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The Impact of Service-Learning among Other Predictors for Persistence and Degree Completion of Undergraduate Students

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THE IMPACT OF SERVICE-LEARNING AMONG OTHER PREDICTORS FOR PERSISTENCE AND DEGREE COMPLETION OF UNDERGRADUATE STUDENTS

A dissertation proposal submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

by

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Abstract

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College completion is an issue of great concern in the United States, where only 50% of students who start college as freshmen complete a bachelor's degree at that institution within six years. Researchers have studied a variety of factors to understand their relationship to student persistence. Not surprisingly, student characteristics, particularly their academic background prior to entering college, have a tremendous influence on college success. Colleges and universities have little control over student characteristics unless they screen out lesser qualified students during the admissions process, but selectivity is contrary to the push for increased accessibility for under-served groups. As a result, institutions need to better understand the factors that they *can* control. High-impact educational practices have been shown to improve retention and persistence through increased student engagement. Service-learning, a pedagogical approach that blends meaningful community service and reflection with course content, is a practice that is increasing in popularity, and it has proven beneficial at increasing student learning and engagement. The purpose of this study was to investigate whether participation in service-learning has any influence in the likelihood of degree completion or time to degree and, secondarily, to compare different methods of analysis to determine whether use of more complex models provides better information or more accurate prediction.

The population for this study was a large public urban research institution in the mid-Atlantic region, and the sample was the cohort of students who started as first-time, full-time, bachelor's degree-seeking undergraduates in the fall of 2005. Data included demographic and academic characteristics upon matriculation, as well as financial need and aid, academic major, and progress indicators for each of the first six years of enrollment. Cumulative data were analyzed using logistic regression, and year-to-year data were analyzed using discrete-time survival analysis in a structural equation modeling (SEM) framework. Parameter estimates and odds ratios for the predictors in each model were compared. Some similarities were found in the variables that predict degree completion, but there were also some striking differences. The strongest predictors for degree completion were pre-college academic characteristics and strength of academic progress while in college (credits earned and GPA). When analyzed using logistic regression and cross-sectional data, service-learning participation was not a significant predictor for completion, but it did have an effect on completion time for those students who earned a degree within six years. When analyzed longitudinally using discrete-time survival analysis, however, service-learning participation is strongly predictive of degree completion, particularly when credits are earned in the third, fourth, and sixth years of enrollment. In the survival analysis model, service-learning credits earned were also more significant for predicting degree completion than other credits earned. In terms of data analysis, logistic regression was effective at predicting completion, but survival analysis seems to provide a more robust method for studying specific variables that may vary by time.

Chapter 1

Introduction

Background for the Study

As dwindling resources began to have an impact on the financing of higher education in the 1990s, demands for accountability began to rise, and student outcomes, such as graduation rates, have come under increasing scrutiny (Burke & Minassians, 2002). Though retention and degree completion have been topics of interest for institutional researchers since the early 1970s, graduation rates are increasingly used as a measure of effectiveness for colleges and universities. The percentage of students in the United States who graduate with a baccalaureate degree from the same institution where they started as first-time freshmen varies widely among higher education institutions (Astin, 2005), but the national average for students who finish within six years of starting college has hovered around 50% for several decades (Nelson Laird, Chen, & Kuh, 2008; Tinto, 2003). Persistence to completion at the same institution where a student begins is even lower at public four-year institutions, where the average completion rate is at 45.5% (Tinto, 2012). Recent studies by the National Student Clearinghouse Research Center (Shapiro & Dundar, 2012) show that the overall rate is actually over 60% when it takes into account students who transfer to other colleges or universities to finish their degrees, but the federal government still looks only at completion in the context of the institution where a student began his/her studies.

In global comparisons, the United States has steadily fallen behind other nations in college completion, ranking 15th among 29 countries compared in a recent study by the National Center for Public Policy and Higher Education (2008). Among adults aged 35 and older, the U.S. still ranks highly among other nations in the percentage who have college degrees, but this ranking reflects the educational progress of earlier times. Among 25- to 34-year-olds, the nation has fallen to 10th in the proportion of the population with an associate's degree or higher. This trend reflects the lack of significant improvement in the rates of college participation and completion in recent years, and it is an indication of decline in educational capital among Americans (National Center for Public Policy and Higher Education, 2008). It also raises concerns about the United States' ability to compete globally. "Many individuals and organizations have picked up on the theme of slippage, including President Obama, who has made improving our rates of college degree completion and attainment a key goal of his administration's aggressive higher education agenda" (Hauptman, 2009, para. 1).

The economic benefits of earning a college degree are far-reaching, both for individuals and for society as a whole. In 2008, the median income for Americans with a bachelor's degree working full-time year-round was $21,900 higher than the median income for those with only a high school degree. In addition, among Americans between the ages of 20 and 24, the unemployment rate for the fourth quarter of 2009 was 2.6 times lower for college graduates than for high school graduates (Baum, Ma, & Payea, 2010). Federal, state, and local governments also reap the benefits of investing in higher education through increased tax revenues from college graduates and lower spending on income support programs. For example, in 2008, less than 2% of individuals aged 25 and older in households with at least a bachelor's degree relied on the federal Food Stamp Program, while 8% of households with only high school graduates received these benefits. The difference in proportions was similar for households utilizing the National School Lunch Program (Baum, Ma, & Payea, 2010).

Although many scholars and higher education professionals find fault with degree completion as a measure of educational success, the fact remains that improving graduation rates is an important issue for states and institutions. Understanding the factors that have been correlated with persistence and degree completion is essential to increasing the number of college graduates. The predictors for student attrition have been studied extensively, and a number of different models have been proposed to explain why students drop out of college. However, as Tinto (2003) cautions, "retention is not the mirror image of drop-out; the factors that help explain why students leave are not the same as those that explain an institution's ability to help students stay and graduate" (p. 2). Thus, a number of studies have investigated factors that are associated with the likelihood of students persisting to graduation. Student characteristics have been found to be strongly correlated with perseverance in college, but the variation in graduation rates is wide, even among schools with students of similar backgrounds. This phenomenon underlies the theory that institutional practices can play a key role in student retention and degree completion (Astin, 2005), particularly the practices that increase student engagement (Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Nelson Laird, Chen, & Kuh, 2008).

Service-learning is one such practice. It is an instructional method that integrates meaningful community service with instruction and reflection in a credit-bearing course. Research shows that service-learning has a positive impact on undergraduate students. Commonly reported outcomes include increases in student learning, engagement, and civic awareness, measures which have all been linked to more traditional indicators of college success such as higher grade point average (GPA), persistence, and degree completion (Bringle & Hatcher, 1996; Markus, Howard, & King, 1993). Correlation is an important first step to understanding the factors that influence the likelihood of degree completion, but the ability to test causal models gives institutions a more robust tool to predict and potentially influence outcomes. This study will investigate the paths and relationships between service-learning and traditional predictors of persistence and degree completion.

Overview of the Literature

Factors related to persistence and degree completion. Tinto (1975) laid the foundation for studying the factors that are most often associated with student attrition and persistence in college. His complex conceptual model made an effort to define the processes of interaction between students and institutions that cause differing individuals to drop out of college. Astin (1991) provides a simpler framework that focuses on the importance of considering both student characteristics (inputs) and institutional practices (environmental factors), as well as measuring the relationships between these variables, when evaluating student outcomes in education. The characteristics of entering students and the institutions they enter are significant predictors for degree completion. Those factors most commonly associated with persistence include academic preparedness, gender, and race/ethnicity (Arredondo & Knight, 2006; Astin, 2005; Terenzini & Pascarella, 1978). Financial aid and concern about financing college are significant factors (Astin, 2005; Bowen, Chingos, and McPherson, 2009; Gross, Hossler, & Ziskin, 2007;), and there are a number of personal characteristics related to self-concept, behavior, and expectations for college that have small but significant correlations with degree completion (Astin, 2005). Institutional selectivity is an additional factor that has an influence on the graduation rate (Astin, 2005). Student characteristics cannot be changed without increasing selectivity, so a number of other variables have been tested to determine their influence on persistence. Educational practices, for example, have been found to have a positive influence on student achievement and persistence. Institutions with higher levels of academic challenge and those with strong active and collaborative learning experiences tend to have higher rates of student persistence (Braxton, Milem, & Sullivan, 2000; Nelson Laird, Chen, & Kuh, 2008). Early research by Bean (1983) suggests that student retention behavior is very similar to employee behavior. Factors such as intent to leave, grades, practical value, opportunity, marriage, satisfaction, campus organizations, courses, and participation were among the variables that cause students to persist.

Methods for modeling persistence and degree completion. A variety of methods have been used to analyze persistence and degree completion. Regression (both linear and logistic) are the most common methods for analyzing the influence of various predictors on the outcomes of interest (Arredondo & Knight, 2006; Astin, 2005; Bean, 1980; Braxton, Milem, & Sullivan, 2000; Bringle, Hatcher, & Muthiah, 2010; Gross, Hossler, & Ziskin, 2007; Lewallen, 1993; Terenzini & Pascarella, 1978). Astin (2005) developed a formula for predicting degree completion using stepwise linear regression, and his formula has been utilized by others to analyze data at their own institutions (Arredondo & Knight, 2006). Using logistic regression, Cragg (2009) studied the student and institutional characteristics that influence the probability for graduation by examining how far students deviate from the institutional mean on certain variables. Bean (1983) and Braxton, Milem, and Sullivan (2000) also use path analysis to test causal relationships between certain variables and persistence. Dey and Astin (1993) compare the practical implications of three different techniques to predict college student retention: logistic regression, probit analysis, and linear regression. Survival analysis, including Cox proportional hazards modeling (Chimka, Reed-Rhoads, & Barker, 2007) and discrete-time hazard modeling, as well as latent growth analysis using a structural equation modeling (SEM) framework (Mohn, 2006) have also been used to analyze the effects of multiple predictors on persistence and degree completion. Each method has advantages and limitations.

Service-learning as an environmental factor. Empirical studies on the impact of service-learning were relatively scarce when this pedagogical approach became popular in the 1990s, and many of the studies to date include only small samples (Astin & Sax, 1998). However, a variety of benefits to service-learning have been revealed. Markus, Howard, and King (1993) show that students in service-learning are significantly more likely than those in the traditional sections to report that they had performed up to their potential in the course, had learned to apply principles from the course to new situations, and had developed a greater awareness of societal problems. Course grades were also significantly higher for service-learning students in their study. Batchelder and Root (1994) show that service-learning students achieve significant gains on certain cognitive dimensions, pro-social decision making, pro-social reasoning, and identity processing. Astin and Sax (1998) reveal that participating in service is significantly correlated with life skill development and sense of civic responsibility. Bringle, Hatcher, and Muthiah (2010) also recently found a positive relationship between enrollment in service-learning and intentions to continue at the same campus, even when pre-course intentions were covaried out. Finally, in a recent meta-analysis, Celio, Durlak, and Dymnicki (2011) evaluated the effect sizes for service-learning outcomes in 62 studies with control group designs. Outcomes fell into five categories: attitudes toward self, attitudes toward school and learning, civic engagement, social skills, and academic achievement. Of the five areas, academic achievement had the largest average effect size, providing strong evidence that service-learning can be an effective practice for encouraging academic success.

Rationale for the Study

Studies on student persistence over the past few decades have revealed a number of factors that aid in predicting the likelihood of completing a bachelor's degree. These factors include both student characteristics and institutional variables (Astin, 2005; Bean, 1983; Bringle & Hatcher, 1996; Cragg, 199; Markus, Howard, & King, 1993). In addition, certain educational practices have been positively correlated with student engagement, academic outcomes, and persistence (Braxton, Milem, & Sullivan 2000; Nelson Laird, Chen, & Kuh, 2008). Service-learning is one of these high impact educational practices which is grounded in theories that parallel college student retention theory, but there is very little research linking the two (Mundy & Eyler, 2002). Although a few studies have focused on retention and degree completion for students involved in a single service-learning experience, these small-scale projects fail to take into consideration the multitude of variables that are associated with persistence. In addition, these studies cannot draw broad conclusions that would be possible by comparing a large sample of students and comparing the persistence patterns for those students involved in service-learning with those who take no service-learning courses at all. Although longitudinal research and efforts to identify causal relationships have become more common in research on student persistence, these studies have not yet included service-learning as a variable. In previous research, it appears as if there has been no effort to follow individual students through every semester of enrollment to determine whether the number of service-learning courses taken or progression through service-learning courses is related to degree completion. Understanding persistence patterns as they relate to service-learning could have implications for support of such practices in colleges and universities. Because this study makes use of data that are routinely available at most postsecondary institutions, it can also serve as a model for institutional researchers who wish to examine the effects of specific educational offerings such as service-learning on the persistence of their own students.

Research Questions

The purpose of this study was to examine relationships between service-learning, student persistence, and degree completion among first-time full-time degree-seeking undergraduates. Research questions included the following:

1. How do students who complete service-learning courses differ from students who do not participate in service-learning?
2. In models that include service-learning as a covariate, is discrete-time survival analysis more effective for predicting degree completion than logistic regression?
3. How do the predictors and the parameter estimates differ between models?
4. Is service-learning a significant predictor for degree completion in either model?
5. For students who complete their degree within six years, is service-learning predictive of time to completion.

Design and Methods

This was an *ex post facto* quantitative study using existing data on students who entered a large, public research university in the mid-Atlantic as first-time, full-time, bachelor's degree-seeking undergraduates in the fall of 2005. These students reached 150% of the time expected to complete their bachelor's degree at the end of the summer 2011 term. Student records include demographic characteristics and academic preparation variables for entering students, academic progress indicators such as semester grade point averages (GPA) and cumulative GPA, and data about individual courses that each student completed during each semester of enrollment. Designated service-learning courses have also been documented. These records were used to construct a longitudinal dataset. Structural equation modeling (SEM) techniques were used to test a longitudinal year-to-year model for degree completion. The model tested service-learning enrollment as a predictor for degree completion in conjunction with other common variables that are known to affect a student's likelihood of persisting to graduation. In addition, the researcher compared the effectiveness of this model with simple logistic regression, a more traditional method of predicting completion. The goal of the comparison was to (a) determine whether SEM techniques provide a more effective mechanism for predicting a student's likelihood of graduating and (b) to understand whether there are patterns related to persistence and completion that vary by year and cannot be uncovered through simple logistic regression.

Definition of Terms

Academic year: An academic year at the university in this study consists of three semesters: Fall (late August through December), Spring (January through the beginning of May), and the summer term that follows the spring semester (mid-May through early August).

Completer: "A student who receives a degree. In order to be considered a completer, the degree/award must actually be conferred" ("IPEDS Glossary", 2011). This study focuses on undergraduates who enroll in programs leading to a bachelor's degree, so a completer is a student in the fall cohort who earns a bachelor's degree within the six-year time period reported for the IPEDS graduation rate survey.

Degree completion: Based on the definition of completer, degree completion refers to whether or not a student in the fall cohort has received a bachelor's degree within the six-year time period reported for the IPEDS graduation rate survey.

Degree-seeking: Students enrolled in courses for credit and recognized by the institution as seeking a degree ("IPEDS Glossary", 2011). For this study, the only students included are those admitted to programs leading to a bachelor's degree.

Fall cohort: "The group of students entering in the fall term established for tracking purposes. For the Graduation Rates component, this includes all students who enter an institution as full-time, first-time degree or certificate-seeking undergraduate students during the fall term of a given year" ("IPEDS Glossary", 2011). In this study, the fall cohort is the group of students who began as first-time, full-time undergraduate degree-seeking students at a large Southeastern public urban research university in the fall semester of 2005.

First-time student: Based on the IPEDS (2011) definition, a first-time student is one who has no prior experience attending any postsecondary institution at the undergraduate level. The exceptions include students who attended college for the first time in the summer term immediately preceding the fall semester (i.e., started early) and those who entered with advanced standing (i.e., college credits earned before graduation from high school). These are the students who are included in the fall cohort for this study.

Full-time student: An undergraduate student who is enrolled for 12 or more semester credits is enrolled full-time ("IPEDS Glossary", 2011).

Graduation rate: "The rate required for disclosure and/or reporting purposes under Student Right-to-Know Act. This rate is calculated as the total number of completers within 150% of normal time divided by the revised adjusted cohort" ("IPEDS Glossary", 2011). At the institution sampled for this study, the expected completion time for a bachelor's degree is four years, so 150% of this time would be six years. For purposes of this study, analysis of persistence and degree completion will focus on the six-year period following matriculation.

Persistence: Berger and Lyon (2005) define persistence as the "desire and action of a student to stay within the system of higher education from beginning year through degree completion" (p. 7). Tinto (2012) further clarifies the distinction between *institutional persistence* and *system persistence*. Institutional persistence refers to a student who remains at the institution where he or she began college as a freshman. System persistence refers to a student who is retained within the baccalaureate degree system but who transfers to another institution to complete his or her degree. For purposes of this study, persistence will be defined as institutional persistence, and it will be measured by completion of courses in a given academic year. Those who finish at least one semester and earn grades will be considered to have persisted during that academic year.

Service-learning: An instructional method that integrates meaningful community service with instruction and reflection in a credit-bearing course (Bringle & Hatcher, 1996).

Structural equation model (SEM): "SEMs are a general class of statistical models consisting of multiequation systems that represent relationships between latent and observed variables" (Baudry & Bollen, 2009, p. 8-9).

Survival analysis: A class of statistical methods that can allow researchers to estimate causal or predictive models in which the probability of an event depends on covariates. Explanatory variables may be time-dependent or invariant, and analyses can account for censoring, or cases in which the event fails to occur during the time frame of the study (Allison, 2010).

Undergraduate: For purposes of this study, undergraduate refers to a student enrolled in a 4- or 5-year bachelor's degree program ("IPEDS Glossary", 2011).

Chapter 2

Review of the Literature

Method for Review of the Literature

The search strategy employed for this review of the literature involved five stages: (a) electronic search of literature databases, (b) hand search of reference lists from primary sources, (c) hand search of the leading journal in research on service-learning, and (d) exploration of secondary statistical texts. These steps were designed to identify literature on the factors affecting persistence and degree completion among undergraduate students, the benefits of service-learning for undergraduate students, and the methods that have been used to analyze persistence and degree completion, particularly the use of causal models with nonexperimental studies.

First, the ERIC database was searched electronically using the following thesaurus descriptors in various combinations: *undergraduate students, college students, academic persistence, graduation, graduation rate, time to degree, predictor variables, causal models, path analysis, comparative analysis, service learning*. No restrictions were placed on publication dates. The ProQuest dissertation database was then searched using similar keywords in various combinations. In addition, the researcher hand searched each issue of the *Michigan Journal of Community Service Learning* (the premier journal for academic research on service-learning) since its inception in 1994. While reviewing the primary sources that were produced by these searches, the reference lists were examined, producing an abundance of additional literature that was selected for review. Excluding duplicate citations that appeared in multiple searches, approximately 350 unique sources were produced, many of which were only peripherally related to the topic of interest. The researcher reviewed titles and abstracts during the search process and then obtained a copy of each of the primary sources deemed relevant. Although qualitative research was not specifically excluded, the researcher focused on peer reviewed quantitative studies since empirical methods will be used to investigate the current research questions. These sources were vetted using the *Standards for Reporting on Empirical Social Science Research in AERA Publications* (AERA, 2006). Finally, the researcher utilized several secondary statistical and research methods texts for information pertaining to methods and analysis.

More than 20 years ago, Pascarella and Terenzini (1991) described the literature on college student persistence and attrition as "extensive to the point of being unmanageable" (Pascarella & Terenzini, 1991, p. 387). The research has only grown more voluminous in the intervening years. This review is not intended to cover every piece of research that has been conducted. Instead, it will highlight the most well-known and most often studied theories and the factors that have been consistently associated with persistence and degree completion. In some cases, it will also highlight areas where the research is contradictory, particularly those areas where the method of analysis is critical. Discussing the methods that have been used to model persistence is inextricably tied to the predictors, so there is some overlap between the first two sections of this review. Finally, this review will focus on the benefits that have been revealed among students who complete service-learning experiences. Service-learning has been linked to a number of positive outcomes (Celio, Durlak, & Dymnicki, 2011; Mundy & Eyler, 2002), but the focus of this study is academic outcomes, so the literature discussed in this section will be limited primarily to the academic benefits associated with service-learning.

Factors Related to Persistence and Degree Completion

Tinto's theory of attrition. Since the early 1960s, when student persistence began to be studied in earnest, most of the research has focused on attrition and the factors associated with student dropout. The predictors for degree completion are not necessarily the reverse of those that predict attrition (Tinto, 2003), but it's helpful to look at attrition studies to understand the historical context for research on persistence and degree completion. In 1975, Tinto proposed one of the first theories that attempted to define the processes of interaction between students and institutions that cause differing individuals to drop out of college. A conceptual model for his theory is displayed in Figure 1.

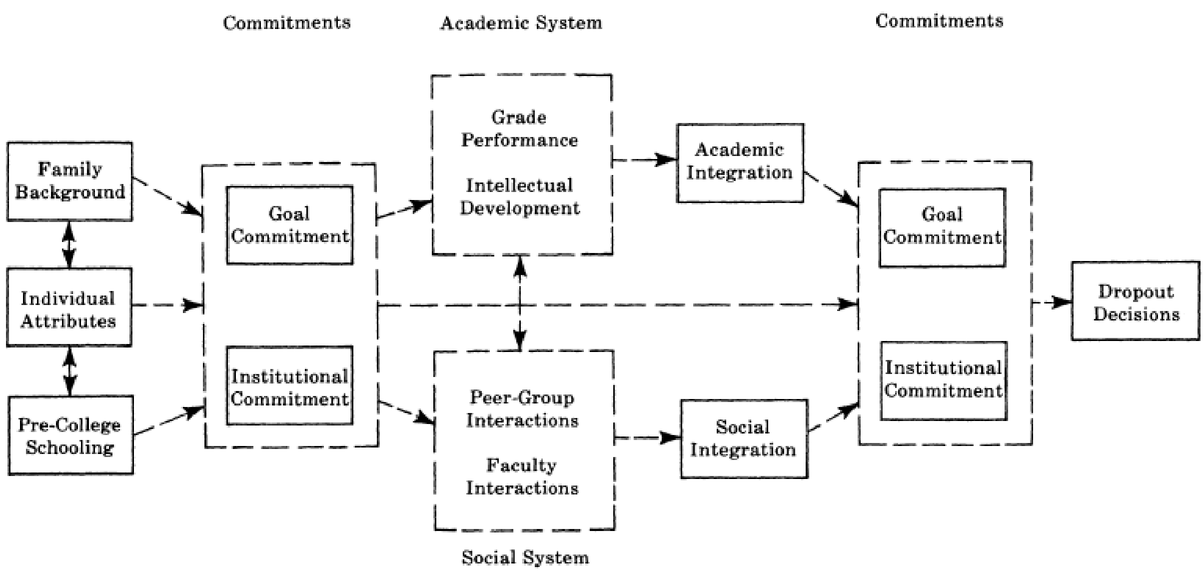

Figure 1. Conceptual model representing Tinto's (1975) theory of attrition.

Tinto's theory distinguishes between the processes that result in different forms of dropout behavior. Dropout is complex. Tinto's model acknowledges that colleges are comprised of both academic and social domains. Dropout can occur as a voluntary decision, or it can be a forced process (i.e., dismissal) resulting from poor academic performance or because a student violated social or academic conduct rules. Voluntary withdrawal in itself is also multifaceted because the decision to leave college can arise from a variety of situational factors. Tinto's theory defines attrition as a longitudinal process that begins before a student even arrives at college. Students bring certain characteristics with them to college. Background factors, personal attributes, and precollege experiences are recognized as variables that influence a student's performance in college, but they also affect the student's initial goals and commitment to an institution. These personal characteristics and commitments help to shape a student's interactions with the institution and the degree to which the student becomes integrated into the social and academic environment. Students who integrate more completely develop a stronger commitment to the individual institution and a stronger commitment to the goal of college completion.

Much of the research that has occurred since the 1970s has been based on Tinto's framework. Terenzini and Pascarella (1978) tested Tinto's theory with a longitudinal *ex post facto* study of students who were freshmen at Syracuse University in the fall semester of 1975. During the summer prior to their matriculation, 1,008 entering students (approximately 40% of the incoming freshman class) were mailed a survey with questions about their background and their expectations about the college experience. Seventy-six percent of the students responded. A follow-up survey was mailed in March of the following year to the initial survey respondents to ask students about their perceptions of their experiences during their first year of college. A total of 536 freshman responded to the second survey, and, through statistical tests, the sample was deemed representative of the university's freshman class with respect to sex, college of enrollment, and SAT scores. Institutional records for these students were examined at the beginning of the fall semester of 1976 (i.e., the sophomore year). The analysis focused on a comparison of the 90 "voluntary leavers" and the 438 students who were retained to the sophomore year.

The independent variables that Terenzini and Pascarella (1978) examined fell into three categories: (a) prematriculation characteristics, (b) academic integration variables, and (c) social integration variables. Prematriculation characteristics consisted of gender, minority or non-minority status, liberal arts or professional major, combined SAT score, high school class rank and class size, personality, mother's and father's levels of education, expectations of academic life and nonacademic life, expected number of informal contacts with faculty per month, and expected number of extracurricular activities per week. The academic integration variables consisted of perceptions of the academic program, cumulative GPA, and perception of intellectual development. The social integration variables were comprised of perceptions of nonacademic life, actual number of informal contacts with faculty per month, actual number of extracurricular activities per week, and perception of personal development.

Their overall regression model was statistically significant, and it explained roughly 26% of the variation in attrition status for the students in the sample. With respect to the three sets of predictors, their study revealed that prematriculation characteristics explain less than 4% of the variance in attrition. When examining the unique contributions of each variable, the actual amount of informal contact with faculty outside the classroom is the largest single predictor of fall-to-fall retention for freshman students. This is closely followed by the appeal that the student finds in his/her academic program. After controlling for prematriculation characteristics and social integration variables, the set of academic integration variables is also statistically related to a student's decision to return for the sophomore year, explaining 6% of the variance in attrition status. Social integration variables as a set account for a smaller amount of variance

(3%) at a less significant level after controlling for other factors. Finally, this study uncovers a variety of interaction terms, which explain a combined 10.6% of the overall variance in the dependent variable after controlling for the other variables. These findings are important because they suggest that what happens to a student after he or she enters college, particularly the academic experiences, may be more influential than a student's precollege characteristics, experiences, and expectations. These findings helped to shape subsequent research.

Astin's I-E-O model. Tinto (1993) revised his theory almost 20 years later, adding some additional factors. Around that same time, Astin (1991) developed a simpler model to guide the assessment and evaluation of student outcomes in education. A visual representation of Astin's input-environment outcome (I-E-O) model is displayed in Figure 2. Similar to Tinto (1975, 1993), Astin proposes that there are personal qualities that each student brings into an educational setting. He calls these qualities *inputs*. Inputs have a direct effect on the student's educational outputs and outcomes, but they also affect the student's interaction with his or her educational environment. In addition, the educational environment has an effect on student outcomes. This model underscores the importance of considering both student characteristics and (inputs) and institutional practices (environmental factors), as well as measuring the relationships between these variables, when evaluating student outcomes in education.

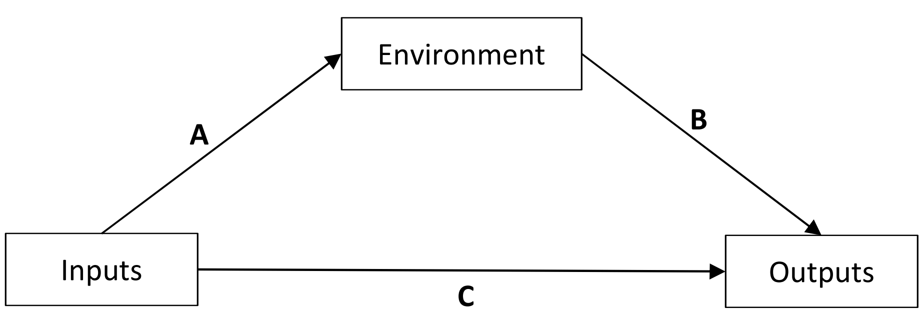

Figure 2. Conceptual representation Astin's (1991) inputs-environment-outputs model

Student characteristics. As suggested by early research (Astin, 1991; Terenzini & Pascarella, 1978; Tinto, 1975), the traits that a student brings to college are highly influential in predicting whether that student drops out or persists to graduation. Astin (2005) examined a variety of student characteristics when he summarized findings from a national study conducted by the Higher Education Research Institute (HERI) at UCLA. Participants included 262 baccalaureate-granting institutions that provided degree completion data on 56,818 students who had completed the Cooperative Institutional Research Program (CIRP) entering Freshman Survey six years earlier. Each student's six-year retention status was compared with his or her freshman survey responses, and a formula for predicting degree completion was derived using stepwise linear regression. Academic preparedness variables, specifically high school GPA, years of foreign language study, years of physical science study, and hours spent studying each week, are strong predictors of degree completion. Several demographic variables are also important. Students whose fathers completed college are more likely to complete their own degree, as well as students who are Jewish, female, or white. Financial aid and concern about financing college are significant factors, and there are a number of personal characteristics related to self-concept, behavior, and expectations for college that have small but significant correlations with degree completion. Finally, institutional characteristics such as selectivity also have an influence on a student's likelihood of completing a degree. The level of detail about the independent variables examined in this study provides important guidance for future research on degree completion.

Arredondo and Knight (2006) extended Astin's (2005) research by examining degree attainment factors at a single institution. Their sample included a cohort of 356 students in the 1996 cohort of degree-seeking, first-time, full-time freshman at Chapman University, and they focused their analysis on the factors related to the four-year and six-year graduation rates. Independent variables included high school GPA, SAT scores (verbal and math), gender, race/ethnicity, entering major/undecided, admit status, distance from home to campus, and in/out-of-state status. The study used the HERI formula developed by Astin (2005) to compare the institution's actual graduation rates with the predicted rates. This study indicated that gender, high school GPA, SAT scores, and race/ethnicity were better able to predict four-year degree completion rates than six-year degree completion rates for the students sampled, but these predictors still only account for 32% to 35% of the variation in bachelor's degree completion, making it clear that student characteristics are not the only variables that affect the likelihood of degree completion.

Financial concerns and ability to pay for college have been the focus of many persistence studies. Gross, Hossler, and Ziskin (2007) used institutional financial aid data from three public Midwestern universities to study the impact of the amount of financial aid on first- to second-year retention among the 2001 first-time full-time cohorts at these schools. Their logistic regression models, which also incorporated variables related to student background, academic preparation, and college enrollment characteristics, showed that the amount of financial aid a student is awarded is positively correlated with greater likelihood of persistence. Among their sample, the effect of financial aid was also stronger for male students than for females. Although institutional aid showed a significant effect on persistence in their study, its impact on the overall explanatory power of the model was small, adding to the evidence that many factors contribute to a student's ability and/or decision to persist. Nevertheless, financial aid remains an important factor that should be examined. Bowen, Chingos, and McPherson (2009) conducted a large national study using data from 124,522 students who matriculated as first-time full-time freshmen at a diverse group of 57 public four-year universities. Their research grouped institutions based on selectivity, and it tracked student withdrawals and completions over a six-year period. Among other findings, the researchers discovered that students from high-income families are significantly more likely to persist to graduation and to graduate on time than students from low-income families, even when academic preparation is similar. They also found that need-based aid increases the graduation rate at universities.

Uncertainty about an academic major is another important student characteristic that has been investigated for its relationship with persistence. Lewallen (1993) studied the impact of being "undecided" on degree completion, basing his analysis on Astin's (1991) I-E-O model. Data were provided by HERI for 18,461 students who completed the CIRP entering Freshman Survey upon entering college in 1985 and who completed the follow-up survey four years later. The sample contained responses from students at more than 400 colleges and universities, spanning a broad spectrum of institutions. The outcome of interest was whether the student had completed a bachelor's degree within the four-year period. Recognizing that it takes many students longer than four years to attain a degree, continued enrollment at the four-year mark was also considered an indicator of persistence. The goal was to determine whether being undecided affects persistence when other inputs and environmental variables are considered. Independent variables included precollege student characteristics (e.g., gender, age, race, parental education levels, family socioeconomic status, high school grades), academic major and career choice (with categories for students who were undecided), college environment characteristics (type of institution, enrollment status as full-time or part-time, and on-campus or off-campus living), and several measures of student involvement. Using stepwise ordinary least squares (OLS) multiple regression to estimate prediction of persistence, Lewallen (1993) found that when the full range of input and environment variables are considered, the fact that a student is undecided about an academic major or career is not significantly correlated with persistence.

Environmental factors. Because of the variation in graduation rates among institutions with cohorts that have similar student characteristics upon entry, we can deduce that some schools have practices that are contributing to a student's decision to stay and finish a degree. Tinto (2012) describes the kinds of institutional practices that have shown the most evidence for increasing retention and the likelihood of graduation. These practices include summer bridge programs, first-year seminars, supplemental instruction, learning communities, embedded academic support, basic-skills courses, social support programs, and financial support programs that are combined with other institutional support services. A number of studies have extended the research by focusing on specific environmental factors. Engagement is one factor that has gained a great deal of attention in the past 20 years. Astin (1993) found that, among students who graduate from college, the ones who report being more engaged with faculty and their peers also report that they experienced greater levels of learning and development.

Nelson Laird, Chen, and Kuh (2008) emphasize that institutions cannot control student characteristics without increasing selectivity in the admissions process. For that reason, their research also focuses on the factors that institutions can control, specifically educational practices that have a positive influence on student achievement and persistence. They developed a model predicting persistence using data from institutions that have administered the National Survey of Student Engagement (NSSE) and examined two groups of institutions: those doing better than expected and those doing as expected with regard to student persistence rates. A comparison between these groups on responses to the NSSE shows that institutions with higher-than-expected persistence rates also show significantly higher levels of student engagement in several areas. Institutions with higher levels of academic challenge and those with strong active and collaborative learning experiences also tend to have higher rates of student persistence.

Braxton, Milem, and Sullivan (2000) tested the influence of active learning practices used by faculty on the likelihood of student departure. Their sample includes survey data from 718 first-time, full-time students at a highly selective, private research university. Participants completed three questionnaires during their freshman year. The CIRP Student Information Form (SIF) was administered during orientation; the Early Collegiate Experience Survey (ECES) was completed during the fall semester; and the Freshman Year Survey (FYS) was administered during the spring semester. Responses were used to develop six sets of variables: student background characteristics, initial commitment to the institution, active learning in classes, social integration, subsequent commitment to the institution, and intentions related to leaving college. Path analysis and multiple regression were used to analyze these sets of variables, resulting in a model which indicates that active learning has a significant influence on social integration, subsequent institutional commitment, and a student's intent to return to the institution after the first year.

In summary, Tinto's (1975) theory of attrition and its subsequent revision in 1993 have provided an enduring framework for research on persistence and degree completion for almost four decades. Astin's (1991) model for evaluating outcomes in education is simpler and more generic, but the essence of both conceptual frameworks is essentially the same. Students come to college with certain personal characteristics. Their demographic and academic background has an influence what happens to them in college and has an influence on their outcome (i.e., whether they persist to completion). The college environment and the things that occur while the student is enrolled also have an impact on that outcome. A variety of student characteristics and environmental factors have been explored in previous studies and found to have an influence on persistence or completion under specific circumstances. Predictors commonly identified in the literature provide the basis for variables chosen for analysis in this study.

Methods for Modeling Persistence and Degree Completion

As a matter of necessity and design, most studies of undergraduate student persistence are longitudinal to some degree. However, many colleges rely heavily on cross-sectional data in evaluating student outcomes and making decisions. Cross-sectional measures such as the National Survey of Student Engagement (NSSE) have become increasingly popular with institutions who seek information about their students, but Astin and Lee (2003) reveal that these measures are often heavily influenced by a student's characteristics upon entering college. They demonstrate the importance of longitudinal designs by comparing the results of a one-shot cross-sectional assessment to a study with similar measures that was also longitudinal. Their results show that student outcomes measured at a single point in time are more difficult to interpret than outcomes which also take into account student inputs (i.e., student characteristics upon matriculation in college), making it clear that institutions must focus on methods that incorporate measures over time when drawing conclusions about student outcomes.

Regression analyses of various types are the most common method for studying the factors that affect persistence and degree completion (Arredondo & Knight, 2006; Astin, 2005; Braxton, Milem, & Sullivan, 2000; Bringle, Hatcher, & Muthiah, 2010; Gross, Hossler, & Ziskin, 2007; Lewallen, 1993; Terenzini & Pascarella, 1978). Dey and Astin (1993) compared the practical implications of three different techniques to predict college student retention: logistic regression, probit analysis, and linear regression. Their study uses a stratified sample of students (n = 947) who entered one of 29 community colleges in the fall of 1987 and who completed the 1987-89 CIRP Follow-Up Survey (FUS). Survey data are paired with subsequent institutional data on enrollment, degree completion, and years to degree if applicable. Models using each of the three analysis methods are found to have the same significant independent variables, with the signs of the coefficients and the ratio of each coefficient to its standard error being nearly identical. Correlations among the three predicted measures were also high, averaging .971. In each model, high school GPA was the strongest predictor for degree completion, while significant negative predictors included concern about finances, attending college to be able to make more money, or attending college to prepare for a graduate or professional school.

Attewell, Heil, & Reisel (2010) take an unusual approach by testing 12 separate logistic regression models to predict completion/non-completion in 6 years. Their analysis uses sheaf coefficients to combine multiple variables into meaningful combinations as weighted linear sums that are similar to latent variables. Their study is an *ex post facto design*, and their sample was the 1996-2001 panel of students who completed the Beginning Postsecondary Students Longitudinal Study (BPS) (n = 6,540). Since the sample included students at multiple institutions, institutional differences were also a factor that was considered in the analysis. For every type of college, seven sheaf variables are each statistically significant predictors of graduation when considered individually in isolation. These seven sheaf variables are: (1) race and gender, (2) parental SES, (3) high school academic preparation, (4) nontraditional student characteristics, (5) financial aid, (6) academic and social integration, and (7) work hours. For the least selective 4-year colleges, an eighth variable—remediation—is also significant, but it is not significant at moderately selective institutions. When the sheaf variables are combined in the final stepwise logistic regression models, all of the sheaf variables are significant except for race and gender. In addition, for moderately selective schools, remediation is also insignificant. Academic preparation has the largest coefficient in each model. In least selective schools, nontraditional status is the second largest, while in moderately selective schools, the rest are all about the same size.

Another method that has been used for analyzing the probability that a student will graduate is to look at the match between student characteristics and institutional attributes. In studying the student and institutional characteristics that influence the probability for graduation, Cragg (2009) examined how far students deviate from the institutional mean on variables related to academics and affordability. Rather than treating student and institutional characteristics independently, as many retention studies do, her model focused on the match between the student and the institution. She used logistic regression to test the validity of her matching model with data from the Beginning Postsecondary Study: 1996/2001 and the Integrated Postsecondary Education Data System (IPEDS). She then compared the results of the matching model to more commonly used models to show that "match" is also a significant factor in understanding the probability for graduation.

Bean (1983) has studied attrition behavior through a slightly different theoretical lens. Rather than focusing on Tinto's (1975) conceptual framework for attrition, Bean applied a causal model of turnover that had been developed to predict employee behavior in the workplace. This model shares some similarities with Tinto's theory and Astin's model in that a group of variables based on the background of the student and the student's interaction with the institution are hypothesized to have an influence on satisfaction or other attitudes, which in influence the intent to leave variable, which immediately precedes dropout. The industrial model upon which he based his theoretical model of student attrition was developed from turnover data on women in the nursing profession. For this reason, the sample of students that he selected to test the model consisted of unmarried, full-time female freshmen who were under the age of 21 at a large mid-western land grant university. Data from 820 students were used in his analysis. Students completed a questionnaire consisting of 98 Likert-type items which ultimately measured 14 independent variables: grades, practical value, development, routinization, instrumental communication, participation, integration, courses, distributive justice, campus organizations, opportunity, marriage, satisfaction, and intent to leave. Data from institutional registration records were added to indicate whether each student in the sample returned for the fall and/or spring semesters of the following academic year. Bean (1980) hypothesized that certain variables would influence satisfaction, intent to leave, and dropping out in a causal sequence. His analysis ranked nine variables for their total causal effects. From strongest causal effect to lowest, these variables were: intent to leave, grades, practical value, opportunity, marriage, satisfaction, campus organizations, courses, and participation. His findings suggest that student retention behavior is very similar to employee behavior, but his study is important more for his methods than his findings. This was one of the first efforts to incorporate causal modeling into the study of student attrition.

Survival analysis, a statistical tool used to describe the duration between events, is yet another method that has been used to study college student graduation. Chimka, Reed-Rhoads, and Barker (2007) used Cox proportional hazards modeling to analyze the survival patterns of 429 undergraduate students who entered an engineering program as freshmen at a large research university. This study is important because it examined data on the cohort of students for six-and-a-half years. Hazard ratios greater than one equate to an increase in the likelihood of graduation. The researchers selected this particular method because significant factors could be tested in the same way they are tested with linear regression, and the model allows predictors to be dependent upon time, unlike logistic regression. As these researchers acknowledge, there are a number of factors that can vary during a student's period of enrollment. Major area of study and grade point average are two variables that fall into the time varying category. The time invariant factors examined in this study included gender, in-state residence, socio-economic status (identified as percent of owner-occupied housing in the student's high school ZIP code area), population of hometown, and ACT and SAT scores. This study confirmed the significance of standardized math test scores, gender, and Science ACT scores in predicting likelihood of graduation among engineering students, but it did not confirm any interaction effects among predictors. The researchers also concede that they were forced to drop some variables because the analysis method requires independence of predictors. This would be a disadvantage when modeling graduation using hazard analysis since some variables found to be correlated with persistence are not independent when measured over time.

Guillory (2008) also used discrete-time hazard analysis to look at retention patterns for a cohort of first-time college students, but his study involved a much larger sample of individuals who were enrolled at a four-year university beginning in the year 1999 (n = 3, 072). These data came from the National Longitudinal Survey of Youth, 1997. He tested both a simple discrete-time hazard model and a two-level model that took into account differences between schools since the data came from students attending a variety of institutions. School type was found to be significant, where students who attended private universities had a greater risk of not returning each year. Time indicators were also found to have a significant impact on the risk of attrition, where the risk of not returning to the university increased each year that a student was enrolled. Ethnicity was not found to have a significant impact on retention in the multi-level model nor was gender. However, in the individual-level discrete-time hazard model ethnicity and gender were found to have a significant impact on the risk of attrition. This study found that white students had a greater risk of not returning to a university the next year than non-white students, and male students were less likely to return than female students.

Mohn (2006) compared three techniques to determine the relative advantages and disadvantages for analyzing student persistence for first-time full-time undergraduates for their first five semesters in college. Independent variables were similar to those tested in studies already mentioned, and parameter estimates for the models tested were generally similar to prior research. The techniques examined were (a) logistic regression, (b) discrete-time hazard modeling (survival analysis), and (c) latent growth analysis using a structural equation modeling (SEM) framework. He found that all three methods provided similar odds ratios for predicting a student's persistence from one semester to the next. While latent growth modeling allows for testing complex theories and questions, survival analysis seems to provide the simplest way to estimate the differential effects of time-varying predictors. This study is important for several reasons. First, persistence in this study is defined as completion of coursework in a given semester as opposed to mere enrollment, which is the more traditional definition of retention. Second, it shows that different techniques can be successfully applied to studies that explore student activity over time as it relates to persistence.

Survival analysis, a class of statistical methods that allows researchers to study both the occurrence and timing of events (Allison, 2010), has also been used for predicting attrition (Chimka, Reed-Rhoads, & Barker, 2007; Mohn, 2006). This framework is advantageous for studying degree completion because it allows the researcher to account for covariates that are time-dependent (i.e., characteristics such as financial need/aid and academic progress that change from year-to-year) and for students who remain enrolled throughout the period of study but do not graduate. These students do not drop out of school, but they fail to graduate within the six-year period covered by the IPEDS Graduation Rate Survey (GRS). In survival analysis terms, these cases are referred to as *censored* (Allison, 2010). The hazard function, represented below, is the most common method for explaining the distribution of events across discrete periods of time (e.g., academic years).

$$h_j = \Pr[T = j \mid T \geq j]$$

T is a discrete random variable that indicates the time period when an event (e.g., graduation) occurs, and h_j is the probability of experiencing the event in time period j (e.g., fourth year of enrollment) given that it was not experienced before j (i.e., in the first three years of enrollment) (Muthén & Masyn, 2005). Maximum likelihood estimation is the most common approach to obtaining hazard probabilities for a population. In discrete-time survival models, the probability of observing the pattern of occurrences of an event in the data is expressed by the likelihood function. Discrete-time survival can be incorporated into an SEM framework by estimating the hazard probabilities for each time period. This can be done simultaneously through a system of logistic models (Bauldry & Bollen, 2009). The diagram in Figure 3 is an example of a discrete-time survival analysis model.

> Each variable u represents whether or not a single non-repeatable event has occurred in a specific time period. The value 1 means that the event has occurred, 0 means that the event has not occurred, and a missing value flag means that the event has occurred in a preceding time period or that the individual has dropped out of the study. The factor f is used to specify a proportional odds assumption for the hazards of the event. (Muthén & Muthén, 2010, pp. 133-134).

```
TITLE:     this is an example of a discrete-time
           survival analysis
DATA:      FILE IS ex6.19.dat;
VARIABLE:  NAMES ARE u1-u4 x;
           CATEGORICAL = u1-u4;
           MISSING = ALL (999);
ANALYSIS:  ESTIMATOR = MLR;
MODEL:     f BY u1-u4@1;
           f ON x;
           f@0;
```

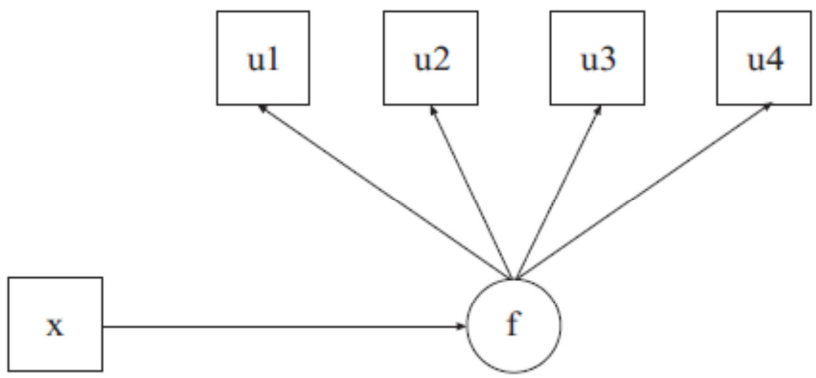

Figure 3. Example of discrete-time survival analysis in a structural equation model (SEM) framework (Muthén & Muthén, 2010, p. 133)

To summarize, a variety of statistical methods have been used to analyze the factors that influence college student persistence. Logistic regression and multiple linear regression are, by far, the most common methods of analysis. These methods focus on the relative importance of different predictors and the overall explanatory power of the combination of variables in terms of likelihood of persistence or time to graduation (Arredondo & Knight, 2006; Astin, 2005; Braxton, Milem, & Sullivan, 2000; Bringle, Hatcher, & Muthiah, 2010; Dey & Astin, 1993; Gross, Hossler, & Ziskin, 2007; Lewallen, 1993; Terenzini & Pascarella, 1978). Other methods include the use of models matching student characteristics to institutional characteristics (Cragg, 2009) and the application of causal models similar to those developed to predict employee turnover in the workplace (Bean, 1983). Latent growth analysis, using a structural equation modeling (SEM) framework, appears to provide versatility for understanding the paths and relationships between predictors for student retention over the first two years of enrollment (Mohn, 2006), so it stands to reason that the technique could be applied a longer process where students may take six years or more to complete a degree. In essence, survival analysis using an SEM approach allows the researcher to apply Astin's (1991) I-E-O model to compare both time-invariant student characteristics and time varying environmental factors to determine whether there are patterns that can provide the institution with information about the factors that have the greatest influence on persistence at different points in the degree completion process.

Service-Learning as an Environmental Factor for Students

Empirical studies on the impact of service-learning were relatively scarce when service-learning became popular as a pedagogical approach in the 1990s (Astin & Sax, 1998; Eyler, Giles, & Braxton, 1997). In an effort to build the body of scientific research on the benefits of service-learning, Markus, Howard, and King (1993) conducted an experimental study to investigate the effects of integrating service-learning into a large undergraduate political science course at the University of Michigan ($N = 89$). The course met twice a week for a 50-minute lecture. The third meeting class meeting was broken into eight smaller discussion sections, two of which were randomly assigned as "community service" sections (the treatment group). Students in the service-learning sections ($n = 37$) engaged in 20 hours of service with a designated community agency during the course of the semester. At the end of the semester, they prepared short reflective papers and presentations based on their experiences. The control group ($n = 52$) consisted of the other six sections, which used traditional instructional strategies to discuss the readings and lectures. Students in the control group were assigned papers that required the equivalent of 20 hours or research and writing. Students had no knowledge about the experiment during course registration, and, after the course began, they were not allowed to transfer from a community service section to a traditional discussion section or vice versa. The treatment and control groups were similar with respect to academic and demographic characteristics as well as desire to take the course. Based on pre-course and post-course surveys, students in the service-learning sections of the course were significantly more likely than those in the traditional discussion sections to report that they had performed up to their potential in the course, had learned to apply principles from the course to new situations, and had developed a greater awareness of societal problems. Course grades were also significantly higher for students in the service-learning sections, showing that objective measures provide evidence of academic benefit along with self-report measures.

A similar study was conducted by Osborne, Hammerich, and Hensley (1998) with four sections of an undergraduate pharmacy communications course at a small private university. Students in two sections of the course ($n = 48$) were assigned to a service-learning project, while students in the other two sections ($n = 44$) completed a traditional research project. Assignment of the sections was random. Pre- and post-test measures were administered in the form of self-report instruments to assess student self-esteem, cognitive complexity, social competency, self-perception, self-concept, and ability to form associations as part of creative thinking. The written work that students completed as part of the course was also assessed, and the groups were compared at the beginning and end of the semester. Since the sections were randomly assigned, students in the service-learning group were similar on each measure to students in the traditional research sections. At the end of the semester, students in the service-learning sections showed significant positive gains on all measures, and their scores were significantly higher than students in the traditional research sections. Non-service-learning participants showed almost no change from the beginning of the semester to the end, except on the self-perception and cognitive complexity measures, where their scores actually decreased. The authors are careful to point out that the measures used in this study were somewhat specific to the course objectives and the professional expectations of pharmacy preparation programs, but the study is important because it provides evidence that service-learning can enhance learning of course content.

Strage (2000) conducted an *ex post facto* study which compared course assessments for students in an introductory child development course over a period of five academic semesters ($n = 477$). Of this sample, approximately 65% ($n = 311$) were enrolled in the course prior to the institution of a service-learning requirement. These students comprised the non-service-learning group. The service-learning students ($n = 166$) were enrolled during the last two semesters. The same instructor taught the course each semester where data were included in the study. During the semesters that were studied, the instructor used the same textbook, and the lectures covered the same content. The exams administered each semester were also virtually identical. The primary difference between the groups was the experiential learning component of the course. The measure of interest in this study was student performance (i.e., scores) on the three course examinations each semester. Two midterm exams each semester were non-comprehensive and included both multiple choice items and short essay questions. The final exam each semester consisted of integrative essays drawing on content from the entire semester. All exams had been graded using a detailed rubric, but the researcher recognized the possibility of bias, so a teaching assistant was employed to score a random sample of essays from the exams using the same rubric. The exams for second scoring were evenly split between service-learning and non-service-learning students. Interrater reliability between the scorers was very high. A comparison of test scores revealed that scores on the earliest midterm exam were not significantly different between groups. On the second midterm exam, scores for the multiple choice items were similar between groups, but the service-learning students scored significantly higher on the short essays. This phenomenon continued with the final exams, where the scores of service-learning students were also significantly higher than students in the non-service-learning cohort. These findings confirm those of earlier studies which found positive learning outcomes for students enrolled in service-learning.

Batchelder and Root (1994) also acknowledged the dearth of empirical evidence on the impact of service-learning. They used experimental methods to investigate the effects of characteristics of service-learning experiences on the cognitive development of undergraduates at a small, mid-western liberal arts college. Their sample was similar in size to that of Markus, Howard, and King (1993). Participants (n = 48) in service-learning courses were compared with a control group of students (n = 48) who were enrolled in courses which were similar in content and taught by the same instructors, but without the service-learning components. Students in both groups completed pre-test and post-test measures where they wrote responses to social situations. Responses were scored by student assistants, and inter-rater reliability was high. In addition, service-learning students kept journals and completed an evaluation of service learning survey. Factor analysis was used to reduce scores on the evaluation to three dimensions, which were then tested as predictors for the outcome variables using hierarchical multiple regression. Paired t-tests were conducted, and service-learning students showed significant gains on certain cognitive dimensions. Service-learning students also showed significant increases in pro-social decision making, pro-social reasoning, and identity processing.

Eyler, Giles, and Braxton (1997) attempted to fill another gap in research on service-learning with a national comparative study that examined whether there are differences in the attitudes, skill, perceptions, and values of students who choose to participate in service-learning and those who do not. They also investigated whether service-learning has an impact on those attributes over the course of a semester. Their study included students at 20 institutions during the spring of 1995, and it involved a comparison of pre- and post-course survey responses from students who participated in service-learning (n = 1140) and students who did not choose service-learning classes (n = 404). The outcomes of interest in this study were citizenship confidence, citizenship values, citizenship skills, and social justice, and the measures were based on student self-assessment. Pre-test comparisons showed that the service-learning group differed significantly from their non-service-learning counterparts with respect to the measure of interest. Specifically, students who chose to participate in service-learning had higher scores on each outcome variable before the service-learning experience tool place. Since the groups were not randomly assigned, equivalence was achieved by statistically controlling for the pre-test difference, as well as controlling for other student characteristics that might be associated with the outcomes, specifically gender, race, parental income, age, and previous volunteer experience in college. Results of the analyses showed small but significant positive gains for the service-learning group on many of the outcome measures following just one semester. Several background characteristics were also important predictors in the model. Previous college participation in service was positively associated with larger gains, suggesting that continued service involvement through one's college career is beneficial. Gender was also an independent predictor for several outcomes, with women showing higher gains regardless of their group.

Astin and Sax (1998) furthered the body of knowledge with a large national study that compared entering freshman and follow-up data collected from 3,450 students attending 42 institutions with federally funded community service programs. Participants had completed the

Cooperative Institutional Research Program (CIRP) Freshman Survey during the period of 1990-1994 and the College Student Survey (CSS), a longitudinal follow-up, in 1995. Of the sample, 2,309 students had participated in some sort of service activity during the 1994-95 academic year, while 1,141 non-participants made up the control group. Analysis was conducted using blocked stepwise regression (i.e., hierarchical regression) to control for institutional environment variables and individual student characteristics at the time of college entry, particularly the predisposition to engage in service, factors which may influence student outcomes. Results show that participating in service is significantly correlated with life skill development and sense of civic responsibility. Ten academic outcomes are also positively influenced by participation in service, but the size of the effect is generally smaller than that of civic or life skills.

In a subsequent study, Vogelsang and Astin (2000) looked at a much larger sample of students (n = 22,236) who completed the CIRP CSS in 1998. Their purpose was to compare the effects of course-based service-learning with generic community service and with outcomes for students who participated in no service at all. They investigated a variety of outcomes, three of which were concerned with academic achievement: GPA, perceived growth in writing skills, and perceived growth in critical thinking skills. The outcome measures included values and beliefs, leadership, and future plans. Using data from the students' earlier CIRP freshman survey responses, the study controlled for institution type, for variables previously shown to predict service involvement (including gender), and for several demographic characteristics that tend to be associated with the outcome measures: religious preference, parental education and income, and race. Both groups of students who participated in service (service-learning and generic community service) showed greater self-reported gains on each of the academic outcome measures than students who participated in no service at all, but, with respect to GPA and writing skills, the effect of service-learning was much stronger than that of generic community service. These results are important because they contrast with the findings on the outcome measures related to values and beliefs, leadership, and future plans, where generic community service shows effects that are similar to those of service-learning. This study is noteworthy because it provides evidence of the academic benefits of service learning in a large sample of students across multiple institutions.

Bringle, Hatcher, and Muthiah (2010) recently investigated whether student enrollment in a fall service-learning course is related to self-reported intentions at the end of the semester to stay on campus and/or actual retention the following fall. Participants were 805 students enrolled in 22 courses taught by faculty at 11 institutions in Indiana. Of the sample, 534 students were enrolled in service-learning courses, while the remaining 271 were enrolled in courses that did not involve service. Participants completed pre-course questionnaires, which consisted of demographic items, intention to graduate from the campus, and intention to re-enroll at the campus. Post-course questionnaires also asked about intentions to graduate and intentions to re-enroll and included additional items related to the quality of the learning environment. Institutions provided data on actual re-enrollment. Multiple regression analysis was used to test the role of post-course intentions in mediating the relationship between pre-course intentions and actual re-enrollment. The study found a positive relationship between enrollment in service-learning and intentions to continue at the same campus, even when pre-course intentions were covaried out. This relationship was mediated by the higher quality of service-learning courses. The same relationship was found between enrollment in service-learning course and actual re-enrollment at the same campus the following year, but the relationship does not persist after controlling for pre-course intentions.

The most comprehensive look at the impact of service-learning on students was a recently published meta-analysis of 62 studies published between 1970 and 2008 (Celio, Durlak, & Dymnicki, 2011). The researchers analyzed published studies that evaluated service-learning programs meeting the same definition used for the research that this study proposes. They included only studies which (a) involved a control group, (b) included sufficient information to calculate effect sizes, and (c) evaluated the service-learning experience as the sole intervention. Although this study included research on elementary and secondary students too, 68% of the studies involved service-learning in postsecondary settings. The analysis evaluated the findings of each study in five outcome areas: attitudes toward self, attitudes toward school and learning, civic engagement, social skills, and academic achievement. Of the five areas, academic achievement had the largest effect size at 0.43, 95% CI [0.29, 0.58]. This measure was significantly higher than the effect size for any of the other outcome areas, which ranged from 0.27 to 0.30 and did not differ significantly from each other. The findings from this study provide strong evidence for the positive academic benefits of service-learning on students, but they also support the case for additional research. Of the 62 studies included in the analysis, 48% appeared after the year 2000, and only 67% appeared in published journals. The results also indicate that only 17 studies actually measured academic outcomes at all.

Because the literature related to service-learning outcomes is still developing, there are no studies that evaluate this educational practice for its effect on degree completion, and only one study could be found that measures its influence on retention (Bringle, Hatcher, & Muthiah, 2010). However, the research on other high-impact educational practices that affect persistence and degree completion is compelling (Braxton, Milem, & Sullivan, 2000; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; Nelson Laird, Chen, & Kuh, 2008); and service-learning has been positively associated with cognitive gains and academic achievement in a variety of settings (Astin & Sax, 1998; Batchelder & Root, 1994; Celio, Durlak, & Dymnicki, 2011; Eyler, Giles, & Braxton, 1997; Markus, Howard, & King, 1993; Osborne, Hammerich, & Hensley, 1998; Strage, 2000; Vogelsang & Astin, 2000). Since degree completion is ultimately influenced by academic progress and achievement, investigating the effects of service-learning on persistence in a more intentional way seems the next logical step in contributing to the body of knowledge.

Summary and Synthesis

This review of the literature provides an overview of the factors that have been correlated with the retention and persistence of undergraduate students. It also summarizes the variety of methods that have been used to analyze student and institutional data in an attempt to understand these factors and predict which students will persist to graduation. In addition to student and institutional characteristics, the educational practices employed by a colleges or universities have been shown to influence graduation rates. Effective use of high impact educational practices tends to be associated with higher graduation rates. As a pedagogical approach, service-learning is a relatively new field, and the research in this area has been limited. Much of the literature surrounding the benefits of service-learning is based on survey data alone or survey data combined with minimal institutional data. Student outcomes most often cited relate to positive effects on students' general personal and cognitive development. The areas of civic awareness, civic responsibility, engagement, and learning are often investigated simultaneously. A variety of studies have looked at the positive benefits of single service-learning courses. These studies tend to have small samples and are frequently limited to a single semester. Additional studies have looked at service-learning in large national samples, but these studies have not focused on degree completion as an outcome. Few studies have investigated outcomes for a broad spectrum of students who participate in service-learning courses across an institution, and this researcher could find no studies which have explored whether participation in service-learning has an impact on an undergraduate student's likelihood of graduating. Finally, there appears to be no research into whether the timing of service-learning courses in a student's enrollment makes a difference. In other words, when does service-learning provide the greatest academic benefit to undergraduate students? Does service-learning have a greater influence on degree completion in the first three years of enrollment or in the fourth, fifth, or sixth year? This study attempts to fill those gaps.

Chapter 3

Methodology

Research Questions

There is a need for additional empirical research on the relationship between service-learning experiences and academic outcomes for undergraduates. Given the current national focus on degree completion in particular, any exploration of these factors should be longitudinal in nature and should focus on the patterns of student persistence that lead to completion. The goal of this study was to investigate the impact of service-learning, if any, on persistence and degree completion. The following research questions were addressed:

1. How do students who complete service-learning courses differ from students who do not participate in service-learning?
2. In models that include service-learning as a covariate, is discrete-time survival analysis more effective for predicting degree completion than logistic regression?
3. How do the predictors and the parameter estimates differ between models?
4. Is service-learning a significant predictor for degree completion in either model?
5. For students who complete their degree within six years, is service-learning predictive of time to completion.

The researcher had several hypotheses. She anticipated that students who completed service-learning courses would be more heavily concentrated in major areas of study such as humanities and sciences, education, and nursing. Beyond that expectation, there were no other presuppositions related to question one. With respect to question two, the researcher hypothesized that logistic regression would be as effective as survival analysis at predicting the likelihood of degree completion within six years. However, it was expected that discrete-time survival analysis would allow the researcher to explore and potentially uncover patterns in completion that would not be revealed by simple logistic regression. For this reason, she expected the strength of the predictors and parameter estimates to differ between models. The researcher had no hypotheses for questions four or five.

Design

This investigation utilized a quantitative nonexperimental *ex post facto* research design to investigate the influences of the independent variables on year-to-year persistence and degree completion at a large, urban public research university in the mid-Atlantic region of the United States. Institutional data were provided by the university's Office of Planning and Decision Support. Files were downloaded from the university's central records system, a database which includes all student information maintained electronically by the offices of admissions, financial aid, and records and registration. For purposes of confidentiality, all variables that could uniquely identify individual students (i.e., student names, email addresses, social security numbers, and university ID numbers) were removed from the files by institutional research staff prior to transmittal to the researcher. The database key, a unique numeric identifier that does not correspond with personal information, remained in each file and allowed the researcher to link longitudinal data for each student.

The design was chosen specifically because the data utilized are routinely available at most postsecondary institutions. All colleges and universities that receive federal funding for student financial aid are required to complete the IPEDS Graduation Rate Survey (GRS) annually, but, in the researcher's experience, analysis rarely goes beyond calculating the percentage of students in each cohort who graduate within the periods requested by the survey. Use of these data to answer more compelling questions about predictors for graduation, including specific institutional programs and practices, could serve as a model for institutional researchers who wish to examine the persistence of their own students in a more robust manner.

Population and Sampling

The population for this study was degree-seeking undergraduate students at a large public urban research university in the mid-Atlantic region of the United States. During the fall 2005 semester, total enrollment for the institution was 29,349, and 18,691 of these students were degree-seeking undergraduates. Overall, 59% of undergraduate students were white, non-Hispanic, 40% were men, and 35% received need-based financial aid. The six-year graduation rate for freshmen entering the university in 1998 was 41%. For each subsequent cohort, the graduation rate increased by two percentage points. For the students who entered in 2003 and 2004, the graduation rate was 51%, a figure that is slightly above the national average for four-year public institutions. Community engagement is an integral component of the university's institutional mission, and service-learning plays an important role in the university's newly adopted strategic plan. Service-learning courses were first offered at the university in 2001. Over the past ten years, the number and diversity of courses has grown steadily. Designated service-learning courses are regularly taught in many disciplines throughout the university, but the preponderance tends to be upper-level courses, and courses are predominantly clustered in the arts, humanities, and social sciences, including education. In addition, the majority of students enrolled tend to be upperclassmen (juniors and seniors).

The sample for this study included all full-time first-time undergraduate students who were part of the fall 2005 cohort and for whom the university currently maintains verifiable student records (n = 3,458). According to information available from the institution's website, the fall 2005 cohort included 98% of the entering freshmen from that semester; the remaining

2% began as part-time students and are not included in the IPEDS Graduation Rate Survey (GRS) calculation. Records for 16 students in the original cohort file could not be located in the central records database by university staff, so these students were omitted from the files provided by the institution. It is assumed that these 16 individuals did not complete their first semester of enrollment and would be considered non-completers in the GRS calculation. Three additional individuals with admissions data had incomplete enrollment data, course data, or degree information. These individuals were included in the sample, so descriptive statistics for some characteristics reflect a slightly smaller sample size than the total. The demographic characteristics for this study's sample were similar to those of the overall degree-seeking undergraduate population at the university at that time. Forty percent were men, 58% were white and non-Hispanic, and 90% were in-state residents at the time of matriculation. The average high school GPA for the cohort was 3.24 (on a four-point scale), and the average combined SAT score for the verbal and mathematics tests was 1077. Fifty-nine percent had documented financial need based on their FAFSA (Free Application for Federal Student Aid) at some point during the course of their enrollment, and 29% received Pell Grant support for at least one semester. Seventy-eight percent received financial aid, which included gifts and other support that was not based on financial need. Detailed descriptive statistics for the sample can be found in Table 1.

Table 1

Characteristics of Students in the Sample (N = 3,458)

	n	%	*M*	*SD*
Gender				
Male students	1373	40		
Female students	2084	60		
Race/Ethnicity				
White	1989	58		
Black or African American	690	20		
Hispanic or Latino	123	4		
Asian	413	12		
Other	243	7		
Residency				
In-State	3108	90		
Out-of-State	350	10		
Academic Characteristics Upon Matriculation				
High School GPA			3.22	.51
SAT Verbal Score			541	84.4
SAT Mathematics Score			535	78.5
Degree Completion Within Six Years				
Non-completers	1597	46		
Completers	1861	54		
Financial Aid				
Students with No Financial Aid	763	22		
Cumulative Financial Need (in dollars) for Students who Applied for Aid	1953	56	$31,489	$26,787
Total Aid Received (in dollars) by Students with Aid	2695	78	$28,395	$26,392
Number of Semesters Supported for Students Receiving Pell	990	29	4.65	3.01

Variables

Variables used in this study were limited to data that are routinely collected and/or maintained by the university. Independent variables are those that have previously been studied and found to be correlated in some way with persistence, degree completion, or other measures of academic success. Table 2 provides a concise list of the measures with references to the literature that describes their relationships with the outcome of interest. Predictor variables fell into four basic categories: (a) student demographic and academic characteristics upon matriculation, (b) course completion data at the university during the six-year period following matriculation, (c) academic progress indicators for each of the six years, and (d) financial need and aid awarded each year. Predictors vary depending on the research question being addressed and the method of analysis.

Degree completion is the primary outcome of interest. It is a dichotomous variable that identifies the students who were awarded a bachelor's degree at any point during the six-year period following matriculation. Time to degree (in years) was also calculated for each student who was awarded a bachelor's degree and analyzed as the outcome variable for the fifth research question.

Table 2

Measures Selected for this Study with References to Prior Research

Variable	References to the Measure in Prior Research	Direction of Reported Correlation with Persistence/Completion
Gender	Arredondo & Knight, 2006; Astin, 2005; Attewell, Heil, & Reisel, 2010; Chimka, Reed-Rhoads, & Barker, 2007; Guillory, 2009; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978	Conflicting evidence; Female students more likely to persist than male students in some studies
Race/Ethnicity	Arredondo & Knight, 2006; Astin, 2005; Attewell, Heil, & Reisel, 2010; Guillory, 2009; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978	Conflicting evidence; White and Asian students more likely to be completers than black or Hispanic students in most studies
High School GPA	Astin, 2005; Attewell, Heil, & Reisel, 2010; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978	Positive correlation between HS GPA and persistence
SAT Scores	Arredondo & Knight, 2006; Attewell, Heil, & Reisel, 2010; Chimka, Reed-Rhoads, & Barker, 2007; Lewallen, 1993; Mohn, 2006	Positive correlation between SAT scores and persistence
In-State vs. Out-of-State Residency	Arredondo & Knight, 2006; Chimka, Reed-Rhoads, & Barker, 2007	Out-of-state students less likely to persist
Financial Need or Ability to Pay	Astin, 2005; Attewell, Heil, & Reisel, 2010; Bowen, Chingos, & McPherson, 2009; Gross, Hossler, & Ziskin; 2007	Inability to pay positively correlated with attrition

Variable	References to the Measure in Prior Research	Direction of Reported Correlation with Persistence/Completion
Financial Aid	Astin, 2005; Attewell, Heil, & Reisel, 2010; Bowen, Chingos, & McPherson, 2009; Gross, Hossler, & Ziskin; 2007; Mohn, 2006	Aid that offsets need positively correlated with persistence
Specific Academic Major or Undeclared	Arredondo & Knight, 2006; Lewallen, 1993; Terenzini & Pascarella, 1978	Conflicting evidence; Undeclared students less likely to persist in some studies
College GPA	Mohn, 2006; Terenzini & Pascarella, 1978	GPA positively correlated with persistence
College Credits Earned	Earning a bachelor's degree at the institution for this study requires completion of a minimum of 120 credit hours. Although this variable is not specifically mentioned in the literature reviewed, it serves as a measure of progress toward a degree, which the researcher believes is critical in understanding year-to-year persistence.	
Service-Learning Participation	The only study reviewed in this proposal that specifically relates service-learning to persistence is Bringle, Hatcher, and Muthiah (2010). However, a variety of studies have found positive correlations between service-learning and cognitive skills and/or academic achievement (Astin & Sax, 1998; Batchelder & Root, 1994; Celio, Durlak, & Dymnicki, 2011; Eyler, Giles, & Braxton, 1997; Markus, Howard, & King, 1993; Osborne, Hammerich, & Hensley, 1998; Strage, 2000; Vogelsang & Astin, 2000), which ultimately affect degree completion.	Positive correlations between service-learning and cognitive skills and/or academic achievement

Analysis

The researcher began the analysis process with five data files that were obtained from the university's central records database by institutional staff. One file contained the variables related to demographic and academic characteristic for each student at the time of admission. The second file contained data for courses completed by these students for each semester during the six year period. The third file contained academic progress data on the students for each semester during the six year period. The fourth file contained financial aid data, and the fifth file contained data on degrees awarded to students in the cohort. A sixth file was constructed by the researcher identifying service-learning courses for each semester during the time frame of the study. This file was created by cross-referencing a list of designated service-learning courses from the university's Office of Records and Registration with records from the university's Service-Learning Program. During the first two or three years of the time period covered by this study, oversight of the course designation process was not as meticulous as it is currently. This extra step was necessary to ensure that all service-learning courses identified for use in this analysis met the true guidelines for service-learning course designation. Course designation requires that students complete a minimum of 20 hours of service during the semester, and it requires documentation that the instructor incorporates reflection on the service into the course activities or assignments. The six data files were cleaned and merged using SAS to yield a single longitudinal record for each student, which was used for descriptive statistics, group comparisons logistic regression, and multiple linear regression. The dataset was exported as a text file for survival analysis using a structural equation modeling (SEM) framework in Mplus. Variables included in each of the analyses are detailed in Table 3 with references to the model(s) in which they were tested.

Descriptive statistics and group comparisons. From the final dataset, descriptive statistics were generated, and comparisons were made between students who participated in service-learning and those who did not. Specifically, continuous variables were tested using independent samples *t*-tests, and categorical variables were tested using Chi square analyses and *z*-tests for difference of proportion. These tests were used to answer the first research question.

Models for predicting degree completion. In order to answer questions two through four, several models were tested. The first model (Model 1) used logistic regression to predict a student's likelihood of graduating. Predictors included entering student characteristics and cumulative data related to academic progress and financial aid for the last semester that each student was enrolled. A dichotomous variable was used to indicate whether each student had completed service-learning courses at any point during his/her enrollment. The second analysis included the same covariates, but the researcher ran the regression by group according to the student's academic discipline at the time of graduation or last enrollment. Since the researcher suspected potential differences in the number of opportunities for students to take service-learning courses in different disciplines, this approach was added in order to compare model fit and parameter estimates between major areas of study. Results from these analyses, as well as a comparison of overall graduation rates between majors, were used to inform a decision to exclude students in health professions and social work, as well as undeclared students, from further model analysis. Model 1 was then re-analyzed with the reduced sample (n = 3,038). Model fit and parameter estimates for each covariate were reviewed, and a more parsimonious model was tested and defined (Model 2).

The third model (Model 3) also used logistic regression, but continuous variables represented the number of service-learning credit hours and non-SL credits each student earned during his/her enrollment. These covariates replaced the dichotomous indictor for identifying SL students and total credits earned. This substitution was tested because some students in the cohort enrolled in service-learning courses but did not earn credit for them, presumably because they failed the courses. Model 3 was tested in an effort to understand whether successful completion of service-learning courses has a different influence on likelihood of degree completion. The other covariates were identical to Model 2.

The fourth model (Model 4) was tested using discrete-time survival analysis with the reduced sample suggested by analysis of Model 1. Initial variables (Model 4a) included both the time invariant student characteristics and the time variant year-to-year data for academic progress and financial aid, rather than the cumulative data used in the logistic regression models. Retention and attrition of undergraduate students during the first two years have been studied extensively (Astin, 1991; Braxton, Milem, & Sullivan, 2000; Gross, Hossler, & Ziskin; 2007; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978; Tinto, 1975, 1993, 2003), so this model focuses exclusively on the cohort in years three through six. Since the outcome of interest is degree completion, and no student graduated in the first two years, academic progress indicators for years one and two were summed and included as a single time-invariant predictor. Only students who persisted in years three though six were included in the analysis (n = 2,402). A visual representation of the initial model is displayed in Figure 4.

During testing, the initial model (Model 4) failed to converge despite a number of adjustments in the starting values for certain parameters. Error messages indicated that the convergence problem was due to the parameter for year-to-year institutional grade point average (GPA_Y*n*). Bivariate correlations indicated that GPA is highly correlated by individual across time, with Pearson r values ranging from .95 to .99, so the researcher made the decision to include each student's first semester GPA as a time-invariant predictor instead of retaining the year-to-year values, since they do not appear to vary significantly across time periods. The researcher also standardized all variables with average values greater than ten in an effort to facilitate convergence. This variation of the model converged successfully, but there were still errors with standard errors and parameter estimates. New error messages pointed to possible problems with year-to-year values for financial aid. The researcher ran bivariate correlations for NEED_Y*n*, AID_Y*n*, and PELL_Y*n*. Correlations among the year-to-year values for each of these variables were significant, but aid correlations were the highest, with Pearson r values ranging from .33 to .82, so the researcher adopted the same strategy and used the cumulative aid value (AID_CUM) as a time-invariant predictor instead. This change was equally unsuccessful, with messages indicating that the standard errors of the model parameter estimates may not have been trustworthy for some parameters due to a non-positive definite first-order derivative product matrix. The error further indicated that the problem could have been due to the starting values of the parameters or it could have been an indication of model nonidentification. As a result, the researcher adopted a different strategy for model testing. Covariates were removed from the model and reintroduced one-by-one, based on the significance of parameter estimates in the logistic regression models, and the starting values for variances were adjusted until a viable model was established (Model 5). In initial testing of Model 5, variances for the time-varying predictors were constrained to be equal from year-to-year in an effort to facilitate convergence. In further testing, the researcher allowed Mplus to estimate the variances, which revealed differences in the significance of these parameters from year-to-year.

The logistic regression models and the final survival analysis model were then compared to determine (a) which model is most effective for predicting degree completion, (b) which of the covariates have the greatest influence on degree completion in each model, (c) how the predictors and the parameter estimates differ between models, and (d) whether service-learning is a significant predictor for degree completion in any of the models., and (e) whether service-learning is predictive of time to completion for those students who do finish the bachelor's degree in six years.

Predicting time to completion. Research question five was answered by testing a single multiple regression model (Model 6) against the subset of data for students who completed a degree during the six-year period of the study. Given the similarities in model fit between Models 1, 2, and 3, the researcher chose covariates that were the strongest in predicting degree completion, with the expectation that the same variables would also show significance in predicting the time it takes a student to earn that degree. In order to preserve additional information provided by the variable reflecting amount of service-learning that students completed (SL credits earned), predictors were identical to Model 3, but the outcome variable (time to degree in years) was continuous, rather than dichotomous.

Table 3

Variables Included for Analysis in Each Model

Variable Name	Values and Notes	Level of Measurement	Time Type	Model 1	2	3	4	5	6
DEG_IND	Degree Completion Indicator. 1 = completed during six-year period, 0 = did not complete	Dichotomous	Invariant	y	y	y			
DEG_TIME	Time in Years to Earn Degree (for students who completed within 6 years).	Continuous	Invariant						y
FEMALE	Gender: Female (ref group: male)	Dichotomous	Invariant	X_1			X_1		
RACE_BLK	Race/Ethnicity: Black (ref group: white)	Dichotomous	Invariant	X_2			X_2		
RACE_HSP	Race/Ethnicity: Hispanic (ref group: white)	Dichotomous	Invariant	X_3			X_3		
RACE_ASN	Race/Ethnicity: Asian (ref group: white)	Dichotomous	Invariant	X_4			X_4		
RACE_OTH	Race/Ethnicity: Other (ref group: white)	Dichotomous	Invariant	X_5			X_5		
OUT_STAT	Residency Status: Out-of-State (ref group: in-state)	Dichotomous	Invariant	X_6			X_6		
HS_GPA	High School GPA	Continuous	Invariant	X_7	X_1	X_1	X_7	X_1	X_1
SAT_V	SAT Verbal Score	Continuous	Invariant	X_8	X_2	X_2	X_8	X_2	X_2
SAT_M	SAT Math Score	Continuous	Invariant	X_9	X_3	X_3	X_9	X_3	X_3
NEED_CUM	Cumulative Level of Financial Need. Dollar amount calculated by the university's office of financial aid for the total time that student was enrolled (based on FAFSA).	Continuous	Invariant	X_{10}					
AID_CUM	Amount of Financial Aid Awarded. Total dollar amount awarded to the student while enrolled.	Continuous	Invariant	X_{11}					
PELL_CUM	Cumulative number of semesters student was awarded Pell grants	Continuous	Invariant	X_{12}					

Variable Name	Values and Notes	Level of Measurement	Time Type	Model 1	2	3	4	5	6
SL_IND	Service-Learning Indicator. 1 = completed at least one SL course, 0 = did not complete any SL courses.	Dichotomous	Invariant	X_{13}	X_4				
CR_T	Total Number of Credits Earned While Enrolled	Continuous	Invariant	X_{14}	X_5				
CR_SL	Total Number of SL Credits Earned While Enrolled	Continuous	Invariant			X_4			X_4
CR_NS	Total Number of Non-SL Credits Earned While Enrolled	Continuous	Invariant			X_5			X_5
GPA_CUM	Cumulative GPA at the End of the Last Semester of Enrollment	Continuous	Invariant	X_{15}	X_6	X_6		X_4	X_{15}
CR_Y1_Y2	Total Number of Credits Earned in Years 1 and 2	Continuous	Varying				X_{10}	X_5	
For Each Discrete Time Period n (Year 3, Year 4, Year 5, Year 6)									
DEG_Y*n* [a]	Degree Earned in Year *n*. 1 = degree awarded, 0 = student still enrolled, missing = student dropped out or graduated in a preceding year	Dichotomous	Varying				u^n	u^n	
NEED_Y*n*	Amount of Financial Need in Year *n* (in Dollars)	Continuous	Varying				X^n_{11}		
AID_Y*n*	Amount of Financial Aid Awarded in Year *n*	Continuous	Varying				X^n_{12}		
PELL_Y*n*	Number of semesters of Pell support in Year *n*	Continuous	Varying				X^n_{13}		
CR_SL_Y*n*	Number of Service-Learning Credits Earned during Year *n*	Continuous	Varying				X^n_{14}	X^n_6	
CR_NS_Y*n*	Number of Non-SL Credits Earned during Year *n*	Continuous	Varying				X^n_{15}	X^n_7	
GPA_Y*n*	Cumulative GPA at the End of Year *n*	Continuous	Varying				X^n_{16}		

[a] For the covariates listed for each discrete time period, *n* refers to the sequence number for the time period. For Year 3, *n* = 1; for Year 4, *n* = 2; for Year 5, *n* = 3; and for Year 6, *n* = 4.

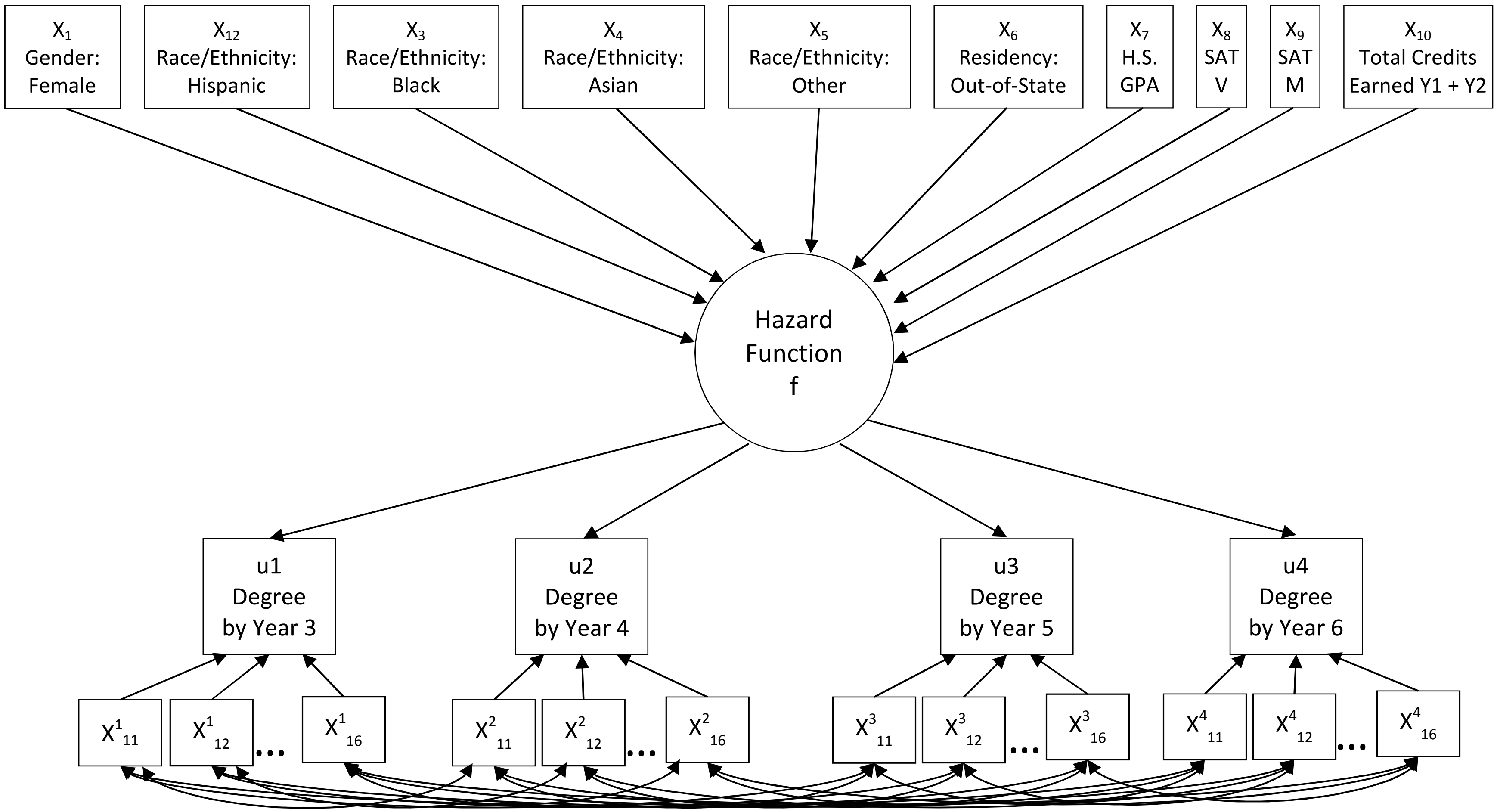

Figure 4. The initial discrete-time survival analysis model that was tested for predicting the odds of degree completion (Model 4). This model tests the effects of the time invariant student characteristics (X_1 through X_{10}) and the time varying covariates (X_{11} through X_{16}) for each year on the proportional odds assumption for the outcome, denoted as f. *Note.* The time-invariant predictors were also allowed to correlate with each other and with each of the time-varying predictors. These correlations are not displayed due to the complexity of the diagram.

Delimitations

Although the goal of this study is to contribute to the body of knowledge on service-learning, persistence, and degree completion, it is important to emphasize that results are delimited to the population of interest in this investigation. These data will only be representative of undergraduate students who entered the institution as first-time full-time freshmen in the fall semester of 2005 and graduated or left the institution prior to the fall semester of 2011.

Institutional Review Board

Prior to requesting institutional data, this study was approved by the Virginia Commonwealth University Institutional Review Board (IRB). Based on the guidelines for human subjects research, this study qualified for exempt review under Category 4: Existing data, documents, records, specimens – secondary data analysis [§46.101(b)(4)]. All data were pre-existing and were provided in such a way that students could not be identified directly or indirectly through identifiers linked to subjects at any time during the study.

Timeline

Upon receipt of IRB approval, the researcher made a request for the necessary data from the university's Office of Planning and Decision Support. The request was routed to the office of the university's Vice Provost for Strategic Enrollment Management, who serves as data steward for the records being requested. Final approval for release of the data was granted several weeks after the request was made. The IRB and data approval processes took 14 weeks total. Preparation of the data files by institutional research staff comprised another four weeks.

Cleaning and verification of the data, merging files, generating descriptive statistics, making group comparisons, and model testing took three weeks.

Chapter 4

Results

Descriptive Statistics and Group Comparisons

Service-learning courses. From the fall 2005 semester through the summer 2011 term, 490 service-learning course sections were taught at the undergraduate level, and another 47 were taught at the graduate/professional level. Of the undergraduate classes, 12% (n = 57) were lower-level courses (taught at the 100- or 200-level), while the remaining 88% (n = 433) were upper-level courses at the 300- or 400-level. Some of these course sections were cross-listed for students in different departments or programs or students at different levels, so the number of actual classes was smaller than the total number of sections, but an accurate count is difficult to determine due to the nature of the data. Table 4 displays the number of course sections taught each year of the study, and Figure 5 provides a visual representation. Of the 3,458 students in this sample, 832 (24%) took at least one service-learning class during the period of the study.

Table 4

Number of Service-Learning Course Sections Taught during Period of Study

Course Level	Year 1 2005-06	Year 2 2006-07	Year 3 2007-08	Year 4 2008-09	Year 5 2009-10	Year 6 2010-11
Lower-Level Undergraduate	7	7	8	6	12	17
Upper-Level Undergraduate	44	78	82	68	80	81
Graduate/Professional	5	4	4	6	13	15
Total	56	89	94	80	105	113

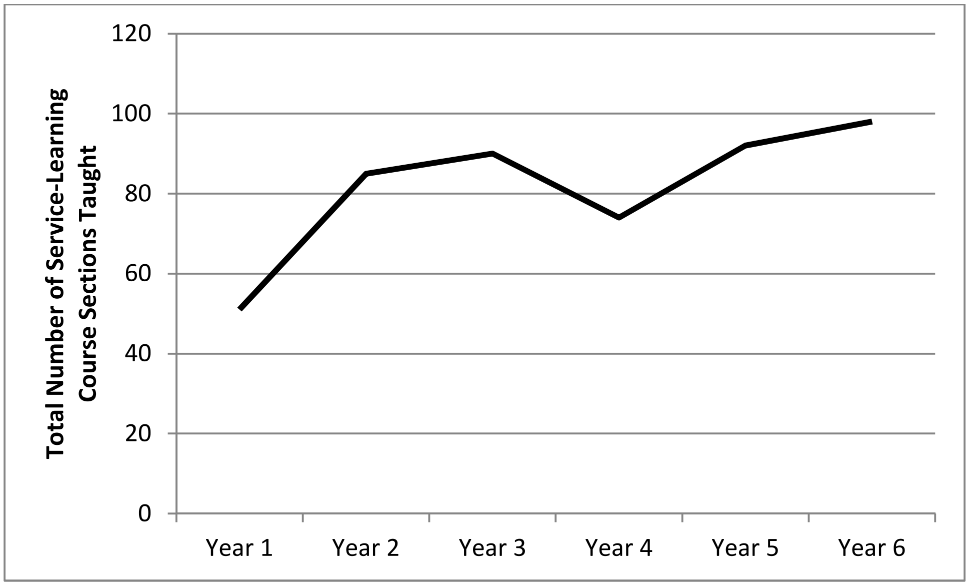

Figure 5. Number of undergraduate service-learning course sections taught during the six-year period of study.

Demographic and academic characteristics of students upon matriculation. For several demographic characteristics, the proportion of students in specific groups who took service-learning courses (SL students) differed significantly from those students who did not take service-learning courses (non-SL students). Detailed frequency distributions for each of these characteristics can be found in Tables 5. Comparisons between SL students and non-SL students are shown in Table 5. The percentage of female SL students was higher than the percentage of female non-SL students, χ^2 (1, N = 3,458) = 6.54, p = .011. Black/African American and Asian students were more likely to be SL students, while white students were less likely to have taken service-learning courses, χ^2 (4, N = 3,458) = 25.34, p = .000. With respect to their pre-college academic characteristics, SL students and non-SL students were similar. There were no significant differences in average SAT scores on either the verbal or mathematics tests, and, although the average high school GPA for SL students was significantly higher than the mean GPA for non-SL students, the effect size for this difference was small.

Table 5

Distribution of Students who Took Service-Learning Courses (n = 832) and Students who did Not Take Service-Learning Courses (n = 2,626)

Characteristic	Non-SL Students		SL Students			
	n	%	*n*	%	$\chi^2(df)$	*p*
Gender					6.54(1)	.011
Male students	1074	41	299	36		
Female students	1548	59	536	64		
Race/Ethnicity					25.34(4)	.000
White	1556	59	433	52		
Black or African American	487	19	203	24		
Hispanic or Latino	96	4	27	3		
Asian	291	11	122	15		
Other	193	7	50	6		
Residency					2.59(1)	.107
In-State	2345	89	763	91		
Out-of-State	278	11	72	9		
Major Area of Study at Last Semester of Enrollment					213.86(7)	.000
Arts	543	21	82	10		
Business	402	15	54	6		
Education	58	2	28	3		
Engineering	112	4	55	7		
Health Professions	77	3	24	3		
Humanities and Sciences	1138	43	566	68		
Social Work	25	1	7	1		
Undeclared	267	10	19	2		
Documented Financial Need					19.56(1)	.000
Students Without Need	1198	46	307	37		
Students With Need	1428	54	525	63		
Financial Aid					30.51(1)	.000
Students Without Financial Aid	637	24	126	15		
Students With Financial Aid	1989	76	706	85		

Characteristic	Non-SL Students *n*	Non-SL Students %	SL Students *n*	SL Students %	$\chi^2(df)$	*p*
Pell Grant Support					4.03(1)	.045
Students Without Pell Support	1897	72	571	69		
Students With Pell Support	729	28	261	31		
Degree Completion Within Six Years					163.51(1)	.000
Non-completers	1373	52	224	27		
Completers	1250	48	611	73		

Academic progress. Students whose major area of study was humanities, sciences, or engineering were more likely to have taken service-learning courses, while art students, business students, and those students who did not declare a major were less likely to have participated in service-learning experiences while enrolled. SL students and non-SL students differed most significantly on measures of academic progress. Students who took service-learning courses were enrolled significantly longer and earned more credit hours while enrolled (M = 115, SD = 32.3) than non-SL students (M = 81, SD = 49.9). On average, SL students were enrolled for almost ten semesters, while average enrollment for non-SL students was slightly more than seven semesters. The effect sizes for differences in earned hours and enrollment time are high. In addition, SL students had a higher average GPA (M = 2.92, SD = 0.65) than the cumulative GPA for non-SL students (M = 2.57, SD = 0.93), a difference of moderate effect size. These comparisons are displayed in Table 7.

The total number of service-learning credit hours earned by SL students ranged from 0 to 14 (M = 3.28, SD = 2.02). In the first year of enrollment, only 2% of students in the sample took service-learning courses. The percentage rose to 10% in year two, and remained constant at 9% through year five. In year six, the proportion of SL students dropped to 6%. The average SL student during year one earned 2.2 service-learning credit hours. This measure includes students who enrolled in service-learning courses but did not pass. The average number of credit hours earned for service-learning courses rose slightly each subsequent year until the mean in year six was 3.4 credits. These descriptive statistics are displayed in Table 6. In terms of total credit hours earned per year, SL students surpassed non-SL students each year of the study. The yearly differences were significant, and the effect sizes were moderate. The year-to-year comparison can be found in Table 8.

Table 6

Year-by-Year Frequency of Students Enrolled, Average Credits Earned, and Frequency Graduated

	Year 1 2005-06	Year 2 2006-07	Year 3 2007-08	Year 4 2008-09	Year 5 2009-10	Year 6 2010-11
Total Number of Students Enrolled	3,454	2,931	2,557	2,329	1,300	508
Number of Enrolled Students Who Took Service-Learning Courses (SL Students)	76	291	242	218	115	29
Proportion of Enrolled Students who Took Service-Learning Courses	2%	10%	9%	9%	9%	6%
Average Number of Service-Learning Credit Hours Earned by SL Students	2.2	2.6	2.7	3.0	3.2	3.4
Overall Number of Students Who Graduated			28	913	682	238
Number of Non-SL Students Who Graduated			19	625	461	148
Number of SL Students Who Graduated			9	288	221	90

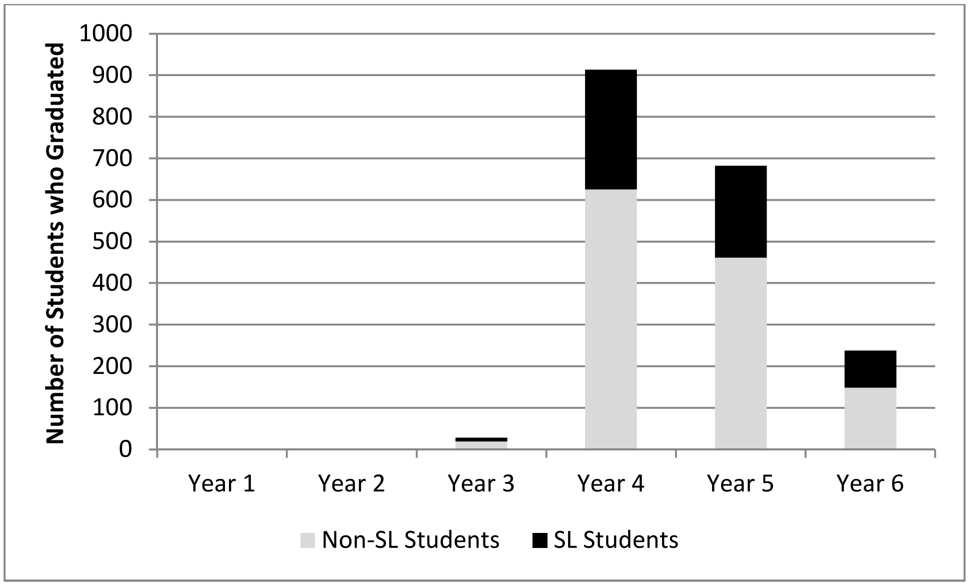

Figure 6. Frequency of students who graduated each year during the six-year period of study.

Table 7

Group Differences for Students who Took Service-Learning Courses (n = 832) and Students who did Not Take Service-Learning Courses (n = 2,626)

		Non-SL Students		SL Students					
	n	*M*	*SD*	*M*	*SD*	*df*	*t*	*p*	Cohen's *d*
Academic Characteristics Upon Matriculation									
High School GPA	3382	3.20	0.51	3.30	0.50	3380	-4.67	.000	0.188
SAT Verbal Score	3315	543	84.2	538	84.9	3313	1.46	.145	-0.059
SAT Mathematics Score	3315	535	77.1	535	82.9	1295	-0.08	.935	0.003
Academic Progress Indicators at the End of the Last Semester of Enrollment									
Number of Semesters Enrolled	3457	7	3.9	10	2.6	2116	-21.31	.000	0.691
Cumulative Institutional Credit Hours Earned	3457	88	53.1	122	34.1	2188	-22.04	.000	0.705
Cumulative Institutional GPA	3457	2.57	0.93	2.92	0.65	1999	-12.04	.000	0.403
Financial Aid									
Cumulative Financial Need (in dollars) for Students who Applied for Aid	1953	29,143	25,490	37,869	29,118	836	-6.07	.000	0.329
Total Aid Received (in dollars) by Students with Aid	2695	25,177	24,606	37,461	29,033	1085	-10.03	.000	0.476
Number of Semesters Supported for Students Receiving Pell	990	4.32	2.95	5.57	3.01	988	-5.84	.000	0.422
Degree Completion									
Time to Completion in Years (Students who Graduated)	1859	4.59	0.71	4.64	0.74	1859	-1.56	.119	0.071

Table 8

Comparison of Total Credit Hours Earned by Year for Students Enrolled in Service-Learning Courses (SL students) and Students Not Enrolled in Service-Learning Courses (non-SL students)

		Non-SL Students		SL Students					
	n	*M*	*SD*	*M*	*SD*	*df*	*t*	*p*	Cohen's *d*
Year 1 (2005-06)	3454	27.5	12.49	32.6	12.40	-3.56	78	0.001	0.411
Year 2 (2006-07)	2931	24.9	10.55	28.1	9.85	-5.23	367	0.000	0.306
Year 3 (2007-08)	2557	25.9	10.27	29.2	8.91	-5.42	312	0.000	0.326
Year 4 (2008-09)	2329	26.0	9.39	28.0	7.87	-3.44	285	0.001	0.212
Year 5 (2009-10)	1300	19.9	10.36	25.1	8.64	-6.06	148	0.000	0.511
Year 6 (2010-11)	508	16.6	11.01	20.6	10.15	-2.02	32	0.052	0.360

Note. Statistics in this table are based on the students who were enrolled in service-learning courses for the stated year.

Financial need and aid. With respect to measures of financial aid and ability to pay, SL students were also different than non-SL students. A significantly larger proportion of SL students had documented financial need than the percentage of non-SL students with need, χ^2 (1, N = 3,458) = 19.55, p = .000, and a larger fraction of SL students received financial aid at some point while enrolled, χ^2 (1, N = 3,458) = 30.51, p = .000. In addition, the percentage of SL students receiving Pell support was higher than the percentage of non-SL students with Pell aid, χ^2 (1, N = 3,458) = 4.03, p = .045. Frequency distribution comparisons are displayed in Table 5. With an average total financial need of $37,869 while enrolled, SL students in this sample proved to be significantly needier than non-SL students, whose total need averaged $29,143. Total aid awarded to SL students averaged $29,033, while average total aid for non-SL students was $25,177. In addition, SL students were supported by Pell grants for more semesters (M = 5.57, SD = 3.01) than non-SL students (M = 4.32, SD = 2.95). Overall, SL students had a higher level of financial need, received more total aid, and were the recipients of Pell assistance for more semesters while enrolled. The effect size for each of these significant differences was moderate. Details for these group comparisons can be found in Table 7.

Degree completion. The six-year graduation rate for the overall sample was 54%, but the graduation rate varied significantly between major areas of study, χ^2 (7, N = 3, 458) = 398.10, p = .000. The overall frequency distribution by academic discipline can be found in Table 9. Among students who did not take service-learning courses while enrolled, the graduation rate was 48%. Among SL students, however, the proportion of students who graduated was significantly higher at 73%, χ^2 (1, N = 3, 458) = 163.51, p = .000. For students in the sample who graduated within six years, there was no significant difference in the average number of years that it took each group to graduate. These comparisons can be found in Table 7.

Table 9

Frequency of Students by Discipline who Completed and who Did not Complete a Degree within Six Years

Area of Study at Semester of Last Enrollment	Non-completers		Completers			
	n	%	*n*	%	$\chi^2(df)$	*p*
					398.10(7)	.000
Arts	199	32	426	68		
Business	221	48	235	52		
Engineering	66	40	101	60		
Health, Physical Education, & Exercise Science	39	45	47	55		
Health Professions	5	5	96	95		
Humanities and Sciences	784	46	920	54		
Social Work	11	34	21	66		
Undeclared	271	95	15	5		

Logistic Regression for Predicting Degree Completion

Model 1. The first analysis utilized binary logistic regression to predict the odds of degree completion from 15 independent variables, which are identified in Table 3. Of the 3,458 students in the sample, 3,293 (95%) had complete data for each of the predictor variables. One hundred sixty-five individuals with incomplete data were excluded from the model. Nagelkerke's R^2 for Model 1 was .80, indicating that the combination of independent variables is strongly predictive of degree completion. The regression model had good fit, χ^2 (8, N = 3, 293) = 286.80, p = .000; and it predicted degree completion for students in the sample with an accuracy level of 93.6%. However, only four of the covariates showed significance at the level of α = .05. Regarding the independent variables in the model, demographic characteristics, including gender, race/ethnicity, residency (in-state vs. out-of-state), were not significant predictors for completion. High school GPA was also not significant. SAT scores, both the verbal and the mathematics tests, showed statistical significance in the model; however, the odds ratio for each of these variables was so close to 1.0 that there is virtually no practical significance of these variables. In other words, an increase or decrease in scores is not associated with a change in the odds that the student will complete his/her degree when all other variables are held constant. With respect to measures of financial need and ability to pay, neither total need, nor aid received, nor Pell semesters were significant with all other variables held constant. In terms of academic progress, total credits earned were the strongest predictor of degree completion with a Wald statistic of 452.5. The odds ratio for this covariate was 1.07, meaning that for each additional credit earned, the odds of degree completion increase by approximately 1.1%. Cumulative GPA is also a critical predictor. Not only was it statistically significant, the odds ratio was higher than that of all other variables; for every point increase in GPA, the odds of degree completion increase by 6.2%. Participation in service-learning courses was not statistically significant in this model. A summary of the results for each variable in Model 1 can be found in Table 10, and the intercorrelations are displayed in Table 11.

Table 10

Summary of Logistic Regression Analysis for Model 1 with Complete Sample (N = 3,458)

Variable	*B*	*SE*	*OR*	95% CI	Wald statistic	*p*
FEMALE	0.03	0.14	1.03	[0.78, 1.36]	0.04	.845
RACE_BLK	-0.19	0.20	0.83	[0.56, 1.22]	0.90	.343
RACE_HSP	0.32	0.37	1.38	[0.67, 2.84]	0.74	.388
RACE_ASN	0.02	0.22	1.02	[0.66, 1.58]	0.01	.942
RACE_OTH	0.44	0.25	1.56	[0.95, 2.55]	3.12	.077
OUT_STAT	0.48	0.29	1.62	[0.92, 2.85]	2.74	.098
HS_GPA	-0.28	0.16	0.76	[0.56, 1.03]	3.10	.078
SAT_V	0.00	0.00	1.00	[1.00, 1.00]	7.39	.007
SAT_M	0.00	0.00	1.00	[1.00, 1.00]	5.45	.020
NEED_CUM	0.00	0.00	1.00	[1.00, 1.00]	0.49	.483
AID_CUM	0.00	0.00	1.00	[1.00, 1.00]	0.02	.882
PELL_CUM	-0.01	0.04	0.99	[0.91, 1.07]	0.07	.785
SL_IND	0.16	0.14	1.18	[0.89, 1.56]	1.29	.256
CR_T	0.07	0.00	1.07	[1.06, 1.08]	452.47	.000
GPA_CUM	1.78	0.15	5.93	[4.40, 8.01]	135.25	.000

Note. CI = confidence interval for odds ratio.

Table 11

Intercorrelations for Degree Completion and Predictor Variables in Model 1 with Complete Sample (N = 3,458)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. DEG_IND	—															
2. FEMALE	.08**	—														
3. RACE_BLK	-.01	.12**	—													
4. RACE_HSP	-.04*	-.01	-.10**	—												
5. RACE_ASN	.04**	-.03	-.18**	-.07**	—											
6. RACE_OTH	-.04*	-.02	-.14**	-.05**	-.10**	—										
7. OUT_STAT	-.05**	.06**	.07**	0.01	.00	0.02	—									
8. HS_GPA	.25**	.14**	-.07**	-.02	.08**	-0.02	.04*	—								
9. SAT_V	.06**	-.10**	-.28**	-.02	-.11**	.02	-.06**	.23**	—							
10. SAT_M	.08**	-.27**	-.32**	-.03	.19**	.00	.00	.31**	.52**	—						
11. NEED_CUM	.19**	.07**	.28**	.03	.06**	-.042*	.11**	.06**	-.21**	-.14**	—					
12. AID_CUM	.33**	.05**	.26**	.01	.01	-.02	.18**	.22**	-.08**	-.03	.73**	—				
13. PELL_CUM	.13**	.06**	.25**	.04*	.10**	-.02	-.04*	.04*	-.21**	-.13**	.81**	.57**	—			
14. SL_IND	.22**	.04*	.061**	-.01	.05**	-.03	-.03	.08**	-.03	.00	.14**	.21**	.09**	—		
15. CR_T	.79**	.07**	-.04*	-.03	.09**	-.02	-.04*	.31**	.12**	.15**	.27**	.43**	.18**	.29**	—	
16. GPA_CUM	.59**	.15**	-.09**	-.03	0.03	-.01	.01	.44**	.19**	.19**	.11**	.27**	.07**	.17**	.68**	—

* $p < .05$, ** $p < .01$.

Since the researcher found significant differences in graduation rates between different academic disciplines (Table 9), there was reason to suspect that model fit and parameter estimates could also be influenced by group differences. For this reason, Model 1 was re-tested, but the researcher ran the regression by group according to the student's major area of study at the time of graduation or last enrollment. Although fit statistics for the overall model were adequate, the model did not do so well within some disciplines. A comparison of fit statistics can be found in Table 12.

Table 12

Fit Statistics for Model 1 by Area of Study

Area of Study at Semester of Last Enrollment	n	Nagelkerke's R^2	Percent of Cases Correctly Classified
Arts	625	.73	92%
Business	456	.90	97%
Health, Physical Education, & Exercise Science*	86		
Engineering	167	.88	96%
Health Professions	101	1.00	100%
Humanities and Sciences	1704	.76	93%
Social Work	32	1.00	100%
Undeclared	286	1.00	100%

*Model estimation failed to converge.

These results were used to inform a decision to exclude students in health professions and social work, as well as undeclared students, from further model analysis. This decision was based on several factors. First, at 95%, the graduation rate for students in health professions (n = 101) was significantly higher than the proportion of students who completed a degree in other disciplines, so variation on the outcome of interest was low, and sample size was small. Though the graduation rate for students in social work (*n* = 32) was not significantly different from the overall graduation rate, the group was also small, and students lacked variation in race/ethnicity, one of the primary covariates tested in the model. Finally, undeclared students also posed a problem in terms of the outcome variable. Logically, students must have declared a major in order to receive a degree, meaning that undeclared students have no chance of graduating. The fact that 15 students who graduated did not have a primary major on record during the final semester of enrollment indicates that there were potential data anomalies that may have biased parameter estimates. Because these disciplines did not provide adequate variation within groups, students in health professions and social work, as well as undeclared students, were excluded from model comparisons.

Following exclusion of these subgroups, Model 1 was re-analyzed with the smaller sample (*n* = 3,038). One hundred forty-three cases were excluded from the analysis due to missing data, so the sample sized was reduced to 2,895 students. Fit statistics remained strong. Nagelkerke's R^2 was .77, and 93% of cases were correctly classified. However, only the same four covariates that were statistically significant predictors with the complete sample were significant among the reduced sample: SAT verbal test score, SAT mathematics test score, cumulative credits earned, and institutional GPA. Service-learning participation was not a significant factor among other predictors. A summary of the results can be found in Table 13 with intercorrelations displayed in Table 14.

Table 13

Summary of Logistic Regression Analysis for Model 1 with Reduced Sample (N = 2,895)

Variable	*B*	*SE*	*OR*	95% CI	Wald statistic	*p*
FEMALE	0.02	0.15	1.02	[0.77, 1.36]	0.02	.875
RACE_BLK	-0.16	0.21	0.85	[0.57, 1.28]	0.58	.447
RACE_HSP	0.28	0.38	1.32	[0.63, 2.78]	0.53	.467
RACE_ASN	-0.02	0.23	0.98	[0.63, 1.53]	0.01	.936
RACE_OTH	0.46	0.25	1.59	[0.97, 2.60]	3.34	.068
OUT_STAT	0.50	0.29	1.65	[0.93, 2.94]	2.91	.088
HS_GPA	-0.29	0.16	0.75	[0.55, 1.03]	3.24	.072
SAT_V	0.00	0.00	1.00	[1.00, 1.00]	7.69	.006
SAT_M	0.00	0.00	1.00	[0.99, 1.00]	6.33	.012
NEED_CUM	0.00	0.00	1.00	[1.00, 1.00]	0.61	.436
AID_CUM	0.00	0.00	1.00	[1.00, 1.00]	0.12	.733
PELL_CUM	-0.01	0.04	0.99	[0.91, 1.07]	0.12	.730
SL_IND	0.19	0.15	1.21	[0.91, 1.61]	1.67	.197
CR_T	0.07	0.00	1.07	[1.06, 1.07]	404.51	.000
GPA_CUM	1.78	0.16	5.90	[4.34, 8.02]	128.96	.000

Note. CI = confidence interval for odds ratio.

Table 14

Intercorrelations for Degree Completion and Predictor Variables in Model 1 with Reduced Sample (N = 2,895)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. DEG_IND	—															
2. FEMALE	.04*	—														
3. RACE_BLK	-.03	.12**	—													
4. RACE_HSP	-.04*	-.01	-.10**	—												
5. RACE_ASN	.06**	-.03	-.19**	-.07**	—											
6. RACE_OTH	-.04	-.03	-.14**	-.05**	-.10**	—										
7. OUT_STAT	-.06**	.07**	.07**	.01	-.01	.03	—									
8. HS_GPA	.22**	.11**	-.07**	-.03	.09**	-.03	.04*	—								
9. SAT_V	.06**	-.10**	-.28**	-.02	-.10**	.00	-.06**	.24**	—							
10. SAT_M	.08**	-.27**	-.32**	-.02	.18**	-.01	.00	.33**	.52**	—						
11. NEED_CUM	.16**	.06**	.27**	.03	.06**	-.04*	.11**	.03	-.21**	-.14**	—					
12. AID_CUM	.29**	.03	.25**	.01	.01	-.01	.18**	.20**	-.08**	-.03	.73**	—				
13. PELL_CUM	.10**	.06**	.24**	.04*	.10**	-.02	-.04*	.03	-.21**	-.14**	.81**	.56**	—			
14. SL_IND	.19**	.04*	.07**	-.01	.05**	-.02	-.04	.07**	-.03	.00	.12**	.19**	.08**	—		
15. CR_T	.77**	.03	-.07**	-.04	.10**	-.02	-.05**	.28**	.12**	.16**	.23**	.39**	.15**	.27**	—	
16. GPA_CUM	.58**	.11**	-.12**	-.04*	.04*	-.02	.01	.43**	.20**	.21**	.08**	.23**	.05*	.15**	.66**	—

* $p < .05$, ** $p < .01$.

Model 2. Since the model fit, the strength of the parameter estimates, and the significance of each covariate remained relatively consistent between the full sample and the reduced sample in Model 1, the researcher determined that a more parsimonious model would be appropriate. Model 2 was thus tested using six predictors that included the four significant covariates from Model 1, plus high school GPA, which had approached the level of significance of α = .05. The service-learning indicator was also retained since one of the goals of this study was to determine the relative influence of service-learning among other predictors for persistence and completion. This logistic regression analysis resulted in a model still predicting 93% of cases correctly and with a Nagelkerke's R^2 of .77. Five of the covariates proved statistically significant in this model. The only variable that did not seem to add anything to its strength was the service-learning indicator. A summary of the model can be found in Table 15 with intercorrelations in Table 16.

Table 15

Summary of Logistic Regression Analysis for Model 2 (N = 2,895)

Variable	*B*	*SE*	*OR*	95% CI	Wald statistic	*p*
HS_GPA	-0.31	0.15	0.73	[0.54, 0.99]	4.12	.042
SAT_V	0.00	0.00	1.00	[1.00, 1.00]	7.69	.006
SAT_M	0.00	0.00	1.00	[1.00, 1.00]	6.95	.008
SL_IND	0.17	0.14	1.19	[0.89, 1.57]	1.38	.241
CR_T	0.07	0.00	1.07	[1.06, 1.07]	432.39	.000
GPA_CUM	1.77	0.15	5.89	[4.37, 7.96]	134.08	.000

Note. CI = confidence interval for odds ratio.

Table 16

Intercorrelations for Degree Completion and Predictor Variables in Model 2 (N = 2,895)

	1	2	3	4	5	6	7
1. DEG_IND	—						
2. HS_GPA	.22**	—					
3. SAT_V	.06**	.24**	—				
4. SAT_M	.08**	.33**	.52**	—			
5. SL_IND	.19**	.07**	-.03	.00	—		
6. CR_T	.77**	.28**	.12**	.16**	.27**	—	
7. GPA_CUM	.58**	.43**	.20**	.21**	.15**	.66**	—

** $p < .01$.

Model 3. The third analysis, which also used logistic regression to predict degree completion, analyzed the same covariates as Model 2, but replaced the binary service-learning indicator and total cumulative credits with two continuous measures: one for total SL credits and the other for total non-SL credits. This substitution was made to test whether the amount of service-learning participation has any influence on completion. Overall, this model behaved almost identically to Model 2. Nagelkerke's R^2 was .77, and the model still predicted completion with an accuracy rate of 93%. High school GPA, SAT scores, institutional GPA, and non-SL credits were the strongest predictors in the model. Service-learning credits were not significant. A summary of the model is displayed in Table 17 with intercorrelations in Table 18.

Table 17

Summary of Logistic Regression Analysis for Model 3 (N = 2,895)

Variable	*B*	*SE*	*OR*	95% CI	Wald statistic	*p*
HS_GPA	-0.32	0.15	0.73	[0.54, 0.98]	4.24	.039
SAT_V	0.00	0.00	1.00	[1.00, 1.00]	7.67	.006

Variable	*B*	*SE*	*OR*	95% CI	Wald statistic	*p*
SAT_M	0.00	0.00	1.00	[1.00, 1.00]	7.06	.008
CR_SL	0.03	0.04	1.03	[0.96, 1.11]	0.81	.369
CR_NS	0.07	0.00	1.07	[1.06, 1.07]	428.62	.000
GPA_CUM	1.78	0.15	5.93	[4.39, 8.01]	135.31	.000

Note. CI = confidence interval for odds ratio.

Table 18

Intercorrelations for Degree Completion and Predictor Variables in Model 3 (N = 2,895)

	1	2	3	4	5	6	7
1. DEG_IND	—						
2. HS_GPA	.22**	—					
3. SAT_V	.06**	.24**	—				
4. SAT_M	.08**	.33**	.52**	—			
5. CR_SL	.22**	.06**	-.06**	-.04	—		
6. CR_NS	.77**	.28**	.12**	.16**	.25**	—	
7. GPA_CUM	.58**	.43**	.20**	.21**	.17**	.66**	—

***p* < .01.

Survival Analysis for Predicting Degree Completion

Model 4, represented by Figure 4, was the most complicated of the degree completion models tested in this study. The initial structural equation model (SEM) tested a total of 645 parameters and failed to converge. Mplus syntax for the initial model analysis is included as Appendix A. By removing covariates and reintroducing them one at a time, the researcher was able to establish a model that included both time-invariant predictors and time-varying covariates. The resulting model (Model 5) was similar in many respects to the logistic regression models. The variables which seemed to create convergence problems in the survival analysis model were some of the same covariates that were insignificant in the initial logistic regression model (Model 1). The following time-invariant predictors were thus excluded from the final survival analysis model: gender, all race/ethnicity indicators, and residency status. Several time-varying predictors were also excluded from the final model: year-by-year need, aid, and number of semesters with Pell support. These covariates each showed high correlations in their year-to-year values (see Tables 19 – 21). An attempt was made to substitute the cumulative values as time-invariant predictors, but these attempts failed to improve the model.

Table 19

Intercorrelations for Year-to-Year Financial Need

	NEED_Y3	NEED_Y4	NEED_Y5	NEED_Y6
NEED_Y3	—			
NEED_Y4	.79	—		
NEED_Y5	.65	.71	—	
NEED_Y6	.35	.46	.56	—

Note. All correlations are significant at $p < .000$

Table 20

Intercorrelations for Year-to-Year Financial Aid

	AID_Y3	AID_Y4	AID_Y5	AID_Y6
AID_Y3	—			
AID_Y4	.82	—		
AID_Y5	.58	.66	—	
AID_Y6	.33	.39	.50	—

Note. All correlations are significant at $p < .000$

Table 21

Intercorrelations for Year-to-Year Semesters of Pell Support

	PELL_Y3	PELL_Y4	PELL_Y5	PELL_Y6
PELL_Y3	—			
PELL_Y4	.72	—		
PELL_Y5	.57	.66	—	
PELL_Y6	.25	.26	.45	—

Note. All correlations are significant at $p < .000$

Institutional GPA, on the other hand, was so highly correlated on a year-to-year basis (see Table 22) that it was determined to be time-invariant, so the student's cumulative GPA value at the last semester of enrollment was used instead of the time-varying values, and it allowed for successful model convergence.

Table 22

Intercorrelations for Year-to-Year Cumulative Institutional GPA

	GPA_Y3	GPA_Y4	GPA_Y5	GPA_Y6
GPA_Y3	—			
GPA_Y4	.97	—		
GPA_Y5	.95	.99	—	
GPA_Y6	.95	.98	.99	—

Note. All correlations are significant at $p < .000$

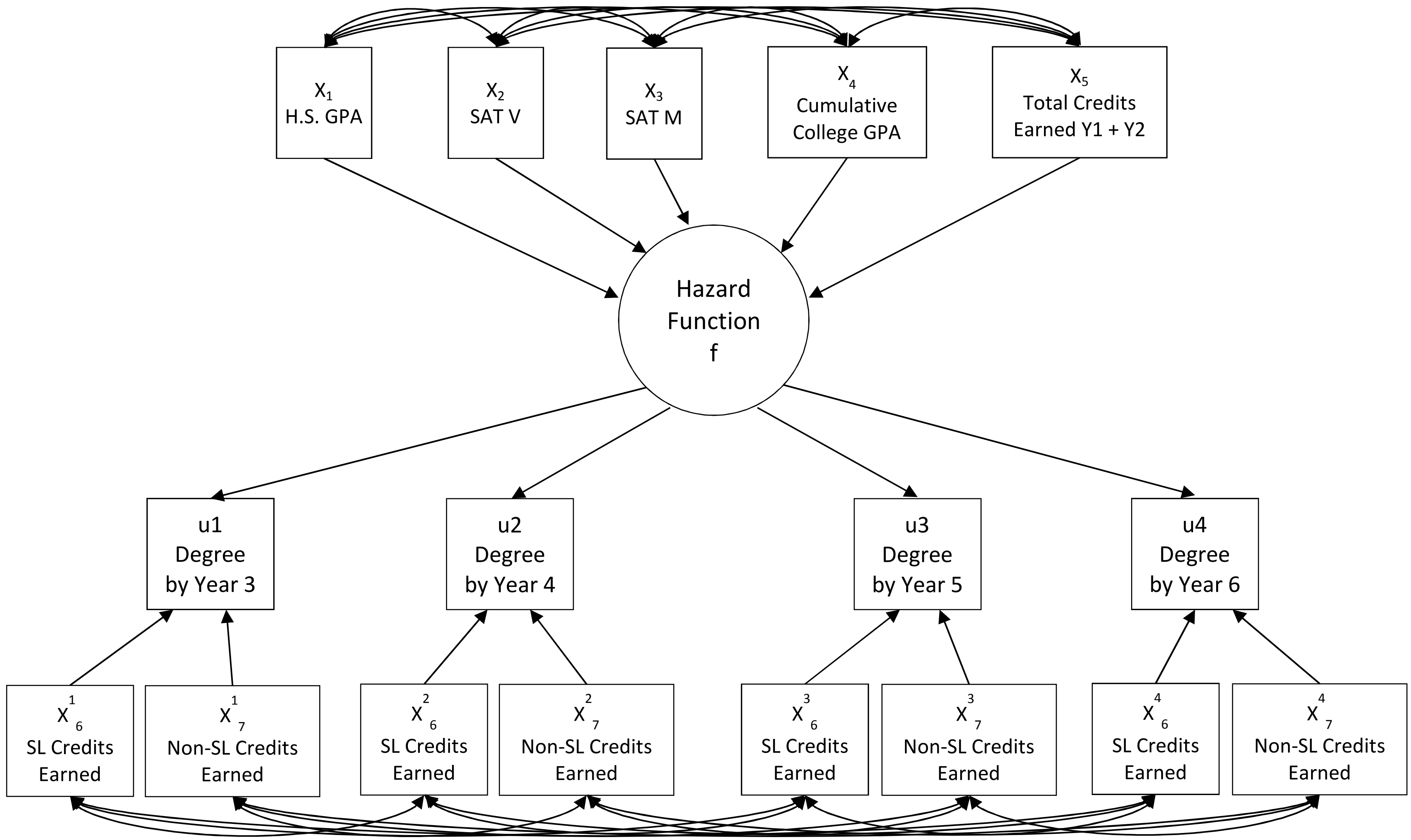

Figure 7. The final discrete-time survival analysis model for predicting the odds of degree completion (Model 5). This model tests the effects of the time invariant student characteristics (X_1 through X_5) and the time varying covariates (X_6 and X_7) for each year on the proportional odds assumption for the outcome, denoted as f.

Figure 7 displays a representation of the final discrete-time survival analysis model. Of the subsample remaining after excluding students who did not persist to year three (n = 2,402), an additional 107 records were excluded from the analysis due to missing data among the covariates. This left a sample of 2,295 students. Table 23 displays the model summary with parameter estimates. Mplus syntax for analysis of this model is included as Appendix B. Since Mplus does not calculate odds ratios or the confidence intervals for the odds ratios, odds ratios were calculated manually by taking the exponential function of the *B* values. Survival analysis does not produce fit indices in the same way that logistic regression models or standard structural equation models do. However, the strength and significance of parameters in the discrete-time survival analysis model are similar to the logistic regression models. In this analysis, variances for SL credit hours and non-SL credit hours were constrained to be equal from year-to-year. This constraint was included during efforts to facilitate model convergence.

Table 23

Summary of Final Survival Analysis Model (Model 5) with Variances for Time-Varying Predictors Constrained to be Equal

Variable	*B*	*SE*	*OR*	*z*-score	*p*
HS_GPA	-0.21	0.06	0.81	-3.64	.000
SAT_V	-1.14	0.33	0.32	-3.43	.001
SAT_M	-1.11	0.37	0.33	-3.05	.002
CR_Y1_Y2	3.33	0.22	27.85	14.89	.000
GPA_CUM	0.96	0.06	2.62	16.57	.000
CR_SL_Y*n*	0.11	0.04	1.12	2.81	.005
CR_NS_Y*n*	1.73	0.52	5.62	3.30	.001

Note. Since variances for year-to-year credit hours (both SL and non-SL) were constrained to be equal, the parameter estimates for each year are equivalent.

Upon further reflection, the researcher questioned the wisdom of constraining variances for the time-varying predictors, particularly since one of the primary goals of the study was to explore patterns that might be different from year-to-year. Therefore, Model 5 was reanalyzed with variances allowed to be freely estimated. Mplus syntax for analysis of this model is included as Appendix C. Table 24 displays the model summary.

Table 24

Summary of Final Survival Analysis Model (Model 5) with Variances for Time-Varying Predictors Freely Estimated

Variable	*B*	*SE*	*OR*	*z*-score	*p*
HS_GPA	-0.22	0.06	0.80	-3.64	.000
SAT_V	-1.07	0.33	0.34	-3.43	.001
SAT_M	-1.07	0.37	0.34	-3.05	.004
CR_Y1_Y2	3.27	0.22	26.31	14.89	.000
GPA_CUM	0.98	0.06	2.66	16.57	.000
CR_SL_Y3	0.26	0.04	1.30	1.99	.046
CR_NS_Y3	6.18	0.52	482.99	1.30	.193
CR_SL_Y4	0.15	0.05	1.16	3.35	.001
CR_NS_Y4	4.30	0.62	73.70	6.93	.000
CR_SL_Y5	-0.03	0.08	0.97	-0.36	.719
CR_NS_Y5	0.45	0.73	1.57	0.61	.540
CR_SL_Y6	0.34	0.17	1.40	1.98	.048
CR_NS_Y6	-1.32	1.25	0.27	-1.06	.289

The strength and significance of the time-invariant predictors remained roughly the same, but this analysis resulted in different parameter estimates for year-to-year SL credit hours and non-SL credit hours. Most notably, the number of service-learning credits earned was significant and positively correlated with degree completion in years three, four, and six, but it was not significant in year five. Also notable is the fact that the number of non-SL credits a student earned was only statistically significant in year four. Table 25 displays the correlations, means, and standard deviations for the variables in the final model.

Table 25

Zero-Order Correlations, Means, and Standard Deviations for Covariates in Final Survival Analysis Model

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. HS_GPA	—												
2. SAT_V	.25**	—											
3. SAT_M	.34**	.53**	—										
4. GPA_CUM	.47**	.25**	.24**	—									
5. CR_Y1_Y2	.47	.30	.32	.63	—								
6. CR_SL_Y3	.00	-.07	-.05*	.04	.03	—							
7. CR_SL_Y4	.06**	-.02	.01	.14**	.09**	.07*	—						
8. CR_SL_Y5	-.03	-.05	-.08**	.01	-.08	.02*	.03	—					
9. CR_SL_Y6	.02	-.06	-.07	.02**	-.06	-.04	-.01	.05	—				
10. CR_NS_Y3	.23**	.05*	.07**	.59**	.50**	.06**	.13**	.02	.00	—			
11. CR_NS_Y4	.11**	-.03	.00	.47**	.26**	.07**	.02	.05*	-.01	.56**	—		
12. CR_NS_Y5	.01	-.02	.04	.25	.03**	.04	.03	.08**	.13**	.13**	.27**	—	
13. CR_NS_Y6	.04	.04	.04	.16**	-.06	-.01	.00	.05	.04	-.05	-.04	.28**	—
M	3.27	.55	.54	2.88	.57	.26	.28	.23	.10	.26	.25	.19	.15
SD	.51	.09	.08	.65	.18	.01	.01	.01	.00	.11	.12	.12	.08

Note. For fitting this model, some data were standardized, so that values would fall between zero and ten. SAT scores were standardized by dividing all values by the constant 1000. Credit hours were standardized by dividing all values by the constant 100.
$^{*}p < .05$. $^{**}p < .01$.

Multiple Regression for Predicting Time to Degree

Model 6 was used to test whether the parameters found to be significant for predicting degree completion are also good predictors the time it takes for students to complete a bachelor's degree. Naturally, this analysis only included the students who earned a degree during the period of this study (n = 1,861), and the sample for analysis was further reduced by 204 cases due to missing data. Overall, this model was not as effective at predicting time to degree as it was for predicting completion. Although the global F-test was significant at $p < .001$, R^2 for the model was only .32. The significance of individual predictors was also slightly different than Model 3. While the mathematics SAT test score was a significant predictor of degree completion, it was not predictive of time to degree. Conversely, the number of service-learning credits, while not predictive of completion, is a significant predictor of time to degree when other covariates in this model are held constant. A summary of the results for Model 6 is displayed in Table 26 with means, standard deviations, and intercorrelations in Table 27.

Table 26

Regression Analysis Summary for Predictors of Time to Degree (Model 6)

	B	*SE B*	β	*t*	*p*
HS_GPA	-0.17	0.04	-0.12	-4.89	0.000
SAT_V	0.00	0.00	-0.06	-2.22	0.026
SAT_M	0.00	0.00	-0.03	-1.12	0.264
CR_SL	0.02	0.01	0.04	2.01	0.044
CR_NS	0.02	0.00	0.38	17.46	0.000
GPA_CUM	-0.67	0.04	-0.42	-17.35	0.000

Note. $R^2 = .32$ (N = 1,657, $p < .001$)

Table 27

Means, Standard Deviations, and Intercorrelations for Time to Degree and Predictor Variables (Model 6)

	M	*SD*	1	2	3	4	5	6
DEG_TIME	4.62	0.73	-.26**	-.20**	-.16	.03	.23**	-.43**
Predictor variable								
1. HS_GPA	3.33	0.52	—	.31**	.40**	-.01	.28**	.51**
2. SAT_V	548	86.3		—	.56**	-.10**	.16**	.35**
3. SAT_M	542	80.5			—	-.07**	.24**	.33**
4. CR_SL	1.17	1.94				—	-.07**	-.01
5. CR_NS	132	14.7					—	.23**
6. GPA_CUM	3.12	0.46						—

**$p < .01$.

Chapter 5

Discussion

Summary of Results

In examining the results from each of the model analyses, there are several covariates that seem to be strong in predicting which students in this population will complete a degree and which students will not. The strength of a student's pre-college academic background, measured by SAT scores, is strongly correlated with college success when all other factors are constant. This is consistent with previous research (Arredondo & Knight, 2006; Astin, 2005; Attewell, Heil, & Reisel, 2010; Chimka, Reed-Rhoads, & Barker, 2007; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978). High school GPA is also a predictor that appears to be significant, but the parameter estimate has a negative value in each of the models. The negative sign would ordinarily indicate a negative relationship between the predictor and the outcome. In other words, higher high school GPA would be correlated with a lower likelihood of degree completion. However, bivariate correlations show that the correlation is actually positive, which is consistent with prior research on the relationship between high school GPA and college persistence (Astin, 2005; Attewell, Heil, & Reisel, 2010; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978).

In this study, strong academic progress, measured by credits earned and college GPA, is also a significant factor in predicting completion, a finding that supports prior research where college GPA has been positively correlated with persistence (Mohn, 2006; Terenzini & Pascarella, 1978). The demographic variables that have traditionally been correlated with degree completion were not particularly important in the models studied with this sample. Neither gender, nor race/ethnicity, nor out-of-state residency was significant as a covariate in the initial models tested. Furthermore, financial need and financial aid variables were also insignificant among other stronger predictors for success. This finding is contrary to studies that have found financial need is strongly correlated with attrition (Astin, 2005; Attewell, Heil, & Reisel, 2010; Bowen, Chingos, & McPherson, 2009; Gross, Hossler, & Ziskin; 2007), while aid received tends to have a positive correlation with persistence (Astin, 2005; Attewell, Heil, & Reisel, 2010; Bowen, Chingos, & McPherson, 2009; Gross, Hossler, & Ziskin; 2007; Mohn, 2006). Finally, when analyzed using logistic regression and cross-sectional data, service-learning participation was not a significant predictor for completion, but it does seem to have some effect on time to completion. The parameter estimate in the time-to-completion model also had a positive value, suggesting that an increase in service-learning credits is correlated with increased time to earn a degree. When analyzed longitudinally using discrete-time survival analysis, service-learning participation is strongly predictive of degree completion, particularly when credits are earned in the third, fourth, and sixth years of enrollment. In this model, service-learning credits earned were also more significant for predicting degree completion than non-SL credits earned.

Interpretation of Findings

Differences between SL students and non-SL students. It is not surprising that students who took service-learning courses had greater total financial need while enrolled since, on average, they were enrolled for more semesters and earned more credit hours than students who did not take service-learning courses. What's not clear from this study is why they were enrolled for more semesters. Based on previous studies that found service-learning students more engaged (Bringle & Hatcher, 1996; Markus, Howard, & King, 1993), the researcher presumes that students in this sample may have remained enrolled longer due to higher levels of student-university engagement, but this still doesn't completely address the issue. One is left to wonder whether students who are already predisposed to be engaged tend to choose service-learning courses or if the service-learning courses lead to greater engagement.

Based on the number and types of service-learning courses offered during the period of this study, the researcher had assumed that most students would not have an opportunity to take service-learning courses until their third or fourth year of enrollment. However, this assumption was disproven by the data. Though the percentage of students enrolled in service-learning courses was small during year one (2%), it went up to 10% in year two, which was the year with the highest percentage of students in the cohort enrolled in service-learning courses. The proportion of students enrolled in subsequent years remained consistent at 9% for years three through five, and it dropped to 6% in year six. This may have been due to the fact that the number of service-learning courses offered increased each year of the study except year four.

Comparison of models for predicting degree completion. In some respects, it is difficult to compare the significance or importance of predictors between the cross-sectional logistic regression models and the model that used longitudinal discrete-time series analysis. The researcher made an attempt to keep the variables as similar as possible, but, by necessity, the details captured in year-to-year data, are collapsed in the cross-sectional models. Collapsing data has consequences. For example, it seems redundant to include credits earned in an equation predicting completion/non-completion. Since earning a degree requires a fixed number of credits, it is expected that completers will have earned more credits than non-completers. However, in a longitudinal model, course completion by certain points in time can have an impact on completion within a six-year period as evidenced by the strength of the parameter estimate for total credits earned during years one and two (CR_Y1_Y2) in the discrete-time survival analysis model.

Results from analysis of Model 1 using both the complete sample and the reduced sample confirm the strength of pre-college academic characteristics in predicting degree completion when all other factors are held constant. They also confirm the importance of a student's academic experiences while in college, and they seem to suggest that a parsimonious model is as effective at predicting degree completion among this sample. Overall, the strongest predictors for degree completion among this sample were a student's SAT scores, high school GPA, institutional credits earned, and college GPA. In other words, among the variables analyzed in this study, the pre-college academic characteristics and the academic progress during college are the factors that seem most influential in determining which students finish their degrees at this institution. The negative parameter estimate for high school GPA, however, is problematic. It may have more to do with multicollinearity with SAT scores than actual direction of the prediction, indicating that one measure or the other might be effective. In the survival analysis model, parameter estimates are negative for all three pre-college academic characteristics, but all three are positively correlated with degree completion. Though bivariate correlations between these predictors are only moderate, and variance inflation factors (VIFs) are not inordinately high, the researcher assumes that multicollinearity with the other covariates is causing the signs to flip.

One of the most interesting findings is that some of the variables typically associated with persistence in the literature were not strongly predictive of degree completion among this cohort of students. For example, financial need and financial aid were not a significant influence on likelihood of graduating in the presence of the other variables. Demographic factors such as gender and race/ethnicity are also not particularly important when other factors are held constant. Since there is conflicting evidence about the importance of gender and race as predictors for persistence, this finding is not surprising (Arredondo & Knight, 2006; Astin, 2005; Attewell, Heil, & Reisel, 2010; Chimka, Reed-Rhoads, & Barker, 2007; Guillory, 2009; Lewallen, 1993; Mohn, 2006; Terenzini & Pascarella, 1978). The importance of these variables may be more strongly related to institutional characteristics such as diversity and student support. The university in this study has a highly diverse student body, with a large percentage of first-generation college students, and it initiated a variety of academic and social support programs for undergraduate students during the period of this study. These initiatives have undoubtedly helped to level the playing field for all demographic groups. The small population of out-of-state students at this institution may explain why residency is not tied to persistence as it has been in previous studies (Arredondo & Knight, 2006; Chimka, Reed-Rhoads, & Barker, 2007). For the most part, the strength and significance of parameter estimates for predictors in the survival analysis model (Model 5) were similar to those using logistic regression. The main difference between the two techniques was the importance of service-learning credits earned on a yearly basis.

Service-learning as a predictor for degree completion. While service-learning was not a significant covariate in any of the logistic regression models predicting the likelihood of degree completion, it was highly significant in the discrete-time survival analysis model, and it was somewhat significant as a predictor for time to completion in the multiple linear regression model (Model 6). When Model 5 was analyzed and variances were freely estimated for the time-varying predictors (SL credits earned and non-SL credits earned each year), SL credits were more significantly related to degree completion than non-SL credits. In fact, they were significant in years three, four, and six. The only year that they do not appear to have a strong effect on completion is in year five. The researcher hypothesizes that students who fail to finish their degree in their fourth year are more concerned with completing specific requirements for their major and have less time to engage in activities or courses not directly tied to completing these requirements. This is an interesting finding because it suggests that service-learning participation is strongly related to time. It could be that students who participate in service-learning more regularly (i.e., each year that they are enrolled in college) have a stronger likelihood for persisting to graduation than those who participate only sporadically. This is a question worth investigating more fully, and it is one that can only be answered using robust longitudinal modeling techniques.

Limitations

Quantitative studies that do not employ probability sampling are restricted in the generalizability of results and conclusions. In the case of this research, caution should be exercised when making inferences about undergraduate students in general. Conclusions should be limited to students enrolled at the institution studied. Although characteristics of the cohort sampled were similar to the population of undergraduates enrolled at the institution at that time, readers should also consider the possibility that there were differences in the cohort that were not explored, making these results specific to this sample of students. There are also differences in the number and type of service-learning courses offered. Course content was not considered among the variables analyzed in these models, and there could potentially be differential effects across course disciplines.

Academic disciplines were collapsed to facilitate data analysis and interpretation. The researcher grouped students by the institution's college or school in which they were enrolled during the semester that they graduated or the semester that they were last enrolled. This was the simplest method of grouping, but it fails to account for students who had double majors that were in different colleges or schools within the university. The researcher made the decision to use the university's primary major only. Collapsing majors into broader groupings also may diminish the effect of service-learning offerings that are more prevalent in smaller departments and programs. The impact on students who major in areas where there are many opportunities to take service-learning courses may be different than the impact on students who have fewer opportunities due to lack of course offerings in their major or program.

None of the models took into account academic progress that may have resulted from dual enrollment credits (college courses taken as a high school student), advanced placement (AP) credit, International Baccalaureate (IB) credit, or transfer credits earned at other institutions. Since these types of non-institutional academic credits undoubtedly have an effect on degree completion, their exclusion could have biased some of the estimated coefficients for other variables in the models.

Financial need and ability to pay are important factors for retention (Astin, 2005; Attewell, Heil, & Reisel, 2010; Bowen, Chingos, & McPherson, 2009; Gross, Hossler, & Ziskin; 2007; Mohn, 2006), but the Free Application for Federal Student Aid (FAFSA) can be confusing for students and families, particularly first-generation college students whose support systems may be ill-equipped to deal with unfamiliar rules and requirements (Tinto, 2012). As a result, there are probably needy students who fail to apply for aid. Although 56% of students in this sample did apply for aid at some point during their enrollment and were found to be needy, there could be others who did not apply. These students may have dropped out or failed to graduate for financial reasons. Paid employment can also have a positive effect on a student's ability to pay, but it can have a negative effect on a student's academic success if the hours devoted to work limit the hours that the student is able to devote to their studies. We don't know which students have paid employment as a substitute for financial aid or a as a supplement to financial aid, which somewhat limits the conclusions that can be drawn regarding financial variables and their influence on degree completion.

Recommendations for Future Research

Given the volume of previous research into multiple factors that are associated with student persistence, particularly the programs and initiatives that institutions implement to promote student success, there are clearly variables that help explain why some students persist to graduation and others do not (Tinto, 2012). Though student background characteristics are strongly predictive of degree completion, those are the factors that institutions cannot control unless they choose to be more selective in the admissions process. When access and equity are an important component of a college or university's mission, the institution must work to create an environment that promotes success and provides support for the academic progress of students whose preparation may not be as strong as others. Although this study makes an attempt to understand the effectiveness of service-learning as one of those academic programs that enhance learning, the number of students participating in service-learning courses may not have reached a volume that has a significant effect on degree completion. Overall, only 24% of students in this cohort took a service-learning course or courses during the six-year period of this study, and in any given year, the proportion of enrolled students taking service-learning never exceeded 10%. Yet, the students who did participate in service-learning graduated at a much higher rate than their peers. Future research should attempt to understand why this phenomenon is occurring.

Since group sizes are unequal, and graduation rates and SL course offerings vary somewhat by academic discipline at this institution, propensity score matching may be an effective way to study comparable samples of SL students and non-SL students to better estimate the impact of service-learning on degree completion. Since course offerings increased steadily during the period of the study, there is evidence that the number of students able to participate in service-learning will also grow, and courses may continue to diversify. Gradual increases in volume and diversity will undoubtedly change the characteristics of students participating. These changes should be monitored on a yearly basis, and each entering cohort should be tracked to determine whether the influence of service-learning changes as it begins to reach a critical mass of students. Another factor worthy of consideration is the possibility that courses in some departments or courses taught by different faculty may have a stronger influence than others. Future research should attempt to understand these instructional factors.

In terms of developing a more complete understanding of the factors that impact degree completion, the institution should ideally make use of additional data. Universities capture a wide variety of data for internal operational purposes and reporting, but these variables are not often used for robust modeling to answer strategic questions. In addition, services like the National Student Clearinghouse (Shapiro & Dundar, 2012) can provide data on students and their enrollment or degrees earned at other colleges and universities after they leave an institution. Finally, colleges and universities can capture additional information from students about the factors that influence their decisions to stay and graduate from the institution, transfer to another institution, or drop out altogether. Such data might include information about their initial goals, effectiveness of academic support programs that the university offers, and outcomes that may occur after a student leaves the institution. For example, did the student go on to complete a degree elsewhere? If these data were collected routinely and used with the kinds of data that this study used, colleges and universities might be able to construct better models to explain student enrollment, drop-out, and degree completion.

Conclusions

While service-learning can be a powerful tool for increasing engagement and enhancing student learning, this study shows that it may not have reached enough students in the population to have a significant impact on the overall degree completion rate. Yet, the differences shown in graduation rates between SL students and non-SL students are dramatic and significant. Discrete-time survival analysis shows that service-learning is a significant predictor for completion when data are analyzed using longitudinal methods. In addition, among students who completed their degree within six years, service-learning was a significant predictor of time to completion. Higher numbers of service-learning course credits were associated with a longer time to completion, which could imply that students who may not have graduated were engaged longer and that longer engagement led to more earned hours and ultimately graduation. Each of these findings suggests that service-learning has the potential to become a more important factor in degree completion.

Survival analysis in the SEM framework has some distinct advantages over logistic regression for understanding the variables that affect an event such as degree completion. There are many factors which affect the likelihood that a student will complete his or her degree. Some variables do not change over time, but others may vary significantly during the course of a student's enrollment in college. Moreover, the time that it takes a student to complete his or her degree can also vary. A few students will complete a baccalaureate degree within three years; many will graduate within the expected four years; others will take five or six years, or even longer; and many will not finish at all. Logistic regression forces the researcher to collapse these time-varying predictors and outcomes into a sum or average, or to pick a value at only one point in time, which limits the ability to understand how the factors that change over time influence the probability of an event occurring. Discrete-time survival analysis, on the other hand, can help researchers gain a better understanding of year-to-year patterns. This is particularly useful in understanding the impact of various factors on an event such as degree completion. However, the intended use of survival analysis is the modeling of time to event data. In most contexts, the event is a negative outcome, such as failure, death, or the onset of disease, which is estimated by a hazard function. When the event is a positive outcome, such as degree completion, interpretation of the results can be somewhat counterintuitive. Nevertheless, this method has the potential to be useful as colleges and universities attempt to evaluate the effectiveness of institutional programs and practices that target students at particular points in their college career.

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Appendices

Appendix A

Mplus Syntax for Initial Survival Analysis Model (Model 4)

```
Title:
   Model 4 - Survival Analysis
Data:
   File is "R:\DataFiles\model_4.tab";
Variable:
   Names are
      ID
  !Time-invariant covariates;
      FEMALE
      RACE_BLK
      RACE_HSP
      RACE_ASN
      RACE_OTH
      OUT_STAT
      HS_GPA
      SAT_V
      SAT_M
      CR_Y1_Y2
  !Time-varying covariates;
      DEG_Y3
      NEED_Y3
      AID_Y3
      PELL_Y3
      CR_SL_Y3
      CR_NS_Y3
      GPA_Y3
      DEG_Y4
      NEED_Y4
      AID_Y4
      PELL_Y4
      CR_SL_Y4
      CR_NS_Y4
      GPA_Y4
      DEG_Y5
      NEED_Y5
      AID_Y5
      PELL_Y5
      CR_SL_Y5
      CR_NS_Y5
      GPA_Y5
      DEG_Y6
      NEED_Y6
      AID_Y6
      PELL_Y6
      CR_SL_Y6
      CR_NS_Y6
      GPA_Y6;
```

```
   Usevariables are
      FEMALE
      RACE_BLK
      RACE_HSP
      RACE_ASN
      RACE_OTH
      OUT_STAT
      HS_GPA
      SAT_V
      SAT_M
      CR_Y1_Y2
      DEG_Y3
      NEED_Y3
      AID_Y3
      PELL_Y3
      CR_SL_Y3
      CR_NS_Y3
      GPA_Y3
      DEG_Y4
      NEED_Y4
      AID_Y4
      PELL_Y4
      CR_SL_Y4
      CR_NS_Y4
      GPA_Y4
      DEG_Y5
      NEED_Y5
      AID_Y5
      PELL_Y5
      CR_SL_Y5
      CR_NS_Y5
      GPA_Y5
      DEG_Y6
      NEED_Y6
      AID_Y6
      PELL_Y6
      CR_SL_Y6
      CR_NS_Y6
      GPA_Y6;
   Missing is .;
   Categorical are
      DEG_Y3
      DEG_Y4
      DEG_Y5
      DEG_Y6;
Analysis:
   Estimator = MLR;
   Integration = montecarlo;
   MITERATIONS = 1000;
```

```
Model:
   DEG_Y3 ON
      NEED_Y3  (b1)
      AID_Y3   (b2)
      PELL_Y3  (b3)
      CR_SL_Y3 (b4)
      CR_NS_Y3 (b5)
      GPA_Y3   (b6);
   DEG_Y4 ON
      NEED_Y4  (b1)
      AID_Y4   (b2)
      PELL_Y4  (b3)
      CR_SL_Y4 (b4)
      CR_NS_Y4 (b5)
      GPA_Y4   (b6);
   DEG_Y5 ON
      NEED_Y5  (b1)
      AID_Y5   (b2)
      PELL_Y5  (b3)
      CR_SL_Y5 (b4)
      CR_NS_Y5 (b5)
      GPA_Y5   (b6);
   DEG_Y6 ON
      NEED_Y6  (b1)
      AID_Y6   (b2)
      PELL_Y6  (b3)
      CR_SL_Y6 (b4)
      CR_NS_Y6 (b5)
      GPA_Y6   (b6);
   f BY DEG_Y3@1;
   f BY DEG_Y4@1;
   f BY DEG_Y5@1;
   f BY DEG_Y6@1;
   f ON FEMALE
      RACE_BLK
      RACE_HSP
      RACE_ASN
      RACE_OTH
      OUT_STAT
      HS_GPA
      SAT_V
      SAT_M
      CR_Y1_Y2;
    f@0;
  !Variances
      FEMALE;
      RACE_BLK;
      RACE_HSP;
      RACE_ASN;
      RACE_OTH;
      OUT_STAT;
      HS_GPA;
```

```
       SAT_V;
       SAT_M;
       CR_Y1_Y2;
       NEED_Y3;
       AID_Y3;
       PELL_Y3;
       CR_SL_Y3;
       CR_NS_Y3;
       GPA_Y3;
       NEED_Y4;
       AID_Y4;
       PELL_Y4;
       CR_SL_Y4;
       CR_NS_Y4;
       GPA_Y4;
       NEED_Y5;
       AID_Y5;
       PELL_Y5;
       CR_SL_Y5;
       CR_NS_Y5;
       GPA_Y5;
       NEED_Y6;
       AID_Y6;
       PELL_Y6;
       CR_SL_Y6;
       CR_NS_Y6;
       GPA_Y6;
!Means/Intercepts;
       [FEMALE];
       [RACE_BLK];
       [RACE_HSP];
       [RACE_ASN];
       [RACE_OTH];
       [OUT_STAT];
       [HS_GPA];
       [SAT_V];
       [SAT_M];
       [CR_Y1_Y2];
       [NEED_Y3];
       [AID_Y3];
       [PELL_Y3];
       [CR_SL_Y3];
       [CR_NS_Y3];
       [GPA_Y3];
       [NEED_Y4];
       [AID_Y4];
       [PELL_Y4];
       [CR_SL_Y4];
       [CR_NS_Y4];
       [GPA_Y4];
       [NEED_Y5];
       [AID_Y5];
```

```
       [PELL_Y5];
       [CR_SL_Y5];
       [CR_NS_Y5];
       [GPA_Y5];
       [NEED_Y6];
       [AID_Y6];
       [PELL_Y6];
       [CR_SL_Y6];
       [CR_NS_Y6];
       [GPA_Y6];
Output:
   tech1 tech8 standardized;
```

Appendix B

Mplus Syntax for Final Survival Analysis Model (Model 5) with Variances Constrained for Time-Varying Predictors

```
Title:
   Model 5 - Survival Analysis with Y-to-Y Variances Constrained
Data:
   File is "model_5.tab";
Variable:
   Names are
        ID
        DEG_TIME
        FEMALE
        RACE_BLK
        RACE_HSP
        RACE_ASN
        RACE_OTH
        OUT_STAT
        HS_GPA
        SAT_V
        SAT_M
        GPA_ONE
        GPA_CUM
        CR_Y1_Y2
        AID_CUM
        DEG_Y3
        DEG_Y4
        DEG_Y5
        DEG_Y6
        NEED_Y3
        NEED_Y4
        NEED_Y5
        NEED_Y6
        AID_Y3
        AID_Y4
        AID_Y5
        AID_Y6
        PELL_Y3
        PELL_Y4
        PELL_Y5
        PELL_Y6
        CR_SL_Y3
        CR_SL_Y4
        CR_SL_Y5
        CR_SL_Y6
        CR_NS_Y3
        CR_NS_Y4
        CR_NS_Y5
        CR_NS_Y6;
   Usevariables are
```

```
          HS_GPA
          SAT_V
          SAT_M
          GPA_CUM
          CR_Y1_Y2
          DEG_Y3
          DEG_Y4
          DEG_Y5
          DEG_Y6
          CR_SL_Y3
          CR_SL_Y4
          CR_SL_Y5
          CR_SL_Y6
          CR_NS_Y3
          CR_NS_Y4
          CR_NS_Y5
          CR_NS_Y6;
     Missing is .;
     Categorical are
        DEG_Y3
        DEG_Y4
        DEG_Y5
        DEG_Y6;
     Dsurvival are
        DEG_Y3
        DEG_Y4
        DEG_Y5
        DEG_Y6;
  Analysis:
     Estimator = MLR;
     Integration = montecarlo;
     MITERATIONS = 1000;
     MCCONVERGENCE = .001;
     PROCESSOR = 8;
  Model:
     DEG_Y3 ON
        CR_SL_Y3 (b1)
        CR_NS_Y3 (b2);
     DEG_Y4 ON
        CR_SL_Y4 (b1)
        CR_NS_Y4 (b2);
     DEG_Y5 ON
        CR_SL_Y5 (b1)
        CR_NS_Y5 (b2);
     DEG_Y6 ON
        CR_SL_Y6 (b1)
        CR_NS_Y6 (b2);
     f BY DEG_Y3@1;
     f BY DEG_Y4@1;
     f BY DEG_Y5@1;
     f BY DEG_Y6@1;
     f ON
```

```
     HS_GPA
     SAT_V
     SAT_M
     CR_Y1_Y2
     GPA_CUM;
   f@0;
!Variances
     HS_GPA;
     SAT_V;
     SAT_M;
     CR_Y1_Y2;
     GPA_CUM;

     CR_SL_Y3 with CR_SL_Y3@4.0;
     CR_SL_Y4 with CR_SL_Y4@4.5;
     CR_SL_Y5 with CR_SL_Y5@3.5;
     CR_SL_Y6 with CR_SL_Y6@3.0;

     CR_NS_Y3;
     CR_NS_Y4;
     CR_NS_Y5;
     CR_NS_Y6;

     HS_GPA pwith CR_SL_Y3@0;
     SAT_V pwith CR_SL_Y3@0;
     SAT_M pwith CR_SL_Y3@0;
     GPA_CUM pwith CR_SL_Y3@0;
     CR_Y1_Y2 pwith CR_SL_Y3@0;

     HS_GPA pwith CR_SL_Y4@0;
     SAT_V pwith CR_SL_Y4@0;
     SAT_M pwith CR_SL_Y4@0;
     GPA_CUM pwith CR_SL_Y4@0;
     CR_Y1_Y2 pwith CR_SL_Y4@0;

     HS_GPA pwith CR_SL_Y5@0;
     SAT_V pwith CR_SL_Y5@0;
     SAT_M pwith CR_SL_Y5@0;
     GPA_CUM pwith CR_SL_Y5@0;
     CR_Y1_Y2 pwith CR_SL_Y5@0;

     HS_GPA pwith CR_SL_Y6@0;
     SAT_V pwith CR_SL_Y6@0;
     SAT_M pwith CR_SL_Y6@0;
     GPA_CUM pwith CR_SL_Y6@0;
     CR_Y1_Y2 pwith CR_SL_Y6@0;

     HS_GPA pwith CR_NS_Y3@0;
     SAT_V pwith CR_NS_Y3@0;
     SAT_M pwith CR_NS_Y3@0;
     GPA_CUM pwith CR_NS_Y3@0;
     CR_Y1_Y2 pwith CR_NS_Y3@0;
```

```
       HS_GPA pwith CR_NS_Y4@0;
       SAT_V pwith CR_NS_Y4@0;
       SAT_M pwith CR_NS_Y4@0;
       GPA_CUM pwith CR_NS_Y4@0;
       CR_Y1_Y2 pwith CR_NS_Y4@0;

       HS_GPA pwith CR_NS_Y5@0;
       SAT_V pwith CR_NS_Y5@0;
       SAT_M pwith CR_NS_Y5@0;
       GPA_CUM pwith CR_NS_Y5@0;
       CR_Y1_Y2 pwith CR_NS_Y5@0;

       HS_GPA pwith CR_NS_Y6@0;
       SAT_V pwith CR_NS_Y6@0;
       SAT_M pwith CR_NS_Y6@0;
       GPA_CUM pwith CR_NS_Y6@0;
       CR_Y1_Y2 pwith CR_NS_Y6@0;

!Means/Intercepts;
       [HS_GPA];
       [SAT_V];
       [SAT_M];
       [CR_Y1_Y2];
       [GPA_CUM];
       [CR_SL_Y3];
       [CR_SL_Y4];
       [CR_SL_Y5];
       [CR_SL_Y6];
       [CR_NS_Y3];
       [CR_NS_Y4];
       [CR_NS_Y5];
       [CR_NS_Y6];
Output:
   standardized tech1;
PLOT:
   Type = Plot2;
```

Appendix C

Mplus Syntax for Final Survival Analysis Model (Model 5) with Variances Freely Estimated for Time-Varying Predictors

```
Title:
   Model 5 - Survival Analysis with Y-to-Y Variances Freely Estimated
Data:
   File is "model_5.tab";
Variable:
   Names are
         ID
         DEG_TIME
         FEMALE
         RACE_BLK
         RACE_HSP
         RACE_ASN
         RACE_OTH
         OUT_STAT
         HS_GPA
         SAT_V
         SAT_M
         GPA_ONE
         GPA_CUM
         CR_Y1_Y2
         AID_CUM
         DEG_Y3
         DEG_Y4
         DEG_Y5
         DEG_Y6
         NEED_Y3
         NEED_Y4
         NEED_Y5
         NEED_Y6
         AID_Y3
         AID_Y4
         AID_Y5
         AID_Y6
         PELL_Y3
         PELL_Y4
         PELL_Y5
         PELL_Y6
         CR_SL_Y3
         CR_SL_Y4
         CR_SL_Y5
         CR_SL_Y6
         CR_NS_Y3
         CR_NS_Y4
         CR_NS_Y5
         CR_NS_Y6;
   Usevariables are
```

```
        HS_GPA
        SAT_V
        SAT_M
        GPA_CUM
        CR_Y1_Y2
        DEG_Y3
        DEG_Y4
        DEG_Y5
        DEG_Y6
        CR_SL_Y3
        CR_SL_Y4
        CR_SL_Y5
        CR_SL_Y6
        CR_NS_Y3
        CR_NS_Y4
        CR_NS_Y5
        CR_NS_Y6;
   Missing is .;
   Categorical are
      DEG_Y3
      DEG_Y4
      DEG_Y5
      DEG_Y6;
   Dsurvival are
      DEG_Y3
      DEG_Y4
      DEG_Y5
      DEG_Y6;
Analysis:
   Estimator = MLR;
   Integration = montecarlo;
   MITERATIONS = 1000;
   MCCONVERGENCE = .001;
   PROCESSOR = 8;
Model:
   DEG_Y3 ON
      CR_SL_Y3
      CR_NS_Y3;
   DEG_Y4 ON
      CR_SL_Y4
      CR_NS_Y4;
   DEG_Y5 ON
      CR_SL_Y5
      CR_NS_Y5;
   DEG_Y6 ON
      CR_SL_Y6
      CR_NS_Y6;
   f BY DEG_Y3@1;
   f BY DEG_Y4@1;
   f BY DEG_Y5@1;
   f BY DEG_Y6@1;
   f ON
```

```
     HS_GPA
     SAT_V
     SAT_M
     CR_Y1_Y2
     GPA_CUM;
   f@0;
!Variances
     HS_GPA;
     SAT_V;
     SAT_M;
     CR_Y1_Y2;
     GPA_CUM;

     CR_SL_Y3 with CR_SL_Y3@4.0;
     CR_SL_Y4 with CR_SL_Y4@4.5;
     CR_SL_Y5 with CR_SL_Y5@3.5;
     CR_SL_Y6 with CR_SL_Y6@3.0;

     CR_NS_Y3;
     CR_NS_Y4;
     CR_NS_Y5;
     CR_NS_Y6;

     HS_GPA pwith CR_SL_Y3@0;
     SAT_V pwith CR_SL_Y3@0;
     SAT_M pwith CR_SL_Y3@0;
     GPA_CUM pwith CR_SL_Y3@0;
     CR_Y1_Y2 pwith CR_SL_Y3@0;

     HS_GPA pwith CR_SL_Y4@0;
     SAT_V pwith CR_SL_Y4@0;
     SAT_M pwith CR_SL_Y4@0;
     GPA_CUM pwith CR_SL_Y4@0;
     CR_Y1_Y2 pwith CR_SL_Y4@0;

     HS_GPA pwith CR_SL_Y5@0;
     SAT_V pwith CR_SL_Y5@0;
     SAT_M pwith CR_SL_Y5@0;
     GPA_CUM pwith CR_SL_Y5@0;
     CR_Y1_Y2 pwith CR_SL_Y5@0;

     HS_GPA pwith CR_SL_Y6@0;
     SAT_V pwith CR_SL_Y6@0;
     SAT_M pwith CR_SL_Y6@0;
     GPA_CUM pwith CR_SL_Y6@0;
     CR_Y1_Y2 pwith CR_SL_Y6@0;

     HS_GPA pwith CR_NS_Y3@0;
     SAT_V pwith CR_NS_Y3@0;
     SAT_M pwith CR_NS_Y3@0;
     GPA_CUM pwith CR_NS_Y3@0;
     CR_Y1_Y2 pwith CR_NS_Y3@0;
```

```
      HS_GPA pwith CR_NS_Y4@0;
      SAT_V pwith CR_NS_Y4@0;
      SAT_M pwith CR_NS_Y4@0;
      GPA_CUM pwith CR_NS_Y4@0;
      CR_Y1_Y2 pwith CR_NS_Y4@0;

      HS_GPA pwith CR_NS_Y5@0;
      SAT_V pwith CR_NS_Y5@0;
      SAT_M pwith CR_NS_Y5@0;
      GPA_CUM pwith CR_NS_Y5@0;
      CR_Y1_Y2 pwith CR_NS_Y5@0;

      HS_GPA pwith CR_NS_Y6@0;
      SAT_V pwith CR_NS_Y6@0;
      SAT_M pwith CR_NS_Y6@0;
      GPA_CUM pwith CR_NS_Y6@0;
      CR_Y1_Y2 pwith CR_NS_Y6@0;

!Means/Intercepts;
      [HS_GPA];
      [SAT_V];
      [SAT_M];
      [CR_Y1_Y2];
      [GPA_CUM];
      [CR_SL_Y3];
      [CR_SL_Y4];
      [CR_SL_Y5];
      [CR_SL_Y6];
      [CR_NS_Y3];
      [CR_NS_Y4];
      [CR_NS_Y5];
      [CR_NS_Y6];
Output:
   standardized tech1;
PLOT:
   Type = Plot2;
```

Vita

Kelly Smith Lockeman was born on January 23, 1970, in Maury County, Tennessee, and is an American citizen. She graduated from Manchester High School, Chesterfield County, Virginia in 1988. She received her Bachelor of Arts in History from The College of William and Mary, Williamsburg, Virginia in 1992 and a Master of Education in Educational Policy, Planning, and Leadership with an emphasis in Higher Education in 2004.

Prior to beginning her doctoral studies, she spent more than ten years working in academic and administrative support at The College of William and Mary and three years working as a research analyst at Virginia Commonwealth University. Her professional background in higher education is varied and includes experiences providing faculty support, serving as registrar, implementing a university-wide information system (Banner), supporting academic planning, and doing institutional research and reporting.

As a doctoral student, Kelly served as a graduate assistant in several programs at VCU. Her research interests include two broad areas: (1) student success in higher education, the factors that correlate with success, and their underlying causes; and (2) the measures that are used by institutions, government entities, accrediting agencies, public media, and academic researchers to assess and evaluate success. She has presented at academic conferences such as the Virginia Educational Research Association (VERA), the Metropolitan Educational Research Consortium (MERC), the International Association for Research in Service-Learning and Community Engagement (IARSLCE), and the International Conference on Service-Learning in Teacher Education (ICSLTE).