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The volume of articles, books, and studies about increasing the retention, persistence, and graduation of undergraduate college students is nothing short of prolific (Seidman, 2005). However, only modest gains in undergraduate graduation rates have been made nationally (Chen, 2012; Seidman, 2005). Six-year graduation rates at all four-year colleges and universities rose minimally from 54.4% for the entering cohort of 1996 to 54.9% for the cohort beginning fourteen years later (U.S. Department of Education, 2019) with 35% of institutions experiencing declines in graduation rates during part of this period (Brainard & Fuller, 2010). Persistently low graduation rates coupled with recent leaps forward in technology, including processing speeds, statistical software, and data warehousing, have led many higher education researchers, practitioners, and companies to apply statistical models to examine what variables have a relationship with graduation. Many multi-university models suffer from a variety of hurdles including large amounts of missing data, missing important variables, questionable data quality and lack of common definitions across colleges or universities, and/ or inappropriate statistical methods that do not account for the nested nature of the data (students within universities).

This study sought to avoid many of the limitations of past studies and used a two-level logistic hierarchical generalized linear model to comprehensively model six-year graduation in the UNC System. Included in this study were 406,909 undergraduate students who began undergraduate degree-seeking enrollment in any of the 16 public universities in the state of North Carolina from 2000 until 2010. Each variable included in the model was selected based on evidence in the literature of significant relationships with retention and persistence found in regression-based models. In comparison to past literature, this study included a wider array of financial and financial aid-related variables and examined more closely the relationship between university characteristics and student characteristics. Most level-1, student, variables included in this study were significant. The level-2, university, characteristics residential status and selectivity were found to have a significant relationship with six-year graduation and to have an influence on the relationship between some of the student-level covariates and six-year graduation. The results confirmed many of the relationships in the literature between the variables studied and student attrition with some fascinating deviations explored in the discussion. Limitations and suggestions for future research are provided. The results of this study will equip university practitioners and policy-makers in North Carolina with information to improve graduation and further explore student attrition. This study can act as a model for how other states or higher education systems use their own administrative data for comprehensive, multi-institutional modeling.

MULTILEVEL MODELING OF UNDERGRADUATE STUDENT ATTRITION ACROSS

THE UNIVERSITY OF NORTH CAROLINA SYSTEM

by

Elizabeth M. Reilley

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Approved by

John T. Willse
Committee Chair

To my family, biological and chosen, especially my husband, Jordan, for sorting my laundry into lights and darks even though he doesn't believe it makes a difference and for everything; to Laura for rolling her eyes when she heard someone tell me that I should just finish my degree (as if I hadn't considered that); to Xan for his prodding and encouraging text messages; to my mom for knowing when not to ask how my dissertation was coming along even when she really wanted to; and to my dad for always being proud of me no matter what I do and no matter how long it takes.

APPROVAL PAGE

This dissertation, written by Elizabeth M. Reilley, has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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CHAPTER I

INTRODUCTION

Thousands of research studies and articles have been written about modeling student attrition in higher education (Seidman, 2005). Keeping students enrolled in college through graduation has been a major dilemma since the 1970s (Demetriou & Schmitz-Sciborski, 2011), but scholars began studying the topic many years. However, only modest gains have been made in the United States over the past decade or more in retention and graduation rates (Chen, 2012; Seidman, 2005). While these gains deserve celebration, particularly in the context of increasing demographic diversity and access, graduation rates at colleges and universities in the United States are still too low. Leaving college and without finishing a degree often leaves students saddled with student loan debt and no income gain to justify the investment of time and money (Kolodner & Butrymowicz, 2017; Torpey, 2018). Low income students, who are less able to absorb the impact of additional debt, are more likely than their higher income peers to drop out of college. Many tout higher education as an equalizer in a society where achievement is supposed to be driven by merit and personal accomplishment rather than the circumstances that one is born into, but persistent achievement gaps and overall low graduation rates undermine this ideal.

Figure 1 shows six-year graduation rates at all four-year colleges and universities rising from approximately 54.4% for the entering cohort of 1996 to 54.9% for the cohort beginning fourteen years later (U.S. Department of Education, 2019) with 35% of institutions experiencing declines in graduation rates during this period (Brainard & Fuller, 2010). When four-year public universities are isolated, they track similarly to the overall six-year graduation rates, rising from approximately 50.6% for the 1996 cohort graduating by 2002 to 54.7% in the 2010 cohort graduating by 2016 (U.S. Department of Education, 2019). For two-year institutions, the picture is even less promising, with a variety of increases and even subsequent declines in completion rates for both degrees and certificates.

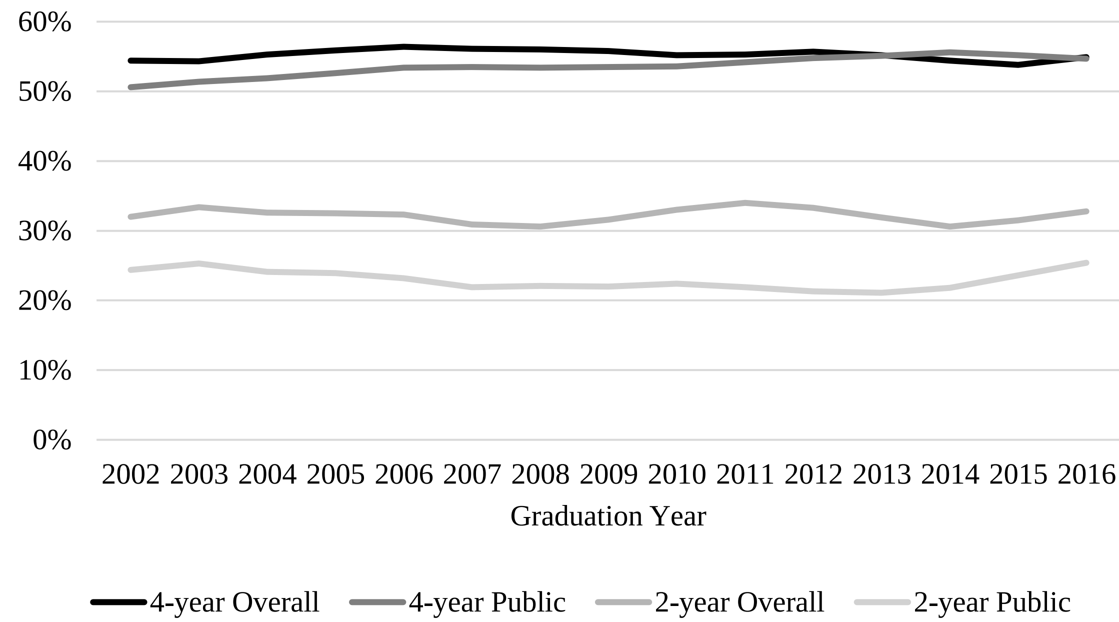

Figure 1. Graduation Rate within 150% of Normal Time at 4-year (6-year Graduation Rate) and 2-Year (3-year Graduation Rate) Postsecondary Institutions from the National Center for Education Statistics (Key Ordered by 2002 Value Highest to Lowest).

Figure 2 shows almost entirely flat first to second year retention rates across two- and four-year higher education institutions (U.S. Department of Education, 2013). Overall, retention rates have hovered around 71% from 2006 to 2012, meaning that approximately two out of every five students who enter college leave that institution at or before their second year without achieving a credential. For the 2006-07 academic year, four-year public institutions had a retention rate of 78%. Five years later, those same institutions have only improved the retention rate by one percentage point. (U.S. Department of Education, 2019). Across all types of institutions, retention rates have remained relatively static over the past decade.

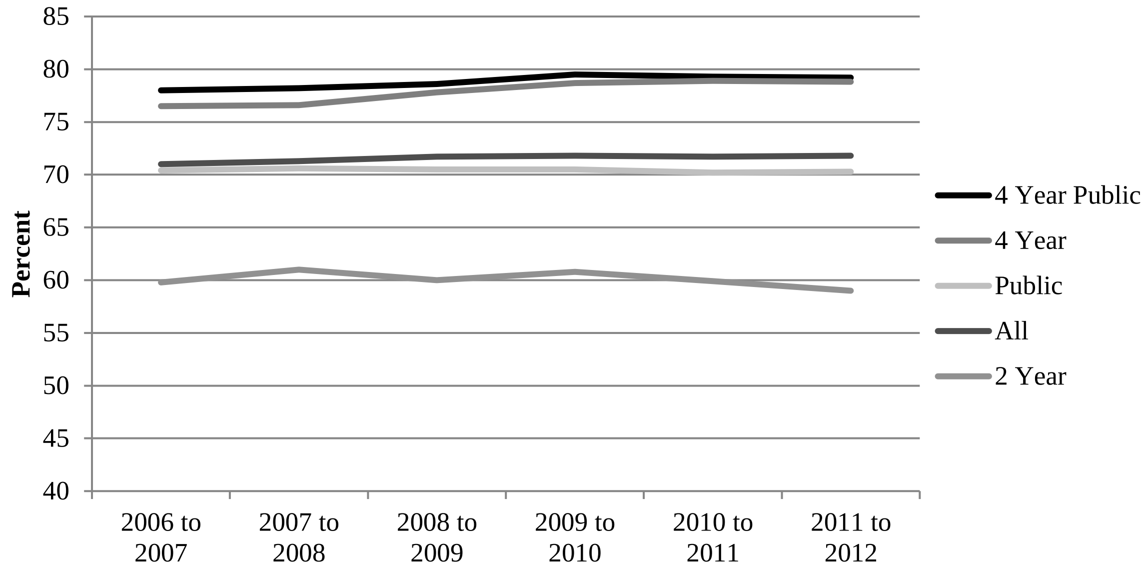

Figure 2. First to Second Year Retention Rates at US Postsecondary Institutions from the National Center for Education Statistics (Key ordered by 2006 to 2007 Value Highest to Lowest).

In addition to collecting data about student demographics and outcomes, The National Center for Education Statistics also collect financial data from post-secondary institutions. Several of the categories of institutional expenditures collected are often thought of as having a relationship with attrition: scholarships, academic support, student services and instructional expenditures (Ryan, 2004; Gansemer-Topf & Schuh, 2006; Scott, Baily, & Kienzl, 2006). Table 1 shows the percent change from the 2006-07 academic year to the 2012-13 academic year in per student expenses in 2012-2013 dollars in these areas. While per pupil expenditures in most categories typically associated with increasing retention and graduation rates have, overall, increased at both public and private institutions, Figures 1 and 2 which show relatively stagnated graduation and retention rates may cast doubt on whether these spending increases have been enough or have been effective.

Table 1

Percent Change in Expenditures Per Full Time Equivalent Student in 2012-2013 Dollars Between the 2006-2007 and 2012-2013 Academic Years

	Scholarships, Net Grant Aid, and Fellowships	Academic Support	Student Services	Total Instruction
4 Year Public	23.69%	1.27%	3.31%	-3.98%
All Public	40.88%	1.41%	0.42%	-3.97%
All Private	-8.86%	6.85%	11.18%	2.56%
4 Year Private	-7.64%	6.85%	11.40%	2.60%

An important aspect to consider in examining descriptive statistics related to graduation and retention is the changing demographic landscape over time at colleges and universities across the country. Between 1976 and 2013, the percent of students who identify as white decreased by 31%, while the percent of students who identify as Hispanic increased by over 300% (U.S. Department of Education, 2013). Over this same time period (1976 to 2013), the percent of males in degree-granting post-secondary institutions decreased by 10 percentage points from 53% to 43%, while the percent of females increased approximately 10 percentage points (U.S. Department of Education, 2013). Over the past 40 years, the demographic landscape of the United States and of its colleges and universities has changed dramatically. Student characteristics such as race/ethnicity (Oseguera & Rhee, 2009; Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003), age (Singell & Stater, 2006), gender (Schibik & Harrington, 2004; Astin & Oseguera, 2005; Porter & Swing, 2006; Kim, Roades, & Woodard, 2003), and socioeconomic status (Ishitani, 2006; Oseguera & Rhee, 2009; Rhee, 2008) have all been found to have a significant relationship with attrition. It follows then that large changes in the demographic make-up of the student body at post-secondary institutions would have an effect on retention and graduation rates. Figure 3 shows the percent of total enrollment of various races/ethnicities at degree-granting post-secondary institutions.

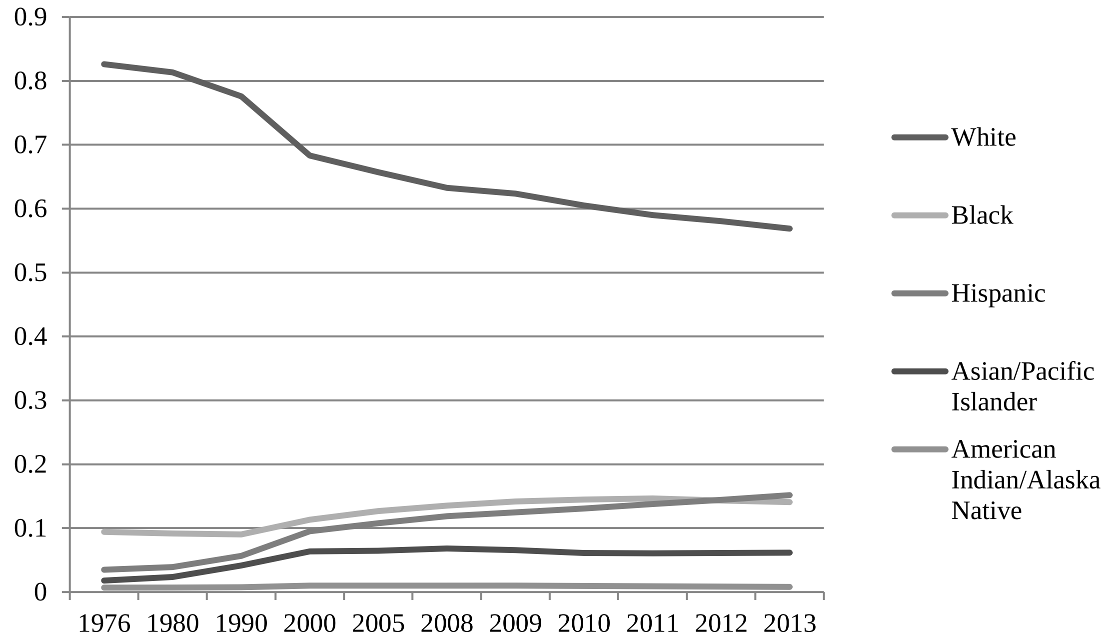

Figure 3. Percent of Total Fall Enrollment in Degree-Granting Postsecondary Institutions by Year by Race/Ethnicity from the National Center for Education Statistics (Key Ordered by 1976 Value Highest to Lowest).

There are many complexities in trying to understand the patterns in student retention and graduation and what factors exert the most influence. With a constantly changing economic and demographic landscape in the United States, it can be difficult to isolate the influences on attrition, particularly with a simple model or small set of variables. Despite a growing canon of research on the matter, significantly increasing rates of retaining and graduating students remains an elusive goal for many colleges and universities in the United State. More recent studies and compilations of literature on the subject identify multilevel and, relatedly, group disaggregation as the types of models that require further research (Chen, 2012) and that have the potential to assist in isolating salient effects. While any studies of attrition that include multiple institutions contain nested data, the vast majority of multi-institutional studies analyze the data at a single level, institution or student, and thus do not account for the nested structure. This can result in a variety of different problems, including violations of the assumptions of independence and homoscedasticity, incorrect standard errors, aggregation bias, and distorted relationships between variables (Raudenbush & Bryk, 2002).

In addition to statistical issues, interpretation and usability issues arise when nested structure is not addressed in the statistical model. Effects may be obscured, especially with the complexities that exist in studying attrition in higher education, when heterogeneous institutions are included in the same model. In these cases, both students and institutions may have disparate and sometimes inverse relationships with the variables studied. While significant effects may be obvious when institutions are studied individually, these effects may get minimized or disappear altogether when data is aggregated to include other institutions. Also, attrition research at the level of the individual institution often generates results that are more actionable for that institution, as the methodology and available variables tend to be more tailored to the institution or type of institution. It does not make sense for a small, private historically black (HBCU) liberal arts college to enact changes based on a study that combines both small HBCUs with large, public, and mostly white schools into one pool to be studied. It would make much more sense for the small HBCU to make institutional changes based on an examination of its own student data and possibly that of other similar institutions.

Hierarchical linear modeling (HLM) accounts for the nested nature of multi-institution studies and eliminates many of the statistical and functional issues that arise when using single level models. Recent improvements in technology and statistics have made these models much more accessible. Nevertheless, relatively few comprehensive attrition studies employ them. This study used a hierarchical generalized linear model (HGLM) to explore which variables and at which levels (student and institution) contribute most significantly to undergraduate attrition at North Carolina's 16 public universities. The two main contributions to existing literature using multilevel modeling to study attrition are: 1) the use of a more robust dataset containing fewer proxy variables and less missing data than previous studies and 2) the inclusion of a more comprehensive set of financial aid variables. This study will provide university practitioners and policy-makers in North Carolina with actionable information by which to improve and further explore student attrition and can act as a model for how other states or higher education systems may use their own administrative data for comprehensive, multi-institutional studies.

CHAPTER II

LITERATURE REVIEW

This literature review is divided into three sections. The first section surveys the history of the study of attrition in higher education in an attempt to give context to this study. The second section identifies the characteristics that have been found—mainly through regression-based studies--to have a relationship with attrition. The purpose of the second section is to identify the institution- and student-level characteristics that should be included in any comprehensive, evidence-based study of attrition. The final section looks at methodology. This section explores the ideal methodology by which the characteristics in the second section can be combined into a cohesive and comprehensive model of student attrition.

History

For the first few centuries of higher education in what is now the United States, retention, persistence, and graduation were not topics of any interest. Berger and Lyon (2005) write that the lack of interest in topics related to attrition is because, from the 1600 to the 1800s, degrees were not a necessary credential in the job market and higher education served a very small and specific segment of the population. College degrees were simply not important in early American history, and, because they were so rare, attrition was not a concern. From the late 1800s into the middle of the 1900s, college and university programs expanded and enrollment grew significantly.

One of the first studies of attrition was conducted by John McNeely (1937) for the United States Department of the Interior and Office of Education. McNeely collected data about student "mortality" (today known as attrition) from 25 colleges and universities. He found that, on average, 28.3% of students who began in academic year 1931-1932 obtained a degree in the expected 4-year time period. An average of 64.5% left the university during the same 4-year period without obtaining a degree. McNeely identified many causes or contributors to attrition that are still included in studies today, including academic performance, “financial difficulties,” family obligations, “participation in extracurricular activities,” and “engagement in part-time work.”

Due to a variety of factors--including the passage of the GI Bill, the National Defense of Education Act of 1958, the Higher Education Act of 1965, the War on Poverty and the Civil Rights Movement--attendance of and access to higher education began to dramatically climb beginning in the 1950s (Berger & Lyon, 2005). The middle of the 1900s marked the beginning of college education and degrees as a driver of social mobility (Berger & Lyon, 2005) as those with college degrees found additional higher paying career paths available to them. The rapid expansion in enrollment drove an increase in diversity in higher education, as students of varying incomes, races, and ethnicities began advocating for their right to have access to college. This expansion in turn led to more research into retention and degree completion rates (Demetriou & Schmitz-Sciborski, 2011).

The politics, societal climate, and various laws and policies of the preceding decades culminated in the 1970s becoming “the dawn of theory in the study of college student retention.” (Demetriou & Schmitz-Sciborski, 2011) Attrition research was, by this point, widespread enough to “construct a knowledge base.” William Spady’s seminal article titled “Dropouts from Higher Education: An Interdisciplinary Review and Synthesis” was published in 1971 (Berger & Lyon, 2005). Spady (1971) summarized the attrition literature up until that point in time and postulated a model of student dropout that contained both student attributes as well as characteristics about student interactions with their environment. Soon after, Tinto’s (1975) still famous and widely cited work “Dropout from Higher Education: A Theoretical Synthesis of Recent Research” built on Spady's work. Both Spady and Tinto applied Durkheim's (1961) theory of suicide. They borrowed from Durkheim the idea that intentional dropout from college (suicide in Durkheim's theory) is more likely when students are not sufficiently integrated into the community. Tinto (1975) extends this concept to distinguish between various kinds of dropout ("forced" and "voluntary") and discusses academic as well as social integration. Tinto's model, like many other models of attrition, focused mainly on the individual rather than the institution. Tinto included both demographic characteristics, as well as behavioral and personality characteristics, but all at the student level.

Furthering interest in attrition research, the 1980s brought a leveling off of higher education enrollments (Berger & Lyon, 2005). Born out of the desire to maintain or increase enrollments, the connection between admissions, retention, and completion was forged and the concept of "enrollment management" was born (Berger & Lyon, 2005). Jack Maguire first used the term in 1976 (Hossler, 2002), but, since the 1980s, it has been the norm to include elements of enrollment management in retention research, such as the inclusion of high school variables and a focus on intentionally shaping the make-up of the student body. Many attrition studies conducted in the 1980s built on previous theories as well as postulated new theories (Berger & Lyon, 2005). Prior to the 1990s there was a large body of research that looked mainly at student characteristics and to a much lesser degree institutional characteristics (Kamens, 1971; Gosman, Dandridge, Nettles, & Thoeny, 1983). Many of these studies integrated theories from various disciplines including sociology (Kamens, 1971; Spady, 1971; Tinto, 1975), organizational behavior (Bean, 1983), and psychology (Bentler & Speckart, 1979).

Researchers during the 1990s and 2000s more rigorously tested the assertions of the seminal attrition literature from the previous decades. Tinto's model in particular was put to the test with numerous studies challenging and revising almost every aspect of it (Braxton, Sullivan,

& Johnson, 1997; Berger & Braxton, 1998). The research of Braxton, Sullivan, and Johnson (1997) suggested that the focus of future research should be on social rather than academic integration and recommended that additional student-level characteristics in this area be explored in future research. Many studies followed that took up the challenge (Berger & Lyon, 2005).

Today the literature on the topics of student attrition, retention, and persistence is vast (Oseguera & Rhee, 2009; Jones-White, Radcliffe, Huesman, & Kellogg, 2010; Seidman, 2005), examining the subject from hundreds of different angles. Many earlier studies focused on student-level characteristics and psychological factors (Berger & Lyon, 2005), but today it is not uncommon to find studies with models that examine institutional factors (Rhee, 2008; Chen, 2012). Only recently have studies that employ multilevel modeling to explore attrition begun to appear. With recent advances in statistical modeling and software, models that combine many relevant institution and student characteristics and their various and sometimes complex interactions can be combined into an overall model. The remainder of this literature review will be divided into two parts: one that explores the various student- and institution-level characteristics that have been found to influence attrition and another that discusses the methodology necessary to combine all those different characteristics into one cohesive model.

Characteristics that Influence Student Attrition

Effects on student attrition can be identified at various levels. Student level characteristics have been widely studied, fewer studies have looked at the institution level, and fewer still have incorporated both student and institution characteristics into the same study (Titus, 2004). Demographic and academic attributes at the student-level, such as GPA and admission test scores, (Oseguera & Rhee, 2009; Ryan, 2004; Schibik & Harrington, 2004; Scott, Baily, & Kienzl, 2006; Kim, Roades, & Woodard, 2003) and readily available institution-level attributes, such as selectivity (Kim, 2007; Titus, 2004; Gansemer-Topf & Schuh, 2006; Oseguera

& Rhee, 2009; Kim, Roades, & Woodard, 2003) and aggregate student demographics (Rhee, 2008; Kim, Roades, & Woodard, 2003; Scott, Baily, & Kienzl, 2006) have also been studied at length. Financial aid is an area notably missing from many attrition studies (Singell, 2004), both at the student and institution level. Even fewer studies have incorporated financial aid variables at both the student and institution level into a single model.

Because of the wealth of research on the characteristics that influence attrition, this section of the literature review will focus only on studies conducted since 2000, reasoning that results from more recent studies will be most relevant to the students in this study, all of whom attended college between 2000 and 2015. Looking at more recent articles also implicitly includes more complex models and more rigorous standards for research and publication as these standards have generally been raised with time as the methods and field have progressed. This study incorporates many of the significant characteristics identified in previous research using multilevel models that incorporate both student and institution level information. No claim of causation is being made for any of the characteristics or variables discussed in this section or in this study. Only the statistical relationship, mainly through covariance, is examined here.

Student-Level

There is a wealth of research on student-level variables that have a relationship with student attrition. Using these established variables allows the construction of a model that is as complete as possible while also minimizing the risk of spurious relationships. Table 2 summarizes the main variables identified in studies as having a relationship with student attrition. All of the variables are put on a common “scale” of attrition: leaving the post-secondary institution. Variables linked to higher drop-out rates have a positive “relationship with attrition.” Conversely, if the study found the variable to be related to remaining at the institution the “relationship with attrition” of the variable is negative. Also, the table divides up the various student-level characteristics into themed segments. These segments are not in any way meant to imply factors or any other type of statistically justifiable grouping. Their only purpose is to assist in the organization and flow of the information in the literature review. However, note that Raudenbush and Bryk (2002) recommend that variables be entered into the HGLM model in conceptually related blocks.

Table 2

Student-Level Characteristics with a Relationship on College Student Attrition

Name	Relationship with Attrition[2]	Reference
	High School or Pre-College Characteristics	
Average High School Grades	Negative	Astin & Oseguera, 2005
High School Class Rank	Negative	Ishitani, 2006
High School GPA	Negative	Oseguera & Rhee, 2009; Porter & Swing, 2006
SAT or ACT Scores	Negative	Oseguera & Rhee, 2009; Ryan, 2004; Schibik & Harrington, 2004; Scott, Baily, & Kienzl, 2006; Kim, Roades, & Woodard, 2003
	Demographic Characteristics	
Age	Positive	Singell & Stater, 2006
Being African-American/ Black[1]	Positive	Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003
Being American Indian[1]	Positive	Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003
Being First Generation[1]	Positive	Ishitani, 2006
Being Hispanic/ Latino[1]	Positive	Oseguera & Rhee, 2009; Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003
Being Male[1]	Positive	Schibik & Harrington, 2004; Astin & Oseguera, 2005; Porter & Swing, 2006; Kim, Roades, & Woodard, 2003
Being White[1]	Negative	Oseguera & Rhee, 2009
Income/ Socioeconomic Status	Negative	Ishitani, 2006; Oseguera & Rhee, 2009; Rhee, 2008
	College Academic and Other Characteristics	
College GPA	Negative	Titus, 2004
Majoring in a Field Requiring Higher Level Math[1]	Negative	Herzog, 2005
Participation in a First Year Seminar	Negative	Clark & Cundiff, 2011
Passing a First Year Math Course[1]	Negative	Herzog, 2005
Semester Hours Attempted	Negative	Schibik & Harrington, 2004; Herzog, 2005
Commitment to Earning Degree	Negative	Ishitani, 2006; Titus, 2004
Desire to Transfer	Positive	Oseguera & Rhee, 2009
Hours Worked	Negative/ Positive	Titus, 2004/ Porter & Swing, 2006

Table 2

Cont.

Name	Relationship with Attrition[2]	Reference
College Academic and Other Characteristics (cont.)		
Living on Campus	Negative	Braxton & Hirschy, 2004; Oseguera & Rhee, 2009; Titus, 2004; Herzog, 2005
Using Recreational Facilities	Negative	Herzog, 2005
Taking Remedial Courses	Positive	Adelman, 2004 (Any Subject); Herzog, 2005 (Math)
Financial Aid Characteristics		
Financial Concern	Positive	Oseguera & Rhee, 2009
Financial Need	Positive/ Negative	Singell & Stater, 2006/ Titus, 2004
Offered Loans	Negative	Herzog, 2005
Offered Scholarships/ Grants	Negative	Herzog, 2005
Offered Work Study	Negative	Herzog, 2005
Received Merit-Based Aid	Negative	Singell, 2004; Singell & Stater, 2006; Chen & DesJardins, 2010
Received Need-Based Aid (Grants and Subsidized Loans)	Negative	Singell, 2004; Singell & Stater, 2006
Received Pell Grant	Negative	Chen & DesJardins, 2008; Chen & DesJardins, 2010
Received Subsidized Loans	Negative	Chen & DesJardins, 2010
Received Unsubsidized Loans	Positive	Herzog, 2005
Received Work Study	Positive	Singell, 2004
Receiving a loan in the first semester then losing it	Positive	Herzog, 2005
Unmet Need	Positive	Herzog, 2005

[1]A dichotomized variable with the statement in the table coded as 1 and its absence or counterpart coded as 0. For example, "Being Male" is coded as 1 while "Being Female" is coded as 0. "Passing a First Year Math Course" is coded as 1 while not passing is coded as 0.
[2]Not all studies represented here are studying the same "type" of attrition. Some look at whether or not the student is retained from their first to second year and others whether the student completes a degree or drops out. Some are framed as whether or not the student remains enrolled while others whether the student drops out. For the purposes of being able to look at all variables in a common way, in the table they are all put on a scale of whether or not the student experiences attrition (or drops out).

Various student academic performance characteristics have been found to have a relationship with attrition. High school and pre-college performance variables such as high school GPA (Oseguera & Rhee, 2009; Porter & Swing, 2006), SAT and Act scores (Oseguera & Rhee, 2009; Ryan, 2004; Schibik & Harrington, 2004; Scott, Baily, & Kienzl, 2006; Kim, Roades, & Woodard, 2003), high school class rank (Ishitani, 2006), and average high school grades (Astin & Oseguera, 2005) are well documented as having a negative relationship with attrition.

Student demographic characteristics appear in most every study of attrition, and thus their relationships with attrition are well studied. Race and ethnicity have varying relationships with attrition in the literature. Being African American/ black (Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003), Hispanic/ Latino (Oseguera & Rhee, 2009; Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003), or American Indian (Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003) generally has a positive relationship with attrition meaning that higher drop-out rates are observed for these groups. Being white (Oseguera & Rhee, 2009) generally has a negative relationship with attrition. As age increases, generally so does attrition (Singell & Stater, 2006). Also, Ishitani (2006) found that first generation college students were more likely to drop out of college than students who had one or more parents that attended college. Increases in family income have been consistently found to be related to decreases in attrition (Ishitani, 2006; Oseguera & Rhee, 2009; Rhee, 2008).

Various aspects of college academic performance have been found to have a relationship with attrition. Not surprisingly, attrition decreases as characteristics indicating high levels of academic performance increase, including college GPA (Titus, 2004), majoring in a field requiring higher level math (Herzog, 2005), and successful completion of first-year math courses (Herzog, 2005). Participation in a first-year seminar is also associated with decreases in attrition (Clark & Cundiff, 2011). As students take more credit hours, attrition also appears to decrease (Schibik & Harrington, 2004; Herzog, 2005) as they progress more quickly toward degree completion. Several studies have found that students taking remedial courses tend to drop out at higher rates (Adelman, 2004 (Any Subject); Herzog, 2005 (Math)). This positive relationship with attrition may be mediated by academic preparation.

Statistical relationships with attrition have been found with other characteristics of student life, both academic and non-academic. Commitment to earning a degree (Ishitani, 2006;

Titus, 2004), living on campus (Braxton & Hirschy, 2004; Oseguera & Rhee, 2009; Titus, 2004; Herzog, 2005), and use of recreational facilities (Herzog, 2005) have all been found to have a negative relationship with attrition. It is not surprising that, as a student's desire to transfer increases, so does their probability of attrition at their starting college or university (Oseguera & Rhee, 2009). The number of hours per week that a student works has been found to have varying linear relationships with attrition, with some studies reporting a positive relationship (Porter & Swing, 2006) and others a negative (Titus, 2004). These varying results may be symptomatic of moderation by institutional characteristics or a possible non-linear relationship between hours worked and attrition, where the relationship is negative up until a particular threshold, after which the relationship becomes positive.

Of all the groupings of student-level variables included in Table 2, the more nuanced financial aid characteristics are the least studied, particularly in the context of multilevel modeling. The findings about financial need (Singell & Stater, 2006; Titus, 2004) and the amount of work study offered (Herzog, 2005; Singell, 2004) have been mixed. Some find that these were positively related to attrition and some negative. As the student's self-rated level of financial concern rose so did their likelihood of dropping out of college (Oseguera & Rhee, 2009). Unmet need is also positively related to attrition; as the amount of financial need not met by the student's financial aid package increases, the student is more likely to drop out (Herzog, 2005).

An important distinction in financial aid literature is between aid that is offered and aid that is received/dispersed. Students do not necessarily use the financial aid or work study opportunities offered to them. In this context, "received" aid refers to any offer that is accepted and presumably used. Herzog (2005) is one of very few that looked at the effects of aid that a student is offered, but not necessarily used. Herzog (2005) found a negative relationship between offered loans, scholarships and grants, and work study and attrition; as offers of financial aid increased, attrition decreased. Singell (2004) found the opposite relationship between actually receiving work study and dropping out, finding that receiving work study appeared to increase the likelihood that the student would leave college. Various studies all confirmed that receiving merit-based aid (Singell, 2004; Singell & Stater, 2006; Chen & DesJardins, 2010), need-based aid in the form of grants and subsidized loans (Singell, 2004; Singell & Stater, 2006), Pell grants (Chen & DesJardins, 2008; Chen & DesJardins, 2010), and non-need based subsidized loans (Chen & DesJardins, 2010) all increased the likelihood of the student remaining enrolled in college. Receiving unsubsidized loans and receiving a loan and then later losing that as a source to pay for subsequent semesters were both found to have positive relationships with attrition (Herzog, 2005).

Institution-Level

Institution-level variables have traditionally been examined in attrition studies that focused solely on institutions or studies that focused on the student but repeated the institution-level variable for every student that attended the institution. When institution-level variables (e.g. whether the institution is public or private) are included at the student-level in a regression model, the assumption of independence is violated and a variety of other issues are introduced. Today multilevel models can look at student and institution level variables together in a unified model that does not violate the important assumption of independence. Table 3 summarizes the main variables identified in studies of attrition at the institution level. As with the student-level variables in Table 2, all of the variables are put on a common "scale." If the study identified the variable as being associated with higher rates of drop-out from college, the variable's "relationship with attrition" is positive. As with Table 2, Table 3 segments the variables into categories that are solely meant to help to organize the information into more manageable pieces. The categories are not meant to imply factors or any other type of statistically justifiable grouping. It is also important to note again here that Raudenbush and Bryk (2002) recommend that variables be added into the HGLM model in groupings with a common characteristic.

Table 3

Institution-Level Characteristics with a Relationship on College Student Attrition

Name	Relationship with Attrition[2]	Reference
Student Demographic Characteristics		
Average Student Age	Positive	Scott, Baily, & Kienzl, 2006
Percent Foreign-Born	Positive	Scott, Baily, & Kienzl, 2006
Percent of Female Students	Negative	Kim, Roades, & Woodard, 2003
Percent of Full-Time Students	Negative	Scott, Baily, & Kienzl, 2006
Percent of Minority Students	Positive	Rhee, 2008; Kim, Roades, & Woodard, 2003
Academic Characteristics		
Doctoral Institution[1] (Level)	Negative	Porter & Swing, 2006
Instructional and Academic Support Expenditures	Negative	Ryan, 2004; Gansemer-Topf & Schuh, 2006; Scott, Baily, & Kienzl, 2006
Percentage of Courses Taught by Part-Time Faculty	Positive	Schibik & Harrington, 2004; Ehrenberg & Zhang, 2005
Research and Development Expenditures	Negative	Kim, Roades, & Woodard, 2003
Other Institutional Characteristics		
Being Religiously Affiliated[1]	Negative	Scott, Baily, & Kienzl, 2006
Diversity	Positive	Rhee, 2008
Private Institution (Institutional Control) [1]	Negative	Kim, 2007; Titus, 2004; Ryan, 2004
Residential	Negative	Titus, 2004
Selectivity	Negative	Kim, 2007; Titus, 2004; Gansemer-Topf & Schuh, 2006; Oseguera & Rhee, 2009; Kim, Roades, & Woodard, 2003
Size	Negative	Ryan, 2004; Titus, 2004

[1]A dichotomized variable with the statement in the table coded as 1 and its absence or counterpart coded as 0. “Private institution” is coded as 1 while all other types of institutions are coded as 0.
[2]Not all studies represented here are studying the same “type” of attrition. Some look at whether or not the student is retained from their first to second year and others whether the student completes a degree or drops out. Some are framed as whether or not the student remains enrolled while others whether the student drops out. For the purposes of being able to look at all variables in a common way, in the table they are all put on a scale of whether or not the student experiences attrition (or drops out).

Many studies aggregate student level variables up to the institution level, even some studies that employ a multilevel modeling methodology. The following section of the literature review discusses potential issues with this approach, but this section will only discuss the relationships between the variables and attrition as found in the studies. Average student age (Scott, Baily, & Kienzl, 2006), percent of foreign-born students (Scott, Baily, & Kienzl, 2006), and percent of minority students (Rhee, 2008; Kim, Roades, & Woodard, 2003) were all found to have a positive relationship with attrition. The percent of female students (Kim, Roades, & Woodard, 2003) and the percent of full-time students (Scott, Baily, & Kienzl, 2006) were found to have the opposite relationship. As these variables increased, drop-out tended to decrease.

Academic characteristics of colleges and universities have also been studied for their relationship with attrition. Institutions offering doctoral degrees were associated with increased retention and persistence (Porter & Swing, 2006). Expenditures on both instructional and academic support (Ryan, 2004; Gansemer-Topf & Schuh, 2006; Scott, Baily, & Kienzl, 2006) and research and development (Kim, Roades, & Woodard, 2003) were also found to have a negative relationship with attrition. The percent of courses taught by part-time faculty (Schibik & Harrington, 2004; Ehrenberg & Zhang, 2005) had the opposite relationship. These studies found that, as the percent of courses taught by part-time faculty increased, so did attrition.

Various other institutional characteristics have been studied for their potential impact on drop-out. Generally, as size (Ryan, 2004; Titus, 2004), selectivity (Kim, 2007; Titus, 2004; Gansemer-Topf & Schuh, 2006; Oseguera & Rhee, 2009; Kim, Roades, & Woodard, 2003), and the percent of first-time, full-time freshman living on campus (Titus, 2004) increased, attrition was found to decrease. Being a religiously affiliated institution (Scott, Baily, & Kienzl, 2006) or a private institution (Kim, 2007; Titus, 2004; Ryan, 2004) were both associated with a decrease in drop-out as well. Interestingly, Rhee (2008) found that as diversity at a college increased so too did attrition.

Many different student-level and institution-level characteristics have been studied during this millennium and found to have a relationship one way or another with attrition. The following section on methodology discusses how these different levels of variables can be combined into one model and why it is important to account for the nested relationship between student and institution when modeling attrition.

Interactions

Some studies of attrition include interactions between variables. Accounting for such interactions is important when “the difference in response between the levels of one factor is not the same at all levels of the other factors" (Montgomery et al., 2001). A common approach is to include all interactions possible in a model and then test for significance. The issues with this approach resemble those that occur in approaches that include all available variables in a regression model: spurious relationships may exist, and many more degrees of freedom are consumed. These issues are particularly prevalent with larger models that include every possible pairings of variables to account for all interactions. In order to avoid these pitfalls, interaction variables should be chosen for inclusion in the model in the same way that any variable is chosen for inclusion: studies should have a theoretical basis for including any variable

Methodology

In studies of student attrition, correlation and regression-based techniques are the most common methodologies used. Astin and Denson (2009) identify ordinary least squares regression (OLS) as the “method of choice” in studies of college’s impact. However, the nature of the data structure in multi-institutional studies in higher education is inherently nested, which lends naturally to the use of hierarchical linear modeling (HLM) (Niehaus, Campbell, & Inkelas, 2013). Using multilevel models with nested data makes up for many of the weaknesses of single level approaches, such as violation of the assumption of independence and uncorrelated error terms (Luke, 2004), increased type I error rates (Thomas & Heck, 2001), aggregation bias (Raudenbush

& Bryk, 2002), and distorted relationships between aggregated and non-aggregated variables (Raudenbush & Bryk, 2002).

Using single-level regression for multi-institutional data has led researchers using institution-level datasets to aggregate student-level data to the institution level (e.g., average high school GPA) and those using student-level data to duplicate institution information at the student level (e.g., public or private institution). There are two main problems with using institution-level variables at the student level: the violation of the assumptions of independence and homoscedasticity (Raudenbush & Bryk, 2002). Errors are no longer uncorrelated. Instead, they are very clearly related, as they cannot be disentangled at an individual level. With the same group level variable repeated for every student in the dataset, degrees of freedom are over-represented (Niehas et al., 2013) and standard errors are incorrect (Astin & Denson, 2009). Patrick (2001) notes that underestimating standard errors results in significance tests that more readily reject the null hypothesis than they would if the nested data was appropriately modeled.

The use of aggregated student level variables for data at the institution level leads to a variety of additional issues. A lot of relevant data is not utilized. For example, all of the within group information is discarded, "which may be as much as 80 or 90% of the total variation" (Raudenbush & Bryk, 2002). The result can be a biased estimation of stronger effects than those that actually exist (Astin & Denson, 2009), sometimes called "aggregation bias." Patrick (2001) shows an example where a correlation of .95 was found between a trait and an outcome variable when it was aggregated at the group level, but when the trait was analyzed at the individual level, the correlation was only .2. The relationships between the aggregated and non-aggregated data may be distorted and inaccurate (Raudenbush & Bryk, 2002).

Luke (2004) notes that ANOVA or ANCOVA approaches to modeling may make up for some of these weaknesses, but they too have weaknesses of their own. With many groups, these approaches become significantly more complex, less parsimonious, and lose significant power. Random variability in the group-level characteristics cannot be modeled, and missing data is not easily handled. It is important to note here that Raudenbush and Bryk (2002) identify ANOVA and ANCOVA approaches as two of the simpler models in the hierarchical linear modeling family. More complex hierarchical linear models make up for the weaknesses of the simpler models that Luke (2004) enumerates.

In addition to their statistical appropriateness for handling nested data, hierarchical models have other benefits over OLS and other commonly used single-level techniques for modeling student attrition. An advantage HLM has over OLS regression is that it can provide "improved estimation of individual effects by borrowing information from the data as a whole" (Astin & Denson, 2009). Groups with small numbers of people may ordinarily lack power to find significant effects and meaningful predictive models. HLM may be able to tease out these effects, as more information on these individuals is modeled with the incorporation of institution-level characteristics and similar individuals from across multiple institutions. When a model that does not account for the nested nature of data is used, effects can wash out or their significance can get mired when nesting affects the variables studied. Additionally, institution effects and individual effects, as well as the interplay between them, can be examined in HLM (Astin & Denson, 2009). HLM allows researchers to explain not only how a student's GPA can affect their likelihood of attrition, but also how this relationship between GPA and attrition can change across different institutions. Titus (2004) also notes that, in HLM, maximum likelihood estimation techniques are often used, a practice that generally generate results that are more asymptotically efficient and more consistent parameter estimates than those generated by OLS.

Using HLM for nested data has many benefits, chief among them is the method's appropriateness for modeling with nested data. Beyond the statistical appropriateness, HLM allows for researchers to ask and answer a broader range of questions about students and their interactions with institutions. Given the increased accessibility of software and models to account for various data types, it is surprising how few studies that seek to comprehensively model student attrition use HLM. Since the outcome variable is often dichotomous in attrition studies (e.g., graduated in 6 years or did not, persisted or did not), those studies using HLM that do exist often use hierarchical generalized linear modeling (HGLM). When the logistic link function is used, a dichotomous outcome can be appropriately modeled.

Titus (2004) used an HGLM model to look at how institution-level characteristics affected attrition above and beyond student-level characteristics. The sample included 5,151 students at 384 four-year institutions across the United States. Several limitations of the study are noted, including a problematic amount of missing data at the student level that is non-random. Oseguera and Rhee (2009) use HGLM to create a model that examines peer and faculty climates, along with many other institution and student characteristics that past studies have shown to have an effect on degree completion. Their study encompassed a large number of students and institutions from many US states. 37,006 students from 170 intuitions were included. While the study contributed to the literature by demonstrating effects on degree completion from faculty and peer climates, it also suffers from a variety of limitations. High school GPA and SAT scores were used as proxies for performance in college, as college GPA and other performance measures were not available. Missing data of greater than 10% in some student-level areas was another limitation similar to that of Titus (2004).

Since attrition studies began in higher education in the early 20th century, many statistical and computing improvements have been made that have allowed for increased accessibility and use of more complex models. In an analysis of the content of studies in three major journals in higher education, Di Bartolo, Dor, Fagioli, Garcia, Graves, Truong, and Thomas

(2011) found that, while in 1985 there were no uses of HLM, in 2009, 11% of quantitative studies featured HLM. Given the increased accessibility of HLM, the clear advantages and appropriateness of the models in handling multilevel data, and the intense and sustained interest in modeling student attrition, it is surprising how few studies employ HLM in comprehensive models of student attrition

CHAPTER III

METHODOLOGY

Conceptual Framework and Research Questions

Building on the works of Titus (2004) and Oseguera and Rhee (2009) this study used a two-level logistic HGLM to comprehensively model six-year graduation. Both the student and institution level were included in the model. All 16 public universities from North Carolina were incorporated in the study. Following a comprehensive review of the literature focusing on studies of attrition since 2000, the variables identified in Table 2 and Table 3 as having a relationship with attrition were used to guide the variables included in the model. The following research questions were addressed:

1. What covariates at the student and institution level, with a focus on financial aid variables, have a significant relationship with the likelihood to persist to degree completion?
2. Do any of these significant covariates vary in their effects across institutions?

Hopefully the outcomes of this study will help to inform decisions by North Carolina policymakers and higher education administrators about how to address student attrition and to better understand the relationship between degree completion and financial aid, as well as provide a framework for other states and higher education systems to use their own data for data-driven decision making.

Sample

Included in this study were all undergraduate students who began undergraduate degree-seeking enrollment in any of the 16 public universities in the state of North Carolina from 2000 until 2010. Despite all universities being public and from one state, there was significant diversity. Undergraduate enrollments, as reported to Integrated Postsecondary Education Data System (IPEDS) for the Fall 2010 semester, ranged from under 737 students to 25,465 students. Nine institutions had enrollments under 10,000 and seven had enrollments above 10,000. The institutions fell into one of three different categories for the highest degree offered by the institution: master's, post-master's certificate, and doctoral. The research expenditures of the institutions ranged from zero dollars to over $500,000,000 and instructional expenses ranged from just over $20,000,000 to over $700,000,000 for the academic year 2010-2011. Out-of-state tuition and fees ranged from $13,234 to $25,280 and in-state from $3,476 to $6,665.

The demographic composition of the universities also differed greatly with IPEDS reporting the percentage of undergraduate women ranging from 39% to 70% of the total undergraduate population. The smallest percentage of black or African American was 3% and highest 89% with significant variation in between. For Hispanic students the range was much smaller, ranging from 1% to 11% of the total undergraduate population for the undergraduate student population in the fall 2010 semester. The percentage of white students had variation that more closely resembled that of black or African American students with percentages that ranged from 5% to 87%. Despite this study's focusing on only 16 public universities in one state, the universities did have a significant amount of diversity in their size, economic, and demographic characteristics.

Variable Selection

This study used the variables in Tables 2 and 3 that were found to have effects on attrition to guide the variables included in the model. The student-level variables that were used were collected by the UNC System office as part of normal data collection procedures for reporting to the IPEDS, state legislative reporting, and other regulatory and non-regulatory research and reporting initiatives. The institution-level variables in this study were taken from the most recent year that students were enrolled in college during the study period and came from the publicly available IPEDS data collection.

Table 4 compares the student-level variables from Table 2 to the dataset that was used for this study. When “Yes” appears in the “Included?” column it means that the variable was included in the study and “No” indicates that it was not. Approximately 63% of the variables identified across a variety of different studies as having a significant relationship with attrition were included.

Table 4

Student-Level Characteristics and their Inclusion in this Study Compared to Table 2

Name	Included?
High School or Pre-College Characteristics	
Average High School Grades	No
High School Class Rank	Yes
High School GPA	Yes
SAT or ACT Scores	Yes
Demographic Characteristics	
Age	Yes
Being African-American/ Black	Yes
Being American Indian	Yes
Being First Generation	No
Being Hispanic/ Latino	Yes
Being Male	Yes
Being White	Yes
Income/ Socioeconomic Status	No
College Academic and Other Characteristics	
College GPA	Yes
Majoring in a Field Requiring Higher Level Math	Yes (in proxy form)
Participation in a First Year Seminar	No
Passing a First Year Math Course	Yes
Semester Hours Attempted	Yes
Commitment to Earning Degree	No
Desire to Transfer	No
Hours Worked	No
Living on Campus	Yes

Table 4

Cont.

Name	Included?
College Academic and Other Characteristics (cont.)	
Using Recreational Facilities	No
Taking Remedial Courses	Yes
Financial Aid Characteristics	
Financial Concern	No
Financial Need	Yes
Offered Loans	No
Offered Scholarships/ Grants	No
Offered Work Study	No
Received Merit-Based Aid	Yes
Received Need-Based Aid (Grants and Subsidized Loans)	Yes
Received Pell Grant	Yes
Received Subsidized Loans	Yes
Received Unsubsidized Loans	Yes
Receiving a loan in the first semester then losing it	No
Unmet Need	Yes

Variables were excluded from this study for a variety of reasons including unavailability and redundancy with other characteristics already included. Average high school grades were not included as the variable is somewhat redundant with high school GPA. All the variables that required survey-type responses to indicate mental or psychological states were not able to be included because they were not collected on all students across the UNC System. Those variables included commitment to earning a degree, desire to transfer, and financial concern. Hours worked, being first generation, and use of recreational facilities were not included because they are not collected. Income was not included because of a lot of non-random missingness. Only received or dispersed financial aid was collected so the offered amounts of loans, scholarships and grants, and work study were not included. Because offered aid was not collected, “receiving a loan in the first semester then losing it” (Table 3) was not included in this study. Data were collected that would show if a student used a federal loan one semester and then did not use a federal loan the subsequent semester, but the student could have been offered one and chosen not to utilize it. That distinction is important and thus the variable was not included in proxy form.

The characteristic “Majoring in a field requiring higher level math” was not specifically included because it is difficult to determine which majors fall into that category with any consistency. Classification of Instructional Programs (CIP) codes were collected from all universities for all majors, which would allow for the common classification of majors across the system. However, there is no widely agreed upon definition of which CIPs require “higher level math” and to create such a list would require significant expert involvement and deliberation that is beyond the scope of this study. Table 6 and the accompanying description explains a proxy variable that is used as a substitute: “majoring in a STEM program.”

Table 5 compares the institution-level variables with a relationship with attrition in Table 3 to what was included in this study.

Table 5

Institution-Level Characteristics and their Inclusion in this Study Compared to Table 3

Name	Included?
Student Demographic Characteristics	
Average Student Age	No
Percent Foreign-Born	No
Percent of Female Students	No
Percent of Full-Time Students	No
Percent of Minority Students	No
Academic Characteristics	
Doctoral Institution (Level)	Yes
Instructional and Academic Support Expenditures	Yes
Percentage of Courses Taught by Part-Time Faculty	Yes
Research and Development Expenditures	Yes

Table 5

Cont.

Name	Included?
Other Institutional Characteristics	
Being Religiously Affiliated	No
Diversity	No
Private Institution (Institutional Control)	No
Residential	Yes
Selectivity	Yes
Size	Yes

Not all variables that were excluded were omitted because of a lack of availability. With only 16 observations at level-2 it was important not to be frivolous with degrees of freedom. No institution characteristics that are simply summaries of student-level characteristics were included because aggregating student-level variables at the institution-level can lead to aggregation bias and distorted relationships (Raudenbush & Bryk, 2002). Additionally, these variables are student-level variables and were thus included at the student level in this model. Being religiously affiliated and institutional control were omitted because the value for all institutions included in this study was the same and so no variance existed to be studied. Of the eight relevant variables that remained only one, diversity, was excluded. A proxy variable of the percent of minority students could have been used here and was used in part to study diversity in the original study that included it (Rhee, 2008). However, that would lead to the same issues discussed previously caused by aggregating student-level variables at the institution level.

The student and institution characteristics in Tables 4 and 5 were not the only variables available with the potential to contribute information about attrition. The variables in Table 6 are related enough to the variables found to have relationships with attrition from previous literature that it is not unreasonable to hypothesize that they might also have a relationship with attrition.

However, they are distinct enough from the variables already included that it is possible that they have additional information to add above and beyond that which was already included in the model.

Table 6

Additional Student- and Institution-Level Variables Included in this Study

Name	Level
Citizenship	Student
Majoring in a STEM program	Student
Student-to-faculty ratio	Institution
Net Price	Institution

Using theory to guide the addition of variables to a model is important to avoid capitalizing on chance and over-saturating a model. All of the additional variables in Table 6 have a theoretical backing. A primary or secondary school's student-teacher ratio has been found in many studies to contribute to student performance and graduation (Smyth, 1999), so it is possible that student-faculty ratio has an effect in higher education. Additionally, the percent of students not born in the United States was found to have a relationship with attrition at the institution level (Scott, Baily, & Kienzl, 2006), so in this study it was included in the model at its appropriate level (student-level). There is no consensus on what majors should be included in "majoring in a field requiring higher level math," which is a characteristic found to have a relationship with attrition included in Table 2. However, there is consensus on which majors, identified by CIP code, are STEM majors. "Majoring in a STEM program" can be included in the study as there is expert consensus through U.S. Immigration and Customs Enforcement. The STEM major variable serves as somewhat of a proxy for "Majoring in a field requiring higher level math." Multiple attrition studies that have included tuition and fees costs in their models have found that the variable does not have a significant effect on attrition (Scott, Baily, & Kienzl, 2006) or an effect above and beyond other included variables (Ryan, 2004). However, most students do not pay the full tuition and fees. The "net price" refers to the actual amount charged to the student after financial aid in the form of scholarships and grants are subtracted from the total cost of attendance, tuition and fees, as well as living expenses. The net price is a much more accurate portrayal of what the student actually pays as opposed to the full, publicized tuition and fees, which was included in past studies. Therefore, citizenship and majoring in STEM at the student level and student-to-faculty ratio and net price were included in this study.

Many of the variables in this study were collected at multiple time points, typically once per semester, and some changed over time. The financial aid variables, including the type and amount of aid used, are almost certain to vary at each observation. It is not unusual for a student to accept a loan one semester but not another or to be offered a scholarship one semester but then lose it the next. The observations at various time points could be conceptualized as an additional level nested within students. However, this increases complexity in estimation and interpretation.

This study did not include the third level of time or observations for several reasons. One of the major goals of this study is to give higher education practitioners and policy makers information that increases their understanding of the various factors that influence degree completion. That audience does not necessarily have a strong statistical background. Keeping the model as simple as possible while not excluding or ignoring vital information is important. If the model and results are confusing to practitioners and policy makers, the usefulness and probability of the application of the results is diminished. Additionally, there are many variables that would have to be included at various time points if time was included as a level in the model. This increases greatly the number of covariates that have to be measured. Even with a large number of students and thus a lot of power, the large number of covariates that need to be measured would still decrease power greatly. An additional complication is that not all students have the same number of observations. Some students may have twelve observations if they were enrolled in fall and spring for six years while others may have only one or two observations if they were only enrolled for a term or two. There may not be enough observations to accurately estimate the model. The financial aid variables would give particular difficulty if multiple time points were estimated as data would be missing for any term where a student was not enrolled. Finally, the research questions in this study only ask generally about the effects that appear to influence degree completion and how they change across institutions.

Time or multiple observations were not implicitly or explicitly relevant in the research questions. However, excluding a relevant variable could cause bias in the estimation of the coefficients in the model. There is some evidence that the recession had an effect on college enrollment decisions of students (Long, 2015). Therefore, a dummy coded variable was included in the study to capture this potential source of variation in six-year graduation. Inclusion of this variable should aid in not biasing the model due to the exclusion of an important characteristic with evidence of a relationship to graduation but avoids the complications and lack of proper research design and power that would come from including time as another level in the model. Because of the lack of interest in time or observations in the research questions, the estimation issues, and the difficulty in explaining in a useful and practical way the results of a 3-level model to the intended audience in this case, a 2-level model was used for this study and a variable to capture enrollment during the recession was added to account for a time-related characteristic with evidence of an effect on graduation.

The Final Dataset

The journey from theory to practice in not linear. Previous sections described the process and theory behind the evidence-based data element selection, methodology selection, and the various theory-based decisions along the way. Going from that theory to the execution of a model requires applying that theory to an imperfect reality. That process involves a series of decisions about data definitions and data element selection from the data that is actually available. This section will describe the process and decisions made to get to the final data elements and their definitions as they were used in the model. Table 7 summarizes the variables used in this study along with the salient calculations and definitional elements.

Table 7

Final Variables Used in Study

Variable Name	Code	Notes on Calculations or Derivations
Dependent Variable		
Graduated Within 6 Years	G	Completed a baccalaureate degree within 6 years from initial enrollment from the institution where initially enrolled.
Level-1 Independent Variables		
Demographic Characteristics		
Being White	W	Last term enrolled where populated
Being African-American/ Black	A	Last term enrolled where populated
Being American Indian	AI	Last term enrolled where populated
Being Hispanic/ Latino	H	Last term enrolled where populated
Unknown Race or Asian	U	Last term enrolled where populated
Being Male	M	Last term enrolled where populated
Citizenship	C	Last term enrolled where populated
Age	AGE	Calculated from date of birth to of August 1 of the first term enrolled.
High School or Pre-College Characteristics		
High School Class Rank (In Hundreds)	HSR	Percentile calculated.
High School GPA	HSG	On 4.0 scale.
SAT Composite Score (In Hundreds)	SAT	SAT Math + SAT Verbal or Critical Reading.
College Academic and Other Characteristics		
Majoring in a STEM program	STEM	Based on majors in last term enrolled.
Average Term Credit Hours	CH	Mean across all fall and spring enrolled terms.
Enrolled during the recession	ER	Calculated based on 6-year enrollment window- 1 if enrolled 2007 to 2009 but didn't graduate before 2007.

Table 7

Cont.

Variable Name	Code	Notes on Calculations or Derivations
College Academic and Other Characteristics (cont.)		
University GPA	UG	Cumulative at most recent enrolled term. On a 4.0 scale.
Taking Any Remedial Course	R	
Passing a First Year Math Course	FYM	Passing any course with a math CIP code in the first year of enrollment.
Living on Campus	LC	Mode of all enrolled terms.
Financial Aid Characteristics		
Need-Based Aid Amount (In Thousands)	NEED	Includes need-based grants and subsidized loans. Mean across each financial aid year.
Merit-Based Aid Amount (In Thousands)	MERIT	Mean across each financial aid year.
Pell Grant Amount (In Thousands)	PELL	Mean across each financial aid year.
Subsidized Loan Amount (In Thousands)	SL	Mean across each financial aid year.
Unsubsidized Loan Amount (In Thousands)	UL	Mean across each financial aid year.
Financial Need (In Thousands)	FN	Mean across each financial aid year.
Unmet Need (In Thousands)	UN	The federal definition is Financial Need- Total Aid Offered, but this variable will be a proxy and be calculated by Financial Need- Total Aid Received. Mean across each financial aid year.
Level-2 Independent Variables		
Academic Characteristics		
Doctoral	D	Mode. Carnegie Classification.
Student-to-Faculty Ratio	SF	Mean.
Instructional and Academic Support Expenses per FTE	IAE	Mean. Instruction expenses plus academic support expenses per FTE.
Research Expenses per FTE	RE	Mean. Research expenses per FTE (GASB).
Percent Part-Time Instructional Staff	PT	Mean. Percent Part-Time Instructional Staff (Primarily Instruction).
Other Institutional Characteristics		
Selectivity	S	Mean. Average 75th Percentile SAT.
Residential	R	Mode. Carnegie Classification Size and Setting.
Size	E	Mean. Total undergraduate enrollment.
Net Price	NP	Mean. Average net price-students awarded grant or scholarship aid.

Level-1 Variables

Because each observation was not included in the study as an additional level in the model, decisions had to be made about how to include and define the variables as a single observation per student or institution. For student level information, the task of defining each potential time varying covariate as one value per student was more challenging because of the increase in the number of variables and higher variability of the variables. For all demographic variables, such as race and gender, that are not likely to change over time, data from the most recent term of enrollment where the data are non-missing were used. This is with the exception of age, which was defined as the age of the student as of August 1st of the first academic year the student was enrolled. Unknown Race and Asian were grouped together as identifying as Asian was not found to have a significant effect in the studies examined as the evidence-base for variable selection for this model.

For data that were expected to vary over time, means across all terms enrolled were used whenever reasonable. The high school characteristics were from the student's application to their baccalaureate degree program, so only one value was reported for high school rank, high school GPA, and SAT, so there is no need to average over time. SAT scores were reported in two different components, math and verbal/ critical reading, so those components were added together and the composite score was used in the analysis.

In the college characteristics category, majoring in a STEM program was defined using the six-digit CIP code for the students' majors, up to two majors, for the last term the student was enrolled in a course. Students often change majors during the course of their enrollment in college. The majors that the student had during their last term enrolled was used for the purpose of this study because that was most likely to be the major that the student graduated with or otherwise was their most current major. Only up to two majors were reported to the UNC System office, so if the student had a third or greater major that was a STEM major, that would not be captured in this study. The average term credit hours was the mean number of credit hours a student was enrolled in across all fall and spring terms where the student had a course enrollment. If the student stopped out for a fall or spring term, then this term was not counted in this variable. The university GPA was the cumulative GPA for the student during the last term that the student was enrolled at the university. If the student took a remedial course of any subject at the university then taking any remedial course was coded as a 1 else a 0. Two-digit CIP codes are reported for all courses to the UNC System. If the student took and passed a course in their first year of enrollment with a CIP code of 27, which stands for “Mathematics and Statistics,” then the student would have a 1 in this field else a 0. Some students may have placed out of any math requirement while others may have taken a course that counts for a math requirement but does not have a math CIP code. These cases would result in the student having a 0, even though the student has met their university’s math requirement. The latter case is rare but does occur. The student was coded as a 1 for living on campus if the mode of their enrolled terms indicated that the student lived on-campus else a 0. It is important to note that some students had multiple modes for their living arrangements while in college. For this study the mode that favored living on-campus was chosen, based on the fact that other studies looked at living on-campus at just a single point in time and found a significant effect (Titus, 2004).

All of the financial aid characteristic variables were reported as the amount over the full financial aid year and is the mean across each financial aid year where the student was enrolled in college. If just one year was chosen, then aid given in many other years, which could influence a students’ outcome, would be ignored. Financial aid variables were reported over the full financial aid year in order to be consistent with the most accurate data that is reported at the end of the financial aid year after all adjustments have been made and data have been checked for quality.

The need-based aid amount was defined as need-based grants or scholarships, including state and federal grant programs, as well as subsided federal loans, as these types of loans are awarded on the basis of financial need. While unmet need is typically defined federally as the student's total aid offered subtracted from the student's calculated financial need, this study uses a slightly different definition. A student may be offered aid but not actually claim or receive the aid. The only aid amounts available were the amount of financial aid the student actually received. Therefore, unmet need in this study is defined as the total aid received by the student subtracted from the student's financial need.

Decisions were made about centering for each variable that was included in the model as well. The choice of centering affects the interpretation of the intercept, how variables are controlled for on different levels of the model, and estimation. A model may be difficult or impossible to estimate when no data exists at the starting point of a variable(s). For example, in this study, there were no students with an age of 0. If age was not centered in any way, the software would be trying to estimate a coefficient for this value where there is no actual data to assist in the estimation. For interpretation and estimation reasons, all level-1 variables were group mean centered. This leads the interpretation of the level-1 intercept (β_{0j}) to be the expected log odds of graduating when all variables are at their average (e.g. at average age, socio-economic status, etc.).

Level-2 Variables

As with the student-level variables, the data about institutions covered a 15-year time period and so decisions had to be made about how to include the variables as a single observation per institution. For the institution-level data, IPEDS was used to select data about each of the 16 UNC System universities. Data was examined for all years available from the academic year 2000-01 until 2015-16, which covers the period from initial enrollment of the first cohort through the 6-year graduation window of the last cohort. The data were examined for consistency over time and to identify any extreme deviations and none were found. Measures of central tendency across all years were used to obtain the value used in the model. For doctoral and residential the mode across all available years was taken. These two data elements were defined by Carnegie classifications. For the rest of the variables, where change over time is expected the mean was used. As a measure of selectivity, consistent with other studies using SAT scores of incoming classes (Oseguera & Rhee, 2009), the average 75th percentile SAT score for the incoming freshmen cohort was used. As IPEDS collects average math and verbal/ critical reading components separately, these component scores were averaged across each year and then the average of those values were used in the study. The size of the institution was defined by the total undergraduate enrollment as the baccalaureate degree-seeking population was the focus for this study. The net price value that was used was the average net price for students who are awarded any grant or scholarship aid, as the majority of UNC System students receive some kind of grant or scholarship, so this value would be representative of the largest number of students compared to net price values for students receiving no grant or scholarship aid. As with the level-1 variables, centering decisions were made for level-2 variables as well. All level-2 variables were grand mean centered allowing for the interpretation for the level-2 intercept to be the mean log-odds of graduation when all level-2 covariates are at their average value.

Analysis Procedure

The choice of variables included in a model is extremely important. Too many variables lead to a model that is not informative or parsimonious with all variables having small and potentially non-significant relationships depending on sample size. Too few variables or not the right variables lead to bias (Raudenbush & Bryk, 2002). Raudenbush and Bryk (2002) warn against the practice of beginning with a model with all variables included and then deleting out variables with insignificant effects. In doing so, the researcher might be capitalizing on chance or may miss data issues or anomalies that ultimately affect the interpretability and utility of the model. Additionally, a model with too many variables may have many insignificant effects without a reliable way to decide which to delete and which to maintain. Instead Raudenbush and Bryk recommend using theory to guide the inclusion of initial variables and then, if one desires to include additional variables, adding variables individually and assessing the amount of information added. This model was run solely with the variables that have been identified above in the literature to have a relationship with attrition.

Some initial analyses were run on each of the variables to test for characteristics of the data that could lead to issues in running the model. The univariate distributions of each variable were examined for outliers and overall quality to avoid coding and other errors or irregularities being introduced into the model without first being examined (Raudenbush & Bryk, 2002). Also, as recommended by Raudenbush and Bryk (2002) a logistic regression analysis for each institution was run to uncover any irregularities in coefficients or intercepts. Irregularities may be the result of bad data or simply irregular data and could influence the estimation in undesirable ways. No irregularities were observed. The correlations of each variable with every other variable included in the study within each level was examined for multicollinearity. When two variables are very highly correlated, they are not adding distinct information to the model and can result in unstable coefficients (Rencher, 2012). All of these preliminary analyses contained no problematic anomalies, so then the assumptions of HGLM were tested.

Logistic HGLM models have relatively few assumptions compared to other linear models. The independence of the errors at level-2 can be assessed in order to evaluate congruence with assumptions. A common assumption of HLM and OLS is the normal distribution of errors, which is violated by many variables included in this study because they are binary. HGLM, however, allows for the inclusion of variables that violate the normal distribution of errors and linear structural model (Raudenbush & Bryk, 2002), so those aspects do not need to be examined. While HGLM (as well as HLM) helps alleviate issues of violations of independence of errors by appropriately modeling multiple levels, the level 1 and level 2 data, considered separately, are assumed to be independent. Here that is the case as each student in level 1 only has one row and each institution in level 2 only has one as well. There are no matched pairs, pre-post- test design, or any other data structure that would obviously violate the assumption of independence. After the initial analysis of data for general quality and outliers was conducted, logistic regression was conducted separately at each level, and all assumptions tested, the building of the model began.

In order to evaluate which factors appear to have a significant effect on whether or not a student graduates within six years, the p-values for the significance tests that test for whether the coefficient is significantly different from 0 were examined. A p-value of .05 was be used as the cut-off to determine significance. As for research question two, any significant $u_{\cdot j}$ value had its variance (τ) examined. The level-2 residual gave information about typical institution deviation from the model-given values and the variance of the residual gave information about how much that deviation changed across universities.

Parameter estimation in HLM today is typically handled by maximum likelihood estimation. Due to the complexities in estimating parameter in HGLM other methods for approximating maximum likelihood must be used (Raudenbush & Bryk, 2002). The parameter estimation method used in this study is referred to as penalized quasi-likelihood estimation (PQL) (Breslow & Clayton, 1993; Goldstein, 1991), which is “based on a first- or second- order Taylor series expansion around an estimate of the fixed and random portions of the model” and has results considered to converge reliably (Raudenbush & Bryk, 2002).

Model

Several models were run to build a reasonable model that best addressed the research questions. A fully unconditional model was run first. In the fully unconditional model, the outcome variable is modeled with no predictors. The fully unconditional model shows how variation in an outcome is distributed at each level of the model, student and institution, and provides a basis for measuring additional variance explained by the addition of level-1 and level-2 covariates (Raudenbush & Bryk, 2002). The following is the fully unconditional model that was run in this study:

Level-1 Model: $Prob\ (G_{ij}=1|\beta_j) = \phi_{ij}$
$log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j}$
Level-2 Model: $\beta_{0j} = \gamma_{00} + u_{0j}$

The outcome variable (G) indicates whether or not the individual graduated with a bachelor's degree within six years. The subscript i indicates individual students (level-1) and j indicates institutions (level-2). The φ_{ij} represents the probability of getting a 1, in this case graduating within six years. The η_{ij} represents the log odds of graduating. The log odds, also called logit, are on a continuous scale theoretically ranging from negative infinite to positive infinite. When η is positive it means that getting a 1 (graduating) is more likely, when η is negative it means that a 0 (not graduating) is more likely. The symbol β represents coefficients, slopes and intercepts, at level-1; γ represents coefficients at level-2 and u represents level-2 residual terms. The value γ_{00} is the average log odds of graduating in 6 years across all UNC System institutions. The value u_0 is assumed to follow a normal distribution with a mean of 0 and a variance of τ_{00}, which describes the variance between schools with respect to the average log-odds of graduating in six years.

In building hierarchical models, Raudenbush and Bryk (2002) suggest adding in variables a few at a time in thematically related chunks. In this approach one builds a model piece by piece and evaluates it at each step instead of starting with the largest model first and then potentially trimming down. There are several reasons for this building up approach to modeling. It is easier to diagnose and address issues that might be occurring whether with data or estimation when the model is built a little at a time and the model parameters and significance are examined at each step. Also, power is preserved and degrees of freedom are saved for variables later in the model that may have more to add. The random effects are initially included and tested for significance in addition to the fixed effects; those variables that have non-significant random and fixed effects were dropped from the model.

The level-1 model was built first by adding in thematically related variables at the same time and then evaluating the model at each step with no level-2 covariates included but having the model unconditional at level-2. The themes from Table 7 were added to the model in the following order:

1. Demographic Characteristics
2. High School or Pre-College Characteristics
3. College Academic or Other Characteristics
4. Financial Aid Characteristics

Only variables with both a non-significant random and fixed effects were dropped from the model. These variables were dropped one variable at a time, beginning with the variable with the highest p-value. The model was rerun after each variable was dropped and the process was repeated until all effects were significant. Below is the final level-1 model with level-2 random effects:

Level-1 Model: Prob(G_{ij}=1|β_j) = ϕ_{ij}

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(A_{ij}) + \beta_{2j}*(AI_{ij}) + \beta_{3j}*(H_{ij}) + \beta_{4j}*(U_{ij}) + \beta_{5j}*(M_{ij}) + \beta_{6j}*(C_{ij}) + \beta_{7j}*(AGE_{ij}) + \beta_{8j}*(HSR_{ij}) + \beta_{9j}*(HSG_{ij}) + \beta_{10j}*(SAT_{ij}) + \beta_{11j}*(STEM_{ij}) + \beta_{12j}*(CH_{ij}) + \beta_{13j}*(ER_{ij}) + \beta_{14j}*(UG_{ij}) + \beta_{15j}*(R_{ij}) + \beta_{16j}*(FYM_{ij}) + \beta_{17j}*(LC_{ij}) + \beta_{18j}*(NEED_{ij}) + \beta_{19j}*(MERIT_{ij}) + \beta_{20j}*(PELL_{ij}) + \beta_{21j}*(SL_{ij}) + \beta_{22j}*(UL_{ij}) + \beta_{23j}*(FN_{ij}) + \beta_{24j}*(UN_{ij})$

Level-2 Model: $\beta_{kj} = \gamma_{k0} + u_{kj}$ K=0,1,2…,24

When the level-1 model was finalized then the level-2 model was built in the same way. All significant level-1 effects were retained. Level-2 effects were added beginning with the random intercept model for each of the themes. Then a random slope model was added for each of the themes. The order of the level-2 themes from Table 7 were added into the model as follows:

1. Academic Characteristics
2. Other Institutional Characteristics

As recommended by Raudenbush and Bryk (2002, p.267), a “tentative” model for the intercept was first established, similar to the concept common to other types of regression of testing the main effects before including interaction effects. The model including with level-2 covariates for the intercept is below:

Level-1 Model: Prob(G_{ij}=1|β_j) = ϕ_{ij}

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(A_{ij}) + \beta_{2j}*(AI_{ij}) + \beta_{3j}*(H_{ij}) + \beta_{4j}*(U_{ij}) + \beta_{5j}*(M_{ij}) + \beta_{6j}*(C_{ij}) + \beta_{7j}*(AGE_{ij}) + \beta_{8j}*(HSR_{ij}) + \beta_{9j}*(HSG_{ij}) + \beta_{10j}*(SAT_{ij}) + \beta_{11j}*(STEM_{ij}) + \beta_{12j}*(CH_{ij}) + \beta_{13j}*(ER_{ij}) + \beta_{14j}*(UG_{ij}) + \beta_{15j}*(R_{ij}) + \beta_{16j}*(FYM_{ij}) + \beta_{17j}*(LC_{ij}) + \beta_{18j}*(NEED_{ij}) + \beta_{19j}*(MERIT_{ij}) + \beta_{20j}*(PELL_{ij}) + \beta_{21j}*(SL_{ij}) + \beta_{22j}*(UL_{ij}) + \beta_{23j}*(FN_{ij}) + \beta_{24j}*(UN_{ij})$

Level-2 Model: $\beta_{0j} = \gamma_{00} + \gamma_{01}*(R_j) + \gamma_{02}*(S_j) + u_0$

$\beta_{kj} = \gamma_{k0} + u_{kj}$ K=1,2…, 24

Following the establishment of the intercept model, the level-2 covariates were added to the level-2 slope models and then removed one by one, with the model re-estimated at each step, when found to be non-significant. The final model that was used to address the research questions is below:

Level-1 Model: $\text{Prob}(G_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(A_{ij}) + \beta_{2j}*(AI_{ij}) + \beta_{3j}*(H_{ij}) + \beta_{4j}*(U_{ij}) + \beta_{5j}*(M_{ij}) + \beta_{6j}*(C_{ij}) + \beta_{7j}*(AGE_{ij}) + \beta_{8j}*(HSR_{ij}) + \beta_{9j}*(HSG_{ij}) + \beta_{10j}*(SAT_{ij}) + \beta_{11j}*(STEM_{ij}) + \beta_{12j}*(CH_{ij}) + \beta_{13j}*(ER_{ij}) + \beta_{14j}*(UG_{ij}) + \beta_{15j}*(R_{ij}) + \beta_{16j}*(FYM_{ij}) + \beta_{17j}*(LC_{ij}) + \beta_{18j}*(NEED_{ij}) + \beta_{19j}*(MERIT_{ij}) + \beta_{20j}*(PELL_{ij}) + \beta_{21j}*(SL_{ij}) + \beta_{22j}*(UL_{ij}) + \beta_{23j}*(FN_{ij}) + \beta_{24j}*(UN_{ij})$

Level-2 Model: $\beta_{0j} = \gamma_{00} + \gamma_{01}*(R_j) + \gamma_{02}*(S_j) + u_{0j}$

$\beta_{1j} = \gamma_{10} + u_{1j}$

$\beta_{2j} = \gamma_{20} + u_{2j}$

$\beta_{3j} = \gamma_{30} + u_{3j}$

$\beta_{4j} = \gamma_{40} + \gamma_{41}*(S_j) + u_{4j}$

$\beta_{5j} = \gamma_{50} + \gamma_{51}*(R_j) + u_{5j}$

$\beta_{6j} = \gamma_{60} + u_{6j}$

$\beta_{7j} = \gamma_{70} + \gamma_{71}*(R_j) + u_{7j}$

$\beta_{8j} = \gamma_{80} + \gamma_{81}*(S_j) + u_{8j}$

$\beta_{9j} = \gamma_{90} + \gamma_{91}*(S_j) + u_{9j}$

$\beta_{10j} = \gamma_{100} + \gamma_{101}*(R_j) + u_{10j}$

$\beta_{11j} = \gamma_{110} + \gamma_{111}*(S_j) + u_{11j}$

$\beta_{12j} = \gamma_{120} + \gamma_{121}*(R_j) + u_{12j}$

$\beta_{13j} = \gamma_{130} + \gamma_{131}*(S_j) + u_{13j}$

$\beta_{14j} = \gamma_{140} + \gamma_{141}*(R_j) + u_{14j}$

$\beta_{15j} = \gamma_{150} + u_{15j}$

$\beta_{16j} = \gamma_{160} + u_{16j}$

$\beta_{17j} = \gamma_{170} + \gamma_{171}*(R_j) + u_{17j}$

$\beta_{18j} = \gamma_{180} + \gamma_{181}*(S_j) + u_{18j}$

$\beta_{19j} = \gamma_{190} + \gamma_{191}*(S_j) + u_{19j}$

$\beta_{20j} = \gamma_{200} + \gamma_{201}*(S_j) + u_{20j}$

$\beta_{21j} = \gamma_{210} + \gamma_{211}*(R_j) + \gamma_{212}*(S_j) + u_{21j}$

$\beta_{22j} = \gamma_{220} + u_{22j}$

$\beta_{23j} = \gamma_{230} + \gamma_{231}*(S_j) + u_{23j}$

$\beta_{24j} = \gamma_{240} + u_{24j}$

CHAPTER IV

RESULTS

Hierarchical generalized linear models were run for the dichotomous outcome variable, six-year baccalaureate degree attainment. The purpose was to examine the effects of student- and institution-level variables on degree attainment and to examine whether those effects varied between universities in the UNC System. After the data were examined descriptively and cleaned, HGLM assumptions were tested, a fully unconditional HGLM model was run, and then the full model was built in pieces, examining for significance and potential issues at each step.

Overview of the Data

Student-Level (Level-1)

The student-level data provided by the UNC System office contained de-identified unit record data on 460,909 students. The start year at the university the student attended ranged from 2000 through 2009. The six-year period that the student was tracked to determine six-year graduation ranged from 2006 through 2015. The data were examined for distributional properties and reasonableness both graphically in the form of scatterplots, histograms, and box and whisker plots as well through a series of summary statistics including means, medians, standard deviations, and minimum and maximum values. Overall, the distributions looked reasonable and appropriate for the analysis. However, as with any dataset of this size and covering approximately 15 years of data, there were several anomalies that needed to be addressed in order to ensure the accuracy of the analysis and results.

All of the demographic values looked reasonable, but there were a few issues in the high school characteristics that needed to be addressed. Both SAT and ACT composite scores were provided. Of the 460,909 students,13,195 (approximately 2.9%) had an ACT score but no SAT score. Due to the small number of missing scores and measurement concerns with the concordance of ACT and SAT scores (Pommerich, Hanson, Harris, & Sconing, 2000) only the SAT composite scores were included in the model. SAT scores were deleted for six records with scores that were outside the 400 to 1600 range for composite scores or 200 to 800 range for the SAT math and verbal component scores. The component scores only were provided and used to create the SAT composite score. Scores outside of these ranges (400 to 1600 composite and 200 to 800 component) are impossible to obtain on the SAT and thus were deleted because they could not be correct. Additionally, SAT scores were divided by 100. This brought the variation in line with other variables in the model for the purpose of easing the considerable estimation burden of such a large model and assisting with interpretability. The high school rank (HSR) variable was also divided by 100 in order to make estimation of model parameters easier. High school GPA (HSG) values of over 6.0 were deleted as these values are unlikely to be accurate on a 4.0 scale. As a result, 11 records were deleted. With course weighting for college-level or other advanced types of coursework, high school GPAs of secondary public-school students in North Carolina could technically range up to 6.0 on a 4.0 scale. As most UNC System students come from North Carolina public high schools, the possible GPA range of North Carolina public high schools was used to determine the reasonable range for the high school GPA variable. Values under 1.0 were also deleted for the high school GPA variable, which affected 52 records. GPAs below 1.0 are below the accepted minimums for UNC System universities and are therefore unlikely to be correct for currently enrolled students.

One of the variables describing student academic or other behaviors while in college was modified. The credit hour variable, which is defined as the average number of term credit hours the student took in their fall and spring terms for all terms that the student was enrolled, was made null for 233 records with values over 21 credit hours (approximately .05% of the total dataset). Values above this are unlikely to be correct and may be unduly influenced by a single incorrect outlier term. In several cases, average term credit hour values over 40 existed in the data. For context, federal financial aid considers a student “full-time” at 12 credit hours and 15 credit hours are needed in the fall and spring terms, assuming no summer courses, to graduate from a typical 120 credit hour baccalaureate degree program in four years. A student taking over 21 credit hours on average in a term would be taking more than seven courses that are three credit hours in length. These extreme values are unlikely to be correct and have an undue influence on variance, which is the basis for this type of analysis, and thus they were removed.

Several financial aid-related variables were adjusted. There was a single outlier value for average unsubsidized federal loans of $78,851, which was deleted. One value of $10,100 was deleted for Pell as this exceeds the maximum annual Pell grant awarded even with allowing for 150% maximum Pell in the years when the federal program was funded in the summer. For the merit-based aid variable, three outliers above $65,000 were deleted as this exceeds the annual cost of attendance of any UNC System institution, which institutions are required to stay within when awarding any state, federal, or institutional aid (Federal Student Aid, 2017). These large values are unlikely to be correct and would have an undue influence on the variance of this variable. For interpretation purposes, as well as to ease the estimation burden of having variables with such large and small variances in the same model, all financial aid data were divided by $1,000.

After the data were cleaned, the descriptive summaries in Tables 8 and 9 were compiled. The level-1 variables had little missing data (see Table 8), with three notable exceptions all in the high school or pre-college characteristics category. Data for these variables were missing at rates ranging from 22% to 29%. Of the 24 level-1 variables in the study, 15 had no missing data.

Outside of the three variables previously mentioned, the six remaining variables had data missing at rates from .0002% to 3%. The missingness of the data was examined by university and by year. There did not appear to be any major deviations between the overall distribution of the total records and the missing records when compared across year and institution.

Of the 460,909 students in the analysis, approximately 59% graduated within six years from the university at which their enrollment originally began. The students identified as white at a rate of 66% and African-American or black at a rate of 24%. Less than half of the students (43%) were male and 97% of all students were citizens of the United States. The average age, as of August 1st of the first year enrolled, was just over 20 years old. The average high school GPA was 3.47 and average composite SAT score was 1064, with scores ranging from 400 to 1600. Students were majoring in a STEM major as of their last term of enrollment at a rate of 19%. The average number of credit hours per term of students in the study was 13.85. The average cumulative university GPA as of the last enrolled term was 2.72. As for course-taking patterns, 69% passed a math course in their first year of enrollment at the university and 8% took a remedial course. The average annual amount of need-based aid, including grants and federal loans, was about $3,800 with amounts ranging from $0 to just over $44,000. The average amount of merit-based aid received annually was approximately $3,500 with amounts ranging from $0 to just over $58,000. The average annual amount of subsidized loan per student was about $1,680 and $1,630 for unsubsidized loans. The average annual financial need that students had was about $5,950 with financial need ranging from $0 to $50,000. After taking into account all of the grants and loans that a student received, the average annual amount of unmet need was about $1,250.

Institution-Level (Level-2)

The institution level dataset contained data from IPEDS from the academic year 2000-01 until 2015-16, which is the complete time period of student enrollment covered in this study. The

16 UNC System public universities were included in the dataset. Table 9 summarizes the characteristics of the institutions across the variables used in this study. Since the study covered students enrolled during a 15-year period, the values for all variables at the institution-level were examined for every year during that time period. All values were examined for changes and trends, which would indicate whether it was reasonable to include a single value at the institution level to describe the 15-year time period. Some variables showed no change over time, while others showed some small changes but nothing extreme enough to indicate that a single summarized value for the institution would not yield meaningful results in examining the impact of institution-level characteristics on six-year graduation. The mean over all years of available data between the academic years 2000-01and 2015-16 was used for size, selectivity, student-to-faculty-ratio, instructional and academic support expenses per FTE, research expenses per FTE, percent part-time instructional staff, and net price. The mode for doctoral designation and residential designation, both determined by Carnegie classifications, was used. These values appear in Table 9.

There was no missing data for any of the level-2 independent variables (see Table 8). Approximately 38% of the universities included in the study were classified as doctoral and 19% as primarily residential. The average size was just over 10,000 undergraduate students. The mean selectivity measure, which is the mean of the 75th percentile SAT math and verbal/ critical reading score of the freshmen class, was 562. The average student-to-faculty ratio was 16 with values raging from approximately six to 19. Instructional and academic support expenses per full-time equivalent ranged from over $4,000 to just over $15,000 with a mean of about $6,315. Research expenses per FTE ranged from $1.67 to over $17,000 with a mean of about $2,298. The percent of part-time instructional staff ranged from 5% to 61% and the net price from just over $2,000 to over $12,000 with a mean of about $9,383.

Table 8

Number of Observations and Missing Data for all Level-1 and Level-2 Variables Included in the Model

Variable	Code	Complete Number	Missing Number	Percent Missing
Dependent Variable				
Graduated Within 6 Years	G	460,909	0	0%
Level-2 Independent Variables				
Doctoral	D	16	0	0%
Residential	R	16	0	0%
Size	E	16	0	0%
Selectivity	S	16	0	0%
Student-to-Faculty Ratio	SF	16	0	0%
Instructional and Academic Support Expenses per FTE	IAE	16	0	0%
Research Expenses per FTE	RE	16	0	0%
Percent Part-Time Instructional Staff	PT	16	0	0%
Net Price	NP	16	0	0%
Level-1 Independent Variables				
Being White	W	460,909	0	0%
Being African-American/ Black	A	460,909	0	0%
Being American Indian	AI	460,909	0	0%
Being Hispanic/ Latino	H	460,909	0	0%
Unknown Race or Asian	U	460,909	0	0%
Being Male	M	460,909	0	0%
Citizenship	C	460,909	0	0%
Age	AGE	456,281	4,628	1%
High School Class Rank (In Hundreds)	HSR	334,574	126,335	27%
High School GPA	HSG	359,350	101,559	22%
SAT Composite Score (In Hundreds)	SAT	328,149	132,760	29%
Majoring in a STEM program	STEM	460,909	0	0%
Average Term Credit Hours	CH	460,676	233	0%
Enrolled during the recession	ER	460,909	0	0%
University GPA	UG	444,789	16,120	3%
Taking Any Remedial Course	R	460,909	0	0%
Passing a First Year Math Course	FYM	460,909	0	0%
Living on Campus	LC	460,909	0	0%
Need-Based Aid Amount (In Thousands)	NEED	460,909	0	0%
Merit-Based Aid Amount (In Thousands)	MERIT	460,906	3	0%
Pell Grant Amount (In Thousands)	PELL	460,908	1	0%
Subsidized Loan Amount (In Thousands)	SL	460,909	0	0%
Unsubsidized Loan Amount (In Thousands)	UL	460,908	1	0%
Financial Need (In Thousands)	FN	460,909	0	0%
Unmet Need (In Thousands)	UN	460,909	0	0%

Table 9

Descriptive Statistics for All Level-1 and Level-2 Variables

Variable	Code	Mean	SD	Min	Max
Dependent Variable					
Graduated Within 6 Years	G	0.59	0.49	0	1
Level-2 Independent Variables					
Doctoral	D	0.38	0.48	0	1
Residential	R	0.19	0.39	0	1
Size	E	10,266	6,839	767	23,884
Selectivity	S	562	72	464	700
Student-to-Faculty Ratio	SF	16	3	6.2	19.1
Instructional and Academic Support Expenditures per FTE	IAE	$6,315.25	$2,853.93	$4,396.71	$15,203.96
Research Expenses per FTE	RE	$2,297.79	$4,526.26	$1.67	17,881.08
Percent Part-Time Instructional Staff	PT	0.28	0.11	0.05	0.61
Net Price	NP	$9,383.24	$2,502.27	$2,144.11	$12,611.78
Level-1 Independent Variables					
Being White	W	0.66	0.47	0	1
Being African-American/ Black	A	0.24	0.43	0	1
Being American Indian	AI	0.01	0.11	0	1
Being Hispanic/ Latino	H	0.03	0.16	0	1
Unknown Race or Asian	U	0.07	0.25	0	1
Being Male	M	0.43	0.50	0	1
Citizenship	C	0.97	0.16	0	1
Age	AGE	20.56	5.84	13	87
High School Class Rank (In Hundreds)	HSR	0.67	0.24	0	1
High School GPA	HSG	3.47	0.69	0.01	5.99
SAT Composite Score (In Hundreds)	SAT	10.64	1.79	4	16
Majoring in a STEM program	STEM	0.19	0.39	0	1
Average Term Credit Hours	CH	13.85	2.52	0	21
Enrolled during the recession	ER	0.74	0.44	0	1
University GPA	UG	2.72	0.94	0.00	4.19
Taking Any Remedial Course	R	0.08	0.28	0	1
Passing a First Year Math Course	FYM	0.69	0.46	0	1
Living on Campus	LC	0.45	0.50	0	1
Need-Based Aid Amount (In Thousands)	NEED	$3.80	$4.45	$0.00	$44.33
Merit-Based Aid Amount (In Thousands)	MERIT	$3.51	$4.42	$0.00	$58.26
Pell Grant Amount (In Thousands)	PELL	$1.16	$1.71	$0.00	$8.33
Subsidized Loan Amount (In Thousands)	SL	$1.68	$1.99	$0.00	$13.51
Unsubsidized Loan Amount (In Thousands)	UL	$1.63	$2.17	$0.00	$17.32
Financial Need (In Thousands)	FN	$5.95	$6.69	$0.00	$50.00
Unmet Need (In Thousands)	UN	$1.25	$2.59	$0.00	$49.13

Model Analysis

Model 1: The Fully Unconditional Model

The fully unconditional model was run first in order to decide if a hierarchical or multilevel model was appropriate for this data. The results of the fully unconditional model help to answer the question: Is there significant variation between universities to justify the use of HGLM? If there is not, then a regular logistic regression is appropriate. In this case, the level-2 random effect (u_0) was found to be significant (see Table 11) indicating that enough variation between universities existed to justify the use of HGLM. The intercept (γ_{00}) describes the overall average log-odds of graduating in six years across all students and schools. Overall, average log-odds of graduating in six years across all students and schools was .23 (see Table 10). The average extent to which universities differ from the overall average log-odds of graduation in six years is described by u_0. The variance of the average log-odds of graduation across the university means or the variability between schools is represented by τ_{00}, which is .36.

Table 10

Intercept for Fully Unconditional Model

Variable	Coefficient (log-odds)	Standard Error	*t*-ratio	*p*-value
Intercept	0.23	0.15	1.56	0.14

Table 11

Variance Component for Fully Unconditional Model

Random Effect	Standard Deviation	Variance Component	*df*	χ^2	*p*-value
Level-2 (u_0)	0.60	0.36	15	30821.33	<0.001

Model 2: Level-1 Covariates Unconditional at Level-2

Because the focus of the study was on the relationship between student-level and institution-level covariates and the likelihood to persist to degree completion and how these covariates vary across institutions, all level-1variables were group-mean centered. Group-mean centering allowed the intercepts to be interpreted as the average unadjusted log-odds of graduating in six years for a student who is average on every level-1 variable. The level-1 slopes are still interpreted as the change in log-odds of graduating in six years for a one unit change in the coefficient associated with the slope. As recommended by Raudenbush and Bryk (2002), first all level-1 variables were added to the model in conceptually related blocks unconditional at level-2. Then the level-1 slopes and level-2 random effects were examined for significance. Only variables with a non-significant random effect at level-2 and a non-significant level-1 fixed effect would be removed. In this case, only being American Indian was non-significant in both random effect at level-2 and fixed effect at level-1, but since the race/ ethnicity variables are all interconnected, the non-significant American Indian values were kept in the model. Therefore, all variables were all retained in the model.

As recommended by Raudenbush and Bryk (2002), the level-2 covariates were first added to the intercept model in conceptually related blocks and then tested for significance before adding level-2 covariates to the slope models. Of the nine variables added, the only level-2 covariates that remained in the intercept model because of their significance were residential and selectivity. The small number of variables significant at level-2 was likely due to the small level-2 sample size of 16. The residential and selectivity variables were then added to all of the slope models at level-2 and tested for significance. If the level-2 covariates were not found to have a relationship with the log-odds of graduation, as tested in the intercept model, then there is less potential for their role as a moderator in the relationship with level-1 covariates and the log-odds of graduation.

After residential and selectivity were added to each of the slope models, any level-2 covariate that was non-significant was removed one at a time beginning with the fixed effect with the highest p-value. The model was then re-run and the process repeated for any additional non-significant level-2 covariates in the slope models. The resulting model included residential and selectivity in the intercept model as well as the slope model for subsidized loans. Selectivity alone was included in the level-2 slope models for unknown race or Asian, high school rank, high school GPA, majoring in a STEM program, being enrolled during the recession, need-based aid, merit-based aid, Pell grant amount, and financial need. Residential alone was included in the level-2 slope models for being male, age, SAT composite score, average term credit hours, university GPA, and living on-campus. No level-2 covariates were included in the models for being African-American/ black, being American Indian, being Hispanic, being a US citizen, taking any remedial courses, passing a first-year math course, unsubsidized loan amount, and unmet need amount. The fixed and random effects estimates are summarized in Tables 12, 13, and 14.

Table 12 shows the fixed effects for the level-1 variables which were included as intercepts in the level-2 models. Without any random effects or covariates at level-2, these values would be equal to the βs in the level-1 model. This model included random effects for all level-2 models and significant level-2 covariates. Therefore, the fixed effect values in Table 12 are interpreted assuming the level-2 covariates included in each level-2 model are at their average, because level-2 variables were grand-mean centered. The values in Table 12 must be understood in the context of the corresponding level-2 covariates in Tables 14. The level-2 covariates model changes the relationship between the effects in Table 12 and the outcome variable, six-year graduation. In extreme cases these changes in effect can even lead to predicted changes in the directional indication of the slope for the level-1 covariate over different values of the level-2 covariate. Most results of this study do not run into this phenomenon, but it does occur and is referenced in the results and discussion when the level-2 covariate is not only significant, but also meaningfully alters the interpretation of the level-1 relationship. The intercept in Table 12 (γ_{00}) of .16 represents the unadjusted average or expected log-odds that a student who is average on all level-1 and level-2 covariates will graduate within six years after controlling for residential and selectivity. Using the unit-specific estimates to compute a probability, the probability of graduating for a student at the average on all level-1 and level-2 characteristics was .54. The non-intercept values in Table 12 represent the expected change or average change in the log-odds of graduating in six years. For example, for being African-American/ black (γ_{10}), .41 was the expected change in the log-odds of graduating in six years controlling for all level-1 covariates. There were no significant level-2 covariates for being African-American/ black, so they are not included in the interpretation.

Table 12

Fixed Effects for Level-1 Variables at Level-2

Fixed Effect		Coefficients (log-odds)	Odds Ratio	Standard Error	*t*-ratio	*df*	*p*-value
Intercept	γ_{00}	0.16	1.18	0.09	1.78	13	0.098
Being African-American/ Black	γ_{10}	0.41	1.50	0.06	7.03	15	<0.001
Being American Indian	γ_{20}	-0.12	0.89	0.12	-0.99	15	0.336
Being Hispanic/ Latino	γ_{30}	0.04	1.04	0.07	0.54	15	0.596
Unknown Race or Asian	γ_{40}	0.10	1.11	0.05	2.10	14	0.054
Being Male	γ_{50}	0.25	1.29	0.04	6.53	14	<0.001
Citizenship	γ_{60}	0.29	1.34	0.08	3.82	15	0.002
Age	γ_{70}	-0.05	0.95	0.02	-3.24	14	0.006
High School Class Rank (In Hundreds)	γ_{80}	-0.77	0.46	0.11	-7.28	14	<0.001
High School GPA	γ_{90}	0.43	1.53	0.07	6.45	14	<0.001
SAT Composite Score (In Hundreds)	γ_{100}	-0.19	0.83	0.01	-12.89	14	<0.001
Majoring in a STEM program	γ_{110}	0.23	1.25	0.11	2.16	14	0.049

Table 12

Cont.

Fixed Effect		Coefficients (log-odds)	Odds Ratio	Standard Error	t-ratio	*df*	*p*-value
Average Term Credit Hours	γ_{120}	0.17	1.18	0.04	4.44	14	<0.001
Enrolled during the recession	γ_{130}	-2.02	0.13	0.08	-25.23	14	<0.001
University GPA	γ_{140}	2.29	9.89	0.11	21.42	14	<0.001
Taking Any Remedial Course	γ_{150}	-0.28	0.75	0.08	-3.45	15	0.004
Passing a First Year Math Course	γ_{160}	0.17	1.18	0.07	2.36	15	0.032
Living on Campus	γ_{170}	-0.66	0.52	0.12	-5.36	14	<0.001
Need-Based Aid Amount (In Thousands)	γ_{180}	0.14	1.15	0.01	11.58	14	<0.001
Merit-Based Aid Amount (In Thousands)	γ_{190}	0.07	1.07	0.01	8.53	14	<0.001
Pell Grant Amount (In Thousands)	γ_{200}	0.01	1.01	0.02	0.40	14	0.692
Subsidized Loan Amount (In Thousands)	γ_{210}	0.13	1.14	0.02	7.31	13	<0.001
Unsubsidized Loan Amount (In Thousands)	γ_{220}	0.09	1.09	0.01	7.94	15	<0.001
Financial Need (In Thousands)	γ_{230}	-0.09	0.91	0.01	-11.30	14	<0.001
Unmet Need (In Thousands)	γ_{240}	0.05	1.05	0.01	4.17	15	<0.001

Table 13 shows the random effects in each level-2 equation including the intercept and all slope models. The random effects describe variation between level-2 units (universities). The hypothesis tests for the random effects indicate if there was still significant variation across universities even after accounting for significant level-2 variables. The random effect for the intercept (u_0) was significant indicating that universities still significantly differed with respect to six-year graduation even after controlling for the residential status and selectivity of the universities. Table 13 shows the majority of the random effects were still significant even after including significant level-2 covariates, indicating that there is still additional variance between institutions that is not accounted for by the included level-2 variable(s). The random effect for being American Indian was non-significant, indicating that when it comes to the relationship between being American Indian and the average log-odds of graduation in six years the differences that exist between universities can be attributed to sampling error. The random effect for age was significant which indicates that even after controlling for the residential status of the universities, significant variation still exists around the relationship between age and graduating from college in six years.

Table 13

Random Effects for Level-1 Variables at Level-2

Random Effect for Variable		*SD*	Variance Component	*df*	χ^2	*p*-value
Intercept	u_0	0.365	0.133	11	2141.51	<0.001
Being African-American/ Black	u_1	0.212	0.045	13	60.96	<0.001
Being American Indian	u_2	0.402	0.162	13	19.46	0.109
Being Hispanic/ Latino	u_3	0.221	0.049	13	24.42	0.027
Unknown Race or Asian	u_4	0.152	0.023	12	23.29	0.025
Being Male	u_5	0.143	0.020	12	81.19	<0.001
Citizenship	u_6	0.217	0.047	13	11.67	>0.500
Age	u_7	0.055	0.003	12	69.53	<0.001
High School Class Rank (In Hundreds)	u_8	0.363	0.132	12	51.02	<0.001
High School GPA	u_9	0.247	0.061	12	106.53	<0.001
SAT Composite Score (In Hundreds)	u_{10}	0.053	0.003	12	91.26	<0.001
Majoring in a STEM program	u_{11}	0.406	0.165	12	681.74	<0.001
Average Term Credit Hours	u_{12}	0.151	0.023	12	422.56	<0.001
Enrolled during the recession	u_{13}	0.308	0.095	12	206.57	<0.001
University GPA	u_{14}	0.421	0.177	12	715.83	<0.001
Taking Any Remedial Course	u_{15}	0.305	0.093	13	113.01	<0.001
Passing a First Year Math Course	u_{16}	0.273	0.075	13	211.84	<0.001
Living on Campus	u_{17}	0.484	0.234	12	1639.06	<0.001
Need-Based Aid Amount (In Thousands)	u_{18}	0.042	0.002	12	72.94	<0.001
Merit-Based Aid Amount (In Thousands)	u_{19}	0.029	0.001	12	165.50	<0.001
Pell Grant Amount (In Thousands)	u_{20}	0.077	0.006	12	145.50	<0.001
Subsidized Loan Amount (In Thousands)	u_{21}	0.066	0.004	11	136.86	<0.001
Unsubsidized Loan Amount (In Thousands)	u_{22}	0.041	0.002	13	153.37	<0.001
Financial Need (In Thousands)	u_{23}	0.030	0.001	12	96.65	<0.001
Unmet Need (In Thousands)	u_{24}	0.042	0.002	13	97.94	<0.001

Table 14 displays the fixed effect coefficients for the level-2 covariates included in each of the intercept and slope equations at level-2. The values in Table 14 give information about how the significant level-2 covariates interact with the level-1 covariates to change the slope across institutions. For the intercept, the .29 value for residential (γ_{01}) gives the expected change in the log-odds of graduating in six years for being a residential university as opposed to a non-residential university with all level-2 variables at their average. In other words, .29 is the expected change in average graduation for residential universities after controlling for selectivity. Even after controlling for selectivity, one would still expect a .29 difference in the log-odds of graduating between the average graduation log-odds of residential versus non-residential universities. The non-intercept γ values in Table 14 provide information about how level-2 covariates are expected to change the relationship between level-1 variables and the log-odds of graduating in six years after controlling for any other level-2 covariates included.

Table 14

Fixed Effects for Level-2 Covariates for Level-1 Intercept and Slopes

Fixed Effect	Level-2 Covariate		Coefficients (log-odds)	Odds Ratio	Standard Error	*t*-ratio	*df*	*p*-value
Intercept	Residential	γ_{01}	0.2889	1.33	0.1335	2.16	13	0.05
Intercept	Selectivity	γ_{02}	0.0149	1.02	0.0008	18.47	13	<0.001
Unknown Race or Asian	Selectivity	γ_{41}	-0.0024	1.00	0.0005	-4.96	14	<0.001
Being Male	Residential	γ_{51}	0.1401	1.15	0.0638	2.20	14	0.046
Age	Residential	γ_{71}	-0.1112	0.89	0.0253	-4.39	14	<0.001
High School Class Rank (In Hundreds)	Selectivity	γ_{81}	-0.0085	0.99	0.0012	-7.29	14	<0.001
High School GPA	Selectivity	γ_{91}	0.0020	1.00	0.0006	3.31	14	0.005
SAT Composite Score (In Hundreds)	Residential	γ_{101}	0.0863	1.09	0.0303	2.85	14	0.013
Majoring in a STEM program	Selectivity	γ_{111}	0.0045	1.00	0.0011	4.05	14	0.001
Average Term Credit Hours	Residential	γ_{121}	-0.3454	0.71	0.0388	-8.91	14	<0.001
Enrolled during the recession	Selectivity	γ_{131}	0.0050	1.01	0.0005	9.52	14	<0.001
University GPA	Residential	γ_{141}	1.2287	3.42	0.1301	9.45	14	<0.001
Living on Campus	Residential	γ_{171}	0.5314	1.70	0.1924	2.76	14	0.015
Need-Based Aid Amount (In Thousands)	Selectivity	γ_{181}	-0.0003	1.00	0.0001	-3.87	14	0.002
Merit-Based Aid Amount (In Thousands)	Selectivity	γ_{191}	-0.0006	1.00	0.0001	-10.17	14	<0.001
Pell Grant Amount (In Thousands)	Selectivity	γ_{201}	-0.0011	1.00	0.0002	-6.45	14	<0.001
Subsidized Loan Amount (In Thousands)	Residential	γ_{211}	0.1268	1.14	0.0215	5.89	13	<0.001
Subsidized Loan Amount (In Thousands)	Selectivity	γ_{212}	-0.0018	1.00	0.0001	-12.98	13	<0.001
Financial Need (In Thousands)	Selectivity	γ_{231}	0.0004	1.00	0.0001	8.39	14	<0.001

Research Question Analysis

Research Question 1

What covariates at the student and institution level, with a focus on financial aid variables, have a significant relationship with the likelihood to persist to degree completion? In the process of building the level-1 model, all level-1 fixed effects identified in Table 7 as being included in the final dataset were found to have a significant relationship with graduation, with the exception of being American Indian. However, this variable was kept in the model for its relationship with all other race values. When level-2 random and fixed effects were added, some additional level-1 fixed and random effects became non-significant. Variables added at level-1 may be picking up on variation that was later accounted for in the level-2 models, making some of the level-1 variables no longer significant. It is also possible that adding in the level-2 covariates reduced power, which could also have led to changes in significance. Therefore, the final model is interpreted as opposed to interim models that were built and tested before arriving at the final model. The remaining significant fixed and random effects are interpreted. The final model is interpreted in response to this research question because it is the most complete model that is likely to have the least amount of bias in terms of the coefficient estimates.

The intercepts for the slope models (see Table 12) provide information about which level-1 variables are significant in predicting six-year graduation when all significant level-2 variables that remain in the model are at their average. The expected change in the log-odds of graduating in six years is .41 for African-American/ black students. With residential at its average, being male resulted in an increase in the expected log-odds of graduating in six years of .25. Similarly, being a citizen shows a .29 increase in the expected log-odds of graduation. The expected change in the log-odds of graduating in six years was -.05 for age, indicating that for a unit increase in age there was a .05 decrease in the log-odds of graduation with residential at its average. After the addition of level-2 variables, the fixed effects for being American Indian, being Hispanic, and unknown race or Asian were no longer significant. The demographic covariates of being African-American or black, being male, being a US citizen, and age were all found to have a significant relationship with the log-odds of graduating in six years.

All three high school or pre-college variables had significant fixed effects holding relevant level-2 variables at their averages. With selectivity at its average, the expected change in the log-odds of graduating in six years on average decreased by .77 for each unit increase in high school rank (in hundreds). High school rank is a percentile that originally ranged from 0 to 100 but was divided by 100, so in the study it ranged from 0 to 1. Therefore, a one-unit increase is not really a meaningful metric. Instead, one could think of it as moving .008 per percentile. So, while this effect seems to move in the opposite direction of what would be expected, it is a fairly small effect. Similarly, the SAT variable had on average an expected change in the log-odds of graduation of -.19 for a 100-point increase in SAT score with all other variables in the model at their averages. So again, this effect is in the opposite direction expected but is a relatively small effect. For every unit change in high school GPA, there was an expected increase of .43 in the log-odds of graduating in six years with selectivity at its average. The covariates of high school GPA, composite SAT score, and high school rank were all found to have a significant relationship with the likelihood to graduate in six years.

All college academic and other characteristic variables were significant in their relationship to six-year graduation. Majoring in a STEM program was used as a proxy for majoring in a field requiring higher-level math. The expected change in the log-odds of graduating in six years was .23 for STEM majors with selectivity at its average. With residential at its average, the expected change in log-odds of graduating in six years was .17 per unit change in average credit hours taken per term. However, for this variable in particular, it is important to take into account the effect of the level-2 covariate, residential. The level-1 effect is .17 (see γ_{120} in Table 12), so considering the effect of level-2 effect of residential (see γ_{121}=-.35 in Table 14), a residential university's credit hours effect would be predicted to be negative. Having the six-year enrollment window for the student overlap with the recession (enrolled during the recession variable) was associated with an expected decrease in the log-odds of graduating in six years of 2.02. Per unit increase in college GPA with residential at its average, the expected change in the log-odds of graduating in six years was 2.29. The expected change in the log-odds of graduation in six years for a student who took one or more remedial courses was -.28. Passing a math course in the student's first year of enrollment was associated with an expected change in the log-odds of graduating in six years of .17. The results of this study show the change in expected log-odds of graduation in six years with residential at its average is -.66 for students living on-campus. Majoring in a STEM program, the average term credit hours taken, enrollment during the recession, undergraduate GPA, taking remedial coursework, passing a math course in the first year, and living on-campus were all found to have a significant relationship with the probability of graduating in six years.

All the financial aid coefficients at the student-level with the exception of the Pell grant amount were significant. For a $1,000 increase in the amount of need-based aid a student received, the expected change in the log-odds of graduating in six years was .14 with selectivity at its average. The amount of merit-based aid had an expected increase in the log-odds of graduation of .07 for an increase in $1,000 in aid with selectivity as its average. For a $1,000 increase in the amount of subsidized loans with selectivity and residential at their averages, the expected change in the log-odds of graduating in six years was .13. The expected change in the log-odds of graduating in six years was .09 for every $1,000 increase in unsubsidized loans. This study found that with selectivity at its average, for every $1,000 increase in a student's financial need, the average log-odds of graduating in six years changed by -.09. In this study, a $1,000 increase in unmet need was associated with an average increase in the log-odds of graduation of .05. In the final model, the need-based aid amount, merit-based aid amount, subsidized and unsubsidized loan amounts, amount of financial need, and amount of unmet need were all found to have a significant relationship with the probability of graduating in six years.

For the intercept model at level-2, this study looked to predict the average log-odds of graduating in six years with a variety of university characteristics. After eliminating non-significant variables, the residential and selectivity variables at level-2 were found to have a significant relationship with the probability of graduating in six years. Table 14 shows that .29 is the average change in the log-odds of graduating in six years for residential status with selectivity at its average. This means that even after controlling for selectivity, one would still expect a .29 difference in the log-odds of graduation in six years for a residential university compared to a non-residential university. The average change in the log-odds of graduating in six years for a one-unit change in selectivity is .015 with the residential status of the university at its average. The result indicates that after controlling for residential, one would still expect to see a .015 difference in the log-odds of graduation as the mean 75th percentile SAT math and verbal score increases by one at a university. Both the residential status of the university and the selectivity of the university were found to have a significant relationship with the probability of graduating in six years.

Research Question 2

Do any of these significant covariates vary in their effects across institutions? For the second research question, the random effects in Table 13 are interpreted as they indicate variation between universities. The fixed effects in Table 14 are interpreted as they give information about how the significant level-2 covariates interact with the level-1 covariates to change the slope across universities. The random effects in Table 13 show if there is still significant variation across institutions after accounting for significant level-2 variables. The random effect for the intercept is significant indicating that universities still significantly differ with respect to the log-odds of graduating in six years even after controlling for the residential status and selectivity of the universities.

The majority of the random effects were still significant even after including significant level-2 covariates indicating that there is still additional variance between institutions that is not accounted for by the included level-2 variables. The random effect for being a US citizen was non-significant, indicating that when it comes to the relationship between being a US citizen and the average log-odds of graduation in six years the differences that exist between universities can be attributed to sampling error. The random effect for identifying as African-American/ black was significant, which indicates that significant variation exists around the relationship between being African-American/ black and graduating from college in six years. Being Hispanic had no significant level-2 covariates, but the random effect is significant indicating that significant variation between universities exists when it comes to the relationship between being Hispanic and graduating in six years. After accounting for the level-2 covariates listed for each fixed effect in Table 14, the following covariates showed significant variation across universities: being African American/ black, being Hispanic/ Latino, unknown race or Asian, being male, age, high school class rank, high school GPA, SAT composite score, majoring in a STEM program, average term credit hours, being enrolled during the recession, university GPA, taking any remedial course, passing a first year math course, living on-campus, need-based aid amount, merit-based aid amount, Pell grant amount, subsidized loan amount, unsubsidized loan amount, financial need, and unmet need.

The values in Table 14 help to answer the question: are there differences with respect to the relationship between the level-1 covariate and graduation at different values of the level-2 covariate? This responds to the part of the research question about how significant level-2 covariates might vary in their effects across universities. The values in table 14 give information about how the significant level-2 covariates interact with the level-1 covariates to change the slope across institutions. The interpretations of these interactions are not always straight forward. Both the strength of the relationship and the direction of the relationship between the level-1 covariate and graduation may be affected by changes in level-2 covariate values. Due to the nature of the research question being about generally whether or not values vary across institutions and for reasons that will be enumerated in the discussion and limitations sections, general results will be reported for Table 14 values.

For the demographic level-1 covariates, only unknown race or Asian, being male, and age had significant level-2 covariates included in the models of the level-1 slopes. As the coefficient for age (γ_{70}) was negative and the coefficient for residential in the age model was also negative (γ_{71}= -.11), for residential universities the relationship between age and graduation tended to become stronger and more negative than at non-residential universities. For being male the relationship was the opposite. The significant γ_{51} value indicates that there are differences with respect to the relationship between being male and the log-odds of graduating in six years at different values of residential. The positive coefficient of .14 indicates that the slope is higher for the being male covariate at a residential university than a non-residential university. For unknown race or Asian, selectivity was significant. Unknown race or Asian had a positive level-1 fixed effect and in modeling the slope the value for selectivity was negative (γ_{41}=-.002). Generally, for increasing values of selectivity, the relationship between unknown race or Asian and six-year graduation weakened, but at more extreme positive values the relationship changed direction and became negative and eventually strengthened.

All three high school or pre-college characteristics had significant level-2 covariates in their slope models. As selectivity increased the relationship between high school class rank and graduation tended to become stronger and more negative. For decreases in selectivity, the relationship stayed negative across the values that one would expect this variable to reasonably take but weakened the relationship between high school class rank and graduation. For increases in selectivity (γ_{91}=.002), the positive relationship between high school GPA and graduation appeared to strengthen. For residential universities (γ_{101}= 0.086), the relationship between SAT composite score and graduation was still negative but became weaker.

Several college academic and non-academic characteristics had significant level-2 covariates in their slope models. For majoring in a STEM program, as selectivity (γ_{111}=.005) increased, so did the strength of the positive relationship with graduation. The effect of residential (γ_{121}= -.35) on the relationship between average term credit hours and graduation was particularly important to pay attention to as being a residential institution changed the relationship from positive to negative. Increases in selectivity (γ_{131}=.005) across the expected range for selectivity were associated with a weakened but still negative relationship between being enrolled during the recession and graduation in six years. For residential (γ_{141}=1.23) universities, the already strong relationship between university GPA and graduation appeared to only increase. The negative relationship between living on-campus and graduating in six years tended to remain negative but weaken at residential (γ_{171}=.53) universities.

Selectivity was a significant and negative value for several of the financial aid amount variables including need-based aid amount (γ_{181}=-.0003), merit-based aid amount (γ_{191}=-.0006), Pell grant amount (γ_{201}=-.001), and subsidized loan amount (after controlling for residential status) (γ_{212} =-.002). As the level-1 fixed effects were all positive, these negative values for selectivity suggested that as selectivity increased, the slope for the financial aid amounts decreased. For subsidized loan amount, residential (γ_{211}=.13) was also significant indicating a strengthening of the relationship between subsidized loan amounts and graduation at residential universities. Over the typical range of values for selectivity (γ_{231}=.0004), the negative relationship between financial need amount and graduation tended to weaken.

CHAPTER V

DISCUSSION AND CONCLUSIONS

Discussion of Results in the Context of the Literature

The previous chapter discussed the results in terms of the units native to the logistic HGLM model, log-odds. In this section, the results of the study will be put in the context of the literature and converted to units that are typically more familiar and more intuitively understood, probabilities and odds ratios. Probabilities are computed based on the unit-specific coefficient values that appear in Tables 12 and 14. The level-1 fixed effects were largely consistent with past studies in terms of significance, but there are several notable exceptions to their directional agreement with past literature. Level-2 fixed effects had some similarities with past studies in terms of significance. However, likely due to power issues, discussed further in the limitations section, there were far fewer significant level-2 fixed effects in the intercept model than reported in previous literature. As the level-2 variables in the slope models were exploratory, also discussed further in the limitations, there is little literature to ground them in, but there are some interesting results for discussion and further research.

This study is largely consistent with past studies in terms of the variables at level-1 that have a significant relationship with the log-odds of graduating in six years, although there are some notable deviations in directional indicators. Holding all other values constant, when a white student has an expected graduation probability of 50%, students identifying as black would have an expected probability of graduation of 60%. This expected increase in the probability of graduating for African-American students was both large and contrary to previous research (Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003). The results for the variable being male were also contrary to previous findings that found females to have a higher probability of graduating (Schibik & Harrington, 2004; Astin & Oseguera, 2005; Porter & Swing, 2006; Kim, Roades, & Woodard, 2003). This study found males to have 29% higher odds of graduating than females after controlling for all other variables in the model. It is impossible to say for certain why inconsistencies with past research were observed in this study. It could be that the UNC System is different than past institutions or combinations of institutions studied. The different findings could also very well be attributed to the mix of variables included in this model when compared to previous literature. More robust and varied financial and financial aid variables were included in this study. However, this study included no survey data of student attitudinal or non-academic engagement characteristics, which were included in some other studies. The potential reasons behind findings contrary to past research are explored in more detail later in this chapter, but in general these differences are likely due to either the sample studied or the covariates included or excluded from the model.

Other student demographic characteristics included in this study were consistent with past research. In an attrition study by Scott, Baily, and Kienzl (2006) the percent of students not born in the United States was found to have a relationship with attrition at the institution level. That study found that increases in the percent of foreign-born students were associated with decreases in graduation rates. In this study, citizenship was included as a proxy variable at the student-level. Results indicated that after holding all other values constant, when a non-citizen would have a 50% probability of graduating, a US citizen would have a 57% probability of graduating. The results of age are also consistent with past studies that found that increases in age were associated with decreases in persistence (Singell & Stater, 2006). Each additional year of age brought a 5% decrease in the odds of graduating.

The directional indicators of high school and pre-college characteristics also deviated in some places from past research findings. In contrast with past research that found high school rank (Ishitani, 2006) and college admissions test scores (Oseguera & Rhee, 2009; Ryan, 2004; Schibik & Harrington, 2004; Scott, Baily, & Kienzl, 2006; Kim, Roades, & Woodard, 2003) had a positive relationship with persistence or graduation, this study found a negative relationship after controlling for all other variables in the model. The directional results for high school rank and SAT composite scores are counter-intuitive. One would expect better performance in high school and in admissions tests to be associated with increases in the probability of graduating from college and not decreases. Holding all other values constant, a unit increase in class rank after converting high school class rank back to its original metric ranging from 0 to 100 was associated with less than 1% lower odds of graduation. For SAT composite score, a 100-point increase was associated with 18% lower odds of graduating in six years, holding all other variables constant. It is possible that the unexpected negative coefficients for high school class rank and SAT score are a statistical artifact. A preliminary analysis removing high school GPA seems to suggest that this is a suppressor effect (see Appendix A for correlation matrix) and the results for the rank and SAT coefficients should be interpreted with great caution. The results for high school GPA were consistent with past research that found that as GPA increased, so did the probability of graduating or persisting in college (Oseguera & Rhee, 2009; Porter & Swing, 2006). With all other variables held constant, assuming a student with a 3.0 high school GPA had an expected six-year graduation probability of 50%, a student with a 4.0 GPA would have an expected probability of graduation of 61%. While high school GPA was consistent with past research findings, SAT composite scores and high school class rank had counter-intuitive results that disagreed with previous literature. Increases in rank and SAT scores were associated with decreases in the probability of graduation, which may be the result of a suppressor effect.

Many of the college characteristic variables had relationships with the likelihood of graduation that are consistent with past research. Majoring in a STEM program was used as a proxy for majoring in a field requiring higher level math. Herzog (2005) found a positive relationship between majoring in a field requiring higher level math and persistence to the second year of college. In the current study, majoring in a STEM program was associated with an increase in the probability of graduation, which is consistent with the findings of Herzog (2005). The STEM major designation in this study was made at the time of the student's last term of enrollment, so this study gives no information about students who may have declared a STEM major earlier in their career and then changed to a non-STEM major.

There is some evidence that the recession had an effect on college enrollment decisions (Long, 2015). However, the effect on the probability of graduating when a student's enrollment in college overlapped with the recession has not been well studied. The results of this study suggest a rather strong effect. Holding all other values constant, when someone whose enrollment did not overlap with the recession would have an expected 50% probability of graduating within six years, someone whose enrollment overlapped with the recession would have an expected probability of graduation of 12%. In terms of odds, this means those enrolled during the recession had 87% lower odds of graduating.

Credit hour accumulation and college GPA are often used, even descriptively, in practice to judge the potential of an individual student to graduate, which is supported in the literature as well as this study. The findings in this study for the average number of credit hours taken per term were consistent with past research that found that as credit hours increased so did persistence (Schibik & Harrington, 2004; Herzog, 2005). This study found that assuming if a student taking an average of 12 credit hours per term had an expected probability of graduating in six-years of 50% holding all other variables at their constant, a student taking an average of 15 credit hours per term would have an expected probability of graduating of 62% or 66% higher odds of graduating. These results for credit hours need to be interpreted in the context of the residential variable (discussed further in this chapter under the heading Level-2 Covariates in Slope Models). Consistent with past research, undergraduate GPA was associated with a positive expected change in the probability of graduation (Titus, 2004). The relationship between university GPA and the probability of graduation found in this study was profound. Holding all other variables constant, if a student with a 3.0 GPA had an expected 50% probability of graduating, then a student with a 4.0 GPA had an expected 91% probability of graduating.

The findings in this study related to course-taking patterns were also consistent with the literature. Other studies found that taking remedial coursework was associated with a decrease in the probability of graduation (Adelman, 2004; Herzog, 2005). This study found the odds of graduating in six years for those students taking one or more remedial courses to be 25% lower than students who took no remedial courses with all other variables held constant. For passing a first-year math course, the effect was the opposite. Assuming a student who did not pass a math course in their first year had an expected 50% probability of graduating, with all other variables held constant, a student who did pass a math course in their first year of enrollment would have a 54% probability of graduating in six years. This increase in the probability of graduation for passing a math course in the first year is consistent with the findings of an increase in the probability of persistence found by Herzog (2005).

The only college characteristic inconsistent with previous findings was living on-campus. Past studies found that living on-campus was associated with an increase in the probability of persistence or graduation (Braxton & Hirschy, 2004; Oseguera & Rhee, 2009; Titus, 2004; Herzog, 2005). However, the finding in this study was that students living on campus had 49% lower odds of graduation in six years with all other variables at their average, including the residential status of the college, compared to those not living on-campus. Outside of the results for living on-campus, the other college academic and non-academic characteristics of students were consistent with past research in terms of their significance and directional relationship with the probability of graduating.

Overall, the financial aid variables included in the model were consistent with previous findings in the literature with the exception of unmet need and unsubsidized loans. It is important to note, however, that the literature including financial aid variables generally lacks as comprehensive a dataset and approach to modeling as in this study. The results for the amount of need-based aid were consistent with previous studies that showed increases in the amount of need-based aid received were associated with expected increases in retention (Singell, 2004) and graduation (Singell & Stater, 2006). Holding all other values constant, assuming a student with $1,000 in need-based aid had an expected probability of graduation of 50%, a student with $2,000 in need-based aid would have an expected probability of graduating of 53%. For the amount of merit-based aid, the results were similar and consistent with past research (Singell, 2004; Singell & Stater, 2006; Chen & DesJardins, 2010), with the expected odds of graduating increased by 7% for every additional $1,000 in merit aid. The amount of Pell grant was not found to be significant after accounting for additional variables in the model, which is inconsistent with the findings of Chen and DesJardins (2008) and Chen and DesJardins (2010), who found receiving a Pell grant to be associated with a significant positive effect on the probability of persistence. Holding all other variables constant, a $1,000 increase in subsidized loan amount, was found to correspond to a 14% higher odds of graduating in six years. This finding is directionally consistent with the findings of Chen and DesJardins (2010). The results of this study found that increases in unsubsidized loan amounts corresponded to increases in the probability of six-year graduation. This is inconsistent with past literature that found decreases in the probability of persistence when students received unsubsidized loans (Herzog, 2005). Financial need had mixed associations in the literature with Singell and Stater (2006) finding a negative relationship with graduation and Titus (2005) a positive relationship. Holding all other variables constant, this study found that assuming a student who has a financial need of $4,000 had an expected graduation probability of 50%, a student with a financial need of $5,000 would have an expected probability of graduation of 48%, agreeing directionally with the results of Singell and Stater (2006).

The findings for the unmet need variable were inconsistent with Herzog (2005) that found that unmet need was associated with decreases in the probability of graduation. In this study, unmet need was found to be associated with a small increase in the probability of graduation with an odds ratio of 1.05. This result is not only inconsistent with findings in the literature, but it defies intuition. Unmet need provides an indication of how much money the student is still estimated to need to cover the cost of their education and living expenses after taking into account the financial aid that the student has been given. If the student needs more money than they have, one would expect their probability of graduation would increase and not decrease. Preliminary analyses indicate that a suppressor effect may be occurring for unmet need, which may be influenced by the other related variables in the model such as the various amount and types of aid a student is receiving and their financial need (see Appendix A for correlation matrix). Additionally, the way unmet need is defined in this study may be contributing to the inconsistent effect. Unmet need is typically defined federally as the student's total aid offered subtracted from the student's calculated financial need. Due to the fact that only aid actually used by the student and not the aid offered was available for this study, unmet need in this study was defined as the total aid received by the student subtracted from the student's financial need. It is possible that unmet need is therefore over-estimated for some students, which could contribute to these inconsistent findings.

For the intercept model at level-2, this study looked to predict the average log-odds of graduating in six years with a variety of university characteristics that were found in the literature to have a relationship with attrition. After eliminating non-significant variables, the residential and selectivity covariates were the only variables left with a significant relationship with the probability of six-year graduation. The results for selectivity were consistent with previous literature that found that as selectivity increased, so did the probability of graduation or persistence (Kim, 2007; Titus, 2004; Gansemer-Topf & Schuh, 2006; Oseguera & Rhee, 2009; Kim, Roades, & Woodard, 2003). The odd-ratio for selectivity in this study was 1.015, indicating that for a unit increase in the average 75th percentile SAT math and verbal score of the freshmen class, the odds of six-year graduation increase by a factor of 1.5%. Similarly, the results for the residential status of the college or university also agreed with previous literature that found, on average, higher probabilities of graduation for residential institutions when compared to non-residential institutions (Titus, 2004). Holding all other values constant, when a non-residential university would have an expected six-year graduation probability of 50% then a residential university would have an expected graduation probability of 57%.

Many of the results of this study were consistent with past research in terms of the directional relationship with six-year graduation and student and university characteristics. The significance and direction of the coefficients for student characteristics such as citizenship, age, high school GPA, university GPA, taking a remedial course, passing a math course in the first year, and the amount of various types of financial aid received were consistent with the literature. Additionally, the results for the significant level-2 covariates in the intercept model, residential and selectivity were consistent with the results of other studies. There were some deviations from past literature in the directional results of the student-level characteristics of high school rank, SAT scores, and unmet need that preliminary analyses suggest might be due to correlations with other variables included in the model and suppressor effects (see Appendix A for correlation matrix). Other deviations from past literature likely have more complex explanations that need further analysis and exploration, including the coefficient values for being African-American or black, being male, and living on-campus. Some of the results inconsistent with past literature may be explained in part by level-2 random effects and level-2 coefficients. With a paucity of multi-level higher education attrition studies including random effects in level-2 slope models and level-2 covariates in the slope models, it was difficult to put the resulting parameter estimates and interactions for those portions of this study in the context of the literature. The following sections in this chapter will explore some key results that deviated from prior studies, effects not well-covered in the literature but that could be important contributions to higher education attrition research, and the limitations that should be considered in interpreting all results of this study.

Contributions and Considerations for Higher Education Attrition Research and Policy

This study included several novel features as well as some interesting results that contribute to higher education attrition research and policy. Some of the main contributions to existing literature include a more robust dataset and overall model in terms of data quality and financial aid data, the inclusion of level-2 covariates in the slope models, and some intriguing results that may lend cause to be more critical of the results of some prior attrition models.

Level-2 Covariates in Slope Models

It is common in HLM literature to see level-2 covariates in the intercept model, but in higher education attrition research level-2 covariates in slope models are almost non-existent. As noted earlier in this chapter, Raudenbush & Bryk (2002) recommend that variables added into each level-2 slope equation be added for theory-driven reasons based on the literature. This recommendation is for the same reasons that all variables in a regression model should be theory-driven, to avoid reporting and acting on spurious relationships capitalizing on chance. However, an important question for higher education attrition research that is not well-addressed in the literature but is a research question in this study is how these significant level-2 covariates vary in their effects across institutions with respect to the level-1 covariates. Does the impact of need-based financial aid on graduation vary by the selectivity of the university? Does being part of a residential campus community make a more significant impact on the probability of graduating for African American students? These are important questions. One of the great benefits of HLM is the ability to address these types of questions, but they are not well-addressed at all in higher education attrition research. Additionally, leaving out important level-2 covariates in any level-2 equation can bias the other parameter estimates in the model. While the approach to level-2 slope model-building in this study is exploratory and could lead to the reporting of spurious relationships, it is also a contribution to the literature as it is not well-covered in other higher education attrition studies.

In the results of this study, there are several examples of interesting relationships between level-1 and level-2 covariates that would be important in interpreting and applying the results of attrition studies if they hold up to scrutiny. The interpretations that follow should be taken with caution due to the small, non-random level-2 sample and lack of theory base for the inclusion of these interactions. It is also important to mention here that by the Carnegie Classification used to define residential, only three universities were identified as residential, one of which is a very large university with high graduation rates. Therefore, this one university may be driving the results seen for the residential variable. Table 14 shows that γ_{121} is -.35, which describes the difference with respect to the average term credit hours and graduation at different values of the residential status of the university. Since this value is negative, it indicates a weaker relationship between credit hours and graduation for residential universities when compared to non-residential universities. In this case, the consideration of the effect of level-2 variables on the level-1 fixed effect for average term credit hours is particularly critical. The level-1 effect is .17 (see γ_{120} in Table 12), so considering the effect of the level-2 covariate residential (see γ_{121}=-.35 in Table 14), a residential university's credit hours effect would be predicted to be negative. Of course, this relationship would need to be further explored, but this result, if duplicated, would be cause for residential universities to pause and question the positive slope for the average credit hour variables. Maybe it makes sense for non-residential universities to invest more resources into programs and incentives for additional credit hour accumulation but not residential campuses. It could be that students at residential universities are more likely to take summer classes to stay on track to graduate or are generally more likely to persist and stay engaged through graduation, so the students do not see a benefit from additional credit hours taken in the fall and spring terms the same way that students at non-residential colleges do. In this context, this is all just speculation, but this example helps to illustrate the potential importance of institutional context for interpreting student effects.

Another interesting relationship with counterintuitive results involved the student characteristic of living on-campus and the residential status of the college. The literature generally finds that living on-campus is associated with an increase in persistence or graduation probability (Braxton & Hirschy, 2004; Oseguera & Rhee, 2009; Titus, 2004; Herzog, 2005). In this study, living on-campus at the student-level was associated with a decrease in the log-odds of graduation (γ_{170}= -.66), after controlling for all level-1 covariates with the level-2 covariate residential at its average. Being a residential university was associated with an overall increase in the log-odds of graduation in the level-2 intercept model (γ_{01}=.29). In modeling the slope for living on-campus, residential was found to be the only significant level-2 covariate (γ_{171}=.53), which indicates a weakling of the relationship between the living on-campus and the log-odds of graduation for residential campuses when compared to non-residential campuses. While the result for living on-campus and the interaction with the residential status of a university is interesting on its surface, it must be interpreted with extreme caution not only for the small level-2 sample size but for other reasons as well. Living on-campus in this study was defined as the mode across all enrolled terms. However, some students had more than one modal housing status, which included other options such as commuter and unknown. This could mean that the mode chosen was not necessarily representative of the student's experience. Additionally, the definitions used for living on-campus vary in the literature. As much attrition research studies the outcome of first-year retention, by nature these studies look at the student's housing during their first year in college. The definition of living on-campus is unclear in some studies, while others include living in a dormitory in the student's first term (Oseguera & Rhee, 2009), living on-campus during the freshmen year (Titus, 2004), and living in an on-campus dormitory at the time of the study but omitted for some parts of the study due to incomplete data (Herzog, 2005). Other researchers speak more generally about the benefits to persistence and graduation over the student's entire undergraduate career (Astin, 1975; Stage & Hossler, 2000). Additionally, this model included level-2 covariates and more financial aid characteristics at the student-level as well as an overall different mix of level-1 covariates, all of which could influence the coefficient estimates for the living on-campus parameter in this study. The definitional inconsistences with previous literature, level-2 sample size, and overall model variable differences suggest that the results for living on-campus and its relationship with residential should be interpreted with great caution. More work, which is outside the scope of this study, would need to be done to attempt to replicate and validate these results.

This study contributes to an important discussion about modeling the differing relationships between student characteristics and graduation probability across different institutions and types of institutions. In this study, differences in the relationship between the student characteristic and graduation were found to vary in some cases for residential and non-residential universities and across different levels of selectivity. This study found that on average for male students, living at a residential campus increases their graduation probability. As the selectivity of a university increases so does the probability of graduation for STEM majors. Having a higher university GPA is associated with higher graduation rates for residential universities. Need and merit-based aid appears slightly less important for graduation at more selective universities. The values in Table 14 give information about how the significant level-2 covariates interact with the level-1 covariates to change the slope across institutions. These results are not meant to suggest any action as they are exploratory, but they are meant to illustrate the type of information that could be gleaned from further research into the relationships between student-level and university-level covariates.

Important Results

The results of this study have given information that might cause some to question their assumptions about UNC System students and the characteristics related to graduation. Several results that were either contrary to previous literature or were particularly strong deserve additional discussion.

When controlling for other student characteristics, identifying as African-American is associated with an average increase across universities in the probability of graduating. This finding is contrary to the findings in other studies (Astin & Oseguera, 2005; Kim, Roades, & Woodard, 2003) as well as to what many in higher education think. There could be a variety of explanations for why identifying as African-American was found to have increase the probability of graduation. This study included more financial aid variables and more detailed financial information (e.g. the amounts of aid and need as opposed to a 0/ 1 indicator) than past attrition research. It could be that, after accounting for demographic characteristics, college performance, and financial need and aid received, there is no longer a negative relationship between the probability of graduating and identifying as African-American, but a positive one. In addition to the controlling variables in the model, this relationship could be explained by programming and other efforts across the UNC System directed at closing achievement gaps around race. These programs may have made an impact on the probability of graduation for African-American students. For example, the University of North Carolina at Greensboro has been featured in the Chronicle of Higher Education for closing achievement gaps in graduation rates and other outcomes for minority, first-generation, and low-income students (June, 2017). However, one would expect efforts to close achievement gaps for minority students to make race ultimately a non-significant predictor of the probability of graduating and not necessarily change the direction of the indicator. More research outside the scope of this study would need to be done to investigate and unpack this positive relationship between graduation and being African-American.

In this study, the results for being enrolled during the recession and university GPA had particularly large effects (see Table 12), which make them important to discuss and explore further. An indicator for being enrolled during the recession (1 if the student's six-year enrollment window overlapped with the recession but they did not graduate before its start, and 0 if the student's six-year enrollment window did not overlap with the recession or if the student graduated before the start of the recession) was added because there is some evidence that the recession had an effect on college enrollment decision (Long, 2015). The coefficient for being enrolled during the recession was -2.02 (γ_{130}) as reported in Table 12. In order to give an idea of the magnitude of this effect probabilities and odds ratios can be examined. When someone whose enrollment did not overlap with the recession would have an expected 50% probability of graduating within six years, someone whose enrollment overlapped with the recession would have an expected probability of graduation of 12%, holding all other values constant. In terms of odds, this means those enrolled during the recession had 87% lower odds of graduating. Most studies of student attrition look at the "traditional" first-time, first-year student who goes straight from high school to college. This study included all incoming students seeking a bachelor's degree regardless of their background. Therefore, this study included larger numbers of students with backgrounds whose enrollment decisions might have been influenced by the recession, such as older students, parents, and transfer students. These student groups would be more susceptible to enrolling in college during the recession due to the loss of a job or lack of employment opportunities and dropping out when work can be found (Long, 2015). The inclusion of these "non-traditional" students in this study might explain the large effect for the recession variable. Additionally, working students encountering job loss or lower wages during the recession may have been forced to drop-out or take fewer courses for economic reasons, lengthening their time to degree. Also, this variable might be picking up on something related to time more generally, which is discussed further in the limitations section. As enrollment during the recession has not been well studied in multi-level modeling of college student graduation and this study is limited to public universities in one state, more research and replication is needed before any generalizations can be drawn. However, this study suggests that significant economic events like a recession could have a large negative impact on a student's probability of graduating in six years.

Not surprisingly, a student's GPA at the university showed a very strong relationship with the probability of graduation. In this study, the coefficient for university GPA is 2.29 (γ_{140}), as reported in Table 12. If a student with a 3.0 GPA had an expected 50% probability of graduating, then a student with a 4.0 GPA would have an expected 91% probability of graduating, with all other variables held constant. The residential status of the university was found to have a significant effect on the relationship between GPA and the probability of graduation, so the value in Table 12 is interpreted when the residential status of the college is at its average. In Table 14, the positive value for residential (γ_{141}= 1.2) for the university GPA fixed effect shows that this relationship between GPA and graduation probability is only strengthened for residential universities. While the strong, positive relationship with GPA is not surprising, it does underscore the importance of universities investing in academic support for students as academic success is vital to graduation.

Robust Dataset

This study also contributes to the literature by using more robust data than previous studies. There were fewer missing data, less use of proxy variables, and more uniformly defined and collected data elements than in most previous attrition models. Much of the literature written about multilevel models cover many colleges and universities from various states within the United States. This sampling can increase the generalizability of the models but also limits the student-level variables that can be used, as there are limited uniform data available for large multi-state studies. For example, Oseguera and Rhee (2009) did not have access to college GPAs for their study, so they used high school performance variables as a proxy for college performance. Titus (2004) also notes limitations on the student-level data available. National datasets often suffer from substantial amounts of missing data. Titus (2004) and Oseguera and Rhee (2009) both note large, not random amounts of missing data as limitations to their studies.

This study only used data from public universities in one state. However, this focus increased the amount of independent, student-level variables available and decreased the amount of proxy variables needed. Because the UNC System office centrally defined and worked with each university at length to collect the data, the definitions of the variables in this study are likely more uniform across institutions than with national data collection efforts. The strength in this study is in its focus on limited institutions, which allows the data to be more robust and uniform. This study can be used as a guide for other states and university systems to then do their own in more in-depth analyses adjusting for the data that they have available to them.

Financial Aid Data

A second contribution of this study is the incorporation of more financial data. Limited financial information, particularly at the student-level, has been included in the previous research using multilevel models. While many single-level studies have found a variety of different financial factors to be influential in affecting student attrition (Singell, 2004; Singell & Stater, 2006; Chen & DesJardins, 2010; Herzon, 2005), attrition studies using HGLM have yet to incorporate many financial indicators. The absence of multilevel models with financial factors is likely due to many student-level financial aid variables not being available in the analyzed datasets. Financial aid has been found to play a key role in retention and completion in college by reducing net price to students and families (Scott-Clayton, 2015). Therefore, leaving this key factor out of a model of graduation probability could result in the misspecification of the model and thus biased parameter estimates. The UNC System has collected a robust and detailed set of financial aid data available on all of its students going back many years, which makes possible the inclusion of more detailed financial aid data in an HLM model than has previously been studied.

Limitations

Any study has its limitations. It is important to be frank about the limitations so that the reader can interpret the results appropriately taking into account what is missing or is otherwise imperfect. While this study attempted to avoid the limitations of other multilevel studies, such as extensive missing data and proxy variables, this study, like any other, has its own limitations. It is important to view the results of this study through the lens of the following limitations.

Missing Important Variables

Although this study used more robust information than other similar studies, there were still important variables missing at the student-level, including involvement and cognitive measures. When variables that have a significant effect on graduation are missing from a model, bias can result (Kim et. al., 2003). Engagement measures such as hours works (Titus, 2004, Porter & Swing, 2006) and using recreational facilities (Herzog, 2005) were found to have a significant relationship with graduation or persistence but were not included in this model. Cognitive and perception measures, often collected through surveys, such as commitment to earning a degree (Ishitani, 2006; Titus, 2004), desire to transfer (Oseguera & Rhee, 2009), and concern about finances (Oseguera & Rhee, 2009) were found to have a significant relationship with attrition but were not available to be included in this study.

Outside of cognitive and student engagement factors, there were several financial and financial aid-related variables not included in this study that were included in other attrition studies. Income was found in the literature to have a significant statistical relationship with attrition (Ishitani, 2006; Oseguera & Rhee, 2009; Rhee, 2008) but was excluded from this study. There was an adjusted gross income (AGI) measure for students and parents available in the dataset that could have served as a proxy for income. The AGI variable had significant missing data that was more prevalent for some universities than others, making the data clearly not missing at random. Additionally, other variables included in the model, such as financial need and Pell grant amount, capture much of the variation of the AGI variable, so the risk of excluding AGI was somewhat mitigated. The remaining financial aid variable not included in this model but found to be significant in attrition literature is offered aid. An important distinction in financial aid is between aid that is offered and aid that is used by the student/dispersed. Students do not necessarily use all of the financial aid or work study opportunities offered to them. In this context, “received” aid refers to any offer that is accepted and presumably used. There is an intuitive sense that if a student is offered aid such as a subsidized loan but does not accept it then that student is better off than a student who is in need of a loan but is not offered one. Herzog (2005) is one of a very few that looked at the effects of aid that a student is offered, but does not necessarily use. Herzog (2005) found a positive relationship between offered loans, scholarships and grants, and work-study and persistence; as offers of financial aid increased, persistence decreased. Other researchers found negative effects on persistence of actually receiving some types of aid, such as work-study (Singell, 2004) and unsubsidized loans (Herzog, 2005). While there is little research that exists around the distinction between offered aid and received aid, the research that does exists suggests that these distinctions are useful in giving a more complete picture of financial aid and its relationship with attrition. This study only includes aid dispersed to students and does not have information about aid offered but not actually used, which is a limitation.

Exploratory Features

Another limitation of this study is the exploratory nature by which the level-2 slope models were built. Ideally, all data elements added into each level-2 equation would be added for theory-driven reasons based on the literature (Raudenbush & Bryk, 2002). If variables are not chosen based on evidence and theory and added into a model anyway, spurious relationships that cannot be verified or replicated may be reported as truth. However, higher education attrition research is severely lacking in the testing and exploration of how level-2 covariates affect and differ across level-2 units in their relationship to level-1 covariates. For this study, following the establishment of the intercept model, the level-2 covariates were added to the level-2 slope models and then removed one by one when found to be non-significant. Raudenbush and Bryk (2002) refer to this approach to building the level-2 slope portion of the model as exploratory.

The exploratory nature of the level-2 covariates included in the slope models is a limitation of this study.

Sample Size and Generalizability

The type (public, four-year), location (North Carolina), and number (16) of universities included in the study is limited, which restricts the generalizability of this study. The generalizability is limited in several ways, including the applicability of the outcomes of the model to other states and types of institutions. While the diversity of the institutions in some ways compensates for this, limitations to generalizability certainly still exist. The small number of level-2 units is a limitation for many of the same reasons that small samples sizes are limiting in single-level regression. The small number of degrees of freedom limits the number of parameters that can be estimated and could lead to instability in estimates. Several studies have examined the effect of a small numbers of level-2 observations on the estimated model parameters and standard errors. Multi-level models with small numbers of clusters have the potential of producing estimates of standard errors that are too small, underestimated, and thus an inflated Type I error rate (McNeish & Stapleton, 2016). Several studies have found that while small level-2 samples size does lead to bias in standard errors, the estimated coefficients and variance components remain relatively accurate and unbiased (Maas & Hox, 2005). One of the major limitations of this study was the limited number of units at level-2 (n=16). The small level-2 sample size made estimation of the more complex and more ideal models impossible and the interpretation of more complex models dubious.

When noting the complexity in sample size recommendations for hierarchical models as compared to single-level regression analyses, Raudenbush and Bryk (2002) recommend 10 observations for each mutually independent level-2 β, which would apply separately to each level-2 equation. Due to likely correlations with outcomes and within and between predictors, the authors caution that greater than 10 observations per coefficient is likely necessary. Therefore, the 16 level-1 observations and nine level-2 coefficients is incompatible with this standard. However, omitting significant level-2 predictors could bias estimated related level-2 coefficients and level-1 coefficients, if they are not group-mean centered. As the level-1 predictors are group-mean centered, reducing the intra-class correlation, then applying the 10 observation rule, the number of level-1 predictors that is reasonable is driven by the number of level-1 observations (Raudenbush and Bryk, 2002), which at 460,909 level-1 observations in this study makes the 24 level-1 βs very reasonable given the sample size. Additionally, the smallest number of students per level-2 unit is over 2,000, which is well over the sample size recommended for stable and reliable results. While the level-1 sample size is large and the number of level-1 units per level-2 unit is also large, the small number of level-2 units remains a limitation and will affect the significance of the level-2 coefficients and will likely bias the standard errors and potentially other level-2 parameters as well.

In addition to sample size, another limitation that affects generalizability is the method of selection of the level-2 units. Typically, in an HLM model, level-2 units are randomly selected in order to allow generalizations to be made to a larger group. In this study, level-2 units are clearly not randomly selected as they are all public universities from one state. This certainly limits the generalizability of the results across other universities and states. However, there are more benefits to using HLM than just generalizing to other level-2 units. Even if one were interested in modeling within just the UNC System, HLM allows for examining effects separately at level-1 and level-2. Using HLM just within the UNC System also allows for the assumption of independence to stay intact. While there are benefits to using HLM in examining the outcome of graduation in the UNC System, the generalizability and power of this study is still certainly limited by the method of selection of level-2 units and small level-2 sample size.

Timespan of Covariates

A major limitation of this study was that the model did not take into account the longitudinal nature of the data. Chen and DesJardins (2010) note two main issues in not using a longitudinal or event history methodology in this type of analysis. The first issue is that "some students may not experience the event," which in this case is dropping out of a university. This issue was mitigated in this study by looking at six-year completion rates and only including in the dataset students who began as a degree-seeking student at the university at least six years or more ago. The second issue that they note that is applicable here is that student characteristics and even institutional characteristics can and do change over time. Many of the characteristics examined remained relatively stable over time (e.g. race/ ethnicity, gender). As discussed previously, for all demographic variables that are not likely to change over time, data from the most recent term of enrollment where the data is non-missing were used. For data that are expected to vary over time, measures of central tendency were used in order to account for, in some way, all data over time and not just a single term or point in time.

Another limitation is the mix of multiple year and single year data. It is important to note that a single value for institutional characteristics was used, which has the potential to lead to a misalignment between the institution characteristics reported and the institution characteristics that actually existed at the time of an individual student's enrollment. However, as with the student data, a measure of central tendency was used for each data element and the data were thoroughly examined for extreme changes over time and none were found. Other major HGLM studies of student attrition also did not include time as a level in the model and had to make similar decisions about how to summarize or otherwise include variables that exist at multiple time points into a single observation (Titus, 2004; Oseguera & Rhee, 2009).

Future Directions

The preceding discussion of the results, contributions, and limitations of this study lead to several next steps and future opportunities to move higher education attrition research forward.

Opportunities for More Robust Data

There are several ways that the UNC System can improve on the missing important variables limitation explained in the previous section. Looking into the future at potential possibilities for the inclusion of a more complete set of variables to model attrition in the UNC System, there is good news. Advances in data warehousing and processes have already been made that enable the collection of additional information, since the cohorts of students included in this study have entered. The launch of the Student Data Mart in 2016 (Sorrells, 2019) has enabled the collection of offered versus dispersed financial aid information and more robust income information. The UNC System Student Data Mart contains a more robust set of variables than those available in the past. The more robust data from the Student Data Mart could be included in persistence modeling now and graduation studies in the future as the time-span of data available continues to grow.

There are several approaches to collecting student engagement and attitudinal data that have been found in the literature to have a significant relationship with attrition. A variety of organizations offer survey instruments that have already been field tested and have evidence of validity and reliability that collect data about student engagement, behaviors, and attitudes. Some examples include the Cooperative Institutional Research Program's (CIRP) Freshmen Survey out of the Higher Education Research Institute, used by Oseguera and Rhee (2009); the Beginning College Survey of Student Engagement (BCSSE) and National Survey of Student Engagement (NSSE) out of the Center for Postsecondary Research at Indiana University Bloomington; and the NASPA Assessment and Knowledge Consortium studies, among others. Some UNC System institutions already participate in these surveys. Existing data could be analyzed as a low-cost pilot for discerning whether System-wide investment in survey administration might be warranted. Additionally, technologies are emerging that track student use of various university resources. Student engagement in Learning Management Systems (LMS) like Canvas and Blackboard can be tracked to identify patterns in behavior such as decreases in course attendance, if online, or lack of use of resources provided (Geant, 2019). Technologies tracking the use of libraries, gyms, and other campus facilities through card swipes or fob detectors can be sources of engagement and behavioral data as well. In addition to survey data, there are several other sources of data such as LMS and card swipe systems that can be mined for additional information about student engagement, perceptions, and behaviors that may impact graduation probability.

In addition to missing important variables, the limitations section also discussed the impact of the small level-2 sample size in this study. The small number of universities (16) limits the generalizability of the results of this study as well as the power to fully examine the university characteristics that may be important contributors to explaining why students graduate. Currently, a trade-off exists in higher education attrition research between using national datasets or local data, individual university or state higher education system data. Data that is more localized has smaller level-2 (college) sample sizes but typically contains more variables with more consistent definitions and often less missing data. National datasets and accompanying studies typically have more limited data elements, reporting and definitional consistency issues, and often more missing data but larger sample sizes.

Fortunately, there are changes and industry trends that will enable more multi-state, multi-institutional studies so that researchers hopefully will not have to choose between sample size or data quality in the future. Higher education has been increasing investment in data warehousing and reporting systems (Lang & Pirani, 2015). These investments have coincided and, even been enabled by, federal investments in Statewide Longitudinal Data Systems (SLDS). The SLDS grant program provides funding to states to create longitudinal data systems across the education pipeline from early childhood through postsecondary and then into the workforce and sometimes other state agencies as well. Since 2002, the SLDS grant program has made awards in all 50 US states totaling over $700 million (National Center for Education Statistics, 2018). The SLDS grant program has provided support and resources for another important trend enabling intra- and inter-state multi-institutional studies, common data standards. It is great for individual states to have robust multi-institutional data systems, but if the data elements do not align with other states, then the small sample size and generalizability concerns for attrition studies persist. It is the ability to share and use unit-record data from multiple, robust, state systems that helps to make alleviate power and generalizability issues. Common Education Data Standards (CEDS) is a national project that works to form common data formatting standards and data element definitions to “streamline the exchange, comparison, and understanding of data” (National Center for Education Statistics, 2014). CEDS provides national standards for data that works within states as they set up SLDSs, but the same standards would apply across states as well. There are a variety of legal barriers that currently exist in multi-state data sharing, but the foundation of data systems and common data standards will enable robust attrition studies in the future. Increasing investments in higher education data and reporting systems, Statewide Longitudinal Data Systems, CEDs and other common data standards, could enable multi-state models using more robust unit-record, administrative data to create models with greater power and generalizability.

A Model for Other States

This study can serve as a model for how other states and higher education systems can approach using their own administrative data for comprehensive, multi-institutional studies. There are many data analyst and researcher roles in state and federal government that are being asked to look at attrition in higher education across multiple colleges and universities. The people in these positions vary in terms of their statistical and methodological education and training. However, one commonality is that these analysts are receiving increasing requests and pressure to use more statistical modeling in their jobs. Gartner and many other consulting firms and analytics organizations tout diagnostic and predictive modeling as steps along the "analytics maturity" journey that all organizations should follow (Puget, 2015; Wakefield, 2016). Managers and administrators are answering this call by demanding such modeling from their organizations and staff. Administrators and even data analysis staff often lack the background to know what a methodologically sound and justifiable approach to this type of modeling should look like. While there is no substitute for education and experience in statistical and research methodology, a guide created from the basic steps in this study and expanded to contain solutions to common data and analysis problems encountered in using higher education data could certainly help. A guide promoting an evidence-based approach to selecting variables and statistically appropriate modeling methodologies would hopefully lead to more informed, data-driven, and methodologically sound decision-making.

Areas for Further Research

Several results in this study lend themselves to further research with the potential to contribute to the literature and understanding of higher education attrition. The positive, relatively large effect for African-American/ black students is important to examine. Future studies could look to replicate the variables included in this study and see if the results are the same. Because this study includes more financial and financial aid variables than past attrition studies, it is particularly important to explore further the impact of controlling for these financial factors on the parameter estimates for being African-American. The large, negative coefficient for being enrolled during the recession brings up important questions about the impact of financial crises on attrition. Future studies where the student enrollments overlap with the recession could include a similar variable to see if the outcome confirms or conflicts with the results this study. Additionally, time could be accounted for in future studies either by an additional level or student-level covariate derived from enrollment year. Studying the impact of the temporal enrollment of the student on graduation probability could give information about whether the large result for the being enrolled during the recession variable was an artifact of an impact of time in general or was attributable to the financial crisis. Additionally, the interaction between age and being enrolled during the recession could be examined as there is evidence that older students might be more likely to base higher education enrollment decisions on external financial situations. In general, replicating the model used in this study with robust administrative data from other state university systems would help to give information on possible spurious relationships and the veracity of the results.

Turning Exploratory Features in Theory-Driven Results

Earlier in this chapter, the contributions section discussed the importance of looking at the interactions between student and university characteristics, but the limitations section explained how this examination is exploratory and results need to be interpreted with great caution. The only way to turn exploratory into confirmatory and theory-based is to iteratively and continually explore what has not been done and replicate past research findings in different contexts. The multilevel modeling literature in higher education could benefit greatly from researchers including and responding to research questions about the interactions between level-2 and level-1 covariates. If individual colleges or even states are going to make decisions based on the results of studies done on other higher education institutions, which is common in higher education policy, they should do so at the very least with the knowledge that “results may vary.” Even better, more informed and more accurate decisions can be made if the research that policy-makers are looking at includes information about how effects vary across institutional characteristics. Additionally, knowing that specific college and university characteristics are taken into account when making decisions based on studies about other institutions will likely help to build the confidence of faculty and staff affected by those decisions.

A lot of important groundwork has been laid in the literature separately for the student-level and university-level covariates that have a significant relationship with graduation. Now it is time to build that same foundation for how university characteristics and student characteristics interact to change the relationship between student characteristics and graduation at different types of colleges and universities. Forming a better understanding of the relationship between college and student characteristics will help multi-institutional studies have results that are more applicable and actionable to individual institutions because results can be interpreted through their specific institutional characteristics.

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APPENDIX A

LEVEL-1 (STUDENT-LEVEL) COVARIATE CORRELATION MATRICES

High School or Pre-College Characteristic Correlations

	HSR	HSG	SAT
HSR	1.00	0.83	0.51
HSG	0.83	1.00	0.65
SAT	0.51	0.65	1.00

College Academic and Other Characteristic Correlations

	STEM	CH	ER	UG	R	FYM	LC
STEM	1.00	0.05	0.00	0.03	-0.06	0.15	0.00
CH	0.05	1.00	-0.07	0.09	0.05	0.29	0.32
ER	0.00	-0.07	1.00	-0.16	0.00	0.03	0.08
UG	0.03	0.09	-0.16	1.00	-0.13	-0.01	-0.05
R	-0.06	0.05	0.00	-0.13	1.00	0.02	0.04
FYM	0.15	0.29	0.03	-0.01	0.02	1.00	0.16
LC	0.00	0.32	0.08	-0.05	0.04	0.16	1.00

Financial Aid Characteristic Correlations

	NEED	MERIT	PELL	SL	UL	FN	UN
NEED	1.00	0.05	0.80	0.76	0.22	0.82	0.23
MERIT	0.05	1.00	-0.02	0.18	0.51	0.16	-0.08
PELL	0.80	-0.02	1.00	0.55	0.11	0.73	0.32
SL	0.76	0.18	0.55	1.00	0.38	0.66	0.18
UL	0.22	0.51	0.11	0.38	1.00	0.17	-0.04
FN	0.82	0.16	0.73	0.66	0.17	1.00	0.60
UN	0.23	-0.08	0.32	0.18	-0.04	0.60	1.00