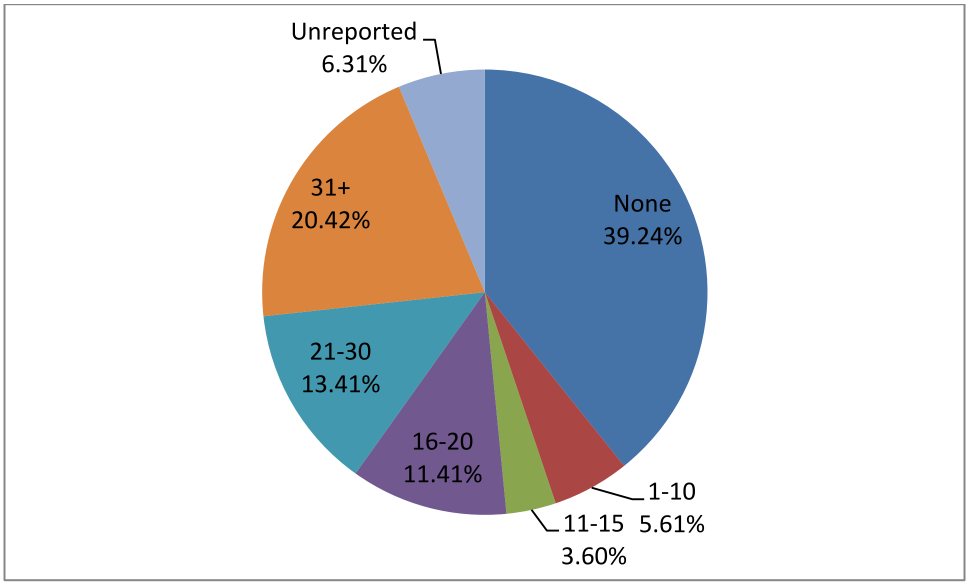

Figure 1: Ranges of Student Hours Worked Per Week (SIS)

Academic Factors

Students enrolled in economics at this community college came from a variety of backgrounds. The plurality of students (39.44%) had transferred from another college or university, but had not earned a degree yet. For many of the other students (35.64%), this was the first higher education institution that they had attended. The rest of the students that indicated a previous educational experience reportedly earned an Associate's degree (0.90%), a Bachelor's Degree (0.72%), or in the case of one student, a Master's Degree or higher (0.18%). See Figure 2 for a summary of students' educational experience.

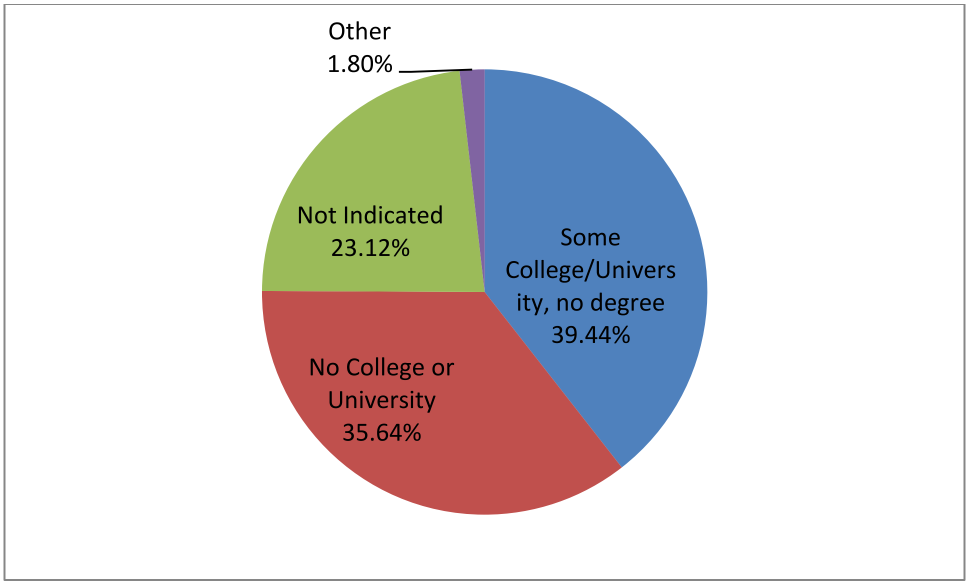

Figure 2: Description of All Students' Previous Educational Experience

Most students (75.59%) passed the economics course that they were enrolled in, including 37.79% who earned an "A," 25.50% who earned a "B," and 12.30% who earned a "C." The rest of the students (24.41%) did not pass the class, either earning a "D" (4.88%), "F" (2.89%), "W" (13.38%), or "Y" (withdrawn from the course while failing) (3.25%).

One hundred and thirty-nine (139) students (25.14%) had an experience with economics in a previous semester at the college. Of those students, 117 (84.17%) completed the course (i.e., did not withdraw) and 101 (72.66%) completed it successfully.

At the completion of the semester in which they enrolled in economics, the students' cumulative GPA ranged from 0.00-4.00, with an average GPA of 3.14 (SD = 0.72). The average student earned about three full-time student semesters' of equivalent credits (M = 36.36, SD = 20.80), ranging from 0 – 103. This suggests that some did not pass the only course they were enrolled in, while others had earned many more credits than they needed for an associate's degree (usually close to 60 credits).

Forty-three students (7.78%) arrived at this community college with transfer credits (ranging from 2-125 credits), with the mean close to sophomore-rising status (M = 32.95, SD = 26.05). Those students that transferred credits had transfer GPAs ranging from 0.00-4.00, with an average transfer GPA substantially lower (M = 2.29, SD = 1.36) than the current GPA of the college cohort (M = 3.17, SD = 0.72).

Four hundred and twenty-five (425) students (76.85%) who took an economics course were enrolled at the community college the previous semester. Fifty-two (52) of these students received a letter grade of D or F (12.24%) in the previous semester, 12 (2.82%) of whom received two of these grades. Eighty-one (19.06%) received a letter grade of W, and 6 students (1.41%) receiving 3 or 4 W's.

Students enrolled in an economics course came to the college with varying degrees of college readiness. Of the 407 students who had an ENG placement score on record, 26.54% of them initially placed below college-level English courses, 20.50% placed into below college-level mathematics courses (out of 439 with placement scores), and 19.27% placed below college-level reading courses (out of 441 placement scores).

Description of Records Excluded and Why

Not all of the above cases became part of the sample used for analysis, and 150 student records were excluded from the sample. This study only examined adult students at the community college, and, therefore, 19 cases were removed because they represented students that were under 18 years of age, regardless if they completed the survey and informed consent form. Of the remaining students, 131 students were removed because they showed no evidence of completing the survey or did not sign their informed consent forms (failure to complete the survey or informed consent form was interpreted as not consenting to participate in the study).

Description of Sample

After removal of some student records, there were a total of 403 records in the sample, representing both ECN211 and ECN212 in a duplicated headcount. There were 365 unique students enrolled in either ECN211 or ECN212 during the academic year that were included in the sample, representing 72.88% of the economics student population enrolled in that year.

As the large majority of the economics student population at the college that year participated in the study, it could be expected that the sample shares many characteristics with the wider economics student population, with proportions and means similar to the population. However, there is also the possibility that the students selected in the sample differ in some important ways from the students who did not participate in the study. This section will highlight statistically significant differences in characteristics between those students who participated in the study and those not participating. This is important to establish in order to show how the sample data used for hypothesis testing and to build the predictive algorithm differ from the economics student population that it is attempting to study and model. Statistical significance was determined by t-tests for independent samples for interval and ratio variables (e.g., GPA, age) and chi-square test (χ^2) for nominal and ordinal variables (e.g., gender, grade in current class), using the conventional $p \leq .05$ cut-off probability rate for measure of statistical significance.

Students in the sample were more likely to take ECN211 than those excluded from the study (59.06% vs. 46.67%, χ^2 =6.80, df =1, p=.009). They were also more likely to take afternoon and evening classes and correspondingly less likely to take morning classes (Table 4).

Table 4: Time of Day of Class

TIME OF DAY	ECN STUDENT POPULATION	STUDENTS INCLUDED IN THE STUDY	STUDENTS EXCLUDED FROM THE STUDY
Morning	319 (57.69%)	214 (53.10%)	105 (70.00%)
Afternoon	106 (19.17)	84 (20.84)	22 (14.67)
Evening	128 (23.15)	105 (26.05)	23 (15.33)
Total	553 (100%)	403 (100%)	150 (100%)

Students included in the study were more likely to be first-generation status (66.75% vs. 54.67%, χ^2 =6.88, df=1, p=.009). They were also more likely to be employed and to work more hours per week (Table 5).

Table 5: Hours Worked Per Week

HOURS	ECN STUDENT POPULATION	STUDENTS INCLUDED IN THE STUDY	STUDENTS EXCLUDED FROM THE STUDY
0	217 (39.24%)	140 (34.74%)	77 (51.33%)
1-10	31 (5.61)	24 (5.96)	7 (4.67)
11-15	20 (3.62)	16 (3.97)	4 (2.67)
16-20	63 (11.39)	51 (12.66)	12 (8.00)
21-30	74 (13.38)	57 (14.14)	17 (11.33)
31+	113 (20.43)	90 (22.33)	23 (15.33)
Total	553 (100%)	403 (100%)	150 (100%)

Perhaps with the greatest ramifications for this study, students in the sample were more likely to earn course grades of A, B, and C's than those excluded from the sample, and correspondingly less likely to earn D, F, W, and Ys (Table 6). This translated into a greater passing rate for the students in the sample than those excluded from the sample (80.65% vs. 62.00%, χ^2 = 20.59, df = 1, p<.001), which impacts the dependent variable of the study. At least part of this difference is explained by students in the sample having a higher cumulative GPA (M=3.17, SD=0.72) than those excluded from the study (M=3.01, SD=0.92) ($t = -2.480$, $df = 551$, $p = .013$), and therefore typically earn higher grades in courses that they are enrolled in. One possible reason for this outcome is that students that eventually passed the course were more likely to be present in the first two weeks of course than those who ultimately did not pass the course.

Table 6: Grades Received in Economics Course

GRADES	ECN STUDENT POPULATION	STUDENTS INCLUDED IN STUDY	STUDENTS EXCLUDED FROM STUDY
A	209 (37.79%)	156 (38.71%)	53 (35.33%)
B	141 (25.50)	114 (28.29)	27 (18.00)
C	68 (12.30)	55 (13.65)	13 (8.67)
D	27 (4.88)	16 (3.97)	11 (7.33)
F	16 (2.89)	6 (1.49)	10 (6.67)
W	74 (13.38)	50 (12.41)	24 (16.00)
Y	18 (3.25)	6 (1.49)	12 (8.00)
Total	553 (100%)	403 (100%)	150 (100%)

Student Success Survey Responses

The 403 students who became part of the sample all completed the student success survey. The survey was designed to elicit information from the students considered pertinent to the student's success in the course and that were either considered impossible to get from their student records (e.g., Question 9: locus of control question) or could be more up-to-date than their students records (e.g., Question 3: number of hours worked per week). This section presents the frequency of response choices by the survey respondents.

The first three questions pertained to how students spent their time outside of class that may contribute to their success in the course. Students that dedicate more time in the week to learning outside of class may have improved outcomes. Question 1 asked, *"How many hours a week (on average) do you read or study for all classes?"* The majority (74.94%) reported studying between 1-10 hours per week, with most in this group studying 1-5 hours.

Question 2 asked, *"How many hours a week (on average) do you read for pleasure?"* Students who tend to read more, even outside of formal course material, may possess and strengthen reading and comprehension skills helpful to their success in college. The majority (56.33%) responded 1-5 hours per week, though the next most frequent response was 0 (28.04%). Less than one in twenty students (4.47%) read 11 or more hours a week for pleasure.

Employment may have a mixed impact on students' success in their college courses, as some hours of employment may encourage students to stay organized and on task in their college career, and perhaps gain some useful job skills (e.g., punctuality, collaboration) that can have benefits for their college career too, whereas working many hours will reduce the number of hours in the week that students can engage in practices considered important to course success (e.g., studying, completing homework assignments).

Question 3 asked, *"How many hours a week do you work for an employer?"* Survey responses show that nearly two-thirds (66.26%) of students worked between 20-49 hours per week, while nearly one in five (21.59%) did not work at all. These results contrast with the SIS information from both the ECN student population that year as well as the sample participants themselves, indicating that the students are working more than was reported in SIS. More than a third (34.74%) of students did not report working when completing the SIS information, while nearly the same (36.47%) reported working more than 21 hours.

The students' comfort level with various mathematics concepts could aid the student in completing assignments, performing well on exams, and generally contribute to student success in economics courses. This is a subjective question for the student and may not reflect their actual abilities, however. Nevertheless, it could be useful as a proxy in the absence of a (more time-consuming and resource-intensive) skills tests. In question 4, students were asked, *"which ones are you fairly comfortable with (mark all that apply),"* with the four possible responses of "graphing data," "algebra," "calculating slopes," and "calculating percentage change," all of which are concepts and operations used in both economics courses. The majority of students reported comfort with "algebra" (80.65%) and "graphing data" (69.48%), but did not feel comfortable "calculating slopes" (52.36%) or "calculating percentage change" (53.35%).

The level of students' computer skills may enhance or block their ability to access course and college materials necessary for success. Perhaps unsurprisingly for this young cohort (nearly three out of four of whom are 24 years old or younger, and all but one are under the age of 50), the students considered their computer skills strong. Question 5 asked, *"Which one is your computer skill level?"* Nearly two-thirds (65.76%) considered their computer skills level at "moderate," and an additional three-tenths (30.02%) considered them "advanced." Only 2 (0.5%) indicated they had "virtually none."

Students' lack of reliable transportation to get to class could be a major impediment to attending class and meeting other college commitments. Question 6 asked, *"On some weeks, I'm not sure how I'm going to get to school on a given day."* Sixty students (14.89%) reported this as "very true" or "occasionally true." The vast majority (83.62%) reported this as "not true."

Students who make long-range goals may have a sense of commitment useful to college completion. Question 7 asked, *"My friends and family believe that I tend to make long-range goals, stay organized and plan routes to goals."* Four out of five (80.40%) either "agreed" or "strongly agreed" with that statement, while a minority (13.9%) either "disagreed" or "strongly disagreed."

Perhaps somewhat related to the last question, students' ability to control impulses and stay focused could help them complete course requirements necessary for successful course completion. Question 8 asked, *"My friends and family tend to believe that I tend to act impulsively or that I can get distracted easily."* Here the findings were more mixed. The plurality (41.19%) "disagreed" with that statement, whereas nearly a third (31.51%) "agreed." Those who "strongly disagreed" with the statement outnumbered those that "strongly agreed" by a 2:1 ratio (14.39% vs. 7.20%).

Students who completed challenging curricula in high school may demonstrate higher success rates in their courses than their peers who had not. Question 11 asked, *"How many honors, dual enrollment, or advanced placement classes did you take in high school?"* Although the plurality (29.03%) of the sample had not taken any of these courses (for various reasons, including not being offered), nearly two-thirds (65.01%) did take at least one. Of those who had taken at least one advanced course, more than a third of them (34.35%), or 22.33% of the total sample, had taken four or more advanced classes.

Previous research has indicated that a student's locus of control is associated with academic performance, such that if students believe that they have control over their own lives, they tend to perform better than students who believe life events are beyond their control (Kuh et al., 2009). Question 9 asked students, *"Events in my life are primarily determined by…,"* the clear majority (74.19%) responded "my own actions and abilities" as opposed to "people and events outside of my control" (18.86%).

The literature also suggests that students' prior academic success can predict their later college success ((Napoli & Wortman, 199, American College Testing Program, 2007). Question 10 asked students, *"During high school, the most frequent letter grades I earned in my classes were:"* This question, like the other survey questions, is subject to reporting error but should serve as a reasonable proxy for prior academic success assuming accurate memories, honesty, and candor. The majority (72.70%) reported letter grades of "As" or "Bs," with the plurality of students reporting "Bs" (46.65%). Only 6 (1.49%) reported average letter grades of D's.

Handling of Missing Data

All questions that were asked of students (e.g., what is your ethnic identification, how many hours a week do you read for pleasure, etc.) either collected in the SIS or through the student success survey, included some responses left blank. This is in contrast to variables generated through running queries of student records (e.g., cumulative credit hours earned, GPA, etc.), which created no missing data as all students had information in their student record from which these variables were derived as they were created by the institution itself.

In cases of missing data, a new response category was created such as "not specified" or "missing" to capture this phenomenon. "Not specified" indicates that the student did not provide a specified response to the question. For example, 4.22% of students did not specify what their primary current language was. In these cases, results of specified categories had percentages reported with these non-specified students in the sample (i.e., all students in the sample, whether they responded or not, were included).

In the cases that students had "missing" data, it was due to a student not completing a reading, English, or mathematics placement exam. For example, a fifth (20.10%) of the students in the sample did not complete a math placement exam. In these cases, percentages are expressed in terms of the whole sample (similar to the "not specified").

Research Question I

Before a predictive model of student success can be built, a series of research questions should be addressed. The first is "*which independent variables in the study significantly relate to the dependent variable?"* The null hypothesis is "there are no independent variables that are significantly related to the dependent variable," and the alternative hypothesis is "there is at least one significant relation between an independent variable and a dependent variable."

Table 7 demonstrates support for the alternative hypothesis, that there are 16 factors that relate to or contribute to students' success in either of the economics courses. The most important variable that predicted student success was the students' GPA.

Although a little more than a third (35.73%) of the students in the class had a GPA between 3.5-4.0, 41.78% of the students that passed the course were in this highest GPA category; only 11.54% of the students that did not pass the course were in this category (that is a 24.19 percentage point underrepresentation in the non-passing category if all students, regardless of their GPA, were randomly assigned to pass or not pass the course). Likewise, students with a 3.0-3.49 GPA were 6.87 percentage points less likely to be unsuccessful in the course than would be suggested by their representation in the class. On the contrary, students with GPAs below 3.0 were disproportionately more likely not to pass the course. Interestingly, students in the 2.5-2.99 GPA category were 14.85 percentage points more likely to be represented in the unsuccessful grade category, higher than for the 2.0-2.49 category (8.64%).

The second most important variable was the instructor that is teaching the class. Success rates averaged 80.65%, though it varied considerably by instructor, ranging from 62.04% to a 100% success rate. Of the eight instructors teaching this academic year, six had above average and two had below average success rates.

The number of W's earned in the prior semester (regardless of course taken) predicted student success in economics courses. Of the sample of students who were enrolled in the previous semester (318), 254 of them (79.87%) were successful in economics in their current semester (just less than the sample overall). However, if the student did not receive any W's in the previous semester, their chances of passing the course jumped to 84.65%. Likewise, if a student had 1, 2, or 3 withdrawals the previous semester, they had between 2 to 5 percentage points lower chance of being successful in their economics course. In other words, students' previous withdrawal behavior (regardless of course) predicted their success in their current economics course.

Likewise, success rates varied by the time of day the course was offered (72.90% for morning, 86.90% for afternoon, 91.43% for evening). However, this could actually be reflecting the times when different instructors are teaching than a time of day effect (or the kind of students that would take classes at that time). A significant chi-square (χ^2) of 501.32 (df=14, p<.001, Cramer's V = .789) indicates that some instructors teach predominantly during certain times of the day. For example, the two instructors with the lowest success rates taught in the morning and two of the three instructors with the highest success rates taught in the evening, thus at least partially explaining why evening courses had higher success rates.

Perhaps unsurprisingly, whether a student had completed or passed an economics class in a previous semester (but not simply having enrolled in a previous economics course) could predict if they would pass their current economics class. Of those that completed ECN in the past (i.e., received a passing or non-passing grade without withdrawal), 90% passed their current course, compared to 53.33% for those that had not completed an economic course previously. If they had passed an economics course (received a passing grade) previously, they had a 87.32% chance of passing it this time, compared to 69.23% chance of passing if they had not passed their previous class (it should be noted, however, that this indicates students attempting an economics course after an unsuccessful attempt have a strong likelihood of passing their next economics course).

The students' experience with English courses at the college was significantly related to their success in their economics course, but in surprising ways. More than half (53.10%) of the students had enrolled in ENG102 or a higher numbered English course, and nearly half the sample (49.38%) were successful in that course. Not surprisingly, students who had passed ENG102 or higher were 7.07% less likely to not pass the economics course (or 1.7% more likely to pass the course) than would be expected if experience in English courses did not impact success in economics. Likewise, those who had taken ENG102 or higher and were not successful had a 6.53 percentage point greater chance of not passing the course than would have been expected. It would therefore be tempting to conclude that English success predicts economics success. However, having no record of completing English led to a 6 percentage point less likelihood of being unsuccessful (or a 1.44% higher chance of being successful). Even more surprisingly, being successful in ENG101 or a developmental English course is detrimental to one's chances of success in economics (2.73 and 3.23 percentage points, respectively).

It should be noted, however, that though the overall sample size (403) is relatively big for statistical analyses, breaking students into 14 different combinations of prior English courses possibilities (7) and outcomes (2, success or non-success) lead to some cells having very small representations. For example, only 2 students were unsuccessful in developmental education and 6 students were unsuccessful in ENG101 as their last outcome. Having such few students per category could lead to huge swings in results when only one or two students would have had different outcomes in those small categories. Therefore, it is illustrative to group students together by success in a previous English course, non-success in that course, or there is no record of it.

In this case, the results are clearer. Students who were unsuccessful in their last English course had a 7.11 percentage point greater chance of not being successful in their economics course (and 1.71% lesser chance of being successful). Likewise, students who were successful in their prior English course were slightly less likely (1.12%) to be unsuccessful in their economics course (and 0.27% more likely to be successful). Either way, though, this is hardly strong evidence to recommend that students take and pass an English course before enrolling in an economics course (though, again, students completing ENG012 are substantially less likely to be unsuccessful in economics; a competing explanation could be an underlying variable leading students to success in ENG102 and economics). To the point, students with no record of English had a 6 percentage point smaller risk of being unsuccessful in economics (and a 1.44 percentage point greater chance of being successful).

The number of hours that the student reported working, both in SIS and on the survey, made a difference to the students' success rate. Using the SIS data, those students who did not work, worked 1-10 hours or 16-20 hours a week tended to have higher success rates than the other students. Results from the survey were less clear cut, as there was not a consistently inverse relation between reported hours worked and student success, yet still students who did not report working or worked less than 20 hours a week tended to have success rates five percentage points higher than the average.

Several survey questions helped predict students' success in the course. Those that self-reported higher typical letter grades in high school tended to have more success in their economics current course. Students who reported earning As in high school passed this class at a 90.48% rate, Bs at a 80.85%, and C's at a 70.49% (6 students reported frequently earning D's in high school, yet 5 of them passed the course for a 83.33% pass rate, above the average).

Question 8 of the survey asked students if they strongly disagree, disagree, agree, or strongly agree with the statement "*my friends and family believe that I tend to act impulsively or that I can get distracted easily*." Those who disagreed or strongly disagreed with the statement passed the class at 84.38%, and those who agreed passed at a rate of 77.56%.

Whether the student's parent went to college had an impact on their success rate. Students who had a parent go to college passed the course at an 86.57% rate, compared to 77.70% for those who did not. Nearly two-thirds of this cohort is first generation students.

The age of the student matters as well, but in an unexpected way. Older students (25 years or older) had an 89.11% pass rate. If the student was 18-24 years old, they had a 77.81% pass rate. Older students had a better chance of passing the course than traditional age students, in contrast to the findings in the literature (Shapiro et al., 2012; Bahr, 2012; Murtaugh, Burns, Schuster, 1999).

Perhaps as surprising as what was found significantly related to student success was what was not found. The number of D's or F's that the student earned in the previous semester (for those that were enrolled the previous semester) was not predictive of student success. A student's placement exam scores or experience in a reading course were not predictive of student success. Also, a student's self-reported comfort level with math or computers was not predictive of their success. The exception is a student's comfort with calculating percentage change, a common math application in either economics course. One hundred and eighty-five (45.91%) of students reported feeling comfortable with calculating percentage change, and those students passed the course at a 86.49% pass rate compared to those uncomfortable with this calculation, who had a 75.81% pass rate.

Table 7: Variables Significantly Related to Student Success (All Economics Students), by Effect Size (Cramer's V)

Variable	Chi-square	DF	Significance	Cramer's V
Cumulative GPA	55.18	5	p < .001	.370
Instructor	46.87	7	p < .001	.341
Completed ECN in Prior Term	10.42	1	p = .001	.328
W's in Prior Semester	15.318	4	p = .004	.219
Time of Day	18.16	2	p < .001	.212
Passed ECN in Prior Term	4.31	1	p =.038	.211
Last English Course Outcome	17.38	6	p = .008	.208
Hours a Week Worked (Survey)	16.17	8	p = .04	.200
Most Frequent High School Grade	15.05	5	p = .01	.192
Last English Success	9.845	2	p = .007	.156
Work Status (SIS)	7.82	3	p = .05	.139
Comfort with Calculating % Change	7.64	1	p =.022	.138
Act Impulsively/Distracted Easily	6.45	2	p = .04	.127
Hours a Week Worked (SIS)	13.36	6	p = .038	.038
First Generation	4.51	1	p = .034	.034
Traditional vs. Non-traditional Age	6.19	1	p =.013	.013

Research Question II

The analysis of the first research question led to the conclusion that 13 variables were significantly related to students' likelihood of passing an economics courses (the third research question will examine student success variables for Macroeconomic Principles and Microeconomic Principles courses separately). Understanding how these variables are related to each other can shape our understanding of the mechanism by which they are related to student success, as well as look for high correlations which could indicate that two variables are actually measuring the same underlying phenomenon, and therefore only one is needed in the predictive model. This knowledge will be crucial for building the student success models, an integral step in answering the fourth research question.

The second research question is "*of the independent variables related to student success, are any significantly related to each other?*" In this case, the null hypothesis is "there are no significant relations between the independent variables related to student success." The alternative hypothesis is "there is at least one significant relation between two or more independent variables related to student success." Analysis shows that there is clear support for the alternative hypothesis, which will be the focus of this section. Variables will be considered in order of most impactful to student success, as measured by Cramer's V (Table 7).

Cumulative GPA

From the analysis of the first research question, the students' cumulative GPA coming into class was the strongest predictor of student success. Table 8 summarizes the relation between cumulative GPA and other factors related to student success that were significantly related to it as well.

Perhaps unsurprisingly, the students cumulative GPA was highly associated with the number of W's they earned in the previous semester. Of the 318 students who were enrolled at the college in the previous semester, 33.96% of them came into their economics course with 3.5-4.0 GPA. These students were disproportionately more likely to have had not withdrawn from a course during the previous semester (38.31%).

Conversely, students with a 3.0-3.49 GPA were 34.59% of this sub-sample and 40.91% of those with one W the semester before. Consistent with this finding, students with a 2.5-2.99 GPA were 23.27% of the sub-sample but were disproportionately more likely to be represented in the group that had one W grade (36.36%) or two W grades (57.14%). This data suggest that earning W's is associated with lower cumulative GPAs.

The students' college cumulative GPA is highly associated with the students' self-reported high school GPA. Those with a 3.5-4.0 GPA were the most likely GPA group to report earning As in high school (42.36% for the GPA group vs. 26.05% for students as a whole). The plurality of students (46.65%) indicated earning mostly Bs in high school and were indeed disproportionately more likely to fall into the GPA categories of 2.5-2.99 (56.67%), 2.0-2.49 (54.55%), and 3.0-3.49 (50.38%). Of the 15.14% who reported most commonly earning C's in high school, they were disproportionately represented in the below 2.0 category (25.00%). It is clear that (self-reported) high school grades are predictors of the students' college GPA.

The students' perception of whether their friends and family believe that the student tends to act impulsively or can get distracted easily is also related to their cumulative GPA in college. For those students with a 3.5-4.0 GPA, they were much more likely to "disagree" (54.17%) and less likely to "agree" with the assessment (20.83%) than for students reporting those responses overall (41.19% and 31.51%, respectively). Likewise, those students with a 2.0-2.49 GPA and 2.5-2.99 GPA were disproportionately less likely to disagree with the statement (27.27% and 30.00%, respectively) and more likely to agree (45.45% and 43.33%, respectively). This shows a clear indication that students' (perception of their) tendency to act impulsively or get distracted easily has a negative relation with their college GPA.

The students' last English course outcome (whether they passed the course, did not pass the course, or had not attempted it) was significantly related to that student's cumulative GPA, but in a surprising way. The students within the GPA category most likely to have passed a previous English course, among all GPA categories, were those in the 2.5-2.99 range, with a 75.56% chance of having a successful English course experience relative to all students in that GPA category. This was only true for 71.76% of students in the 3.0-3.49 category. Most surprisingly, only 61.81% of 3.5-4.0 students were in this category, which was actually less than for students overall (66.50%). This anomaly could be explained by the relatively low number of students per category with 6 GPA categories and 3 English outcomes. However, given that students in the 2.0-2.49 and below 2.0 GPA categories (54.55% and 41.67%, respectively) were much lower than the overall average, it could be interpreted that higher GPAs generally align with a greater chance of success in a prior English course. It should also be noted, however, that about a quarter (27.79%) of the students had not attempted an English course yet.

Whether a student is in the traditional college age category (18-24 years) or older relates to their cumulative GPA. There is evidence here that age is correlated with GPA. Those students with a 3.5-4.0 GPA were disproportionately more likely to be older (36.81% vs. 25.06% overall) and correspondingly less likely to be younger (63.19% vs.74.94% overall). Likewise, those with a lower GPA of 2.5-2.99 tended to be younger (84.44%) and less likely to be older (15.56%) (these results are similar to those with GPAs below 2.0). These results are in line with the view that older students have a leg up on the skills or attitudes necessary to succeed in a college environment relative to their younger counterparts.

The students' instructor, whether the student completed an economics course in a prior semester, the time of day they took the course, whether the student passed an economics course in a prior semester, how many hours a week they work, their first generation status, or the students' self-reported comfort with calculating percentage change were not associated with the students' cumulative GPA.

Table 8: Variables Significantly Related to Students' Cumulative GPA, by Effect Size (Cramer's V)

Variable	Chi-Square	DF	Significance	Cramer's V
W's in Prior Semester	94.167	20	p < .001	.544
Most Frequent High School Grade	53.459	25	p = .001	.364
Acts Impulsively/Distracts Easily	42.487	25	p = .016	.325
Last English Course Outcome	27.629	10	p = .002	.262
Traditional vs. Non-traditional Age	24.079	5	p < .001	.244

Instructor

From the analysis of Research Question I (Table 7), the students' instructor was the second most significant factor for determining if a student would be successful in economics, both in terms of chi-square calculations and Cramer's V measure of importance. To find evidence to help explain why some instructors have higher success rates than others, students with instructors having above average student success rates (6 of 8 instructors) were compared to students with instructors having below average success rates (2 of 8 instructors). The six above average instructors taught 255 (63.28%) of the students and the two below average instructors taught 148 students (36.72%). The significant results are presented in Table 9.

The below average instructors taught exclusively in the morning, compared to only 25.88% for the above average instructors. All of the afternoon and evening sections were taught by above average instructors.

Whether a student was of traditional college age (18-24) or non-traditional age (25 years old or older) was also significantly related to the instructor that taught them. The instructors with lower average success rates taught classes where 81.76% of the students were of traditional age, compared to 70.98% of instructors with above average success rate. This helps explain this difference, as results from Research Question I showed that older students tend to pass at a higher rate than their younger peers. It should be noted, however, that because the instructor is highly related to the time of day that the class is taught, this might only be reflecting that younger students tend to take morning classes and older students tend to take afternoon or evening courses. It could be the case that older students tend to succeed at a higher rate not only because of developed skills, but because they tended to be taught by instructors with higher success rates in general.

The instructor by which students were taught did not relate to if a student had previously completed an economics course at the college, the students current work status, the students' self-reported most common grades in high school, the students' tendency to act impulsively or to get distracted, the students' first generation status, their successful completion of their previous English course, or their comfort calculating slopes.

Table 9: Variables Significantly Related to the Instructor of the Course, by Effect Size (Cramer's V)

Variable	Chi-square	df	Significance	Cramer's V
Time of Day	501.326	14	$p < .001$	0.789
Traditional vs. Non-traditional Age	21.144	7	$p = .004$	0.229

Completed Economics in a Previous Semester

Ninety-seven (97, 24.07%) students attempted an economics course at their community college in a previous semester. Of these, 82 (84.54%) completed the course (i.e., received a letter grade of “A,” “B,” “C,” “D,” or “F”) while 15 (15.47%) did not complete the course (i.e., withdrew before completing and received a letter grade of “W” or “Y”). Table 10 shows the variables associated with completing an economics course in a prior semester.

Not surprisingly, completing an economics courses in a previous semester was related to passing an economics course in a prior semester. The vast majority (86.56%) of students who had completed a previous economics course passed it, while no students who withdrew from the prior economics course would be eligible to pass it.

Completing an economics course the previous semester was significantly related to the number of W’s the student earned the previous semester (for those students enrolled in the previous semester). Eighty-six (86) of the 403 students (21.34%) in the sample had attempted an economics course in the previous semester, and of these students, 74 (86.05%) completed the course (i.e., did not receive a W or Y letter grade). Despite this high rate, students had an even better chance of completing the course if they did not receive a W in that semester (93.15%). Conversely, 7 of the 13 students (53.85%) who earned at least one W that semester did not complete the economics course. The students may have earned a W in the economics course they did not complete or in another course taken that semester, or both.

Completing an economics course in the prior semester was significantly related to the student’s current work status. Ten of the fifteen (66.67%) students who did not complete a previous economics course worked full-time, compared to only 29.27% who did pass the course. Those that completed the previous course (vs. those that did not) were correspondingly more likely to work part-time (28.05% vs. 20.00%) or not at all (37.80% vs. 13.33%). The evidence suggests that working full-time during college is not conducive to passing economics.

Students completing economics in a previous semester did not relate to the time of day that they took their current course, their self-reported most frequent grade earned in high school, their self-reported tendency to act impulsively or distract easily, whether they are of first generation status, their age (traditional vs. non-traditional age bracket), their success in a prior English course, or their self-reported comfort with calculating percentage change.

Table 10: Variables Significantly Related to a Student Completing Economics in a Prior Semester, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Passed ECN in Prior Term	48.46	1	$p < .001$	.707
W's in Prior Semester	24.304	3	$p < .001$	.532
Work Status	8.33	3	$p = .04$	.293

Number of W's in the Prior Semester

Three hundred and eighteen (318) students of the 403 (78.91%) sample were enrolled at the college prior to the semester they attempted their current economics course. Of these, the vast majority (82.08%) received no W's the semester before. However, the number of W's students received did significantly relate to not only student success in the course but also to other factors related to student success. Table 11 shows the relation between these other factors and the number of W's received the prior semester. The relation between the number of W's earned in the previous semester and the students cumulative GPA, as well as the rate of passing an economics course in a previous semester, were discussed earlier.

Also mentioned earlier, there were 86 students of the 403-person sample that had enrolled in an economics course prior to enrollment in the current semester (21.33% of the sample). Of those, 64 (74.42%) successfully passed their course. However, if the student had received no W's that semester, they were 80.82% likely to pass the course. Conversely, only 8 out 13 (61.54%) passed their previous economics course if they had at least one W that semester. That W grade could have been earned by withdrawing from that economics course or in another course that semester, or both.

Whether a student is a full-time worker (in this study defined as working 21 or more hours per week), part-time worker (works 1-19 hours per week), or does not work was significantly related to the number of W grades earned during the previous semester. This was most clearly seen for the 44 students of this sub-sample who had earned one W in the previous semester. These 44 students were more likely to work a full-time job (43.18%) relative to the students overall who had earned one W (35.85%), and correspondingly less likely to work part-time (25.00%) or not at all (27.27%). This evidence suggests that working many hours per week promotes withdrawals from courses.

The observation of the number of W's earned by students in the previous semester was not significantly related to the instructor they had this semester, the time of day they took the current economics course, their success in a previous English course, their self-reported number of hours worked according to the survey, their self-reported most frequent letter grade earned in high school, their self-perceived tendency to act impulsively or get distracted easily, their first generation status, their age category, or their self-reported comfort with calculating percentage change.

Table 11: Variables Significantly Related to the Number of W Letter Grades Earned the Previous Semester (of Those Students Enrolled in the Previous Semester), by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Cumulative GPA	94.167	20	$p < .001$	.544
Completed ECN in Prior Term	24.304	3	$p < .001$	.532
Passed ECN in Prior Term	12.775	3	$p = .005$	.385
Work Status (SIS)	21.359	12	$p = .045$	.150

Time of Day of Class

Economics students had the option of enrolling in either a morning (214, 53.10%), afternoon (84, 20.84%), or evening (105, 26.05%) course. Table 12 shows the variables significantly related to the time that a student was enrolled in the course. The relation between the time of day that students enrolled in their economics course and their instructor was discussed in a previous sub-section.

Age, in this case as categorized as traditional college age (18-24 years of age) or non-traditional age (25 years of age or older), was significantly related to when they chose to enroll in their economics course. Although most students in this cohort were of traditional age (74.94%), they were most likely to take morning coursers (81.78%). Non-traditional age students, accounting for 25.06% of the sample, were more likely to take afternoon courses (26.19%) and especially evening courses (38.10%).

The work-status of the student was strongly related to the time of day that they were enrolled in their course. Students who worked full-time represented 30.84% and

33.33% of the students in the morning and afternoon classes respectively, but they accounted for 50.48% of the students enrolled in the evening courses. Morning class students were more likely to report not working (30.84%) than afternoon (28.57%) or evening courses (34.29%). Students enrolled in evening courses were the least likely to report working part-time (12.38%), relative to students enrolled in morning (24.30%) or afternoon (30.95%). This data supports the interpretation that many students who work full-time prefer or need to take evening courses, while those that do not work or work part-time either prefer or need to take morning or afternoon courses.

Knowing the time of day that the student enrolled in their economics course did not relate to if they passed an economics course in a previous term, their most frequent grade in high school, their reported tendency to act impulsively or distract easily, their first generation status, or comfort with calculating percentage change.

Table 12: Variables Significantly Related to the Time of Day That a Student was Enrolled in the Course, by Effect Size (Cramer's V)

Variable	Chi-Square	DF	Significance	Cramer's V
Instructor	501.326	14	$p < .001$	.789
Traditional vs. Non-traditional Age	14.881	2	$p = .001$	.192
Work Status	19.388	6	$p = .004$	.155

Passed Economics in a Previous Semester

A sub-sample (97) of the larger sample (403, 24.07%) had enrolled in an economics course prior to their current attempt. Of these, 71 (73.20%) were successful in their previous course and 26 (26.80%) were not. Table 13 shows the variables significantly related to the time that a student was enrolled in the course. The relation between students' passing economics in a previous semester and completing economics in a previous semester as well as the number of W's received in the prior semester were discussed in a prior sub-section.

Age, in this case as categorized as traditional college age (18-24 years of age) or non-traditional age (25 years of age or older), was significantly related to if they had passed an economics course in a previous semester. Of the 26 students who were not successful at their attempt at a previous economics course, 24 of them (92.31%) were between the ages of 18 and 24. Correspondingly, of the 71 students who were successful in their attempt, a disproportionate 21 (29.58%) were non-traditional age students (relative to 23.71% of the sub-sample that were of non-traditional age).

The observation that students completed economics in a previous semester did not relate to their current work status (full-time, part-time, or not employed), their most common high school grade, their reported tendency to act impulsively or distract easily, whether they were successful in an English course, their first generation status, or comfort with calculating percentage change.

Table 13: Variables Significantly Related to if the Student Passed an Economics Course in a Previous Semester, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Completed Economics in Previous Semester	48.46	1	$p < .001$	.707
W's in Prior Semester	12.775	3	$p = .005$	.385
Traditional vs. Non-traditional Age	5.039	1	$p = .025$	.228

Work Status (SIS)

Students were grouped by their employment status, either working full-time (21 or more hours per week), part-time (1-20 hours per week), not working (0 hours), or unspecified. Table 14 shows the variables significantly related to a student's work status. The relation between students' work status and the time of day of class they were enrolled in class, if they had previously completed an economics course, and the numbers of W letter grades earned in the previous semester were previously described in earlier sub-sections.

The students' work status significantly related to their self-reported most common grade in high school. For full-time working students, they were less likely to report earning A's (19.73%) than the average students reporting A's (26.05%), and more likely to earn B's (52.38%) than the average students reporting B's (46.65%) in high school. Part-time working students were more likely to report earning A's (37.36%) than the average student reported earning A's (26.05%), and less likely to report earning C's (7.69%) than the average student reported earning C's (15.14%). Students who were not working were less likely to report earning B's (39.29%) than the average student reported earning B's (46.65%).

Work-status was also significantly related to the age of the student (traditional vs. non-traditional). Students in the sample were disproportionately between the ages of 18-24 years old (74.94%), but were underrepresented in full-time work (65.99%) and overrepresented in part-time work (84.62%). Conversely, older students (25 years of age or older) were more likely to be working full-time (34.01%) and less likely to be working part-time (15.38%) than their overall representation in the sample (25.06%). Interestingly, students who were not working did not differ by more than a few percentage points from their overall sample representation. These data show that the average older adult student works more hours a week than their younger counterparts do.

There was also a significant relationship between a student's work status and their first generation status. Full-time working students were more likely be first generation students (69.39%) than average (66.75%), and part-time working students were less likely to be first-generation students (59.34%).

Knowing the work status of students did not relate to their reported tendency to act impulsively or distract easily, whether they were successful in an English course, or comfort with calculating percentage change.

Table 14: Variables Significantly Related to the Students' Working Status, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Completed Economics in Previous Semester	8.33	3	p = .040	.293
Most Frequent Grade in High School	36.634	15	p =.001	.174
Traditional vs. Non-traditional Age	12.068	3	p = .007	.173
Time of Day of Class	19.388	6	p = .004	.155
W's in Prior Semester	21.359	12	p = .045	.150
First Generation Status	7.991	3	p = .046	.141

Most Frequent Grade in High School

Students were asked to report the most frequent letter grade that they earned in high school. The other variables that were associated with student success and were also significantly related to this variable are presented in Table 15. The relation between this and the students' high school GPA as well as the students' current work status were described in previous sub-sections.

There was a very strong relation between a student's self-reported most frequent letter grade earned in high school and their perception of their friends and family belief that they act impulsively or can be distracted easily. Students who reported frequently earning A's in high school tended to strongly disagree (21.90%) or disagree (52.38%) with this assessment relative to the typical student (14.39% and 41.19%, respectively); only 18.10% agreed with the statement, relative to 31.51% overall. Students who reportedly earned C's in high school tended to disagree with the statement (27.87%) at a lower rate and to agree with it (49.18%) at a higher rate than students overall (41.19% and 31.51%, respectively). Similarly, students who self-reportedly earned D's in high school showed a similar level of disagreement (33.33%) and agreement, but were more than 2:1 likely to strongly agree that they tend to act impulsively and get distracted easily than the average (16.67% vs. 7.20% overall, though this could be partly explained by the very few students [6] that reportedly earned primarily D's in high school). Interestingly, 37.77% of B students agreed with the statement, higher than for students overall (31.51%).

The students' self-reported most frequent grade in high school was significantly related to their comfort level with calculating percentage change. Students who reported earning mostly A's in high school also reported feeling comfortable calculating percentage change (53.33%) as compared to the sample as a whole (45.91%). Conversely, students who reported earning C's and D's tended to respond not feeling comfortable with the mathematical operation by a rate of 67.21% and 83.33%, respectively (as compared to 53.35% for the overall sample).

The students' self-reported most frequent grade in high school was also significantly related to if they were the first in their family to go to college. Of the 61 students who reported earning primarily C's in high school, 72.13% were first-generation students compared to 66.75% of students overall. Of the 105 students who reported receiving primarily As in high school, 42.86% were not first generation students, disproportionate when compared to the 33.25% of the population that were not first generation students.

Knowing the students' self-reported most frequent grade in high school did not relate to their age or whether they were successful in an English course.

Table 15: Variables Significantly Related to Student's Self-Reported Most Frequent Letter Grade Earned in High School, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Act Impulsively/Distracted Easily	626.710	25	$p < .001$	.558
Cumulative GPA	53.459	25	$p = .001$	.364
Comfort with Calculating % Change	37.456	10	$p < .001$	.305
Work Status	36.634	15	$p = .001$	.174
First Generation Status	11.115	5	$p = .049$	.166

Reported Tendency to Act Impulsively or Distract Easily

Students were asked on the survey to mark "strongly agree," "agree," "disagree," or "strongly disagree" with the statement, "*My friends and family believe that I tend to act impulsively or that I can get distracted easily.*" The relation between the most frequent letter grade students earned in high school and their cumulative GPA, as well as their reported tendency to act impulsively or distract easily, was described in their respective previous sub-sections. These and the other variables (as described below) that were both associated with student success and were also significantly related to this variable are presented in Table 16.

The students' self-perception of their friends and family's belief that they act impulsively or can get distracted easily is related to their comfort level with calculating slopes in an interesting way. For the minority (45.91%) who felt comfortable calculating slopes, they disproportionately were more likely to both "strongly disagree" that they act impulsively or get distracted easily (55.17%) as well as "strongly agree" (58.62%) relative to the majority of students.

The students' age significantly related to their perception of their family and friends belief that they behave impulsively or distract easily. Although only 29 of the 403 students in the sample "strongly agreed" that they act impulsively or get distracted easily, 27 of these (93.10%) were in the 18-24 year range. Likewise, 85.83% of the "agreed" responders were of this younger group. Conversely, the older students disproportionately represented "strongly disagreed" (43.10%, compared to their 25.06% representation in the sample) and very few (6.9%) "strongly agreed." With age, it seems, comes (the perception of) self-control and focus, at least among those striving for a higher education.

The students' tendency to act impulsively or become distracted easily does not relate to if they are a first generation college student or have had previous success in an English class.

Table 16: Variables Significantly Related to Student's Perception of Friends and Family Believing That They Tend to Act Impulsively or Can Distract Easily, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Most Frequent Grade in High School	626.710	25	p < .001	.558
Cumulative GPA	42.487	25	p = .016	.325
Comfort with Calculating % Change	61.788	10	p < .001	.277
Traditional vs. Non-traditional Age	26.661	5	p < .001	.257

First Generation Status

As previously described in their respective sub-sections, the most frequent letter grade earned in high school as reported by students on the survey and the students' work status were significantly related to their first generation status. Table 17 recaps the variables significantly related to students' first generation status.

Whether students were the first generation in their family to attend college was not significantly related to their age, success in a prior English course, or their comfort with calculating percentage change.

Table 17: Variables Significantly Related to Students' First Generation Status, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Most Frequent Grade in High School	11.115	5	p = .049	.166
Work Status	7.991	3	p = .046	.141

Age

For this study, students were categorized into traditional college aged students (18-24) or non-traditional college aged student (25 years of age or older). Previous sub-sections have described the relation between students' age and their cumulative GPA, their reported tendency to act impulsively or distract easily, their work status, whether they had passed an economics course before, and the time of day they took the class, and their instructor. Table 18 shows the variables that were both significantly related to student success as well as the students' age.

Students in the older cohort were significantly more likely to report comfort in calculating percentage change on the survey (54.08%) relative to the sample as a whole (46.25%). Conversely, younger students were relatively more likely to not report comfort calculating percentage change (56.29%) relative to the sample as a whole (53.75%).

The students' age was not related to if they were successful in a previous English course.

Table 18: Variables Significantly Related to Students' Traditional vs. Non-traditional Age, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Act Impulsively/Distracted Easily	26.661	5	$p < .001$	.257
Cumulative GPA	24.079	5	$p < .001$	.244
Previous Passed an Economics Course	5.039	1	$p = .025$	.228
Time of Day of Class	14.881	2	$p = .001$	.192
Comfort with Calculating % Change	12.192	2	$p = .002$	.174
Work Status	12.068	3	$p = .007$	.173
Instructor	21.144	7	$p = .004$	.229

Success in a Prior English Course

Whether students were successful in a prior English course or not was not related to if they were comfortable with calculating percentage change. However, as was discussed in previous sub-sections, successful completion of an English course was significantly related to the students' cumulative GPA and the time of day that the student was enrolled in class.

Table 19: Variables Significantly Related to Students' Traditional vs. Non-traditional Age, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Cumulative GPA	27.629	10	p = .002	.262
Time of Day of Class	8.438	2	p = .015	.145

Comfort with Calculating Percentage Change

Students were asked on the survey to report their comfort with calculating percentage change. As described in the previous sub-section on age, there was a significant relation between the students' age (if they were a traditional college age student or older) and their comfort with calculating percentage change. Table 20 recaps this relation.

Table 20: Variables Significantly Related to Students' Traditional vs. Non-traditional Age, by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Traditional vs. Non-traditional Age	12.192	2	p = .002	.174

Research Question III

The third research question is *"are there different relations between the factors (independent variables) and student success (dependent variable) depending on which course is taken (Macroeconomic Principles vs. Microeconomic Principles)?"* One purpose of this study is to find the unique factors that contribute to student success in economics courses as a specific discipline (Research Question I), but it is possible that different factors contribute to student success in Macroeconomic Principles and Microeconomic Principles, independently of each other. If that is the case, then faculty members and other college personnel could custom tailor materials and recommendations to those students seeking to take a specific course or for helping students decide which of the courses would best suit them to take first, given their academic background.

The null hypothesis for Research Question III is "there are no differences in the variables associated with student success between the Macroeconomic Principles and Microeconomic Principles courses." The alternative hypothesis is "there is one or more variables associated with student success that differ between the Macroeconomic Principles and Microeconomic Principles courses." In order to test these hypotheses, the sample data set (used for testing Research Questions I and II) was divided based on if the student was enrolled in ECN211 (Macroeconomic Principles) or ECN212 (Microeconomic Principles), in effect creating two mutually exclusive data sets. These data sets were then tested similarly to Research Question I for relations between student success in the course and other variables. Tables 21-23 provide evidence for the alternative hypothesis, that there are differences in predictors between success in ECN211 and ECN212. Specifically, there are five factors that predict both student success in ECN211 and ECN212, six factors that predict success in ECN211 but not ECN212, and four factors that predict success in ECN212 but not ECN211.

Of the 403 students in the larger sample, 238 (59.06%) of the students took ECN211 and 165 (40.94%) took ECN212. Unsurprisingly, there were multiple variables that predicted student success for both ECN211 and ECN212 (combined sample) as well as for ECN211 or ECN212 individually. As the relation between student success and the significantly related independent variables were articulated in Research Question I and generally remain consistent in pattern, the remainder of this section will focus on confirming the relation between these independent variables and student success, as well as describing unique relations between variables not uncovered when the two courses were considered together in Research Question I.

Macroeconomic Principles

The independent variables that were significantly related to student success in ECN211 are presented in Table 21. Some of these were also identified for economics students as a whole, include cumulative GPA, instructor, the time of day of the course, if the student had completed an economics course in a prior semester, number of hours worked per week, the number of W's received in the previous semester, and their self-reported comfort with calculating percentage change.

Of all the 238 students enrolled in ECN211, 59 (24.79%) of them had enrolled in a reading course in a previous semester. For these students, success in their reading course predicted success in ECN211. Although only 3 of the 59 students were not successful in their previous reading course, only 1 of those 3 (33.33%) students passed ECN211 while 47 out of the 56 (83.93%) students who passed their reading class also passed ECN211. Although there are too few students who did not pass their reading course to make a definitive judgment, it does lend support to the idea that strong reading skills is beneficial to completing ECN211.

Unlike for the sample as a whole, the students' self-reported comfort with graphing data was a predictor of student success in ECN211, though in a surprising way. More than two thirds of students (68.49%) reported feeling comfortable graphing data. However, of the 40 students who did not pass ECN211, 30 of them (75.00%) reported feeling comfortable with graphing data, higher than for the sample overall. These results are not well understood.

Also, unlike for economics students overall, the number of D's and F's earned in the previous semester predicted student success in ECN211. Most students (81.42%) who were enrolled in the previous semester ended up successfully completing their current ECN211 course, but that rate jumped to 90.60% for those that had received no D's or F's the semester before. Conversely, of the 16 students who had a D or F grade the previous semester, only 9 of them (56.25%) were successful in their ECN211 course during the current semester. This suggests that the number of D's or F's in the previous semester does impact their likelihood of success in their current semester of ECN211. (It should be noted that five students had received two D's or F's the prior semester, and all of them passed their ECN211 class this semester).

As in Research Question I, there were many independent variables that were not related to student success in ECN211. Much of their academic background such as the number of transfer credits attempted or earned, transfer GPA, whether a student was enrolled in the previous semester, attempted an economics course in a previous semester, or passed an economics course in the previous semester did not impact their success. The semester that the student took the course or how many credit hours they attempted that semester did not seem to matter to their success. The students' English, mathematics, or reading placement results or their success in these developmental courses were not predictive of success. The total number of credits hours that students had enrolled in that semester, their overall enrollment status, or the cumulative credit hours earned was not related to student success. The students' personal characteristics such as age category (traditional vs. non-traditional), students' ethnicity or gender, first generation status, military active duty or dependent of an active duty family member, military veteran, primary current language spoken or primary language spoken as a child, or their current work status (SIS) did not seem to matter. Activities outside of class such as the number of hours per week spent reading for pleasure or engaged in homework was not predictive. Their self-reported comfort with algebra or calculating slopes, self-reported computer literacy, self-reported reliability of transportation, self-perception of ability to make long-range goals and stay organized, self-perception of tendency to act impulsively or get distracted easily, belief of locus of control, or self-reported most common grade earned in high school or number of advanced classes taken in high school again did not help explain their success in ECN211.

Table 21: Variables Significantly Related to Students' Success in Macroeconomic Principles (ECN211), by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Cumulative GPA	37.645	5	p < .001	.398
Instructor	37.168	5	p < .001	.395
Completed ECN in Prior Term	4.219	1	p = .04	.375
Last Reading Course Success	4.806	1	p = .028	.285
Last English Course Outcome	19.480	6	p = .003	.286
Hours a Week Worked	16.480	8	p = .036	.264
W's in Prior Semester	10.723	3	p = .013	.242
D's or F's in Prior Semester	8.234	2	p = .016	.212
Time of Day	9.198	2	p = .01	.197
Comfort with Graphing Data	6.389	2	p = .041	.164
Comfort Calculating Percentage Change	6.854	2	p = .032	.170

Microeconomic Principles

Of the 403 students in the larger sample, 165 (40.94%) of the students took Microeconomic Principles (ECN212). The independent variables that were significantly related to student success in ECN212 are presented in Table 22 below. As was the case for the ECN211 sample, some of these variables were also identified as success indicators for economics students as a whole, including cumulative GPA, the time of day that the students took the course, if the student had completed an economics course in a prior semester, and their self-reported comfort with calculating percentage change. In other cases, such as first generation status of the student and their self-reported most frequently earned grade in high school, there was a significant impact related to student success found for ECN212 and for economic students as a whole, but not explicitly found in the ECN211-only analysis. The following paragraphs will describe newly found or uniquely related variables.

The effect of the instructor that the student had was not as strong of a predictor of student success as it was in ECN211. Indeed, the "instructor" variables (chi-square = 10.869, df = 5, p = .054) did not pass the statistical threshold for being considered statistically significant in this study ($p \leq .05$). However, when student success was contrasted between those instructors with higher than average student success rates (6 of 8) from those with lower than average students success rates (2 of 8), what is labeled here as "Instructor Success," there was a statistically significant difference (Table 22). Most students (54.55%) were taught by one of the six instructors with higher than average student success rates, and those students disproportionately passed the course at a rate of 61.42%. Likewise, students who were taught by one of the two instructors with lower than average student success rates (45.45% of the ECN212 sample) had only a 38.58% chance of being in the successful category. Clearly the instructor plays a significant role in the success of student in ECN212.

Surprisingly (as it was not a significant predictor of success for ECN211 students or economics students overall), the outcome of the students' previous reading course was strongly and significantly related to the students' successful outcome in ECN212. Forty-three (43) of the students taking ECN212 that year had a record of taking a reading course at the college. Although a clear majority of the students who had taken a reading course were successful at a college-level reading course (60.47%), these students were disproportionately more likely to pass the economics course (73.53%); indeed, just 1 of the 26 students who had successfully completed a college-level reading course was not successful in ECN212. Surprisingly, however, success in development reading courses alone did not predict student success. Although these students were 27.91% of all those

ECN212 who had a record of enrolling in a reading course, this group represented 55.56% of those students with a reading course on record who did not succeed in ECN212. Another way of looking at this is that only 7 of the 12 students who had only completed a developmental reading class passed ECN212. Although these are relatively small numbers compared to the sub-sample as a whole (only 26.06% of the ECN212 had taken a reading course), it does lend support to advising students to have strong reading foundations before enrolling in ECN212. However, it may be interesting to note that student success in their previous reading course (regardless of developmental or college level) was not significantly related to student success (χ^2= 1.540, df = 1, p=.215).

As was found in the analysis of Research Question I and the examination of student success predictors in ECN211, there were many independent variables that were not related to student success in ECN212. Much of their academic background such as the number of transfer credits attempted or earned, transfer GPA, whether a student was enrolled in the previous semester, attempted an economics course in a previous semester, or passed an economics course in the previous semester did not predict their success in this class. Unlike for the ECN211 analysis, the number of W's that the student earned or the number of D's or F's they received in the previous semester did not predict success in the ECN212 course. The semester that the student took the course or the time of day of the course did not seem to matter to their success. The students' English, mathematics, or reading placement results or their success in English or mathematics developmental education courses were not predictive of student success. The total number of credits hours that students had enrolled in that semester, their overall enrollment status, or the cumulative credit hours earned were not related to student success. The students' personal characteristics such as age category (traditional vs. non-traditional), students' ethnicity or gender, military active duty or dependent of an active duty family member, military veteran, primary current language spoken or primary language spoken as a child did not matter. Activities outside of class such as the number of hours per week spent reading for pleasure or engaged in homework was not predictive, nor was knowing the number of hours worked per week (either through the survey or SIS data). The number of courses that the student attempted or their enrollment status (full-time vs. part-time) that semester was not significantly related. Their self-reported comfort with algebra, graphing data, or calculating slopes, self-reported computer literacy, self-reported reliability of transportation, self-perception of ability to make long-range goals and stay organized, or self-perception of their tendency to act impulsively or get distracted easily, or belief of locus of control did not help explain their success in ECN212.

Table 22: Variables Significantly Related to Students' Success in Microeconomic Principles (ECN212), by Effect Size (Cramer's V)

VARIABLE	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
Last Reading Course Outcome	15.538	4	p = .004	.601
Last Reading Course Success at College Level	9.592	1	p =.002	.490
Cumulative GPA	35.094	5	p < .001	.461
Most Frequent High School Grade	14.755	5	p =.011	.299
Completed ECN in Prior Term	5.951	1	p = .015	.298
Instructor Success	10.503	1	p = .001	.252
Time of Day	10.012	2	p = .007	.246
Comfort Calculating Percentage Change	6.822	2	p = .032	.204
First Generation Status	5.001	1	p = .025	.174

Compilation of Success Factors

Table 23 provides a summary of the uncovered factors associated with student success in economics, whether for economics students as a whole or specific to one of the two individual courses. This study found 22 separate factors that were statistically associated with student success in at least one analysis. It is important to mention that not all of these 22 factors are independent of each other. This was showed through the analysis of Research Question II, but also factors may be similar by measuring the same phenomena through different lenses. For example, “Instructor” and “Instructor Success Average” are both measuring success factors differences from one instructor to another, yet the way this data was categorized made a difference in the statistical analyses.

The five factors that were significant related to student success in all three separate analyses are bolded in Table 23. These factors are the student’s cumulative GPA, if they had completed an economics course in a prior semester (regardless if they passed it or not), the time of day that the course is offered, and the students’ self-reported comfort with calculating percentage change. As discussed in the previous paragraph, the fifth factor highlighted is Instructor, or the student success factors associated with the instructor’s course, in combination with the closely related variable Instructor Success Average (ECN212 only).

Although all of these 22 factors were considered in the building of the student success models for the next research question, these five highlighted factors were the foundational analysis for the building of the models. During the building of the models, not only did these twenty-two factors serve as the building blocks, but the findings uncovered in Research Question II helped to enlighten its construction as it indicated how any of the two independent variables are significantly related, and therefore perhaps measuring the same phenomena, and therefore only one should be considered for use in the model.

Table 23: Variables Significantly Related to Students' Success in Total Sample, Macroeconomic Principles (ECN211) only, or Microeconomic Principles (ECN212) only, by Effect Size for All Sample (Cramer's V)

FACTOR	ALL SAMPLE	ECN211 ONLY	ECN212 ONLY
Cumulative GPA	**.370**	**.398**	**.461**
Instructor/Instructor Success Average[1]	**.341**	**.395**	**.252**
Completed ECN in Prior Term	**.328**	**.375**	**.298**
W's in Prior Semester	.219	.242	
Time of Day	**.212**	**.197**	**.246**
Passed ECN in Prior Term	.211		
Last English Course Outcome	.208	.286	
Hours a Week Worked	.200	.264	
Most Frequent High School Grade	.192		.299
Last English Success	.156		
Work Status (SIS)	.139		
Act Impulsively/Distracted Easily	.127		
Hours a Week Worked (SIS)	.038		
First Generation	.034		.174
Traditional vs. Non-traditional Age	.013		
Comfort with Calculating % Change	**.138**	**.170**	**.204**
Last Reading Course a Success		.285	
D's or F's in Prior Semester		.212	
Comfort with Graphing Data		.164	
Last Reading Course Outcome			.601
Last Reading Course Success at College Level			.490

1. *The "Instructor" variable was significant for the compiled economics students as well as ECN211 students, but not for ECN212. "Instructor Success Average" was significant for ECN212. This table combines these two variables for clarity of the importance of the instructor to student success.*

Research Question IV

The main purpose of this study is to identify the factors that lead students to success in the economics principles courses. Research Question IV is "*what factors, in* *combination, best predict student success before enrollment in the economics principles courses?"* Findings from analyses of Research Questions I and III lend support to the position that there are 22 factors that are statistically associated with student success in the course. However, it remains to be seen if knowing more of these predictive variables at once could improve our understanding of student success.

The null hypothesis is "knowing two or more independent variables does not lead to a more accurate understanding of a students' likelihood of success in economics courses than only consider one significant independent variable." The alternative hypothesis is that "knowing two or more independent variables can significantly improve predictions of student success in the economics principles courses relative to only considering one significant independent variable." The following will illustrate support for the alternative hypothesis, that models using two or more predictor variables can significantly improve the prediction accuracy of student success. First, however, the reader needs to become familiar with the theoretical basis of these models in order to interpret the results.

The Binary Logistic Regression Model

To test the hypotheses of Research Question IV, student success outcomes will be regressed using the binary logistic regression technique. Binary logistic regression is "the standard way to model binary outcomes (that is, data y_i that takes on the values 0 or 1)" (Gelman & Hill, 2007, p.79). Many disciplines have used binary logistic regression to analyze the probability of events occurring when the outcome variable is binary (can have only one of two outcomes). For example, logistic regression has been particularly popular in medical research in which the outcome is whether a patient has a disease or not (Wuensch, 2014), as well as political science (will the voter vote for Candidate A or B?) and social science research (will the participant change his or her behavior or not?) (Gelman & Hill, 2007). In this study, the binary outcome is the student passing the economics course (1) or not (0).

One reason for its popularity is that, unlike Pearson chi-square tests used in Research Questions I-III, binary logistic regression can be used with predictor variables that are either continuous or categorical. It also makes no assumptions about the distribution of the predictor variable, as general linear regression models do (Wuensch, 2014).

The basic binary logistic regression model is $b_0 + b_1X_1 = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = \ln(ODDs)$. Note that $b_0 + b_1X$ is the standard linear model, where b_0 is the y-intercept, b1 is the slope (coefficient), and X_1 is the predictor value. Instead of predicting "Y" (the outcome variable) directly, however, in binary logistic regression the outcome variable is the logit (natural log of the odds) of having one outcome occur relative to another. $\hat{Y}$ is the predicted probability of the event occurring, and 1-$\hat{Y}$ is the predicted probability of the event not occurring (because there are only two potential outcomes for binary variables, the probabilities that one event will occur or the other, when summed, is equal to 1). Therefore, $\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ are the odds of one event occurring relative to the other. In order to find the odds of an event occurring, exponentiate both sides of the equation ($ODDS = e^{a+bx}$). In other words, when the values of b_0 and b_1 are estimated in the equation, and the known predictor value x is inserted into the equation, its exponentiation will result in the estimated odds of the event occurring. Once the odds of the event are estimated, it is straightforward to convert odds to a probability of the event occurring through the equation $\hat{Y}=\frac{ODDS}{1+ODDS}$ (Wuensch, 2014).

The variables in the equation themselves have an ability to explain the relation between individual predictor variables and the outcome variable through an odds ratio, or the odds that one will event will occur given the odds of another event occurring. In order to calculate the odds ratio, "raise the base of the natural log to the b^{th} power, where b is the slope from our logistic regression equation" (Wuensch, 2014, p.4).

According to Szumilas (2010), the odds ratio (OR) "is a measure of association between an exposure and an outcome…[it] represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure." An OR of 1 indicates that exposure to the phenomenon does not increase or decrease one's odds of experiencing a different outcome. Therefore, the greater the OR is from 1 (either as a fraction approaching 0 or a number greater than 1 approaching positive infinity), the more significant that exposure is to the outcome.

The basic binary logistic regression model ($b_0 + b_1X_1 = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = \ln(ODDs)$) previously discussed can be refined by adding other predictor variables to more accurately estimate the odds and probability of an event occurring relative to not occurring. The more generalized binary logistic regression model is $b_0 + b_1X_1 + b_2X_2 + \ldots + b_mX_m = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$. Under this somewhat more complicated model, the linear regression will be a multiple regression of *m* predictors. The resulting equation, however, will be interpreted the same way as described in the previous paragraph.

The y-intercept (b_0) and slopes ($b_{1,2,..,m}$) coefficients of the binary logistic regression model can be tested for statistical significance using the Wald chi-square test.

The Wald chi-square statistic "…tests the unique contribution of each predictor, in the context of the other predictors—that is, holding constant the other predictors—that is, eliminating any overlap between predictors" (Wuensch, 2014, p. 13). In the context of the odds ratio (OR), it is used to test if the population parameter that is being estimated in the study (through analysis of the sample) is OR=1 (the null hypothesis, or that exposure to the variable does not increase one's odds of an outcome) or OR≠1 (the alternative hypothesis, or that exposure to the variable does impact one's odds of an outcome occurring) (Harrell, 2001). The Wald chi-square is calculated by finding the squared difference between the estimated parameter and the null hypothesis, divided by the variance of the estimated parameter $\left(\frac{(\hat{\theta}-\theta_0)^2}{var(\hat{\theta})}\right)$.

Plan of Analysis

There will be five steps in the analysis of Research Question IV. In step one, all 22 variables identified as being related to student success in at least one economics course will be regressed using binary logistic regression in three separate scenarios. The first scenario will be to regress the predictor for all economics students in the sample (i.e., both ECN211 and ECN212 students combined). The second and third scenario will regress these variables to outcomes of ECN211 and ECN212, respectively. Although not all 22 variables were found to be related to ECN211, ECN212, and the total sample, out of conservatism all variables will be tested using logistic regression techniques as the calculations between binary logistic regression and the Pearson Chi-square tests performed for Research Questions 1-3 can have slightly different p-values (Wuensch, 2014), which may make the difference for some variables close to the p = .05 cutoff level. Only variables that were identified as significant under hypothesis 1 or 3 will be retested using logistic regression techniques here.

Predictor variables identified as significant in one or more of the three scenarios will be reported in Tables 24-26. In order to determine if the predictor variable is significant in the model, The Wald chi-square (χ^2) statistic is computed and tested. As in the analyses for Research Questions I-III, the cut off probability level for significance will be p = .05. These variables will be listed with the estimated value of the linear predictor (b) of the equation, the Wald chi-square (χ^2) value, the degrees of freedom (df), the Wald chi-square (χ^2) significance level in the model (p), and the associated odds ratio for the linear predictor in the table.

In step two, all of the predictor variables that were found to be significant in their respective scenarios will be tested against each other for interaction effects. These interaction effects are important as they may provide more explanatory power for the final model building (step three) than the predictor variables themselves.

In step three, the "best-fit," multivariate binary logistic regression models will be built for each scenario (all economics students, ECN211 students only, and ECN212 students only). By including significant variables (step one) and interaction effects (step two) from the previous steps, the model can be compared to see if it is a better fit. "Best fit" is determined by examining the model's corresponding -2 Log Likelihood statistic, as well as the Nagelkerke R^2 value. The -2 log likelihood statistic "measures how poorly the model predicts the decisions- the smaller the statistic the better the model" (Wuensch, 2014, p. 4). The Nagelkerke R^2 value is similar to the more common R^2 statistic as it ranges from 0 to 1, with 0 meaning it has no explanatory power as a variable and 1 meaning it completing explains the outcome variable. Therefore, new models will be considered iteratively better than the previous model if its -2 log likelihood statistic decreases or its Nagelkerke R^2 increases. The best-fit model creation process will end when further iterations of addition of variables and interactions identified in the first or second steps yield no further reductions in the -2 log likelihood statistic or increases in the Nagelkerke R^2, or all factors under consideration are considered in the model.

In step four, the accuracy of the multivariate linear regression models will be tested on the data set used to create the model. For each student-participant in the overall sample or sub-sample (respective of the model), a prediction will be made if the student was successful in the course or not. Given that the student's final grade is known, that prediction will either be accurate or in error. However, there could be three possible outcomes (and two types of errors). One outcome, called accuracy, measures if the predicted outcome is the same as the actual outcome, that is, the prediction was correct. A second outcome, called the *false positive rate*, shows the percentage of predicted occurrences that were incorrect. A third outcome, called *false negative rate*, shows the percentage of predicted non-occurrences that were incorrect (Wuensch, 2014).

In the final step, step 5, the models will be tested with new student data collected and compiled in the semester after the original data set was created. This analysis will show how robust these models are when applied to a new student sample, separate from the ones used to create the models.

Step One: Univariate Binary Logistic Regression Models

Tables 24-26 shows the statistically significant ($p \leq .05$) predictor variables that, individually in the binary logistic regression model, are related to student success in economics principles courses, for both courses together (ECN211 or ECN212) (Table 24), ECN211 students only (Table 25), and ECN212 students only (Table 26). They are sorted by highest Wald chi-square (χ^2) as that is the most reliable measure of effect size available for binary logistic regression. The reader should be cautioned when interpreting the b coefficient in these models as this number is highly associated with the unit of measurement of the variable, and changing the scale could change the value of the slope by several decimal places. Some significance (p values) are identical and so cannot be used for sorting. The odds ratio is a good measure of the predictor variables impact on student success, but whether it is above or below 1 depends on how the statement of relation is framed.

Each sub-section that follows will focus on the similarities and differences between the significant variables identified using the Pearson chi-square tests (Research Questions I-III) and the Wald chi-square tests using the binary logistic regression technique. It will also interpret the implied odds ratio of slope coefficient in the model (b_m), given the measurement units of the predictor variable found to be statistically significant in the model.

All Sample (Both ECN211 and ECN212)

Table 24 shows the statistically significant ($p \leq .05$) predictor variables that, individually in the model, are related to student success in economics principles courses, regardless of course taken (ECN211 or ECN212). Eleven (11) factors individually predicted student success using the binary logistic regression model, compared to 16 factors identified through the Pearson Chi-square method in Research Question I. When comparing Tables 7 and Table 24, there is significant overlap between the student success areas. After acknowledging that work is measured in two separate ways in Table 7 (one through SIS and one through the survey), then there are three variables that were found to be statistically significant to student success through the Pearson chi-square analysis but not in the binary logistic regression (Wald chi-square) analysis. These variables are completing an economics course in a prior term (though passing an economics course is still significant), the last English course outcome or success, and the student' self-perception of acting impulsively or tendency to distract easily. However, taking a reading course that had a successful outcome was found significant in the binary logistic regression model. What explains the differences in significant outcomes are the statistical methods used in calculating the chi-square statistics and corresponding p-values for the Pearson chi-square analysis vs. the Wald chi-square used in binary logistic regression.

Furthermore, there were some slight changes in the way some variables were measured to accommodate the unique or theoretical structure of the two statistical techniques. For example, "instructor success" (instructors categorized as below average vs. above average student success) was used in this model instead of looking at individual instructors against each other, which was appropriate for the Pearson chi-square. Although a time of day effect was determined in the Pearson chi-square method, only evening vs. morning courses were significant in the regression model. Similarly, only full-time employment (in this study defined as working more than 20 hours a week) was statistically different from students who did not work. Lastly, the only difference between self-reported most common letter grades earned in high school in the regression model was between those students that earned A's and B's and those who earned C's, D's (or did not answer the question).

The OR of 4.682 for cumulative GPA indicates that for every full GPA point that a student increases at the college (e.g., moves from a 2.0 GPA to a 3.0 GPA), they are 4.682 greater likelihood of passing the course than an "identical" peer but with a one point lower GPA. Students enrolled in a course with an above average student success instructor are 5.529 more likely to succeed than with a lower average student success instructor. Students taking courses in the evening are 3.12 times more likely to succeed than those taking courses in the morning (as discussed earlier, this could be due to the instructor success effect). Students who work full time (20 hours a week or more) are 0.498 as likely to pass the course; OR below one can be difficult to interpret (Wuensch, 2014), so discussing the inverse of the situation will allow one to take the inverse of the OR and make it above one. Therefore, students who do not work at all are 2.008 (1/.498) more likely to pass the course as those who work full-time (note there was no statistically significant difference between those who did not work and those who worked part time, i.e., between 1 and 19 hours a week). Students who report feeling comfortable calculating percentage change are twice as likely to pass the course as those who did not report feeling comfortable with the concept. Those who self-reported earning mostly A's in high school were 2.809 times more likely to pass the course than those who did not report earning that grade, while earning mostly C's in high school cuts one's odds of passing the course in nearly half (0.508) relative to if one did not report that as their most frequent grade in high school. Being of non-traditional college age (25 years of age or older) made one 2.333 more likely to be successful as being of traditional college age (a result running counter to the literature, e.g., Burns, 2010). If the student had a successful attempt at a reading course, they were 7.9 times more likely to pass the economics course. Likewise, if they have a record of passing another economics course, they are 3.062 times more likely to pass their current economics course than if they did not. Finally, and surprisingly given the literature (e.g., Burns, 2010), a student who is a first-generation student is 1.85 times more likely to pass the course than someone who had their parents attend college.

Table 24: Predictors Significantly Related to ***(Overall)*** *Students' Success in Univariate Logistic Regression Model, by Wald* χ^2

PREDICTOR VARIABLES	B_M	WALD[1] X^2	SIGNIFICANCE[1]	ODDS RATIO
Cumulative GPA	1.544	42.268	$p < .001$	4.682
Instructor Success	1.710	38.911	$p < .001$	5.529
Time of Day – Evening Course[2]	1.168	9.709	$p = .002$	3.214
Number of W's Last Term	-0.593	8.592	$p = .003$	.553
Work Fulltime	-0.698	7.473	$p = .006$	0.498
Comfort with Calculating % Change	0.698	7.442	$p = .006$	2.009
Earned Mostly As in High School	1.033	8.231	$p = .004$	2.809
Earned Mostly C's in High School	-0.677	4.625	$p = .032$	.508
Traditional vs. Non-traditional Age	0.847	5.919	$p = .015$	2.333
Last Reading Course a Success	2.067	4.681	$p = .031$	7.900
Passed ECN in Prior Term	1.119	4.068	$p = .044$	3.062
First Generation	0.615	4.420	$p = .036$	1.850

1. All variables have a df = 1
2. Relative to morning courses

These significant predictor variables for student success can be represented by a binary logistic regression equations, or models, and tested for accuracy in steps four and five. Although analyses show that all the slopes (bs) in Table 24 are significant, this does not guarantee the usefulness of the model in improving the prediction rate of student success above the average success rate in the course. In fact, only three variables, represented by models 1.1-1.3, have shown to have predictions rates above the success rate of the class (i.e., is more accurate than simply assuming all students will pass the course, which 80.6% of the overall sample passed).

Model 1.1: -3.275+1.544* Cumulative GPA = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.2: 1.555-.593*Number of W's Last Semester = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.3: -.405+2.067*Last Reading Course a Success = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

ECN211 Students Only

Analysis of the 22 variables that were identified as significantly related to student success using the Pearson chi-square test (Research Question I and III, Tables 7, 20, and 21) found that 7 of them were statistically significant individually for the ECN211 students only group. That is in contrast to the 11 variables found related to student success using the Pearson chi-square test (Table 21). As was the case when modeling student success for all economics students (see previous sub-section), some of these variables were measured in slightly different ways given the nature of the test. Given that, the statistically significant variables found in common between the two methods include instructor success (high success vs. low success instructors), cumulative GPA (either measured continuously or as categories), the students' success in their last English course, the time of day they were enrolled in the course, and the number of W's earned in the previous semester. One variable, the student's most common high school letter grade earned (in this case, if the student reportedly earned mostly As in high school or not), was significant in the binary regression model but not in the Pearson chi-square model. Several variables found significant in the Pearson chi-square method, including if the student completed an economics course in a prior semester, their success in a previous reading course, the number of hours a week they worked, the number of D's and F's they earned in the previous semester, and their comfort with graphing data and calculating percentage change, were not found to be significant using the Wald chi-square test.

Several of the predictor variables were found to be significant for both economics students overall and ECN211 students in particular, such as instructor success, cumulative GPA, time of day of class, most frequent high school grade earned, and the number of W's earned in the previous semester (see the previous sub-section for an interpretation of the odds ratio for these variables). New to this analysis is there success, or non-success, in their previous English course. In this analysis, success in a previous English course made one 10.333 times more likely to pass ECN211 than if they had not reported success in the course (i.e., were not successful in a previous English course or had not taken one yet). An unsuccessful attempt at an English course made one 4.643 more likely to be successful in ECN211 as would otherwise be the case. This result could be construed as counterintuitive as one might expect that likelihood of passing ECN211 to go down, not up, as a result of not being successful in a previous English course. Possible explanations are that students, despite being unsuccessful, still learned to improve their writing conventions, proving useful in their ECN211 course. Another possible explanation is that an attempt at an English course may correlate with a seasoned college student who has other skills, abilities, and habits associated with student success (despite the fact that neither cumulative credit hours earned or participation in Math or reading courses showed similar effects).

*Table 25: Predictors Significantly Related to **ECN211** Students' Success in Univariate Logistic Regression Model, by Wald χ^2*

PREDICTOR	B_M	WALD X^2	SIGNIFICANCE	ODDS RATIO
Instructor Success	2.071	29.020	p < .001	7.933
Cumulative GPA	1.477	22.698	p < .001	4.382
Last English Course Successful[1]	2.335	10.567	p = .001	10.333
Time of Day – Evening Course	1.342	7.189	p = .007	3.828
Last English Course Unsuccessful[1]	1.535	6.257	p = .012	4.643
Earned Mostly As in High School	1.506	5.873	p = .015	4.508
W's in Prior Semester	-.720	5.811	p = .016	.487

**All variables have a df=1*
1. Relative to those who have no record of enrolling in an English course

Like the all sample models, these significant predictor variables for student success can be represented by binary logistic regression models and tested for accuracy in steps four and five. Although analysis shows that all the slopes (bs) in the Table 25 are significant, this does not guarantee the usefulness of the model in improving the prediction rate of student success above the course success average. In fact, only one variable, the number of W's a student earned in the prior semester, actually performed better than just knowing what the pass rate was for the sub-sample overall.

Model 2.1: 1.683+-.720* Number of W's in Prior Semester = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

ECN212 Students Only

Analysis of the same 22 variables that were identified through analysis of Research Questions I and III found that 8 of them were significant for the ECN212-only group of students. That is in contrast to 9 variables found related to student success using the Pearson chi-square test for the ECN212-only dataset. As was the case in the previous sub-sections, some of these variables were measured in slightly different ways given the nature of the statistical test. For example, instead of looking at the relation between all reported high school letter grades and student success (as was performed using Pearson chi-square for Research Questions I-III), the only significant predictor variable related to high school grade were those students reporting earning C's and D's in high school. These students had a 4.049 (the inverse of the odds ratio) higher chance of not passing the economics course than if the student did not respond that way (i.e., earned A's, B's, or did not respond to that question). A second example is that, under Research Questions I-III, all three times of day to take a course (morning, afternoon, evening) were analyzed with student success, but in the binary regression model only the contrast between those who took afternoon courses and everyone else was significant.

Students who took afternoon courses were 3.147 times more likely to pass the course than other students. A third example is that reading course outcome (success in college reading course, success in developmental reading course, non-success in college level reading course, non-success in developmental reading course, other) was significantly related to student success, but in the binary logistic regression model, only having a record of success in a college level reading course (versus students with no record of this) was significant. In this case, students who successfully completed a college-level reading course were 9.069 times more likely to pass ECN212 as were students that had no record of completing it.

*Table 26: Predictors Significantly Related to **ECN212** Students' Success in Univariate Logistic Regression Model, by Wald χ^2*

PREDICTOR	B_M	WALD X^2	SIGNIFICANCE[1]	ODDS RATIO
Cumulative GPA	1.766	20.130	p = .001	5.850
Instructor Success	1.238	9.888	p = .002	3.449
C's or D's Most Frequent Grade in High School	-1.398	9.420	p = .002	.247
Completed ECN in Prior Term	1.763	5.074	p = .024	5.829
Time of Day – Afternoon Class	1.146	4.934	p = .026	3.147
First Generation	.956	4.783	p = .029	2.600
Last Reading Course a Success at College Level	2.205	4.514	p = .034	9.069
Comfort with Calculating % Change	.779	4.452	p = .035	2.179

1. All variables have a df = 1

Like the all student sample and ECN211 sample models, these significant predictor variables for student success can be represented by a binary logistic regression model and tested for accuracy in steps four and five. Although analyses show that all the slopes (bs) in the Table 26 are significant, this does not guarantee the usefulness of the model in improving the prediction rate of student success above its average. In fact, like the ECN211 predictor variables, only one variable, the students' cumulative GPA, actually performed better than just knowing what the pass rate was for the sub-sample overall.

Model 3.1: -4.283+1.766* Cumulative GPA = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Step Two: Tests for Interaction Effects

Now that the statistically significant predictor variables of the binary logistic regression have been uncovered in step one, interaction effects between variables must be examined before attempting to build the "best fit," multivariate binary logistic regression models. Interaction effects occur when the outcome of one predictor variable differs with different level of a second predictor variable.

For example, say a hypothetical medical research study was looking at the effects of vegetable consumption and the likelihood of getting a cold (becoming ill) within a year. The study could find that eating more broccoli and eating more carrots by themselves each contribute to a reduced likelihood of getting a cold. However, when participants ate increased servings of both broccoli and carrots, their chances decreased by much more than would have been predicted by the sum of their individual own effects. This would be an example of interaction effect, and they need to be taken into account in order to increase the chances of finding the best-fit model with the given data set.

The test for interactions is similar to how the Wald chi-square tests is used to see if there is a significant difference between the estimated parameter ($\hat{b}$) and the null hypothesis that the parameter is not significant (0), relative to the standard error of the estimation. The interaction effect tests to see if the outcomes of one variable are significantly different at different levels of a second predictor variable, relative to the standard error. If the ratio is high (the effect great relative to the standard error), and the corresponding probability low that this result was found by chance, then we conclude that there is a significant interaction. Closer examination, however, will be needed to explain exactly how.

Tables 27-29 show all the significant interaction effects between each of the other predictor variables within the variables identified as significant in their respective binary logistic regression models in step one. Each interaction effect (A x B) was included with the predictor's main effect (A, B) in the model to test the interaction effect within the context of the main effects.

All Economics Students Model

As seen in Table 27, there were two significant interactions within the predictor variables for the all economics students model: cumulative GPA by Earned Mostly C's in High School and cumulative GPA by Instructor Success. Note that no interaction effect was able to be calculated between instructor success and time of day (evening vs. other) as no low success instructors taught evening courses that academic year.

Table 27: Interactions Between Predictor Variables Significantly Related to ***All Economics*** *Students' Success In Univariate Logistic Regression Model, by Wald χ^2*

PREDICTORS INTERACTIONS	B_M	WALD χ^2	SIGNIFICANCE[1]	ODDS RATIO
Cumulative GPA x Earned Mostly C's in HS	2.020	4.679	p = .031	7.353
Cumulative GPA x Instructor Success	-1.140	4.194	p = .041	.320

1. *All variables have a df = 1*

Table 28 shows student success by students' GPA category for two different categories of students, those that self-reported on the survey earning mostly C's in high school, and for all other students in the sample (including the three students who earned mostly D's and those that did not respond to the question). There were 61 students (of the 403 sample, or 15.14%) who reported earning mostly C's in high school.

Regardless of GPA, the OR is nearly twice as great (1.967) that non-C students will be successful in their economics course relative to those that reported earning mostly C’s in high school. The interaction effect, however, can be seen in the variance of odds ratios at different GPA categories. Of the 36 students who self-reported earning C’s in high school but now have between a 3.0-4.0 GPA, nearly all (34) passed the course, for an odds of 17 to 1. Non-C students had somewhat lower odds of passing the course, for an odds ratio of less than 1. On the other hand, the 23 students who self-reported earning mostly C’s in high school and currently earned a college GPA less than 3.0 struggled to succeed in economics compared to their counterparts who earned similar GPAs in college but did not report primarily earning C’s in high school. For these non-C students, the odds ratio was approximately 2.5 times greater that they would pass the course than for C-level students in high school. One potential explanation for this is that those students who made an improvement in their academic performance between high school and college, for any number of reasons, realized extra benefits in the sense of improved likelihood of passing economics in college than those students with relatively poor performance in high school that continued on that trajectory into their college career.

Table 28: Frequency, Odds and Odds Ratio of Students' Success in Economics Courses, by Students' Cumulative GPA and Time of Day of Class (Evening vs. Non-Evening, for All Economics Students' Success)

		STUDENTS' CUMULATIVE GPA						
		NONE	BELOW 2.0	2.0-2.49	2.5-2.99	3.0-3.49	3.5-4.0	TOTAL
Non-C's in High School	Successful in Economics	1	5	11	53	94	118	282
	Unsuccessful in Economics	1	4	7	21	19	8	60
	Odds[1]	1	1.250	1.571	2.524	4.947	14.750	4.7
C's in High School	Successful in Economics	0	1	0	8	17	17	43
	Unsuccessful in Economics	2	2	4	8	1	1	18
	Odds[1]	0	0.5	0	1	17	17	2.389
	Odds Ratio[2]	undefined	2.5	undefined	2.524	0.291	0.868	1.967

1. *Successful/Unsuccessful*
2. *Successful Odds/ Unsuccessful Odds*

Table 29 shows the frequency of student success in all economics courses, by students' cumulative GPA category and their instructor's average success level. There were 255 students in the "high instructor success" category and 148 students in the "low instructor success" one. Unsurprisingly, the odds of passing the economics course increase at a pitched rate as students move from lower GPA categories to higher ones, with few exceptions (e.g., for students with 2.5-2.99 GPAs in the low instructor success courses and students with 2.0-2.49 GPAs for high success instructors). For high success instructors the odds are less than 2 to 1 of passing the course if they have a cumulative GPA of 2.0-2.49, but are greater than 23 to 1 if they are in the GPA range of 3.5-4.0. However, the odds are significantly better at each GPA category if the student is taught by a high success instructor relative to a low success instructor. Indeed, the overall odds ratio of success between high success and low success instructors (i.e., the odds of passing the course if you are with a high success instructor relative to a low success instructor) is 5.528 overall. Yet, the interaction effect (the changes in the odds ratio at different GPA categories) is seen through observing the odds ratios at different GPA categories. The odds ratio (i.e., the increased likelihood of passing the course because one is enrolled with a high success instructor) is lowest for students with GPAs between 3.5-4.0. These students do benefit by 2.866 times greater likelihood of success in a high success instructor course, but they tend to succeed in their economics courses (and college courses overall) at a higher rate in general. The real premium for a high success instructor is for those students with GPAs lower than 3.5, particularly students with GPAs between 2.5-2.99. For these students, they have 7 to 1 odds of passing the course with a high success instructor, but a 1.833 chance of not passing the course if they have a low success instructor.

Table 29: Frequency, Odds and Odds Ratio of Students' Success in Economics, by Students' Cumulative GPA and Instructor Success Level for ***All Economics*** *Students' Success*

		STUDENTS' CUMULATIVE GPA						
		NONE	BELOW 2.0	2.0-2.49	2.5-2.99	3.0-3.49	3.5-4.0	TOTAL
High Success Instructors	Successful in Economics	1	6	7	49	74	94	231
	Unsuccessful in Economics	1	2	4	7	6	4	24
	Odds[1]	1	3	1.75	7	12.333	23.5	9.625
Low Success Instructors	Successful in Economics	0	0	4	12	37	41	94
	Unsuccessful in Economics	2	4	7	22	14	5	54
	Odds[1]	0	0	.571	.545	2.643	8.2	1.741
	Odds Ratio[2]	undefined	undefined	3.065	12.844	4.666	2.866	5.528

1. *Successful/Unsuccessful*
2. *Successful Odds/ Unsuccessful Odds*

ECN211 Only and ECN212 Only Students Model

No significant interaction effects were found between the identified predictor variables in step one for the ECN211 and ECN212 only student models. Note that no interaction effect was able to be calculated between instructor success and time of day (evening for ECN211 students, afternoon for ECN212 students) because the low success instructors only taught morning courses during the academic year in which this study took place.

Step Three: Building the "Best Fit" Models

Steps one and two provided the foundational work from which to build the "best fit" multivariate binary logistic regression models for predicting student success in economics courses (i.e., all economics students, ECN211 only, and ECN212 only). Step one allowed the discovery of the factors that were significant by themselves in the binary regression model; these will be the predictor variables under consideration when building the "best fit" model. Step two identified which of these predictor variables significantly interact with each other in the model, and thus must be accounted for in the following models.

Creating a "best fit" binary logistic regression model is an iterative process, that is, it requires the addition of predictor variables (or their interactions) one at a time, and then analyzing if the model is more robust as a result of the change or not. If the model helps predict student success more than the previous model, then that model is kept and is the new starting point with further additions of predictor variables. If the model is no better off (or worse off), then that new model is discarded and another variable is tested in its place.

To indicate if the new iteration is superior to the older one, two indications can be used. One indication is the -2 log likelihood statistic (Wuensch, 2014). As discussed earlier, it is logical then that if the new model has a lower -2 log likelihood, it is a better model. Another measurement of model robustness is the Nagelkerke R^2 statistic (Wuensch, 2014). Also discussed earlier, higher R^2s are an indication that the model is explaining more of the variability in the data and therefore is a better fit.

Together, the -2 log likelihood statistic and Nagelkerke R^2 statistic will be used to indicate if the iterative model is superior to the base model, and therefore should replace the base model for future iteration tests. Once possible additional iterative change to the model from the set of potential predictor variables (step one) and interactions (step two) have been exhausted, the standing model becomes the "best fit" model.

For each of the three types of models (all economics, ECN211 only, ECN212 only), an "additive method" will start with the strongest predictor variable (identified in step one), and then add each of the other predictor variables one at a time. Any bivariate model that shows a lower -2 log likelihood and/or raise Nagelkerke R^2 than the univariate model will become the new base model. At this point, a third variable will be added to the base model to analyze improvements. This process will continue until all predictor variables are included in the model, adding new variables fails to lower the -2 log likelihood and/or raise Nagelkerke R^2, or the model perfectly fits the data.

If the first and second methods yield a different final model from each other, the one with the lowest -2 log likelihood and highest Nagelkerke R^2 statistic will be labeled the "best fit" model.

All Economics Student Model

The process begins with the predictor variable with the highest Wald χ^2 value discovered in step one, cumulative GPA. Tables 30 and 31 build on the predictive power of this univariate model by adding one additional variable from the set to test if it reduces the -2 Log Likelihood (Table 30) or raises the Nagelkerke R^2 value (Table 31). For each iteration, the previous predictor variables were included in the model along with the new variable to tests if it increases the robustness of the model. In these cases, this process continued until the -2 Log Likelihood became 0.000 and the Nagelkerke R^2 value became 1.000, signifying that the model predicted every case 100% accurately.

Although adding more variables to the model increases its predictive ability, it also simultaneously tends to limit the number of cases of the overall sample that could be examined. This is because students that had missing data for an included predictor variable in the equation (e.g., students who had not attempted an economics course before at the current institution do not have data related to if they passed a previous economics course) were not included in the model building, and thus the generalizability of the model is reduced. There is indeed a trade-off between exactness in prediction and generalizability to the students in the sample, which will be seen in steps four and five. Indeed, a likely significant contributor to the perfect fit of the last models in each table is likely due to the limited sub-sample (it is easier for a model to perfectly fit a dataset containing 29 students than it is for 403 students, despite its corresponding lack of usefulness).

Table 30: Iterative Improvements in the Binary Logistic Regression Model for All Economics Students' Success, with -2 Log Likelihood Criteria for Selection

ITERATION	MODEL	CASES (% OF SAMPLE)	PREDICTOR VARIABLES INCLUDED	-2 LOG LIKELIHOOD	NAGELKERKE R^2
1	1.1	403 (100%)	Cumulative GPA	340.347	.206
2	1.4	97 (24.07%)	Passed ECN in Prior Semester	67.752	.339
3	1.5	29 (7.20%)	Last Reading a Success	8.717	.629
4[1]	1.6	29 (7.20%)	Earned Mostly C's in High School	0.000	1.000

1. *No further iterations were possible past this point, due to a combination of low sample selection for model (only able to include students with known data for all included predictors) combined with model's perfect accuracy in predicting observations*

Model 1.1: -3.275+1.544*Cumulative GPA= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.4: -5.764+2.310*Cumulative GPA+.578* Passed ECN in Prior Semester = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.5: -13.080+4.287*Cumulative GPA+1.076* Passed ECN in Prior Semester+2.671*Last Reading Course a Success = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.6: -175.823+72.296*Cumulative GPA-26.604*Passed ECN in Prior Semester+22.782*Last Reading Course a Success-74.164*Earned Mostly C's in High School = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Table 31: Iterative Improvements in the Binary Logistic Regression for All Economics Students' Success, with Nagelkerke R^2 Criteria for Selection

ITERATION	MODEL	CASES (% OF SAMPLE)	PREDICTOR VARIABLES INCLUDED	-2 LOG LIKELIHOOD	NAGELKERKE R^2
1	1.1	403 (100%)	Cumulative GPA	340.347	.206
2	1.7	403 (100%)	Instructor Success	297.895	.345
3	1.8	99 (24.56%)	Last Reading Course a Success	54.733	.533
4[1]	1.9	29 (7.20%)	Passed ECN in Prior Term	0.000	1.000

1. *No further iterations were possible past this point, due to a combination of low sample selection for model (only able to include students with known data for all included predictors) combined with model's perfect accuracy in predicting observations*

Model 1.7: -4.647+1.683*Cumulative GPA+1.886*Instructor Success= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.8: -12.598+3.353*Cumulative GPA+3.564*Instructor Success+2.540*Last Reading Course a Success= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 1.9:-478.870+153.395*Cumulative GPA+112.759*Instructor Success+19.698*Last Reading Course a Success+42.211*Passed ECN in Prior Term= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

ECN211 Students Only Model

Table 32 shows the model building process for predictor variables of student success for ECN211 students only. Note that though the -2 Log Likelihood criteria was used in adding new variables to the model, since ultimately all variables were found to be significant to student success and were included in the final model, it is redundant to include a table and equations based on the criteria of Nagelkerke R^2.

Table 32: Iterative Improvements in the Binary Logistic Regression Model for ***ECN211*** *Students' Success, with -2 Log Likelihood Criteria for Selection*

Iteration	Equation	Cases (% of Sample)	Predictor Variables Included	-2 Log Likelihood	Nagelkerke R^2
1	2.2	238 (100%)	Instructor Success	183.214	.213
2	2.3	183 (76.89%)	Number of W's in Prior Term	133.022	.337
3	2.4	183 (76.89%)	Cumulative GPA	103.928	.526
4	2.5	183 (76.89%)	Last English Course a Success	95.997	.572
5	2.6	183 (76.89%)	Mostly As in High School	91.619	.597
6[1]	2.7	183 (76.89%)	Evening Class	89.866	.607

1. *Iterations concluded because all factors identified as independently significant with student success in step one have been included in the model.*

Model 2.2: 0.474+2.071*Instructor Success= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)
Model 2.3: 0.513+2.748*Instructor Success -1.359*Number of W's in Prior Term = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 2.4: -7.546+3.396*Instructor Success-1.393* Number of W's in Prior Term +2.589*Cumulative GPA= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 2.5: -9.754+3.618*Instructor Success-1.229* Number of W's in Prior Term +2.772*Cumulative GPA+2.951*No English Class on Record+1.527*Successful in Last English Course= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)
Model 2.6: -9.558+3.854*Instructor Success-1.261* Number of W's in Prior Term +2.537*Cumulative GPA+2.891*No English Class on Record+1.772*Successful in Last English Course+1.788*Earned Mostly As in High School= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 2.7: -9.707+3.487*Instructor Success-1.453* Number of W's in Prior Term +2.624*Cumulative GPA+2.804*No English Class on Record+1.657*Successful in Last English Course+1.824*Earned Mostly As in High School+1.281*Evening Course= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

ECN212 Students Only Model

Table 33 shows the model building process for predictor variables of student success for ECN212 students only. Note that though the -2 Log Likelihood criteria was used in adding new variables to the model, since ultimately all variables found to be significant to student success were included in the final model, it is redundant to include a table and equations based on the criteria of Nagelkerke R^2. The only exception was instructor success, which, when added to the model after all of the other predictor variables have been included, did not reduce the -2 Log Likelihood or increase the Nagelkerke R^2 value.

*Table 33: Iterative Improvements in the Binary Logistic Regression Model for **ECN212** Students' Success, with -2 Log Likelihood Criteria for Selection*

Iteration	Equation	Cases (% of sample)	Predictor Variables Included	-2 Log Likelihood	Nagelkerke R^2
1	3.1	165 (100%)	Cumulative GPA	147.893	.253
2	3.2	67 (40.61%)	Completed ECN in Prior Term	40.585	.423
3	3.3	67 (40.61%)	First Generation	35.824	.510
4	3.4	67 (40.61%)	Afternoon Course	27.531	.648
5	3.5	67 (40.61%)	Last Reading Course a Success at College Level	22.076	.729
6	3.6	67 (40.61%)	Mostly C's and D's in High School	21.739	.734
7[1]	3.7	67 (40.61%)	Comfortable Calculating % Change	21.070	.744

1. *Iterations concluded because all factors identified as independently significant with student success in step one have been included in the model.*

Model 3.1: $-4.283+1.766*\text{Cumulative GPA} = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = \ln(\text{odds of student success})$

Model 3.2: -8.737+2.865*Cumulative GPA+1.999*Completed ECN in Prior Term= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 3.3: -10.675+3.257*Cumulative GPA+2.297*Completed ECN in Prior Term+2.390*First Generation= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 3.4: -13.135+3.805*Cumulative GPA+2.571*Completed ECN in Prior Term+2.749*First Generation+1.451*Afternoon Courses= $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 3.5: -19.601+5.054*Cumulative GPA+4.269*Completed ECN in Prior Term+5.814*First Generation+4.991*Afternoon Courses+20.538*Last Reading Course a Success at the College Level = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 3.6:-20.806 +5.393*Cumulative GPA+4.244*Completed ECN in Prior Term+5.587*First Generation+4.856*Afternoon Courses+20.542*Last Reading Course a Success at the College Level+.991*Most Common High School Grade a C or D = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Model 3.7: -20.913+5.326*Cumulative GPA+4.384*Completed ECN in Prior Term+5.635*First Generation+4.867*Afternoon Courses+20.017*Last Reading Course a Success at the College Level+.700*Most Common High School Grade a C or D+.837*Comfortable Calculating % Change = $\ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right)$ = ln(odds of student success)

Step Four: Accuracy of Models with Original Data Set

In order to test the usefulness of the models with student data, each model discussed in steps 1 and 3 were checked for robustness as shown in tables 34-36, including for accuracy improvement on knowing the success average for the sample, false positives, false negatives, and the cases considered in the model. “Accuracy” (the percentage of correctly identified student outcomes relative to the respective sample) measures how accurate the model was in predicting outcomes. “Improvement on success average” shows the improvement in prediction accuracy by using the model, relative to only knowing the pass rate for the sample.

For those students whose outcomes were predicted incorrectly by the model, they can come in the form of either a false positive or a false negative. A false positive refers to the prediction error in which the model predicted that the student would pass, but in fact, did not pass. A false negative refers to the prediction error in which the model predicts that the student would not pass, but in fact, did pass. These percentages are reported as a percentage of their respective sample.

The cases considered are the number of individual student cases that were selected from the sample for inclusion in the model building. Some predictor variables did not report any data for some students. For example, students who had never taken an economics course in a previous semester did not have any data for "completed economics in a prior semester." Otherwise, students who had never attempted an economics course would be conflated with those that have tried an economics course in the past and was not successful, thus distorting the data.

All Students Sample

Table 34 includes all models discussed in steps one and three for the sample containing all students (ECN211 and ECN212 students). The models were developed in one of three ways. The first way (models 1.1-1.3) was to test significant predictor variable identified in Table 7, and include them if they led to higher accuracy than just knowing the sample average pass rate. Models 1.4-1.6 were developed in step three during the model building process using the -2 log likelihood measurement of improvement. Models 1.7-1.9 were also developed in step 3, but using the Nagelkerke R^2 measurement of improvement.

A striking outcome of the findings is the trade-off between model accuracy and the percentage of cases considered. Some predictor variables have only limited data available on students, and students without this data were excluded from the model testing. Therefore, as more variables are included in the model, there tends to be a decrease in the % of the sample that this model can be used with. For example, only models 1.1 and 1.7 include 100% of the sample, but it tops out in accuracy at 85.36% (model 1.7). On the other hand, models 1.7 and 1.9 show 100% explanatory power on the sample data (no false positives or negatives), but it would only apply to 7.20% of the students in the sample, which makes it of no practical use for the vast majority of students.

Table 34: Accuracy of Predictors Variables Within Sample[1] ***for All Students****, by Model Number*

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
1.1	Cumulative GPA	82.38	1.74	15.63	1.98	403 (100)
1.2	Number of W's Last Term	80.50	0.63	18.87	0.63	318 (78.91)
1.3	Last Reading Course a Success	82.83	3.03	15.15	2.02	99 (24.56)
1.4	Cumulative GPA, Passed ECN in Previous Semester	85.57	3.10	12.37	2.06	97 (24.07)
1.5	Cumulative GPA, Passed ECN in Previous Semester, Last Reading Course a Success	93.10	3.45	3.45	3.45	29 (7.20)
1.6	Cumulative GPA, Passed ECN in Previous Semester, Last Reading Course a Success, Earned Mostly C's in High School	100	10.34	0	0	29 (7.20)

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
1.7	Cumulative GPA, Instructor Success	85.36	4.71	12.16	2.48	403 (100)
1.8	Cumulative GPA, Instructor Success. Last Reading Course a Success	89.90	8.08	7.07	3.03	99 (24.56)
1.9	Cumulative GPA, Instructor Success. Last Reading Course a Success, Passed ECN in a Prior Semester	100	10.34	0	0	29 (7.20)

1. *The overall chances of passing any economics course this academic year was 80.6%, but will change with particular sub-samples. The model must have prediction accuracy above the overall pass rate for it to have utility.*

Unlike the all student sample models, the ECN211 student sample model building process did not terminate with a 100% model prediction — here, the model's best predictive capability was at 89.07%. Curiously, however, there were two examples where adding another predictor variable to the model actually reduced its accuracy (models 2.5 and 2.7). This is despite the fact that adding these variables to the model reduced the -2 Log Likelihood and/or increased the Nagalkerke R^2 value in Step 3.

As a result, a post-hoc analysis (model 2.8) was conducted to see if prediction could be improved by removing those predictors from the model that reduced the models accuracy with their inclusion. On the contrary, the model matched the accuracy of the simpler model 2.4 with an accuracy rate of 89.07%

Table 35: Accuracy of Predictors Variables Within Sample[1] ***for ECN211 students****, by Model Number*

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
2.1	W's in Prior Semester	82.51	1.09	17.49	0	183 (76.89)
2.2	Instructor Success	83.19	0	16.81	0	238 (100)
2.3	Instructor Success, Number of W's Last Semester	83.61	2.19	15.3	1.09	183 (76.89)
2.4	Instructor Success, Number of W's Last Semester, cumulative GPA	89.07	7.65	7.65	3.28	183 (76.89)
2.5	Instructor Success, Number of W's Last Semester, cumulative GPA, Last English Course a Success	87.98	6.56	8.20	3.82	183 (76.89)
2.6	Instructor Success, Number of W's Last Semester, cumulative GPA, Last English Course a Success, Earned Mostly As in High School	89.07	7.65	7.10	4.90	183 (76.89)
2.7	Instructor Success, Number of W's Last Semester, cumulative GPA, Last English Course a Success, Earned Mostly As in High School, Evening Course	88.52	7.10	7.65	3.82	183 (76.89)
2.8 (Ad Hoc)	Instructor Success, Number of W's Last Semester, cumulative GPA, Earned Mostly As in High School	89.07	7.65	7.10	3.82	183 (76.89)

1. *The overall chances of passing any economics course this academic year was 83.19%, but will change with particular sub-samples. The model must have prediction accuracy above the overall pass rate for it to have utility.*

ECN212 Student Sample

The logistic regression modeling for the ECN212 sample set showed that a higher accuracy rate can be found in some models (e.g., models 3.5 and 3.6 have an accuracy rate of 94.03%). However, as was found for the all student sample, a higher accuracy rate typically comes with a lower percentage of the sample used in creating the model (for models 3.5 and 3.6, only 40.61% of the student sample was used).

*Table 36: Accuracy of Predictors Variables Within Sample[1] for **ECN212 students**, by Model Number*

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
3.1	Cumulative GPA	82.42	5.45	16.36	1.21	165 (100)
3.2	Cumulative GPA, Completed ECN in a Prior Semester	91.04	7.46	7.46	1.49	67 (40.61)
3.3	Cumulative GPA, Completed ECN in a Prior Semester, First Generation	91.04	7.46	8.96	0	67 (40.61)
3.4	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course	92.54	8.96	4.48	2.98	67 (40.61)
3.5	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course, Last Reading Course a Success at College Level	94.03	10.48	4.48	1.49	67 (40.61)
3.6	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course , Last Reading Course a Success at College Level, Mostly C's and D's in High School	94.03	10.48	4.48	1.49	67 (40.61)

MODEL #	PREDICTOR VARIABLE(S)	ACCURACY (%)	IMPROVEMENT ON SUCCESS AVERAGE (PERCENTAGE POINTS)	FALSE POSITIVE (%)	FALSE NEGATIVE (%)	CASES CONSIDERED (PERCENT OF SAMPLE)
3.7	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course , Last Reading Course a Success at College Level, Mostly C's and D's in High School, Comfortable Calculating % Change	92.54	8.96	4.48	2.98	67 (40.61)

Step Five: Accuracy of Models with New Data Set

The models that were developed in steps one and three, and internally tested in step four, were all created using the data set of participating economics students in the sample during one academic year. In order to test the utility of the model for future students, however, a new data set was created, consisting of students enrolled in economics courses in the immediately subsequent fall semester.

Description of New Sample

There were a total of 445 records in the new sample (more in this semester than in the original data set, consisting of two semesters). This section will highlight statistically significant differences in characteristics between those students in the new sample and those in the original sample. Statistical significance was determined by t-tests for independent samples for interval and ratio variables (e.g., GPA, age) and chi-square test

(χ^2) for nominal and ordinal variables (e.g, gender, grade in current class), in both cases using the standard $p \leq .05$ as the cut probability for significance.

Although it should be expected that the academic and demographic statistics of the student population of any particular class will change from year to year, how different or how similar the new sample is to the original sample will provide information on the stability of these student characteristics over a period of time. More specific to the purpose of this study, however, is it will also uncover the effectiveness of the developed binary logistic regression models with student data not used in the creation of the model. It therefore provides a test of reliability and validity of the models. If characteristics of the students in the new sample are very different from the original sample, it would tend to confound the ability of the algorithm from having much predictive power at all.

A striking difference between the original sample set and the new sample was the proportion of students taking one course relative to another. As seen in Table 37, nearly 60% of students in the original sample took ECN211, whereas that ratio approximately flipped for the new sample, a statistically significant difference ($\chi^2 = 25.859$, df = 1, $p < .001$).

Table 37: Course Taken by ECN Students by Sample

Course	ECN Student Original Sample (% of N)	ECN Student New Sample (% of N)
ECN211	238 (59.06)	185 (41.57)
ECN212	165 (40.94)	260 (58.43)
Total	403 (100)	445 (100)

There was a statistically significant difference ($\chi^2 = 11.603$, df = 2, $p = .003$) in the time of day that students attended their courses between those students in the original sample and the new sample. Table 38 shows that the new sample students tended to enroll in more morning sections, and correspondingly fewer afternoon and evening courses.

Table 38: Time of Day of Class, by Sample

	ECN Student Original Sample (% of Sample)	ECN Student New Sample
Morning	214 (53.10)	287 (64.49)
Afternoon	84 (20.84)	66 (14.83)
Evening	105 (26.05)	92 (20.67)
Total	403 (100)	445 (100)

As shown in table 39, students in the new sample were much more likely to have been enrolled in a previous semester than those in the original sample ($\chi^2 = 55.618$, df = 1, $p < .001$).

Table 39: Students Enrolled in the Previous Semester, by Sample

	ECN Student Original Sample (% of Sample)	ECN Student New Sample
Enrolled	318 (78.91)	426 (95.73)
Not Enrolled	85 (21.09)	19 (4.27)
Total	403 (100)	445 (100)

The students in the new sample have a slight higher credit accumulation. The original sample earned an average of 36.88 credits (SD=20.894), and the new sample earned 37.52 credits (SD=22.689), a statistically significant difference ($t = -4.31$, df = 846, $p = .032$). They did not, however, have a significantly different GPA.

However, there were many more ways that the two samples were not statistically different from each other. Demographically, students were not significantly older or younger in the new sample, or categorize themselves by different ethnic or gender descriptions. Students in the new study were no more or less likely to be of first-generation status or work a different number of hours per week. Academically, they were no differences in their current intentions for going to college. Linguistically, there was no significant difference between the samples in terms of language they currently speak as well as the language they spoke primarily as a child. The samples did not demonstrate a difference in their distribution of letter grades in economics or the corresponding student success rates. There were no statistically significant differences between the number of W's, D's or F's that the students earned in the previous semester.

Model Accuracy — All Economics Students

Disappointingly, none of the models for predicting student success using the all sample dataset turned out to be better than just knowing the pass rate for the class. Indeed, using the models reduced one's accuracy in predicting student success by 0.81% and 8.7% relative to just predicting that everyone would be successful in the class (the class average success rate).

*Table 40: Accuracy of Predictors Variables Within Sample[1] for **all students**, by Model Number*

Model #	Predictor Variable(s)	Prediction Accuracy (%)	Improvement on Success Average (Percentage Points)[2]	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
1.1	Cumulative GPA	74.38	-4.50	19.33	6.74	445 (100)
1.2	Number of W's Last Term	78.22	-3.98	17.56	3.98	426 (95.73)
1.3	Last Reading Course a Success	73.33	-7.62	19.05	7.62	105 (23.06)
1.4	Cumulative GPA, Passed ECN in Previous Semester	71.43	-6.01	21.80	6.77	133 (29.89)

MODEL #	PREDICTOR VARIABLE(S)	PREDICTION ACCURACY (%)	IMPROVEMENT ON SUCCESS AVERAGE (PERCENTAGE POINTS)[2]	FALSE POSITIVE (%)	FALSE NEGATIVE (%)	CASES CONSIDERED (PERCENT OF SAMPLE)
1.5	Cumulative GPA, Passed ECN in Previous Semester, Last Reading Course a Success	74.19	-0.81	22.58	3.23	31 (6.97)
1.6	Cumulative GPA, Passed ECN in Previous Semester, Last Reading Course a Success, Earned Mostly C's in High School	78.26	-8.7	8.70	13.04	23 (5.17)

1. *Models 1.7-1.9 could not be considered because the "instructor success" variables used in these models could not be constructed with the new sample.*
2. *The overall chances of passing any economics course this semester was 78.88%, but will change with particular sub-samples. The model must have prediction accuracy above the overall pass rate for it to have utility.*

Model Accuracy — ECN211 Students

Only one model for the ECN211 students was able to be tested, model 2.1. The other models included "Instructor Success" as part of the equation. However, this variable was not able to be constructed for the new sample because the two instructors who were categorized in the "low success" courses did not teach during the semester in which the new sample was created. Nevertheless, model 2.1 does show a modest improvement in predicting student success above just knowing the pass rate for the course overall that semester. Knowing how many W's the student had in the previous semester is predictive of student success in the current semester.

*Table 41: Accuracy of Predictors Variables Within Sample,[1,2] for **ECN211 students**, by Model Number*

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)[3]	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
2.1	W's in Prior Semester	84.86	4.86	14.59	0.54	185 (100)

1. *The overall chances of passing ECN211 this semester was 80.00%, but will change with particular sub-samples.*
2. *Models 2.2-2.8 could not be considered because the "instructor success" variables used in these models could not be constructed with the new sample.*
3. *The model must have prediction accuracy above the overall pass rate for it to have utility.*

Model Accuracy — ECN212 Students

All models created using the ECN212 data set (models 3.1-3.7) were tested with the new student sample, and all models showed to have predictive utility, ranging from 2.97%-6.54% improvements in predictions above just knowing the student success rate for the course that semester (except for models 3.6 and 3.7, which showed no improvement). It is of interest to note that the model that displayed the most utility (had the most improvement of prediction accuracy above the course success average) was model 3.1, which only looked at the cumulative GPA of the students. In other words, despite adding more variables to the equation that were previously found to be significantly related to student success and useful in inclusion in the model, it actually decreased the model's improvement over the status quo. One reason for this is that adding more variables inherently adds more variability to the model, so the variables examined must hold important information about the underlying nature of the dependent variable (student success) if it is to overcome this drawback. Another shortcoming of adding more variables is that, in some cases, some student data pertaining to the variable was missing and therefore cannot be considered for prediction in the model. The smaller the share of the sample that can be predicted, the less useful the model could be in helping inform decision making.

*Table 42: Accuracy of Predictors Variables Within Sample[1] for **ECN212[1] Students**, by Model Number*

MODEL #	PREDICTOR VARIABLE(S)	ACCURACY (%)	IMPROVEMENT ON SUCCESS AVERAGE (PERCENTAGE POINTS)	FALSE POSITIVE (%)	FALSE NEGATIVE (%)	CASES CONSIDERED (PERCENT OF SAMPLE)
3.1	Cumulative GPA	84.62	6.54	12.31	3.08	260 (100)
3.2	Cumulative GPA, Completed ECN in a Prior Semester	87.13	4.95	9.90	2.97	101 (38.85)
3.3	Cumulative GPA, Completed ECN in a Prior Semester, First Generation	85.15	2.97	13.86	0.99	101 (38.85)
3.4	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course	86.14	3.96	11.88	1.98	101 (38.85)
3.5	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course, Last Reading Course a Success at College Level	90.00	5.00	10.00	0	20 (7.69)
3.6[2]	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course, Last Reading Course a Success at College Level, Mostly C's and D's in High School	92.86	0	7.14	0	14 (5.38)

Model #	Predictor Variable(s)	Accuracy (%)	Improvement on Success Average (Percentage Points)	False Positive (%)	False Negative (%)	Cases Considered (Percent of Sample)
3.7[2]	Cumulative GPA, Completed ECN in a Prior Semester, First Generation, Afternoon Course, Last Reading Course a Success at College Level, Mostly C's and D's in High School, Comfortable Calculating % Change	92.86	0	7.14	0	14 (5.38)

1. *The overall chances of passing ECN212 this semester was 78.08%, but will change with particular sub-samples.*
2. *Due at least partly to their small sub-sample sizes, models 3.6 and 3.7 predicted that all students would be successful, which is the same as the null hypothesis. These models have no predictive value.*

Though the models for the overall ECN student success were shown not to be effective at predicting student success, there was strong evidence of the efficacy of the binary logistic regression models for ECN211 and ECN212 courses uniquely. One possible explanation for this is that these are distinct academic populations, so combining them together and trying to predict has too much variability and drivers of student success. Nevertheless, these models demonstrate that there is the ability to predict student success in economics courses by examining students' data.

Conclusion

Chapter four laid out the analyses conducted in support of the four research questions central to this study. First, the overall student population who took any economics course during the academic year of the study at this college was described in order to give the reader a background on this particular student population. Second, an explanation was provided as to how and why some students in this population were not included in the sample, as well as statistical tests performed to find significant differences between the students included in the sample and those who were not. This helps the reader understand how the sample may differ from the overall population it is attempting to represent. Third, the first research question was stated with corresponding hypotheses, examining if there are any variables in the data set that are statistically significantly related to student success using t-tests and the Pearson chi-square tests, and found that there were. Fourth, the second research question was stated with corresponding hypotheses, investigating if there are any statistically significant relations between the variables identified as relating to student success using the Pearson chi-square method, and found that there were. Fifth, the third research question was pondered, focusing on if there were differences in predictors of student success for ECN211 and ECN212 courses, respectively, using the t-tests and chi-quare test, and found that there were. Sixth, the fourth research question was analyzed, including an explanation of the binary logistic regression model, and was broken into five steps.

Step one examined which of the 22 student success variables found to be significantly related to student success in economics courses in steps one or three were also significant in the binary logistic regression models, of which multiple were. Step two explored any interaction effects between these predictor variables, and three were found. Step three built the multivariate binary regression models that were used to answer the fourth research question. Step four tested these models with the students in the original data set used to build the model and found their effectiveness in predicting student outcomes above the student success rate. Step five tested these models again, but this time with students of a new semester that were not part of the original sample from which these models were constructed. Results found that these predictive models had utility in predicting pass rates above knowing the pass rate for the course in general, at least of for individual courses (ECN211 and ECN212 courses respectively, but not when combined). In the final chapter, Chapter 5, the study will conclude with a summary of the chapters, discussion of ramifications of the results from the study, and recommendations for future pathways of research.

CHAPTER 5: DISCUSSION AND RECOMMENDATIONS

Introduction and Review

In Chapter 1, the case was made for community colleges to improve student success. To make significant progress in helping to reach President Obama's (2009) goal of America once again leading the world in the proportion of its adult population with postsecondary credentials by 2020, community colleges need to better understand why some students succeed and why others do not. This data is necessary to create and refine policies and programs to support students in their learning, persistence, and ultimate completion of their certificate or degree programs. Changes in policy and programs that are not data-informed are just shots in the dark. By addressing the overarching question of "*what factors, in combination, predict student success before enrollment in the economics principles courses*," this study aimed to provide an answer to it, if only for one community college in one academic year. As opposed to seeing this study as providing the definitive answer on the topic, it should be viewed merely as a starting point, a proof of concept, and this question will need to be continuously tested and refined with more student data overtime and in more disciplines in order to make significant progress in improving student completion rates. This study provides evidence devoting consistent and systematic institutional resources to understanding student success through data analysis could yield knowledge helpful in improving student success institution-wide.

Community college leaders already know a great deal about the factors that impact student success. In Chapter 2, a review of the literature related to the question “which factors contribute to student success in higher education?” set the stage for what factors would be tested in predicting student success in economics courses. The chapter focused on four broad categories of predictor variables: demographic/social predictors (relating to students’ social and economic status within the broader society), academic predictors (academic performance in high school and college), personal/cognitive predictors (of or relating to the students themselves, outside of the two previous categories), and institutional predictors (how the institution of higher learning that the students attend can impact their success, both through actions institutional leaders can take as well as factors seemingly outside of their control). The reader was also introduced to a relatively new tool in higher education that can be used to help Research Question IV, learning analytics. The combination of an explosive increase in both the creation and collection of student-generated data points, combined with Moore’s Law (the historical observation and prediction that computers double in processing power per dollar expenditure approximately every 18 months), learning analytics looks set to revolutionize the higher education sector in the same way that it has impacted other parts of our lives, from the media that we consume, to the way that we shop, to the way we meet potential romantic partners. Although this study does not seek to replicate the methods used by these largely autonomous programming of mainstream analytics, it does seek to show how the use of statistics and modeling can be useful in capturing student characteristics and past behavior to help predict their success in a college course. If this concept is scaled up to include many more classes, students and possible predictor variables, the models will only become more robust and more useful to everyone from college advisors, faculty members, college administrators, and state or national policymakers.

Methods and Procedures

In Chapter 3 the methods and procedures of the study were laid out. This study focused on all participating adult students enrolled in a principles of economics course (either Microeconomic Principles, Macroeconomic Principles, or both), in the 2013-2014 academic year at one mid-sized, Hispanic-serving community college in the Southwest United States, located in the suburbs of a major metropolitan area. Based on the literature review and the professional judgment of the instructors of these students, data were collected through an in-class survey and through the retrieving of supplemental student data in the college's Student Information System (SIS). As is common in a learning analytics study, this was not an experimentally designed study, but observational in nature and did not attempt to include or exclude students beyond the requirements that they be at least 18 years of age and that they give voluntary consent to participate.

Although an experimental design would have lead to higher internal validity and a stronger causal relationship (due to the reduction in confounding variables), the observational study is both preferred (as it has a higher degree of external validity in that it measures the participants of the population intended to be understood) and necessary (it would be logistically impossible and ethically dubious to include and exclude students from enrollment in the course solely for purposes of conducting this research). The survey was piloted during the 2012-2013 academic year, before the actual study was conducted to ensure procedures and data collection were handled smoothly and accurately, as well as to test the survey instrument. With the help of instructor-facilitators, the surveys were distributed, collected, and delivered to the college's institutional research office for processing. The institutional research office processed the surveys and pulled the students' relevant SIS data to create this study data set, used for analysis in chapter 4.

Major Findings

Chapter 4 focused on answering the four research questions of the study by applying descriptive statistics (Research Questions I-III) and inferential statistics (Research Question IV). It started with an overview of the entire economics student population (n=553) during the 2013-14 academic year, including repeater students (and why they repeated), as well as a description of their academic, social, demographic, and personal characteristics as reported in the SIS system. Not all students in this population were eligible for participation in the study sample, however, due to being minors (under 18 years of age) or not completing the survey or informed consent form, leaving a sample of 403 students. Using t-tests or Pearson chi-square (χ^2) tests to look for statistically significant differences between the students included and excluded from the sample, it was found that students did differ on the time of day they took the course, hours worked per week, and perhaps most importantly, the grades they earned. Having established how the sample differs from those students excluded, the survey responses were described as well as a description of how missing data were dealt with.

Chapter 4 then turned to addressing the four research questions of this study. Research Question I asked "*which independent variables in the study significantly relate to the dependent variable?*" The null hypothesis was "there are no independent variables that are significantly related to the dependent variable," and the alternative hypothesis was "there is at least one significant relation between an independent variable and a dependent variable." There was strong evidence for the alternative hypothesis, that some data collected about the students were significantly related to student success in either economics course. Indeed, 16 individual variables (including two ways of measuring hours worked per week) were found to be statistically significant in relation to the students' chances of success. The most important factors identified were the students' cumulative college GPA, the instructor that taught and graded them, and if they had completed an economics course in a prior semester (all with Cramer's V effect sizes above 0.3). These variables, along with the other significant variables, were the basis of Research Questions II, III, and ultimately IV.

Research Question II was "*Of the independent variables related to student success, are any significantly related to each other?*" In this case, the null hypothesis was "there are no significant relations between the independent variables related to student success." The alternative hypothesis was "there is at least one significant relation between two or more independent variables related to student success." Table 43 shows that there is clear support for the alternative hypothesis. There were nine pairs of variables that were each individually related to student success (as found in Research Question I) and were also relatively strongly related to each other (had a Cramer's V effect size greater than 0.3). Set 1 reflects that instructors with lower than average student success rates only taught in the morning and not in the afternoon or evening. Set 2 shows that students that completed an economics course in a prior semester were also likely to have passed the subsequent course. Set 3 reflects that students who self-reported acting impulsively or distracting easily tended to also report earning lower grades in high school. Set 4 shows that students with higher cumulative GPAs tended to withdraw from classes less often. Set 5 shows that students that completed economics in a previous semester tended to withdraw from their present classes less often. Set 6 reflects that students that had earned less W's in the previous semester were also more likely to pass their previous economics course (if they had attempted one before). Set 7 shows that students who self-reported earning higher grades in high school also tended to earn higher college GPAs. Set 8 indicates that those that disagreed or strongly disagreed that their friends and family thought that they acted impulsively or got distracted easily had higher cumulative GPAs. Set 9 reflects that students who self-reported earning higher grades in high school felt more comfortable calculating percentage change.

Table 43: Variables Significantly Related to Students' Success Course Outcome that were Also Significantly Related to Each Other and that had a Cramer's V Effect Size of at Least 0.3, by Effect Size (Cramer's V)

SET	VARIABLE 1	VARIABLE 2	CHI-SQUARE	DF	SIGNIFICANCE	CRAMER'S V
1	Instructor	Time of Day	501.326	14	p < .001	.789
2	Completed Economics in a Prior Semester	Passed Economics in Prior Term	48.46	1	p < .001	.707
3	Most Frequent Letter Grade Earned in High School	Act Impulsively/ Distracted Easily	626.710	25	p < .001	.558
4	Cumulative GPA	W's in Prior Semester	94.167	20	p < .001	.544
5	Completed Economics in a Prior Semester	W's in Prior Semester	24.304	3	p < .001	.532
6	Number of W's Earned the Previous Semester	Passed ECN in Prior Term	12.775	3	p = .005	.385
7	Cumulative GPA	Most Frequent Letter Grade Earned in High School	53.459	25	p = .001	.364
8	Cumulative GPA	Act Impulsively/ Distracted Easily	42.487	25	p = .016	.325
9	Most Frequent Letter Grade Earned in High School	Comfort with Calculating % Change	37.456	10	p < .001	.305

Research Question III was *"are there different relations between the independent variables and student success depending on which course is taken (Macroeconomic Principles [ECN21] vs. Microeconomic Principles [ECN212])?"* This research question was similar to Research Question I in that they both attempted to associate student success with the independent variables, but differ in that Research Question I combined all students (regardless if they were taking ECN211 or ECN212) into one group whereas Research Question III separated students by course taken (either ECN211 or ECN212) to examine if they differ by success variables.

For Research Question III, the null hypothesis is "there are no differences in the variables associated with student success between the ECN211 and ECN212." The alternative hypothesis is "there are one or more variables associated with student success that differ between ECN211 and ECN212." Table 44 summarizes the variables that each course shared in common as well as unique predictors for each course (i.e., variables that were significant in one class but not in the other when the sample was split for analysis), and thus provides support for the alternative hypothesis. There were six closely related variables that were independently significantly related to both ECN211 and ECN212. However, there were five unique variables that were significant only for ECN211, and two unique variables that were significant only for ECN212.

Table 44: Variables Significantly Related to Students' Success, by Course and Greatest Effect Size (Cramer's V)

COURSE(S)	VARIABLE	ECN211 SIGNIFICANCE	ECN211 CRAMER'S V	ECN212 SIGNIFICANCE	ECN212 CRAMER'S V
Both	Last Reading Course Success (ECN211) or Outcome (ECN212)	p = .028	.285	p = .004	.601
Both	Cumulative GPA	p < .001	.398	p < .001	.461
Both	Instructor (ECN211) or Instructor Success Average (ECN212)	p < .001	.395	p = .001	.252
Both	Completed ECN in Prior Term	p = .04	.375	p = .015	.298
Both	Time of Day	p = .01	.197	p = .007	.246
Both	Comfort Calculating Percentage Change	p = .032	.170	p = .032	.204
ECN211	Last English Course Outcome	p = .003	.286		
ECN211	Hours a Week Worked	p = .036	.264		
ECN211	W's in Prior Semester	p = .013	.242		
ECN211	D's or F's in Prior Semester	p = .016	.212		
ECN211	Comfort with Graphing Data	p = .041	.164		
ECN212	Most Frequent High School Grade			p =.011	.299
ECN212	First Generation Status			p = .025	.174

Research Question IV was "*what factors, in combination, best predict student success before enrollment in the economics principles courses?*" Unlike the first three research questions, which looked at variables related to student success one at a time, this question looks at predictors of student success in tandem in order to create the best explanatory model for student success in ECN211, ECN212, and both courses. In order to do this, a different statistical technique was used, binary logistic regression.

The null hypothesis of Research Question IV was “knowing two or more independent variables does not lead to a more accurate understanding of a students’ likelihood of success in economics courses.” The alternative hypothesis is that “knowing two or more independent variables can significantly improve predictions of student success in the economics principles courses.” Through a five-step process, there was substantial evidence supporting the alternative hypothesis.

Step one identified 12 independent variables (of the 22 variables previously identified as significantly related to student success in Research Questions I and III) that were found to be significant predictors of student success. However, only three of these predictors (models 1.1-1.3, including Cumulative GPA, Number of W’s Last Semester, and Last Reading Course a Success, respectively) were useful in predicting student success above the baseline of simply knowing the pass rate for the course. Similarly, seven predictors were identified as significant for ECN211 using the binary logistic regression model, but only one model (model 2.1, number of W’s in prior semester) predicted student success above the student success pass rate. Likewise, eight predictors were identified as significant for ECN212 using the binary logistic regression model, but only one model (model 3.1, Cumulative GPA) predicted student success above the student success pass rate.

In step two, the significant variables within the three datasets (all ECN students, ECN211 students, and ECN212 students) were tested for interaction effects. There were two interaction effects found for the all ECN students’ data sets, and none for the ECN211 or ECN212 only data sets. The first interaction explored, in which cumulative GPA significantly interacted with students who self-reported earning mostly C’s in high school, showed that students were nearly twice as like (1.967) to be successful in economics if they reported not earning mostly C's in high school, relative to students reporting that they earned mostly C's in high school, regardless of their current cumulative GPA. However, this odds ratio varied depending on the students' current GPA. Students who self-reported earning C's in high school who currently had a GPA of less than 3.0 were much less likely to be successful than those students who had a GPA less than 3.0 and did not report earning mostly C's in high school. However, those students who did report earning mostly C's in high school but currently had a GPA above 3.0 showed a much higher rate of passing the course than students with a similar GPA who did not earn C's in high school. This data is consistent with the explanation that students who performed poorly in high school (i.e., earned mostly C's) but changed academic trajectories in college and now have a good GPA (3.0 or higher) had a particularly high tendency to pass their current ECN course.

The other significant interaction effect discussed in step two was between students' cumulative GPA and rather they were enrolled with an instructor that had higher than average student success or lower than average student success. Regardless of the students' GPA, students enrolled with a high success instructor were more than 5 times as likely (5.528) to pass the course than if they were enrolled with a low success instructor. However, this likelihood of passing differed considerably depending on the students' cumulative GPA. Those students that had the highest GPAs (3.5-4.0) gained the least by having a high success instructor; their chances of passing the class increased by less than 3 times (2.866). However, if the student had a lower GPA (2.5-2.99) then they were more than 12 times more likely (12.844) to pass the course if they had a high success instructor.

In step three, the information gathered in steps one and two were used to build the best fit models at the heart of Research Question IV. For each of the three datasets (all economics students, ECN211 students only, and ECN212 students only), the predictor variable found to be most significantly related to student success in the binary logistic regression models in steps 1 and 2 became the base of the model, which were then combined with the second most significant variable, and then the third, and so on. If the model was found to be most robust as a result (i.e., the -2 log likelihood decreased and/or the Nagelkerke R^2 statistic increased), then this became the new base model by which new variables would be combined and tested.

Step three terminated for different reasons depending on which of the three datasets were used. For the all ECN dataset, two separate criteria were need for building the models due to the -2 log likelihood and Nagelkerke R^2 statistics giving competing indications as to the next iteration. Using the -2 log likelihood method, the process ended after adding the fourth predictor variable (model 1.6, including earning mostly C's in high school) to the three predictor model (model 1.5, including cumulative GPA, passing economics in a previous semester, and last reading course a success). At this point, the -2 log likelihood reached 0 and the Nagelkerke R^2 statistic reached 1.0, indicating that the model predicted the data perfectly. Before rejoicing, however, it is important to note that only 29 (7.20%) of the students qualified for inclusion in this model, based on needing to have data for all four of the variables integral to the model. Using the Nagelkerke R^2 criteria, instructor success substituted for earning mostly C's in high school, but the iteration terminated for identical reasons (a value of 0 for the -2 log likelihood and a 1 for the Nagelkerke R^2 statistic). In contrast, the model building process for the ECN211 only and ECN212 only datasets concluded not when the -2 log likelihood and Nagelkerke R^2 reached their respective limits, but when all variables of potential use (as identified in step one) were exhausted.

In step four, the models developed in step one and step three were tested using the data sets used to create the models, that is, the economics students of the 2013-2014 academic year. This was one way of testing the usefulness of the models that were developed. To do this, each students' values for the relevant predictor variables were inputted directly into the binary logistic regression model, and then the outcome variable were exponentiated to determine the odds of the student passing the course. Students with odds equal to or greater than 1.0 were predicted to pass the course. Students with odds less than 1.0 were predicted not to pass the course. This prediction was then compared to the actual observed course outcome for the student, and the student (the case) was categorized into one of three categories: accurate (the student who was predicted to pass or not, did indeed, pass or did not pass, respectively), false positive (the student was predicted to pass the course, but did not), or false negative (the student was predicted to not pass the course, but did pass the course). Because all students were categorized into one of these categories, the summation of the percentages of each category equals 100 percent. If the accuracy percentage of the model was greater than the class' passing average (i.e., the accuracy rate of assuming that each individual student would pass the course), then the model was determined to have utility for predicting success in this dataset.

As in the other steps, three samples were under consideration —the all economics students (i.e., including ECN211 and ECN212 students), the ECN211-only sample, and the ECN212-only sample. The results were impressive. In the all ECN sample, the models predicted student success accurately as high as 10.34 percentage points higher than simply knowing the course's overall success rate. The same effect was true for the ECN211 only sample (a high of 7.65 percentage points) and the ECN212 only sample (a high of 10.48 percentage points). These results show that the binary logistic regression modeling did help in predicting student success above what would be expected without the development of these statistical techniques, at least for the student data used in building the models in the first place.

However, one could reasonably point out that because the models created in step four were created from the same dataset from which they are attempting to predict, that this could lead to problems in extrapolation. The models were designed to fit the data well, so lack of an ability to do so would be highly problematic. Step four showed this was indeed not the case. However, it was up to step five to show that these models could be of service for student data that was not used in the model creation process; therefore, a new dataset of students was created based on the students enrolled in ECN211 and ECN212 in the subsequent (i.e., fall 2014) semester.

After describing the statistical differences between the new sample of students and the established sample, step five applied the models created in steps one and three to this new sample. In this step, the results were not as striking as was found in step four. Indeed, the models completely fell apart when applying them to the all ECN student group; not one of the models achieved a prediction success rate even equal to just knowing the pass rate of the course.

Furthermore, not all models developed in steps one and three were applicable to the new sample of students, due to missing data. For the ECN211 sample, models 2.2-2.8 were not eligible for use because the "instructor success" variable was missing; the two instructors that were categorized as below average in student success the previous academic year were not teaching that semester, and so the variable lacked variability (i.e., all instructors were either high success or were missing data in this field because they were new hires).

However, the relevant models for the new ECN211 only and ECN212 samples showed value. The ECN211-only sample model improved prediction accuracy by 4.86 percentage points and the ECN212-only sample had a prediction accuracy 6.54 percentage points higher than simply knowing the pass rate for the respective courses. This is strong evidence that modeling student success can provide meaningful prediction capabilities.

Discussion

Higher education leaders in general and community college leaders in particular have been tasked with increasing the number of students who earn post-secondary credentials, quickly and sustainably, without watering down standards. Despite decades of research focused on the factors associated with student success, completion rates among community college students remain alarmingly low. Information technology, including predictive analytics, has quickly and profoundly entered many parts of our lives. In addition to many everyday sectors that have been disrupted by predictive analytics, higher education is ripe for positive transformation to drastically improve student success.

This study examined four research questions concerning factors related to student success in one community college course, at one community college, in one year. Despite the limit of the focus, the study shows abundant evidence that all four of the alternative hypotheses of the research question were supported; that is to say, there are factors that we can know about students before they enroll in a course that could inform college personnel and students' decisions about the timing and the preparedness of the student that could influence their success in the course. If such a limited set of factors and scope could nonetheless predict student success significantly above the class' passing average, then consider what could be accomplished if these processes were scaled up to include many years worth of data. The future could entail ever improving tools we can use to help students make the best decisions in their academic careers to complete their courses and eventually their program, complete in less time, and complete at a lower total cost to students, colleges, and taxpayers.

One discovery from this study was the apparent trade-off between prediction accuracy and generalizability of the model to the students in question. As can be seen when examining the tested models in step four of Research Question IV, as the models become more complex (new variables were added to the model), the percentage of the sample that could participate and therefore benefit from it tends to shrink, even into single digit percentages. Although there are some variables that are applicable to all students (e.g., cumulative GPA tends to be a very good predictor and every student has a value for it), there are other variables that show predictive value in the model but few students have data for (e.g., knowing if the last reading course that the student took was a success was predictive in the ECN212 model, but a student would have had to take a reading course in a previous semester for the model to be applicable to her or him). This suggests that instead of having a single model that is applicable to all students (a "one-size-fits-all" model), there are likely to be myriad models for predicting student completion, with the most sophisticated ones being the most accurate but also requiring the students to have and provide the most information (either through giving permission for access of outside databases or by through their continuing tenure at the institution). Indeed, one might imagine a predictive algorithm changing in close to real-time as more and more information about students is collected, thus increasing the ability of the institution to provide accurate advice.

There were, of course, findings in the study that were not surprising. Table 7 of Research Question I identified 16 factors related to student success in either economics course. Cumulative GPA had the greatest association with student success (as measured by Cramer's V effect size), suggesting that past collegiate performance does predict current course performance (indeed, cumulative GPA was also the strongest predictor variable in the binary logistic regression models). Perhaps related to cumulative GPA, the number of W's that the student received in the previous semester was also predictive. Students' academic record in their last English course outcome (and success), along with if they completed or were successful in a prior economics course, also predicted student success. Students who did not work or worked part-time (i.e., less than 20 hours a week) had an advantage in passing their economics course. The students' status as a first-generation student also was significant to student success as was suggested in the literature (Burns, 2010; Kuh et al., 2008; Sparkman, Maulding, and Roberts, 2012).

However, there were plenty of surprises to be found in what was significantly related to student success, and how strong the relations were. As shown in Table 7 (Research Question I), the instructor in the class was nearly as important to students' success at the students' GPA, and more important than if they had completed or succeeded in a previous economics course or their previous course withdrawal patterns. An assumption coming into this study was that student success was largely a function of students' preparedness, actions, and other factors specific to the student; the course and instructor were thought of as merely the mechanism by which these other factors of student success operated. The evidence suggests otherwise. Indeed, the instructor factor was so powerful as to influence other factors related to it, such as the time of day that the student took the course.

Given that the purpose of this study was to find the factors that lead students to success in economics courses so that prospective students can use that knowledge to make data-informed decisions about how to best prepare and when to take the course, giving them information about the success rates of possible instructors does not seemed to be aligned with that goal. Funneling more students to those instructors with higher success averages may indeed increase overall success rates, but there could be unintended consequences of this practice. After all, there could be multiple reasons why some instructors had higher student success averages than others. It could very well be that high success instructors teach more effectively, and thus students get both a better education and a higher chance of success by taking their courses. However, it could also be the case that these instructors teach courses that are less rigorous in nature, or have easier tests or assessments, or curves their course grades so that more students pass relative to the low success instructors. It may also be that part-time, contingent faculty members feel either a conscious or unconscious pressure to pass more of their students in order to retain employment for subsequent semesters, whereas full-time faculty may feel less of that pressure, provide a more rigorous course, and have lower student success rates as a result. Given that we want students to have both a quality learning environment as well as pass their courses, it is not clear that driving students to instructors with higher success rates will achieve both of these goals simultaneously. Indeed, one may predict that if that were the case, there could be an "arms race" to water down standards in the class in order to promote enrollment in their classes and thus retain employment. What this study can conclude for certain, however, is that instructors and their courses are not simply passive means by which students' own background, attitudes, and aptitudes determine wholly their success; instructors and their course structure do matter, and is a worthy focus of further discussion.

That age was a significant predictor of student success was not surprising given the literature (e.g., Costra, 2013a, Shapiro et al., 2012), but it was surprising that older students (25 years or older) had an 89.11% pass rate relative to their traditional aged counterparts (18-24 years old), who only had a 77.81% pass rate. Although older students may be burdened with more work and family commitments than younger students, they may also benefit from greater life experience (to put learning into context), a sharper focus or motivation on achieving college outcomes, or face greater stakes for not being successful in college.

Another surprise was the lack of utility of the student survey in collecting predictor variables of student success. Except for the survey question related to work (which could be retrieved in a somewhat different form from the students' SIS records), the only four factors significantly related to student success was their self-reported most common high school grades, perspective that friends and family tend to view them as acting impulsively or distracting easily, their self-reported comfort with calculating percentage changes, and most frequent letter grade earned in high school. Two of these (number of hours worked per week and high school GPA) could theoretically be collected when the student enrolls. In some ways, this could be a relief to colleges' institutional research office as it implies that they can create relatively good models of student success without having the material and labor burden of surveying all potential students of interest.

Just as surprising, however, were the variables that were not found to be significantly related to student success in this study. Although students with a higher number of W's in the previous semester tended to have worse course outcomes, everything else being equal, there was only evidence that the number D's and F's the student received impacted student success in ECN212. Although colleges place a great deal of stock in entrance placement exams, these placement scores did not predict student success, nor did the students' successful completion of a development education course. Although students tended to enroll in their economics course with an average of about three semesters worth of credits on record ($M = 36.36$, $SD = 20.80$), the number of credits earned did not predict their success in the course. The students' prior math background at the college was not predictive of their success in the course.

Although some survey questions were predictive of student success (as discussed in the previous paragraph), there were many more that were not. The number of hours that students read or studied for class per week, or read for pleasure for that matter, was not statistically significant related to student success in the course. Their self-assessed level of computer skills (though most students believed they had relatively advanced skills), their tendency to set long-range goals, or taking advanced classes (e.g., honors, dual enrollment credit, advanced placement) in high school did not predict their success. Also surprising, given the literature (e.g., Murtaught, Burns, Schuster, 1999; Bahr, 2012a; Sparkman, Maulding, and Roberts, 2012; Grimes, 1997), was that a students' reported ethnic or gender identity did not statistically matter to their chances of course completion.

In terms of what we have learned in this study that can inform advisor and faculty members' advice to prospective economics students in general, there is abundant evidence that having a strong academic record coming into their economics class leads to better course outcomes (though this is likely true of most college courses). Table 7 shows that cumulative GPA and the number of W's earned in the previous semester are the first and fourth most important factors related to student success in economics as a whole, respectively. This suggests that not only would it be ill-advised to enroll as a freshman in an economics course (except perhaps if they had a particularly strong academic record in high school), but that students need time to develop the academic skill sets needed to be successful in sophomore level courses (i.e., 200 level) like Microeconomic Principles (ECN212) or Macroeconomics Principles (ECN211). Students' outcomes in their last English and Reading course (particularly if it was a success) were both predictive of student success, suggesting that students are learning important skills in these classes that spill over to their future coursework. Although the data here do not address it, students' first year student experience courses, college success workshops, and experience working with tutors could all be ways of developing these skills. This study does suggest that strategies that could help some students cope with acting impulsively or distracting easily could benefit them academically. Refreshing students on some basic math skills, such as calculating percentage change or graphing data, could bolster knowledge acquired in high school that will lead to greater success in economics courses. Making students aware that working too many hours a week at their job could have negative effects on their coursework may encourage them to work less and find alternative means of financing school and life, such as scholarships, grants or student loans.

Conclusions

The purpose of this study was to find empirical evidence of what factors predict student success in the economics principles courses. To find this evidence, it surveyed and examined the student records of participating students at one community college in one academic year.

The study focused on four research questions, and all four of them found support for the alternative hypotheses. Collectively, they showed that there were factors that can be known about students ahead of their enrollment that would predict their success in the course, and that different factors were predictive of student success depending on which course they were taking. There were also factors that were significantly related to each other that must be taken into account. One could think of this as a web of interrelated factors in a student's life, many of which ultimately touch upon success in individual courses, and when combined, chances of graduation. If we are to reach President

Obama's (2009) goal of having America lead the world again in college graduates by 2020, it is hard to see how we will get there without a better understanding of this complicated but important web of interdependence.

At the local level, the results of this study will be used to inform prospective students, academic advisors, and economics faculty members serving in an advising role of which factors are most important for students to achieve if they are to maximize their chances of passing the course. With this knowledge, unprepared students can delay enrollment in economics courses until they have developed the skills to maximize their prospects for achievement. From an institutional perspective, this should result in higher course completion rates and a higher proportion of students persisting and completing degrees or transferring to four-year institutions on time. The research conclusions could eventually contribute to the creation of data-informed policies that impact student choices in a way that increases student completion.

At the national level, the findings from this research will contribute to the body of knowledge about associational relations between student characteristics/abilities and college completion. Indeed, given the dearth of research conducted on student success factors for specific classes, this research could serve as an example of what is possible not only in economics courses across the country but in all other disciplines as well. One day, a meta-analysis of this and other similar research could be conducted to make generalizable conclusions about the factors that most influence student success in the economics principles courses. Combined with similar analyses in other general education courses, a multitude of "road maps" of varying probabilities of student success could be synthesized and create a powerful tool for advisors and students. For example, if it is found that taking First Year Composition is integral to success in nearly all other general education courses, completion of this course could be made mandatory before sophomore-level classes may be attempted. Given the continued advancements in information technology, one could imagine computer applications ("apps") that could inform not only academic advisors but prospective students themselves of the classes that they have both the highest chance of passing and that are also crucial for success in their program of study, all with the goal of completing their degree in as little time as possible by reducing the number of unsuccessful course attempts.

Recommendations

This study should be seen as a preliminary step on a long, iterative journey to having a detailed, data-driven analysis of the factors that lead to student success, both at the course level and at the program level. There should be replications of this basic research design for economics courses at other community colleges, and four-year institutions, and in diverse geographical regions of the United States that serve students of diverse backgrounds. Only then will researchers be able to draw conclusions on the reliability of these findings

More generally, similar types of analyses should take place for all other developmental and college-level courses that a college offers, starting with the courses with the highest enrollment. Not only would this allow prospective students and their faculty and academic advisors to give them data-informed advice as to how best to prepare for each individual course, but a second, broader benefit could be realized. Having a detailed understanding of how courses relate to each other in student success can allow colleges to develop data-informed pathways to guide students, either through recommendations or prerequisites, to achieve their stated program outcome efficiently, at a lower cost in terms of tuition dollars and time than they are currently spending.

Furthermore, these studies should never terminate, but constantly be refined as new students enter and new data collected. This will allow the institution to continuously improve the accuracy of its predictive models and measure reliability overtime. This may require a reallocation of institutional resources towards the institutional research office or reassigned time for employees to engage in this work, but the benefits to the college in terms of higher retention (and, in some states, performance-based funding) should at least partially offset if not completely pay for itself in due time.

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APPENDIX A: STUDENT SURVEY

ESTRELLA MOUNTAIN
COMMUNITY COLLEGE

A Maricopa Community College

ECN Student Success Survey

Your Full Name: ____________________ **Section:**

Your Instructor's Name: ____________________

0	0	0	0	0
1	1	1	1	1
2	2	2	2	2
3	3	3	3	3
4	4	4	4	4
5	5	5	5	5
6	6	6	6	6
7	7	7	7	7
8	8	8	8	8
9	9	9	9	9

1. How many hours a week (on average) do you read or study for all classes?

   O 0   O 11-15
   O 1-5   O 16-20
   O 6-10   O More than 20

2. How many hours a week (on average) do you read for pleasure?

   O 0   O 11-15
   O 1-5   O 16-20
   O 6-10   O More than 20

3. How many hours a week do you work for an employer?

   O 0   O 30-39
   O 1-9   O 40-49
   O 10-19   O 50-59
   O 20-29   O 60 or more

4. Which ones are you fairly comfortable with (mark all that applies)?

   O Graphing data   O Calculating slopes
   O Algebra   O Calculate percentage change

5. Which one is your computer skill level?

   O Advanced   O Moderate
   O Beginning   O Virtually None

6. "On some weeks, I'm not sure how I'm going to get to school on a given day." How true is this statement for you?

   O Very True
   O Occasionally True
   O Not True

ESTRELLA MOUNTAIN
COMMUNITY COLLEGE
A Maricopa Community College

7. "My friends and family believe that I tend to make long-range goals, stay organized and plan routes to these goals".

   O Strongly Agree
   O Agree
   O Disagree
   O Strongly Disagree

8. "My friends and family believe that I tend to act impulsive or that I can get distracted easily".

   O Strongly Agree
   O Agree
   O Disagree
   O Strongly Disagree

9. Events that occur in my life are primarily determined by?

   O People and events outside my control
   O My own actions and abilities

10. During high school, the most frequent letter grades I earned in my classes were:

    O As
    O Bs
    O Cs
    O Ds

11. How many honors, dual enrollment, or advanced placement classes did you take in high school?

    O 1
    O 2
    O 3
    O 4 or more
    O Not applicable

12. Short Answer: What challenges do you believe lead students to **not** be successful in their academic course? Do you experience any of these challenges yourself? (Use the back of the page if you need more room)

APPENDIX B: INFORMED CONSENT FORM

INFORMED CONSENT STATEMENT – "Student Success Survey"

I understand that this survey is administered by Estrella Mountain Community College, Avondale, AZ. This survey is part of a faculty research study focused on understanding the characteristics and backgrounds of students that lead to their successful completion of the principles of economics courses (data collected as part of this project will be used as part of a doctoral dissertation). By participating in this study, participants are helping to benefit future economics students be prepared for taking economics classes. The survey is expected to take less than 10 minutes to complete.

I hereby affirm that I am 18 years of age or older and voluntarily give permission for my responses to be used as data in this study. I understand that my name and other identifying factors provided in this survey will be matched with information stored in the Maricopa Community College's Student Information System. All information collected will remain secure and confidential. No information identifying individual participants will be made public. All surveys will be destroyed once the data has been collected and documented, and the informed consent forms destroyed three years after the completion of the study. I understand that I can express my ideas and opinions without consequence, that risks to participating in the study are minimal (no greater than the risks of everyday life), and that I may withdraw from this study at any time before the end of the semester without penalty by contacting the principal investigator, Erik Huntsinger, by calling 623-935-8137, or visiting his office at Estrella Mountain Community College, 3000 North Dysart Rd., Avondale, AZ, 85392.

Additionally, I may contact the Maricopa County Community College District Institutional Review Board Office (Lori Thorpe at 480.731.8701) or lori.thorpe@domail.maricopa.edu, if I have any issues or questions regarding my participation in this study.

____________________	____________________________	__________________
Printed name	Signature	Date

☐ Check this box if you are under 18 years of age

APPENDIX C: LIST OF VARIABLES CONSIDERED IN STUDY, BY STUDENT INFORMATION SYSTEM (SIS) AND SURVEY

VARIABLE	TYPE	DEFINITION
Cumulative GPA	Ordinal	The grade point average at the current institution through the completion of the current semester
Enrolled Last Semester	Categorical	First semester students in “no” category. Otherwise, they are in the “yes” category
Number of D’s or F’s Last Term	Ratio	For students enrolled in previous semester, the summation of “D” or “F” letter grades received in the previous semester
Number of W’s Last Term	Ratio	For students enrolled in previous semester, the summation of “W” letter grades received in the previous semester
Class	Categorical	Students enrolled in the Macroeconomic Principles are in the “ECN211” category. Students enrolled in the Microeconomic Principles are in the “ECN212” category.
Instructor Success	Categorical	Student taught by an instructor with a higher than average student success average coded “1” or lower than average coded “0”
Semester	Categorical	Course enrollment in “August 2013” or “January 2014” semester
Time of Day	Categorical	Class start time, in the morning (before noon) coded “1,” afternoon but before 5pm coded “2,” or evening after 5pm coded “3”
Afternoon Class	Categorical	Class start time in afternoon but before 5pm coded “1,” otherwise “0”
Evening Class	Categorical	Class start time in evening after 5pm coded “1,” otherwise coded “0”
Grade	Ordinal	Letter grade received in economics
Student Success	Categorical	Letter grade of “A,” “B,” or “C” coded as “1”; otherwise coded “0”
Attempted ECN in Prior Semester	Categorical	If enrolled in an Economics course before coded “1”; otherwise coded “0”
Completed ECN in Prior Semester	Categorical	Of those who coded “1” to *Attempted ECN in Prior Semester*, coded “1” if student completed their course, otherwise “0”
Passed ECN in Prior Semester	Categorical	Of those who coded “1” to *Attempted ECN in Prior Semester*, coded “1” if student passed their course, otherwise “0”
ENG Placement	Ordinal	Of those who took an English Placement exam, course placed into.
ENG Placement Recode	Categorical	Of those who took an English placement exam, placed into below ENG101 or equivalent (Developmental English) coded “1,” placed into ENG101 or equivalent (College level) coded “2”
MAT Placement	Ordinal	Of those who took a math placement exam, course placed into.
MAT Placement Recode	Ordinal	Of those who took a math placement exam, placed into below MAT090 (developmental math) coded “1,” placed into MAT090-102 (developmental math) coded “2,” placed into MAT120-149 coded “3,” placed into MAT150-199 coded “4,” placed into MAT200+ coded “5”
Dev MAT	Categorical	Of those who took an math placement exam, If they did not place into developmental math coded “0,” placed into developmental math coded “1”
Had MAT	Categorical	If a student had a record of attempting a mathematics course at the college. “0” represents no, “1” represents yes.
Last MAT Success	Categorical	.”” If a student had not completed a math course at the college, “0” if the course was not successful, “1” if the course was successful
Last MAT Success Dev Ed	Categorical	.”” If a student’s last math course at the college was not at the developmental education level or did not attempt a math course, “0” if the course was not successful, “1” if the course was successful

VARIABLE	TYPE	DEFINITION
Last Mat Succ 090 or Higher	Categorical	."" If a student's last math course at the college was not at the Introduction to Algebra level or higher, "0" if the course was not successful, "1" if the course was successful
Last Mat Succ Coll Lev	Categorical	."" If a student's last math course at the college was not at the 100 level or higher, "0" if the course was not successful, "1" if the course was successful
Last MAT Succ 120 or Higher	Categorical	."" If a student's last math course at the college was not Intermediate Algebra or higher, "0" if the course was not successful, "1" if the course was successful
Last MAT Succ 140 or Higher	Categorical	."" If a student's last math course at the college was not College Mathematics or higher, "0" if the course was not successful, "1" if the course was successful
Last MAT Succ 150 or Higher	Categorical	."" If a student's last math course at the college was not College Algebra or higher, "0" if the course was not successful, "1" if the course was successful
Last MAT Succ 180 or Higher	Categorical	."" If a student's last math course at the college was not Plane Trigonometry or higher, "0" if the course was not successful, "1" if the course was successful
Last MAT Succ 200 or Higher	Categorical	."" If a student's last math course at the college was not Brief Calculus or higher, "0" if the course was not successful, "1" if the course was successful
RDG Placement	Ordinal	Of those who took a reading placement exam, course placed into.
RDG Placement Recode	Ordinal	Of those who took a reading placement exam, below RDG090 coded "1" (developmental reading); RDG090-099 coded "2" (developmental reading); RDG or CRE101 coded "3" (college-level reading); Reading Exempt coded "4"
Dev RDG	Categorical	Of those who took a reading placement exam, not placed into developmental Reading coded "0"; Placed into developmental reading coded "1"
Last RDG Recode	Categorical	Of those who took a reading placement exam, those unsuccessful in development reading class coded "1," those unsuccessful in college-level development reading class coded "2"; those successful in development reading class coded "3," those successful in college-level reading course coded "4"
Last RDG Success	Categorical	Of those who took a reading course, those who passed the course coded "1," those who did not coded "0"
Last RDG Success College	Categorical	Of those who took a reading course, those who passed the course and it was at the college level coded "1," those who did not coded "0"
Last ENG Course	Categorical	Last English course completed and grade
Last ENG Recode	Categorical	No record coded "0," unsuccessful in developmental English classes coded "1," Unsuccessful in ENG101 coded "2," Unsuccessful in ENG102 or higher coded "3," successful in developmental English Class coded "4," successful in ENG101 coded "5"; Successful in ENG102 or higher coded "6"
Last ENG Recode 2	Categorical	Of those who had enrolled in a previous ENG course, if passed the course coded "successful," if not passed the course coded "unsuccessful"
Last ENG Success	Categorical	If successful in a previous ENG course coded "1," otherwise coded "0"

VARIABLE	TYPE	DEFINITION
Attempted Hours	Ratio	The number of credit hours enrolled in during the current semester
Status	Categorical	During current semester, students enrolled in 12 or more credits coded “1”; students enrolled in 7-11 credits coded “2”; students enrolled in 1-6 credits coded “3”
Cumulative Earned Hours	Ratio	Cumulative earned credit hours through end of current ECN term
Age	Ratio	Age (Years)
Age Recode	Categorical	Students 18-24 years of age coded “0,” 25 years or older coded “1”
Ethnicity Short Description	Categorical	Ethnicity
Ethnicity Recode	Categorical	Of Ethnicity Short Description, merge Hawaiian, American Indian, and Unspecified to "other"
Gender Description	Categorical	Gender (Male, Female, Other, Unknown). Other does not necessarily represent transgender.
First Generation Flag	Categorical	First generation college student (neither parent attended college) (Y/N)
GI Active Duty	Categorical	Active duty in the military (Y/N)
GI Active Duty Dependent	Categorical	Dependent of active duty in the military (Y/N)
GI Veteran	Categorical	Veteran (Y/N)
Current Intent Descr	Categorical	Current intent of attending college description
Language Current	Categorical	Most Frequent language currently spoken
Language Child	Categorical	Most Frequent language spoken as a child
Language Child_Recode	Categorical	Of language spoken as child, merge all languages that are not English, Spanish, or Vietnamese, as “other”
Prev Educ Exp Descr	Categorical	Description of previous educational experience
Work Hours Descr	Ordinal	Work Hours Description (using ranges)
Work Status	Categorical	Works 20 or more hours per week coded “fulltime,” work 1-19 hours per week coded “part-time,” does not work coded “none”
Work Full-time	Categorical	Work 20 or more hours per week code “1,” otherwise code “0”
Work Part-time	Categorical	Work 1-19 hours per week code “1,” otherwise code “0”
Work Any Hours	Categorical	Work any number of hours code “1,” otherwise code “0”
Transfer Student	Categorical	Student enrolled in a prior institution code “1”
Transfer Attempted Hours	Ratio	Of students who transferred, number of transfer hour attempted
Transfer Earned Hours	Categorical	Of students who transferred, number of transfer hour earned
Transfer GPA	Categorical	Of students who transferred, grade point average from transfer institution
Q1	Categorical	Number of hours a week (on average) read or studied for all classes (range)

VARIABLE	TYPE	DEFINITION
Q2	Categorical	Number of hours a week (on average) read for pleasure (range)
Q3	Categorical	Number of hours a week work for an employer (range)
Q3_Parttime	Categorical	Work 1-19 hours per week code "1," otherwise code "0"
Q3_FullTime	Categorical	Work 20 or more hours per week code "1," otherwise code "0"
Q4_1	Categorical	Fairly comfortable with graphing data (Y/N)
Q4_2	Categorical	Fairly comfortable with algebra (Y/N)
Q4_3	Categorical	Fairly comfortable with calculating slopes (Y/N)
Q4_4	Categorical	Fairly comfortable with calculating percentage change (Y/N)
Q5	Categorical	Computer skill level. "Virtually none" coded "1"; "Beginning" coded "2," "Moderate" coded "3," "Advanced" coded "4"
Q6	Categorical	"On some weeks, I'm not sure how I'm going to get to school on a given day." Blank or multiple responses for same question coded "-1," "Very true" coded "1," "Occasionally true" coded "2," "Not true" coded "3"
Q7	Categorical	"My friends and family believe that I tend to make long-range goals, stay organized and plan routes to these goals." Blank or multiple responses for same question coded "-1," "Strongly disagree" coded "1," "Disagree" coded "2," "Agree" coded "3," "Strongly agree" coded "4."
Q8	Categorical	"My friends and family believe that I tend to act impulsive or that I can get distracted easily": Blank or multiple responses for same question coded "-1," "Strongly disagree" coded "1," "Disagree" coded "2," "Agree" coded "3," "Strongly agree" coded "4."
Q8_Recode	Categorical	Recode Q8. "3" or "4" recoded "Disagree," "1" or "2" recoded "Agree."
Q8_Agree	Categorical	Recode Q8_Recode. "Agree" recoded "1"; otherwise recoded "0."
Q9	Categorical	"Events that occur in my life are primarily determined by?": "People and events outside my control" coded "1." "My own actions and abilities" coded "2."
Q10	Categorical	During high school, the most frequent letter grades I earned in my classes were: Blank or multiple responses for same question coded "-1," "As" coded "1," "Bs" coded "2," "C's" coded "3," "D's" coded "4."
Q10_Recode	Categorical	Recode Q10. "1" and "2" recoded "1"; "3" and "4" recoded "0."
Q10_As	Categorical	Recode Q10. "1" recoded "1"; all others recoded "0."
Q10_Bs	Categorical	Recode Q10. "2" recoded "1"; all others recoded "0."
Q10_C's	Categorical	Recode Q10. "3" recoded "1"; all others recoded "0."
Q10_D's	Categorical	Recode Q10. "4" recoded "1"; all others recoded "0."
Q10_C'sD's	Categorical	Recode Q10. "3" and "4" recoded "1"; all others recoded "0."
Q11	Categorical	"How many honors, dual enrollment, or advanced placement classes did you take in high school?" "1"coded "1"; "2" coded "2," "3" coded "3," "4 or more" coded "4," "Not applicable" coded "5"

APPENDIX D: RECRUITMENT SCRIPT

Student Success Survey

Faculty Information for Facilitating the Surveys

Instructor:

Course/ Section Number(s):

BEFORE you administer the survey:

1. Make sure that you have enough surveys and informed consent forms for each student in your course. If you do not, contact me (Erik).
2. Please plan to reserve the final 10 minutes of a class period within the first two weeks of class to administer the materials to the students. Place your name and your section number on the board.

3. Read the following statement (verbatim) to the students:

"The EMCC economics instructors are interested in learning what helps our students successfully complete the principles of economics classes. We invite you to help us find the answer by taking part in a survey that should take less than 10 minutes to complete. Participation in the study is completely voluntary, and participation or non-participation will result in neither rewards nor punishments. Shortly, I will be passing around two documents to you, the survey and the informed consent form. After reading the informed consent document, if you choose to participate, you may sign and return it to me with the completed survey. Please complete the survey and consent form before leaving class. If you are unwilling or unable to participate in the survey, please sit at your desk until I dismiss the class. We appreciate your help in this important study".

4. Pass both the informed consent form and the survey to the students. **Please do not staple documents together, but include consent forms with surveys, one after the other.**

5. Emphasize to students what their MEID is, their unique series of letters and numbers (i.e., abcde12345). It should be the same one they use to log-in to campus computers and their Maricopa email.

5. Once they have submitted both documents to you, you may dismiss the students.

AFTER you administer the survey:

1. Place surveys and informed consent forms into the provided manila folder. Address the folder to Erik Huntsinger.

2. You can slide this under my office door (KOM-C, Old Student Life Center), put into my mail folder in MON Hall, or give to Denise Sievwright. **Thank you for your help!!!**

APPENDIX E: FERRIS STATE UNIVERSITY’S IRB APPROVAL

Ferris State University

Institutional Review Board (FSU - IRB)

Office of Academic Research
Ferris State University
1201 S. State Street-CSS 310 H
Big Rapids, MI 49307
(231) 591-2553
IRB@ferris.edu

To: Dr. Kristen Salomonson and Mr. Erik Thor Huntsinger
From: Dr. John Pole, Interim IRB Chair
Re: IRB Application #130701 (Title: *Prepped for Success: The Factors that Lead to Student Success in Economics Courses Prior to Course Enrollment*)
Date: July 16, 2013

The Ferris State University Institutional Review Board (IRB) has reviewed your application for using human subjects in the study, *"Prepped for Success: The Factors that Lead to Student Success in Economics Courses Prior to Course Enrollment"* (#130701) and approved it as expedited – 2G from full committee review. 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 *July 16, 2014.* 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 (#130701) which you should refer to in future applications 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 one-year reminder to complete the final report or note the continuation of this study. The final-report form is 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.

APPENDIX F: IRB APPROVAL FROM COMMUNITY COLLEGE OF STUDY

Maricopa County Community College District
2411 West 14th Street
Tempe AZ, 85281
TEL: (480) 731-8701
FAX: (480) 731 8282

DATE:	July 24, 2012
TO:	Huntsinger, Erik, Economics
FROM:	MCCCD Institutional Review Board
PROTOCOL TITLE:	"Prepped for Success: Identifying the Factors that Lead Students to Persist and Pass the Principles of Economics Courses"
FUNDING SOURCE:	NONE
PROTOCOL NUMBER:	2012-06-203
FORM TYPE:	NEW
REVIEW TYPE:	EXEMPT

Dear Principal Investigator,

The MCCCD IRB reviewed your protocol and determined the activities outlined do constitute human subjects research according to the Code of Federal Regulations, Title 45, Part 46.

The determination given to your protocol is shown above under Review Type.

You may initiate your project.

If your protocol has been ruled as *exempt*, it is not necessary to return for an annual review. If you decide to make any changes to your project design which might result in the loss of your exempt status, you must seek IRB approval prior to continuing by submitting a modification form.
If your protocol has been determined to be *expedited or full board review*, you must submit a continuing review form prior to the expiration date shown above. If you make any changes to your project design, please submit a modification form prior to continuing.

We appreciate your cooperation in complying with the federal guidelines that protect human research subjects. We wish you success in your project.

Cordially,
MCCCD IRB