THE ENROLLMENT PATTERNS OF HIGHER EDUCATION: 
DO SOCIAL BACKGROUNDS REALLY MATTER?

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ABSTRACT

The first purpose of this study was to identify different attendance patterns and trajectories from the college-going young adult period onwards as a whole while still maintaining and emphasizing the individualized nature of the trajectory itself. Although social backgrounds affect comparatively different college experiences, few if any studies exist that explore how social background relates differently within the college-going population. Thus the study’s second purpose was to explore how social background affects different higher education enrollment trajectories. The study used the National Longitudinal Survey of Youth 1997 (NLSY97) to test the research questions. The outcome variable was credits earned, which reflected the cumulative percentage of credits earned toward a BA degree by a respondent in a given year. The outcome variable was rearranged by both age and high school graduation year. This study applied growth mixture modeling (GMM) to explore the variability in the data concerning credits earned. In this way, discrete growth trajectories (classes) were identified, and predictors of membership in those classes were gauged. As a result of GMM analysis, the findings indicate that a quadratic 4-class model based on the high school graduation timing variable, which included traditional and non-traditional trajectories of credits earned, best explained variations in enrollment patterns in higher education in the present sample. This study also investigated whether the credits-earned trajectories within higher education could be differentiated in terms of academic, social, cultural, or economic background factors. The results support the contention that historically disadvantaged students are likely to follow nontraditional college enrollment patterns compared to their advantaged counterparts. Therefore, while existing research has focused on the significant influence of academic, social,
cultural, and economic background, this study provides evidence that students follow notably different credits-earned patterns once they have entered the higher education system.
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CHAPTER 1

Introduction

Statement of the Problem

Today, the enrollment patterns of college students are complicated. As a variety of studies have shown, a modal sequence of college enrollment patterns exists but the proportions following the traditional pathway have decreased over the latter part of the past century (Shanahan 2000). For example, a nontraditional pattern of college enrollment has emerged regarding college entry timing. Studies examining recent trends in college enrollment have noted a significant growth in the population of students who choose to delay their entrance into higher education. In academic year 1995-96, approximately 30% of high school graduates delayed enrollment (Horn, Cataldi, & Sikora, 2005), but in 1999-2000 this proportion grew to 46% (Barton, 2002). As Choy (2002) has shown, from the 1970s, when only 28% of college students were above the age of 25, the population of such students increased to 39% in 1999. Another report found a similar increase in the population of older students attending university for the first time: in 1967, they represented only 13.7% of the student body, but in 2006, this number increased to 29.6%.

Meanwhile, the proportion of students who interrupt their college education has been increasing. Marini (1987), for instance, found that this trend has its roots in the 1950s when a significant population of the student body would frequently change their enrollment status. Drawing on the 1972 National Longitudinal Study (NLS), Rindfuss, Swicegood, and Rosenfield (1987) demonstrated such transitions in enrollment status can lead to detrimental consequences: Only one out of three students who interrupted their education returned to college to complete
their degree. Pallas (2003), after reviewing a body of recent scholarship, found that the trends in such changing patterns partly stemmed from the intersection between differences in college attendance patterns and the conditions of adulthood like the formation of a family, the obtainment of gainful employment, etc.

As a result of interrupting college enrollment, growing numbers of students are prolonging their enrollment beyond eight semesters (Niu & Tienda, 2013). This partly follows a trend that began in the 1970s when fewer and fewer students started graduating in the typical four-year span (Adelman, 2004; Barton, 2002). Only half of the higher education student body received their degree in four years, while three quarters received it in six, but these numbers dropped to 39% and 59% respectively in the 1970s. In other words, for students who remain enrolled, the length of time to obtain a bachelor’s degree has increased significantly (Bound, Lovenheim, & Turner, 2007; Wang & Wickersham, 2014).

Consequently, these changes have led to a diversification in enrollment patterns of college students in the United States. Each individual who pursues a bachelor’s degree maintains a unique attendance pattern of higher education that incorporates a series of decision-making processes affecting the continuation, delay, leaving, transferring, or returning of schooling until graduation as well as the curricular pathways of participation. Some students begin college immediately upon high school graduation and then complete a BA within 4 or 6 years after entering college which is the traditional pathway. Others, however, experience different life events (e.g., entering the workforce or getting married) and return to college later on to complete the degree. As such, the identification of such diverse enrollment patterns
would allow researchers to understand better the nature of current cohorts compared with the more traditional pathway.

Therefore, it is crucial to understand how a college-going individual develops a unique attendance pattern trajectory during young adult years. Surprisingly, few, if any, studies exist that identify higher education trajectories. For instance, most studies so far have tended to examine separately dimensions of higher education enrollment patterns, such as college choice process (e.g., Hossler et al., 1989; Hossler & Stage, 1992; Kortesoja, 2009), delay entry timing (e.g., Goldrick-Rab & Han, 2011; Niu & Tienda, 2013; Wells, & Lynch, 2012), retention and persistence (e.g., Braxton 2000; Braxton et al., 2004; Seidman 2005; Tinto 1993), or student engagement (e.g., Campbell & Cabrera, 2014; Kub, 2009; Kuh, Cauce, Shoup, Kinzie, & Gonyea, 2008). While these educational outcomes have great implications for understanding an individual's educational trajectory, it is often not easy to view the enrollment pattern as whole through separate concepts.

Nevertheless, currently little empirical evidence exists to aid in identifying these types of different attendance patterns during the transition to young adulthood in higher education. Therefore, in this study, I will focus on college-going populations to identify and compare different attendance trajectories as heterogeneous characteristics within the group. Attendance patterns in higher education could be qualitatively distinct from within college-going population. Goldrick-Rab (2006), for example, grouped college students using four distinct labels drawn from the variations in attendance patterns. Fifty-two percent of students fell into the first group that followed the “traditional pattern,” which refers to students who did not attend multiple schools and who did not interrupt their studies. The “interruption” group, which includes
individuals who remained at a single institution but halted or paused their study at some point, accounted for 2% of the sample. The researchers labeled the third group as the “fluid movement” group. Made up of 37% of the study’s sample (1,726 students), this group consisted of individuals who moved between various colleges or universities but who also undertook their studies consistently and without pause. Those individuals who attended multiple institutions and who did not maintain a steady pattern of attendance comprised the final group (9% of the population, or 409 students), the “interrupted movement” group.

While Goldrick-Rab’s study valuably adds to our understanding of the differences between these groups, it nevertheless contains several significant limitations. First, the study did not consider the population who had not or did not complete their BA degree. In other words, by leaving out the non-completion population, their categories did not comprehensively cover the student body (which, as numerous studies have shown, is made up of significant number of students who do not complete their degree) and did not address the important implications in the educational patterns of that population. In addition, these four categories were labeled descriptively rather than analytically, meaning that their predetermined nature could not capture the intricate characteristics of within category differences even though a sub category still maintained crucial differences within that category. For example, researchers can differentiate the interruption attendance pattern by the length of the absence from school. If a researcher, however, predetermines the interruption pattern by considering all subjects within the same group, they would not be able to measure the within difference of the interruption population. On the other hand, if we do not posit several categories, then we can test an analytical model to aid us in identifying and understanding the reality of the situation.
In this study, therefore, I will focus on the person-centered latent modeling to take into account the characteristics of different attendance patterns within the college-going population. Person-centered latent model approaches do not predetermine within group differences based on descriptive (observed) characteristics, but determine within group difference based on latent characteristics that allow researchers to assess unobservable differences within the group.

In other words, methodologically, I am interested in the heterogeneous characteristics of within group (college-going population) differences through a person-centered analysis approach. According to Denson and Ing (2014), although person-centered approaches are used frequently in related fields (e.g., K-12 education, educational psychology, or sociology), such methodologies have only been applied recently in field of higher education (e.g., Pastor et al., 2007; Weerts et al., 2013). Researchers applying person-centered approaches understand the mechanism through which predictors act on outcome variables to be different for the each individual of the population. Such approaches are best employed when a researcher intends to investigate the unique aspects of individuals within a larger body (I will discuss details comparing the two approaches in Chapter 3). In contrast, many researchers in the field of higher education so far have focused mainly on variable-centered approaches (e.g., regression, logistic regression, or multi-level modeling) to determine whether different college experiences (persistence vs. none-persistence group, or early entry group vs. delay entry group) can differ by specific variables (e.g., socio-economic level difference, first-generation vs. continuing generation, gender difference). With variable-centered studies like these, researchers see the same relationships between variables for the entire population; such a methodology is best used when exploring differences between outcome variables and their predictors. In other words,
variable-centered approaches (such as regression analysis and factor analysis) identify associations among variables (e.g., graduation rate association with college entry timing, or socio-economic status association with persistence). On the other hand, person-centered approaches, as used in this study, identify sub-groups differences (e.g., early college entry and early completion group, early college entry and late completion group, or late entry timing and late completion group) within a group (college-going population) of individuals who share common attributes (Laursen & Hoff, 2006).

The enrollment pattern differences among the American college-going population signify the growing need to consider how heterogeneous patterns are affected by student academic, social, cultural, and economic backgrounds, such as students of color, first-generation students, low-income students, or other historically underrepresented groups (Hurtado & Carter, 1997; Rendon et al., 2000). It is time, as Braxton (2000) reminded us almost 15 years ago, to find new ways of exploring the mechanisms that play into the heterogeneity of attendance patterns. Although a variety of concept as outcome variables (e.g., retention and persistence, or degree completion) inspired numerous studies examining predictor factors associated with baccalaureate completion and time-to-degree (e.g., Astin & Oseguera, 2004; Ishitani, 2006; Pascarella & Terenzini, 2005), research along this line still has barely touched upon the potential impact of predictor factors on different higher education attendance patterns as an outcome variable. Many studies reveal that human, social, cultural, and economic capital are important theoretical frames in testing the effects of academic, social, cultural, and economic backgrounds as predictor factors not on direct heterogeneous pattern of enrollment but on the general higher education experience. Thus, in this study I will use these several theoretical capital framework in order to
discuss academic, social, cultural, and economic factors for predicting heterogeneous enrollment patterns.

First, human capital theory posits that students participate in higher education to obtain a knowledge base that will translate directly into economic benefits (Becker, 1993; Schultz, 1971). In this theory, more education leads to more money. Perna (2000) has argued that human capital theory relates to the decision-making process when students elect whether or not to enter into higher education. In this study, I consider academic factor (i.e., academic preparation and achievement, and multiple attendance patterns) through the lens of human capital theory.

Individuals equipped with the training of higher education, which emphasizes group collaboration and networking (two forms of social capital), are better able to reproduce and attain advantaged statuses. Oppositely, disadvantaged students would reproduce disadvantaged status attainment if unable to participate in higher education or if they were limited in their college engagement due to social background. Thus, as previously mentioned, social backgrounds can affect differently college enrollment trajectories even among BA populations. Therefore, in this study I consider social factor (i.e., secondary educational environments, and ethnic/racial minorities) as a series of crucial covariate variables.

Within this educational context, parents try to maintain their social status by reinforcing the value and importance of a college education as cultural capital for their offspring (McDonough, 1997), and in doing so they reproduce status attainment. In other words, greater cultural capital leads to greater advantages and increased resources in both the social and educational landscapes, while lesser cultural capital leads to an inverse situation. Thus, students with high levels of cultural capital enter higher education with a distinct advantage
compared to those students with lower levels. For the purposes of this study I consider cultural factor (i.e., parental educational attainment and parental higher education expectation) as a set of covariate variables.

Lastly, Massey, Charles, Lundy, and Fischer (2003) point out that economic factor encompasses a person’s entire economic resources—their family’s income, assets, and combined savings—and that increased economic capital directly correlates with increased privilege and vice versa. Thus, this study will consider economic factor (i.e., socioeconomic status, SES) as covariate variables. Also, in Chapter II, I will discuss and outline each theoretical framework.

**Purpose of the Study and Research Questions**

The first purpose of this study is to identify different attendance patterns and trajectories from the college-going young adult period onwards as a whole while still maintaining and emphasizing the individualized nature of the trajectory itself. Although social backgrounds effect comparatively different college experiences, few, if any, studies exist that explore how it relates differently within the college-going population. The study’s second purpose, thus, is to explore how a social background affects these different higher education enrollment trajectories.

This study explores two research questions:

**Research Question 1**

How many latent class trajectories can be identified to capture the heterogeneity of experiences regarding attendance patterns of higher education over a 10-year age range?

**Research Question 2**

What factors (i.e., academic, social, cultural, and economic) are associated with the trajectories for attendance patterns?
Significance of the Study

First of all, this study presents an opportunity to broaden sociological perspectives concerning the role of human, social, cultural, and economic factors in constructing and reproducing forms of higher education trajectories in terms of social mobility. Identifying attendance differences in higher education will help generate systematic support structures. Furthermore, this study provides a deeper understanding of how social backgrounds directly affect the college enrollment patterns. Without recognizing the heterogeneous nature of higher education experiences, students struggling with adjustment issues may continue to suffer from a multitude of problems while also grappling with considerable negative effects stemming their social backgrounds. A lack of support can prevent proactive social mobility and negatively affects students’ trajectory adjustment. Ultimately, a deepened awareness of the effects of disadvantaged backgrounds on higher education enrollment trajectories would better prepare society to improve the higher education process, reduce negative effects from embedded characteristics, and assist students in adjusting to their chance for upward mobility. If disadvantaged social backgrounds continue to influence negatively higher education achievement, socioeconomic disparity in the United States will continue to grow, thus preventing the proactive social mobility offered by a college education.

Second, this will allow both faculty and student affairs professionals to understand better factors related to college students’ diverse enrollment trajectories when designing environments and practices in support of higher education success. This study’s comparison between those students who come to college after ten years with unobservable sub-groups beneficially answers how such data allows not only for disadvantaged social backgrounds but also for counterpart
comparisons. Nevertheless, detecting suggests that college students with disadvantaged statuses may experience unique trajectories, and, as such, it has important implications for faculty, student affair professionals, and other student support personnel. With the population of socially disadvantaged students continuing to escalate in the coming years, college faculty, including both administration officials and student affairs employees, must identify at-risk students and ease their transition into the college world through various campus agencies. This study, therefore, is significant for practitioners in understanding the basic characteristics of attendance pattern differences in higher education. Consequently, such evidence can facilitate student success both academically and socially while also ensuring the retention of under-privileged populations.

Finally, this study is also significant in that it examined a nationwide representative sample. Conducting research of this nature on broader, more diverse samples allows for wider generalizations of the findings and also provides a more in-depth investigation of specific student needs across different social statuses. In this study, for example, larger sample sizes provide the framework to examine specific types of social disadvantage, which can lead to further understanding about the specific needs associated with a variety of predictors. In particular, based on theoretical background, it is clear that students with a disadvantaged social status differ from their counterpart students in levels both earned credits as well as several trajectories reflecting longitudinal perspectives. As a result, I hypothesize that providing more structured opportunities to build support would be a viable and beneficial action.
CHAPTER 2
Literature Review

Higher Education Experiences

Several concepts illustrate the experience of higher education. The first occurs when students initially arrive at universities (entry timing); the second relates to the maintenance of enrollment (retention and persistence, or multi-institutional attendance patterns and discontinuity enrollment); and the third and final one is when students are able to graduate. In this chapter, I describe the different attendance patterns students face in relation to these concepts.

College Entry Timing

Now that individuals are expected to obtain a college degree, the question of whether to attend college has shifted to where and when (Goldrick-Rab & Han, 2011). A number of researchers have recently devoted significant attention to college entry timing (e.g., Goldrick-Rab & Han, 2011; Niu & Tienda, 2013; Wells & Lynch, 2012), and found that taking a "gap year" between high school and college is a relatively common phenomenon. Horn, Cataldi, and Sikora (2005) found that among students who enrolled in higher education for the first time in 1995-1996, nearly a third waited one or more years after graduating from high school before attending college (Horn, Cataldi, & Sikora, 2005). As Goldrick-Rab and Han (2011) have noted, recent enrollment patterns indicate that more students choose to delay their college enrollment. In fact, the percentage of students over 25 taking part in higher education increased from 28% in 1970 to 39% in 1999 (Choy, 2002). Part of this increase likely stems from the growth in part-time post baccalaureate enrollment, but this does not fully account for the
increasing number of high school students choosing to delay their higher education (Goldbrick-Rab & Han, 2011).

The college choice process theory helps explain the sequential pathway of students’ precollege steps. Researchers have suggested that the college choice process encompasses when students gain proper academic skills, graduate from high school, and send out their applications to various universities (Hossler, Braxton, & Coopersmith, 1989). Furthermore, Hossler, Schmit, and Vesper (1999) have pointed out that the decision making process associated with college enrollment consists of three phases: the first is the initial desire to attend a higher education institute; the second is the search for appropriate universities; and the third is graduation from high school. As Niu and Tienda (2013) have pointed out, the student’s initial experience with the predisposition stage remains slightly murky. One explanation for this early lack of definition is the students’ negotiation between goals, tastes, values, and expectations (Kao & Tienda, 1998; DesJardins, Dundar, & Hendel, 1999; Messersmith & Schulenberg, 2008). Another possible explanation for delaying enrollment relates to economic, personal, or institutional causes. During the next stage, the search for an ideal academic institution, students weigh their goals in relation to their chances for acceptance (Fuller, Manski, & Wise, 1982). The process concludes with the submission of students’ application (Niu & Tienda, 2013).

Many studies have suggested that delaying entrance into higher education negatively impacts students’ degree completion, and that the timing of college entrance from high school greatly affects the likelihood of a student obtaining their diploma (Adelman, 2004; Bozick & DeLuca, 2005). The National Education Longitudinal Study (NELS) has shown that only 9% of students who delayed their entrance time completed their bachelor’s degree in a timely
manner (8 years); students who immediately begin their higher education have a 55% degree completion rate. Based on their findings, Bozick and Deluca (2005) have noted that students who postpone immediate college enrollment are 64% less likely to earn their degree compared to those who make the immediate transition (p.543). For every month that a student delays their admission, their chances of degree completion decreases by 6.5%. Ultimately, students’ delay in beginning their higher education not only increases their time to completion, but also decreases their chance in actually obtaining their degree.

However, little evidence exists to demonstrate how length of postponement affects students’ likelihood in enrolling at baccalaureate-granting institution. Researchers originally assumed a linear relationship between entry timing delays and degree completion (Bozick & DeLuca, 2005), but current literature has suggested otherwise. The assumption of linearity stems from existing studies’ different measures of assessment for the delay behavior and the different criteria used to define postponement (Niu & Tienda, 2013). For example, Eckland and Henderson (1981) categorized both students who entered college in the same year of high school graduation and those delayed enrollment by one semester as on time enrollees. Hearn (1992), on the other hand, defined on time enrollment as any student who commences higher education within one year of high school graduation. Yet, Bozick and DeLuca (2005) designated students as on time when they begin their college education within 7 months of high school graduation.

Niu and Tienda (2013) claimed that delaying college enrollment timing and college attendance are not linearly associated and posited that a qualitative difference exists between students who delay enrollment by a semester and those who delay enrollment by a year or more. When students only withhold enrollment for a semester, they are still able to take classes with
members of their graduating high school year. Students who choose to delay their higher education by two or more years can face significantly different challenges than those who only waited one (Niu & Tienda, 2013). College entry timing is consequently a complicated matter. Put simply, students who postpone the college entry timing are more likely to experience life events that will prevent them from enrolling in a four-year college such as marriage or childbirth, and thus lowering the likelihood of degree completion. However, as Niu and Tienda (2013) have pointed out, there may be an important and overtly immeasurable difference in students who delay their college entrance. While some students must delay higher education enrollment, the evidence clearly indicates that these decisions could greatly lower students’ chances of completing their degree. In the following subsection, I will describe some of the reasons student delays are necessary. College entry timings have become highly and individually diversified, yet little research discuss the heterogeneous trend of entrance timing. Therefore, in this study I consider entry timing as a type of heterogeneous trajectory and not a descriptive concept.

Retention and Persistence

Enrollment issues in higher education can be measured against various criteria, although student retention and persistence have been the most invaluable criterion for higher education institutions (Hagedorn, 2005). While some understandings about retention and persistence can seem similar to one another, they actually denote very different things. According to Hagedorn (2005) and Reason (2009), the differences between retention and persistence can be explained as follows: although these two terms are often mistaken and used interchangeably, retention represents an organizational phenomenon whereas persistence is an individual one. Higher
education institutes “retain” students and the institutional retention rates represent the percentage of students who are “retained.” In contrast, individual students “persist” toward a personally-defined goal, which may include graduating from college.

The topic of student retention has received attention from higher education researchers. Summerskill (1962), for example, reviewed studies on retention in the 1960s and found that institutional retention rates ranged widely from 18 - 88%. In his study, Summerskill also pointed out that an accurate comparison of the reported rates can only be possible by establishing a standard formula to calculate retention rates (Hagedorn, 2005). Although a standard formula for measuring retention is currently unavailable (Hagedorn, 2005), the U.S. government has announced a federal definition of “graduation rate,” which is “the percentage of full-time, first-time, degree-seeking enrolled students who graduate after 150 percent of the normal time for completion, defined as six years for four-year colleges (eight semesters or twelve quarters, excluding summer terms) and three years for two-year colleges (four semesters or six quarters, excluding summer terms).” This was done as part of the Student Right-to-Know and Campus Security Act (November 8, 1990), which required colleges to reveal their graduation rates so that prospective applicants could make more informed choices during their college application process.

Research on college student retention rates has been actively carried out for over 70 years (Braxton, 2000). Although researchers have approached the question of why students discontinue their higher education studies from various perspectives, the most comprehensive theory to explain this phenomenon is Tinto’s Interactionalist Theory (1975). This theory is grounded on student persistence rather than institutional retention. According to Tinto (1975),
it is essential that academic and social integration lead toward an environment that plays a main role in determining students' successful college completion. Many studies have sought to empirically test Tinto's paradigmatic theory and as a result, they have deepened our understanding of student dropout. However, federal and state governments have recently required all colleges and universities to report their retention rates (Hagedorn, 2005), although this continues to pose certain challenges (Hagedorn & Castro 1999). This reporting ultimately pressures universities to maintain a good record of student attendance because their reputations and funding levels depend on these retention rates as an indicator of positive academic outcomes for students (Tichenor & Cosgrove, 1991).

Furthermore, Tinto's interactionalist approach has been criticized by many studies for its lack of focus on other factors such as specific qualities of a university or its application to a broad range of races or ethnicities (Hurtado & Carter, 1997). More recent studies on student persistence have followed upon Tinto's initial premises, for example, as a function of external exigencies (Weidman, 1989; Bean, 1990), college involvement (Astin, 1993), organizational characteristics (Berger & Milem, 2000), and college choice (Paulsen & St. John, 2002). According to Reason (2009), however, consistently academic and social integration approaches were crucial components for understanding persistence.

**Multi-institutional Attendance Pattern and Discontinuity Enrollment**

While retention and persistence have been useful in identifying factors that allow students to attend or stay on track with their higher education programs, these two concepts tend to limit researchers’ ability to address concerns of student mobility patterns (Goldrick-Rab, 2006). The current study, therefore, also focused on multi-institutional attendance and discontinuous
enrollment, as these patterns constitute students' movement in, out, and among higher education institutions. For example, while students on the traditional track tend to only move in an upward direction (i.e., from two-year institutions to four-year institutions), there has been an increased number of different mobility patterns.

In particular, the percentage of students taking the standard path to receiving a bachelor’s degree has decreased over the years; today this population only constitutes a fourth of the larger student body (Choy, 2002). Since the 1990s, higher education students have been far more likely to attend between one and three universities; this is a dramatic increase considering in the 1970s, the same number hovered between one and two (Adelman, 1999; Adelman, Daniel, & Berkovits, 2003). Currently, approximately half of all undergraduates at four-year universities enroll at another institution over a six-year timeframe; between 15 and 19 percent ultimately enroll at more than two institutions over the span of their college years (McCormick, 2003). Furthermore, between a fourth to almost a third of all college students will interrupt their studies before returning to the institution to complete their degree (Carroll, 1989; Berkner, He, & Cataldi, 2002). Even though the most prevalent attendance type across multiple universities is students’ movement from two-year to four-year institutions, this movement is often only temporary. We can see this trend, for example, in the 1982 graduating high school class in McCormick’s (2003) study. More specifically, only 40% of students who enrolled at more than one university remained at the second university; the majority (60%) returned to their original higher education institution (McCormick, 2003). Indeed, researchers have found a number of distinct educational tracks within the population attending multiple institutions (Adelman, 2004; Goldrick-Rab, 2006; McCormick, 2003).
These new forms of higher education attendance patterns raise questions on student persistence. This study will consider multi-institutional attendance patterns as a predictor for students’ higher education pathway. Most of the current literature considers this factor to be an influence rather than an outcome variable; I will be discussing the role of multi-institutional attendance as a predictor in the following section. Additionally, discontinuity patterns can capture growth mixture modeling and are applied within the current study (see Chapter III).

This study addressed that concern by examining the intersection of several dimensions of student movement occurring within contemporary college pathways; this includes college entry timing, retention and persistence, multi-institutional attendance, and discontinuous enrollment by measuring earned credits. I have chosen to assess these dimensions through the number of completed credits to ensure the data does not become overly broad. Otherwise, a great deal of heterogeneity exists that merits attention in both the composition and outcomes of students who receive earning credits for a BA degree. Thus, in order to examine the different pathways among students attempting a bachelor’s degree, this study's sample was limited to credit earning students. Furthermore, student attendance patterns can be assessed at various levels, with the smallest unit of analysis being course completion (Hagedorn, 2005). The number of credits earned per term most directly influences students' overall collegial success. Important factors affecting how much value students put in their academic performance in college can also be indicated by their earning credits of each semester or academic year.

However, not many institutions and researchers systematically consider students’ dynamic of earning credits or how earned credits change throughout the semesters. This dynamic and change can have a detrimental effect on degree completion rates; they may even
eventually influence retention and persistence. In this study, I will thus focus on the trajectory of credits earned as the main outcome variable to evaluate maintained college enrollment with entry timing and time to degree completion as whole. With the above information, I can model the whole process of the higher education experience.

Based on previous literature on entry timing, retention, persistence, and diversified enrollment patterns, I hypothesize that (Hypothesis 1) students in tertiary education institutes between ages 18 and 27 undertake various heterogeneous credit earning patterns per year. For instance, the traditional pathway sub-group consists of students who start earning credits on time at age 18 and complete their BA degree within 4 to 6 years. There is also another sub-group is made up of students who delay their college entrance until they are approximately 21 but complete their degree within the normal 4- to 6-year duration. Yet another sub-group is comprised of students who begin college at age 18 but delay the completion of their degree for over 6 years (on time and discontinuous enrollment pathway). Those students who delay their entry time but complete their degree within the regular timeframe are a part of the sub-group that moves along the delayed timing and continuous enrollment pathway. The final sub-group is the incomplete population, which can be further divided into two sub-groups: the first consists of students aged 18 or 19 years who do not complete their degree by age 27, and the second is made up of students who delay entry timing and never finish by age 27.

Covariates for Higher Education Enrollment Patterns

While researchers have been given increasing attention to the lack of linearity and stability in educational pathways, relatively little information is available on the target populations and why they pursue a certain pathway (Rindfuss, Swicegood, & Rosenfeld, 1987;
Higher education researchers consistently report that risk factors (low academic preparation, ethnic/racial minority status, or low-income and first generation status) negatively affect high school completion, college matriculation, and higher education outcomes. In this chapter, I explain these complicated predictors and explore reasons why students experience different higher education enrollment patterns through their academic, social, cultural, and economic backgrounds. Ultimately, these perspectives can guide research on college access, choice, retention, and persistence.

**Academic Factor**

Following Becker (1993) and Schultz (1971), the current study is grounded in the human capital theory, which posits that students participate in education/training to obtain a knowledge base that will directly translate into economic benefits. Human capital therefore represents the exchange of knowledge for monetary profit and more education leads to more money. As Perna (2000) points out, students deciding whether to enter higher education must base their choices on the flow of human capital and whether pursuing higher education will provide them with a greater advancement opportunities than directly entering the workforce (e.g., Lundy-Wagner, 2014; Veenstra, Orr, Ohland, & Long 2014). Typically, the decision to enter into higher education matches the increase in human capital. According to Baum and Ma (2007), in the year of 2005, employees with only a high school diploma earned 62% less than those with a college education; this gap expanded a projected 61% across a worker’s lifetime.

As Lundy-Wagner, Veenstra, Orr, Ohland, and Long (2014) point out, the human capital theory not only recognizes monetary import but also accounts for factors in students' decision making process. For example, students tend to predict their acceptance chances by comparing
their higher education expectations and their actual academic preparation. In this context, Rowan-Kenyon (2007) has suggested that academic preparation and achievement is also a type of human capital. This study follows this line of research; I will treat academic preparation and achievement as important predictors for higher education enrollment patterns.

Substantial evidence suggests that high school academic preparation and achievement directly affect students’ entry timing and enrollment in higher education. For example, Eckland and Henderson (1981) analyzed the NLS 72 and discovered that students who delay college entrance were often from lower income families, frequently had inferior educational preparation, and were more likely to attend two-year institutions than their on-time counterparts. Using a logistic approach, Hearn (1992) analyzed the High School and Beyond dataset to compare a 1980 high school graduating class’ on-time enrollees with those who put off higher education for one to two years after graduating high school. The results showed that students who delayed college entry tend to be less prepared than those who enrolled immediately upon graduation. Furthermore, there is evidence that academically well-prepared students are less likely to delay college entrance. According to Kirst and Venezia (2004), students who took more science courses were less likely to delay their entrance into higher education. The researchers also reported that many U.S. states are currently increasing math and science course requirements. Rowan-Kenyon (2007) analyzed a 1992 high school graduating class and concluded that approximately 10% of entrance delays stemmed from differences in students’ academic preparation and achievement. In terms of enrollment, empirical evidence suggests that academic under-preparedness negatively influences retention and persistence (Reason, 2009) and therefore represents a crucial predictor for students’ academic trajectories. In fact, ACT (2007)
reported that students’ level of academic preparation for college through a rigorous high school curriculum (Adelman, 2006) is one of the strongest predictors of university persistence and degree attainment.

Meanwhile, multi-institutional attendance is an umbrella category and consists of different patterns like co-enrollment, supplemental enrollment, or swirling (Wang & Wickersham, 2014). Thus, specific attendance patterns may result in different academic outcomes. In this study, I will focus on the co-enrollment pattern as academic factor predictors. The co-enrollment pattern refers to simultaneously enrolling at more than one institution. The forms of multi-institution patterns may accelerate students’ degree completion as well as increase the availability or scheduling of courses (Goldrick-Rab, 2009; McCormick, 2003).

Empirical evidence supports the notion that the multiple institution attendance pattern, co-enrollment, positively influences students’ college outcomes. McCormick (2003) has demonstrated that students who co-enrolled have higher persistence rates. Wang (2012) also pointed out that co-enrolled students tend to report better GPAs than their counterparts. Other recent studies consistently concluded that co-enrollment significantly and positively impacts higher education outcomes, specifically students’ persistence and rate of BA completion (e.g., Wang, 2012; Wang & McCready, 2013; Wang & Wickersham, 2014).

Therefore, I hypothesize that (Hypothesis 2) students with a lower academic factor (i.e., academically underprepared students) are more likely to be in the delayed entrance sub-group, discontinuous sub-group, or a non-completer group. This is because these students put off their education or fail to acquire the necessary graduation credits by age 27. Conversely, students with a higher level of academic factor (i.e., academically well-prepared students or multi-
institution enrolled students) tend to pursue the traditional pathway; be in a sub-group that begins earning credits on time at age 18 and completes their BA degree within 4 or 6 years.

**Social Factor**

As Lin (2001) has pointed out, social capital represents the interpersonal relationships individuals develop to facilitate networking and career advancement. According to Bourdieu (1986), social capital increases when individuals engage with their peers and generate a stable body of individuals to which they can turn to for knowledge or advantage. Bourdieu also theorized that an individual’s social capital level directly correlates with both their network size as well as their current monetary and social position. Like Bourdieu, Colleman's (1988) understanding of social capital is centered on an individual’s interpersonal network. Colleman, however, devoted more attention to familial, religious, educational, and communal structures; he also examined how individuals draw resources from these structures. Furthermore, he emphasized both the inter- and extra-familial social capital flows, arguing that its production and distribution emerges from the connections between agents. Furthermore, Colleman (1988) deems the informational potential inherent in social relationships as one of the most important forms of social capital. Information provides individuals with an agential foundation, but is often prove elusive to attain. Individuals gain information when they are attentive, but usually this is a difficult task. One can gather knowledge through social networks that ultimately represent a type of capital that can lead to action.

As previously mentioned, Colleman (1988) emphasized the role of social networking, which often represents an important and potent type of social capital. If attending a better high school and frequently participating in a social network creates an improved atmosphere for
college attendance and promotes students' desire to attend higher education institutes, then students themselves will expect to enroll in higher education. In contrast, a school that fails to create this environment or cannot provide adequate information about college attendance often prevents disadvantaged students from attending college. Lower socioeconomic status (SES) background students may therefore be exposed to social networks or information channels that significantly constrain their higher education experiences.

In particular, Coleman (1988) has defined social support as another type of social capital. For example, higher-SES students often attend well-resourced high schools (Orfield & Lee, 2005) and receive adequate college counseling (McDonough, 2005). These privileged high schools also offer a better educational environment through factors such as good teacher-student relationships or an improved learning atmosphere. As result, students in these schools easily begin their college education after graduation. The benefits obtained from interacting with networks in superior high schools can allow students to more easily pursue higher education. Thus, I consider secondary education environments, specifically teacher-student relationships, peer atmosphere, and learning environment as forms of social factor measurements.

I will also consider historically underrepresented groups (e.g., ethnic/racial minority populations) as a negative predictor of social factor. As a relatively small percentage of the underrepresented groups attend college, I assume that this partly stems from a lack of social network in campus environments. Many studies have examined ethnic/racial minorities and their underrepresented status for higher education attainment; the literature subsequently calls for an increase in their populations, specifically African American, Hispanic, and Native American
students. The U.S. Census Bureau (2012) found that underrepresented racial/ethnic groups composed 25% of the population, but the U.S. Department of Education (2012) discovered that this group only made up 15% of the student population at 4-year institutions. For African American students, researchers consistently reported that they were less likely to be adequately prepared for college entrance and tend to originate from lower SES backgrounds (Flowers, 2002; Flowers & Pascarella, 1999; Outcalt & Skewes-Cox, 2002). Furthermore, studies frequently found that African American students attending historically white institutions are more likely to experience alienation. This therefore results in decreased interaction with peers on campus (Feagin, Vera, & Imani, 1996; Pascarella & Terenzini, 2005; Patton, Bridges, & Flowers, 2011; Rankin & Reason, 2005).

Hypothesis 3: Students with a higher social factor (i.e., better secondary education environment) are more likely to be in the traditional pathway sub-group. In contrast, students with a lower social factor (i.e., ethnic/racial minority populations) are more likely to delay entry timing, engage in a discontinuous enrollment pattern, or never complete their degree.

Cultural Factor

Bourdieu and Passeron (1977) define cultural capital as the transmission of norms and values down generational lines. As McDonough (1997) points out, although all social strata possess this “symbolic good,” only the middle and upper classes possess its most valued forms; this thus allows them to exclude others without the same types of access (Bourdieu, 1986). In the context of higher education, cultural capital can affect students' choice of college, their enrollment timing, as well as their retention and persistence, and cultures (Paulsen & St.John, 2002). Using the cultural capital perspective, Wells and Lynch (2012) employed the concept of
habitus to describe the higher education experience. According to Bourdieu (1977), habitus refers to the social power that unconsciously affects individuals; it inures them to their social classes and provides various forms of cultural capital to promote achievement in their fields. Based on the norms or beliefs derived from their family background, students may plan to enroll immediately or delay, persist or drop out, get a job or get a bachelor degree. When college-graduated parents expect their children to obtain pursue higher education, their children are more likely to assume obtaining a degree to be the norm (McDonough, 1997). The opposite may be true for students whose parents did not attend higher education institutes, who are not employed somewhere that offers proper informational support in regards to higher education, or whose culture does not recognize university attendance as a norm. Thus, parents’ educational attainment likely determines familial values and norms concerning college attendance. In particular, Bourdieu and Passeron (1977) have argued that while all students have some form of cultural capital, capital from families with better cultural background plays a greater role and more effectively encourages students to pursue higher education. For example, students with parents who have a four-year degree, sufficient knowledge of the application process, and have greater college expectations are more likely to enroll at a four-year institution. Thus, this study measures cultural factor using parents’ higher education expectation and educational attainment.

Numerous studies have examined how parent educational level affects their offspring’s college entry timing and have found that decreased parental education levels negatively impact students' academic trajectories (e.g., Cabrera & La Nasa, 2001; Goldrick-Rab & Han, 2011; Perna, 2000; Rowan-Kenyon, 2007; Wells & Lynch, 2012). Much of this literature has focused on the first-generation students, which refers to students who have parents without a BA degree
(Thayer, 2000). Even when first-generation students enroll in college, they were twice as likely as their peers to attend public two-year institutions instead of four-year colleges and universities (Choy, 2001).

According to Gupton, Castelo-Rodriguez, Martinez, and Quintanar (2009), the transition to college life can be a cultural shock to first-generation students. During the college entrance process, these students often feel experience an uncomfortable and incomplete negotiation between two or more educational, familial, and socioeconomic cultures (Thayer, 2000). The culture shock especially affects first-generation students because of the difficulty in bridging their home culture with the unfamiliar institutional one (Hsiao, 1992). For example, first-generation students are more likely to be new to a welcoming campus environment (Pascarella, Edison, Hagedorn, Nora & Terenzini, 1996). Researchers also discovered that these students view the college environment as materially and culturally foreign because their family, friends, and colleagues are unable to provide them with any first-hand accounts or descriptions (Saufley, Cowan, & Blake, 1983). Ishitani (2006) analyzed the NELS:88, the NELS:1988-2000, and the Postsecondary Education Transcript Study (hereafter, PETS:2000) and concluded that during their first to fourth year of study, first-generation students are 1.3 times more likely to terminate their studies as compared to students with BA-certified parents. For first-generation students, the highest risk of dropping out occurs during the second year, where they were 8.5 times more likely to drop out than their counterparts. Furthermore, first-generation students were 51% less likely to graduate in the fourth year and 32% less likely in the fifth year than their counterparts.

Hypothesis 4: Students with a higher cultural factor (parental higher education expectation and educational attainment) are more likely to be a part of the traditional pathway
Furthermore, students with a lower level of cultural factor are more likely to be in the one of the sub-groups with delayed entry timing, discontinuous enrollment, or a failure to complete the degree by age 27.

Economic Factor

Massey, Charles, Lundy, and Fischer (2011) have argued that economic capital encompasses a person’s entire economic resources and that increased economic capital directly correlates with increased privilege and vice versa. Thus, this study will consider SES as an economic factor predictor for higher education trajectories. First, lower SES background students may have difficulty academically and socially preparing for higher education. Because their surrounding family members, peers, and mentors usually lack college experience, these students do not have the adequate social support (Phinney & Hass, 2003). Tierney and Auerbach (2004) have pointed out that students’ families play a crucial role as their support network during college preparations. Parents with college or graduate degrees are more equipped to provide their children with information about college or career preparation (Brewer & Landers, 2005). Lower SES background students, however, tend to have no knowledge or skills to seek out proper educational resources and advice (Oliverez & Tierney, 2005). As a result, these students must look for other forms of support to face the challenges of gathering information on colleges and acquiring financial resources. During this difficult process, students may decide to postpone their educational pursuits (McDonough, 1997; Hagedorn & Fogel, 2002) and lower their college aspirations. According to Fitzgerald (2004), lower SES students face many financial difficulties because of student loans and their families’ inability to pay the tuition; this often causes the students to use the cost-benefit analysis.
A recurring theme throughout the delayed entry literature is that the majority of lower SES students choose to delay their studies, while students with high SES backgrounds are more likely to enroll immediately following high school graduation (Bozick & DeLuca, 2005; Goldrick-Rab & Han, 2011; Hearn, 1992; Horn, Cataldi, & Sikora, 2005; Rowan-Kenyon, 2007). Bozick and DeLuca (2005) have reported that students from the lowest SES quartile generally delay entry for approximately 13 months whereas student from higher quartiles only delay about 4 months. Cabrera and La Nasa (2001) and Fitzgerald (2004) have argued that the risks these students face on the path to college are quite prevalent throughout the entire entry process. As such, it is common for lower SES students to not complete high school, receive their diploma, expect a bachelor’s degree, meet college admission requirements, receive family support, and understand the college application or financial aid processes.

As previously discussed, many observable and unobservable barriers to college access exist for low-income, first-generation students; these challenges continue to affect their higher education experience even after entering college. Successful adjustment from high school to college and students’ subsequent persistence can be especially difficult for lower income students (Gupton, Castelo-Rodriguez, Martinez, & Quintanar, 2009). Academic competencies are best facilitated through interactions with university professionals and students on campus. Lower income students, however, tend to work extensively (Corrigan, 2003) or have family pressures that prohibit them from concentrating solely on their academic responsibilities. This therefore means these students spend less time studying or participating in on- and off-campus activities (Walpole, 2003). The lack of social support can hinder these students’ personal development, which can result in further decreases in their academic performance and social
interactions. According to Tinto (1987), lower income students may feel isolated and disconnected from their peers at the institution. Some of these students ultimately choose to transfer to other institutions or drop out completely. In addition, the financial burdens lower SES students face typically continue to influence many different aspects of their college experience.

Regarding enrollment issues, Pascarella and Terenzini (2005) have shown that after controlling for other variables (gender, race, and ethnicity), a lower SES backgrounds are significantly related to students’ collegial persistence. In particular, Walpole's (2003) study illustrated that lower SES students were more likely to have lower educational attainment levels compared to higher SES peers nine years after enrolling. In another report, ACT (2004) found that students' SES was the second most powerful variable associated with college retention. As a result, as students from lower SES backgrounds have a greater chance of interrupting higher education enrollment and ultimate risk of the acquisition of a degree (Bozick & DeLuca, 2005; Rowan-Kenyon, 2007).

_Hypothesis 5: Students from higher income are more likely to be in the traditional pathway, while students with a lower income are more likely to be in sub-groups with delayed entry timing, discontinuous enrollment, or non-completion._

The concepts of academic, social, cultural, and economic backgrounds are overlapped in many ways (see the previous section for a description of lower SES issues under the social capital approach). For instance, low-income and first-generation students overlap in terms of their access, engagement, and persistence in college (Gupton, Castelo-Rodriguez, Martinez, & Quintanar, 2009). Researchers have found that first-generation students typically come from
lower-income families (Bui, 2002; Terenzini et al., 1996). In fact, two-thirds of low-income students are also first-generation students (Corrigan, 2003). McSwain and Davis (2007) found that the higher education experiences of low SES students are parallel to those of first-generation college students. Furthermore, both groups lack equitable access to higher education in contradistinction to their peers. Data from NELS revealed that college enrollment among high school seniors was only 65% for students with parents who had not attended college; this number rose to 87% for students whose parents had obtained higher education degrees (Choy, 2001).

I will address these concepts separately to explain their effect on students’ social background for the following reasons: First, these concepts concentrate on the term “capital,” which is relatively value-neutral and does not emphasize a specific side of an individual’s social background such as lower or higher SES. In other words, explanations of human, social, cultural, and economic capital are beneficial not only in their value neutrality but also in their ability to illustrate a more complete picture of students’ social backgrounds. Second, different social backgrounds uniquely contribute to the students’ heterogeneous credit-earning patterns. However, as these concepts are highly correlated, comprehensive theories (e.g., social reproduction theory) often cannot fully reveal the nuances of the interrelationship between them. As previously mentioned, SES and first-generation students’ experiences greatly overlap, but these two variables have dramatically different impacts on students’ credit-earning trajectories.
CHAPTER 3
Data and Methods
Sample and Procedures

In 1997, the Bureau of Labor Statistics (BLS), a division of the U.S. Department of Labor, conducted a set of surveys called the National Longitudinal Survey of Youth 1997 (NLSY97) to represent the youth population at that time. The survey used a multiple cohorts design including birth years ranging from 1980 to 1984. The total sample of the NLS97 contained 8,984 individuals. As its name indicates, the NLSY97 longitudinally surveyed the population each year from 1997 (i.e., Round 1) to 2011 (i.e., Round 15).

As this study focused on a college-going population, I selected cases from the NLSY97 by eliminating those individuals who had not earned at least one college credit by 2011. In this way, 5,522 individuals were eliminated, leaving 3,462 for this study. According to the Digest of Education Statistics by the National Center for Education Statistics (NCES 2012), approximately 60% of the population had attended at least one form of higher education. The present data, however, show that only 38.53% of these respondents reported earning at least 1% of the total necessary credits. There are several possible reasons for this finding. First, the NLSY97 dataset measured bachelor’s and associate’s degrees separately, measuring the associate’s degree using a variable titled CV_ASSOC_CREDITS in same way it measured the bachelor’s degree variable, CV_BA_CREDITS. In other word, the present study did not reflect the trajectories of students who began at a two-year college rather than a four-year degree granting institution, although many students begin their postsecondary studies at 2-year institutions. This study, thus, included individuals who are attended at least a BA grant
institution through CV_BA_CREDITS. For example, if someone started at community colleague but eventually transferred to a 4-year institution, then he/she can be deemed in the CV_BA_CREDITS variable after transferred. In the NLSY97, 833 respondents reported that they had obtained at least an associate’s degree. If the NLSY97 had included respondents who did not complete their associate’s degree, then the total population with an associate’s degree may have been larger. A second possible explanation lies in the fact that the credits earned variable was self-reported. Thus, certain respondents may have not reported any higher education experiences.

I then rearranged the data in my sample of 3,462 NLSY97 respondents by age. Recall that the original dataset included respondents born from 1980 to 1984, but examined variables across the period of 1997 to 2011. As a result of this arrangement, respondents born in 1980 had results for four more variables than those born in 1984, respondents born in 1981 had three more variables than those born in 1984, and so forth. To balance the data, I eliminated the extra variables for each age group. Consequently, I had the same number of time points for each group.

**Outcome Variables**

**Age Based Outcome Variable: Credits Earned between Ages 18 and 27**

In the NLSY97, the variable of credits earned, titled CV_BA_CREDITS, reflected the cumulative percentage of credits earned toward a BA degree by a respondent in a given year. This variable was rated on a percentage scale, with the value of 100 indicating 100% completion of the credits required for a BA degree. Of particular interest for present purposes, CV_BA_CREDITS was coded to record the credits earned by a respondent in a specific institution, as well as to provide information in terms of his/her multi-institution enrollment.
However, the way in which the variable was originally coded was not suitable to delineate the overall individual trajectory of credits earned across multiple years. Thus, the present study created a new outcome variable that captured the representative credits earned for each year, which reflected not only institution specific patterns but also the trajectory across every institution in which a respondent was enrolled. The original coding method is reviewed below in terms of its usefulness and shortcomings, and the steps in creating the new outcome variable are set out in greater detail.

First, in terms of an institution specific perspective, for example, if institution A requires 120 credits to obtain a BA, then 30 credits count for 25% of degree completion. In contrast, 30 credits might count for 20% at institution B, if 150 credits are required for a BA degree. The CV_BA_CREDITS variable measured a variety of patterns in credits earned. For example, an individual enrolled at one university for four consecutive years could accumulate credits until reaching 100% of these, the point of completion for a BA degree. Table 3.1 displays an example of an enrollment patterns for a specific institution.
As is clear from Table 3.1, an individual on track to complete a BA degree could follow any one of a range of different patterns. The case of a traditional college completer (matriculating on time after four to six consecutive years of enrollment) is indicated as having earned 20% of the necessary credits by age 18 or 19 (the average age at college entrance), accumulating a further 20% during each growth period (typically one year) until reaching 100% with BA degree completion in the fourth to sixth year. In the case of individuals who did not complete their BA degree, the percentage of credits earned stagnated as of a particular year. For example, if an individual stopped earning credits at 40% and did not graduate for some
reason, his/her credits earned trajectory was indicated as 20% at age 18, 30% at age 19, and 40% at ages 20 to 27. Furthermore, if an individual was discontinuously enrolled over one or more academic years, the credits earned variable was coded as being the same throughout that period. For instance, if an individual did not enroll at a school between the ages 19 and 22 due to a full-time job, the pattern of his/her credits earned trajectory may have been 20% at age 18, 35% from ages 19 to 22, 50% at age 23, and so forth.

Second, in terms of multiple institution enrollment, the CV_BA_CREDITS variable also reflected patterns of enrollment, coding the credits earned variable individually for each institution. In the NLSY97, the variable of credits earned for a BA degree had a great advantage in that it considered every institution at which an individual had enrolled for a specific year. Thus, if an individual enrolled at one school at the beginning of the year, this institution was coded as the first school. If the same individual then enrolled at another institution after transferring, or simply attended another institution for a semester, this institution was coded as the second school. Thus, within each age year, there were a number of possible ways for an individual to earn credits, such as earning credits at one institution and then earning further credits through courses taken at another institution during the summer, or by permanently transferring from the primary institution to another. Ultimately, the credits earned variable in the NLSY97 was coded so as to be specific with regard to different institutions (e.g., first, second, third, and fourth institution). Table 3.2 shows examples of multi-institution enrollment patterns, namely one of co-enrollment and one of lateral transfer.
Table 3.2

Examples of Multi-institution Enrollment Patterns

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Age</th>
<th>Cumulative Percentage of Credits Earned</th>
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<th></th>
<th>Given Age</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>School #1</td>
<td>School #2</td>
<td>School #3</td>
<td>School #4</td>
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<tr>
<td>Lateral Transfer</td>
<td>18</td>
<td>20</td>
<td></td>
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<td></td>
<td>20</td>
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<tr>
<td>Pattern</td>
<td>19</td>
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<td>35</td>
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<td>21</td>
<td>55</td>
<td></td>
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<td>55</td>
</tr>
<tr>
<td>Co-enrollment</td>
<td>22</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>30</td>
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<tr>
<td>Pattern</td>
<td>23</td>
<td>25</td>
<td>27</td>
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<td>27</td>
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</tr>
</tbody>
</table>

Note that the value of the credits earned variable does not decrease in Table 3.2, due to the accumulation of credits earned toward the BA degree. To overcome this generalization over academic years, I created and analyzed an outcome variable reflecting the total credits earned across several institutions as representative of the credits earned for any given year. Thus, I analyzed the total credits earned in each year from the age of 18 to the age of 27. This means that every individual in the sample has one variable per year for 10 years.
Regarding multi-institutional enrollment patterns, as mentioned above, the outcome variable was not calculated separately for each institution at which an individual was enrolled. Instead, the variable reflected the cumulative credits for every institution attended per year through the calculation of a new outcome variable for participants of each age. Thus, the original CV_BA_CREDITS variable reflected data from every institution for a given year. For example, in the case of an individual aged 23 enrolling part-time at multiple institutions, earning 25% of his/her credits at the primary institution, and then a further 2% and 3% at two further institutions, respectively, the credits earned in that year was shown as 30%, despite the second and third institutions not being the primary one. The credits earned at the second and third institutions are in such a case transferred to the primary institution, and such an individual can then return to the primary institution (the initial institution of enrollment) and take further credits beyond the 30% accumulated. Thus, the CV_BA_CREDITS variable reflects a cumulative score. To provide another example, an individual aged 26 enrolled at three different institutions may have reported 45% credit completion at the first institution, and 47% and 49% at the second and third institutions, respectively, the earned credit for this individual at age 26 would be 49%, regardless of which institution was the primary institution, as the individual was enrolled at the second and third institutions on a part time basis, with the credits earned at both these institutions counting toward (transferring to) the eventual BA at the primary institution. In the case of an individual transferring permanently from a primary to a second institution, the second institution becomes a primary institution, once the individual has enrolled in the second institution. Thus, the variable automatically reflects transferring patterns. Furthermore, if an individual transferred certain credits from a previous institution to a new institution, then this variable
automatically reflects the credits transferred to the new school. In other words, the individual would not begin with zero credits at the new institution. To reflect this impact of a multi-institution enrollment pattern, multi-institution enrollment was specified as one of the academic background predictors, as mentioned in Chapter 2.

**High School Graduation Based Outcome Variable**

In the second part of the analysis, regarding the timing of college entry, I rearranged respondents’ data on the basis of the time at which they graduated high school. Regarding the rationale for this procedure, consider, for example, an individual who graduated from high school at age 19 and immediately entered college, who would have been classified as reflecting delayed entry in the previous analysis, in which the credits earned variable was analyzed by arranging data on the basis of age alone. To overcome this issue, I linked the time of high school graduation to the credits earned variable, which showed whether or not an individual started earning college credits within one year of his/her high school graduation. Note that many studies have reported an interesting trend by which credit earning patterns are affected by dual enrollment, which occurs when higher education institutions allow high school students to take certain college courses and earn college credits (Allen, 2010; Blackboard Institute, 2010). According to many reports (e.g., Allen, 2010; An, 2013; Hoffman et al., 2008), participation in dual enrollment has an influence on individuals’ higher education trajectories. Therefore, in the present dataset, I arranged the credits earned variable according to the high school graduation variable, which indicated the year of high school graduation. A relatively small proportion of respondents (29.9%) showed delayed high school graduation (i.e., at age 19 or older). Furthermore, few respondents graduated high school over the age of 20 (1.6%). For detail in
In this regard, consider Table 3.3, which presents the frequency data for age at high school graduation. I recoded the credits earned data in terms of high school graduation age (either 18 or 19 and over). This led to nine time points for the credits earned variable based on high school graduation age. As a result of this new arrangement of the data, this second analysis could consider the theoretical importance of the timing of high school graduation, especially as “delayed entry” was a key element in the classification.

Table 3.3

*Frequency of Three High School Graduation Ages*

<table>
<thead>
<tr>
<th>Age</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 18</td>
<td>2174</td>
<td>66.2</td>
</tr>
<tr>
<td>Age 19</td>
<td>980</td>
<td>29.9</td>
</tr>
<tr>
<td>Age 20 and later</td>
<td>54</td>
<td>1.6</td>
</tr>
<tr>
<td>Total</td>
<td>3208</td>
<td>97.7</td>
</tr>
<tr>
<td>Missing</td>
<td>74</td>
<td>2.3</td>
</tr>
</tbody>
</table>

**Covariate Variables**

In addition to analyzing the credits earned variable in terms of age and high school graduation timing, I also extracted a number of variables considered in the literature to affect college experience (Hurtado & Carter, 1997; Rendon et al., 2000). As mentioned in Chapter 2, I classified these variables into several conceptual categories, including academic, social, cultural, and economic background factors. Table 3.4 presents the basic descriptive statistics in terms of these variables.
Table 3.4

Descriptive Statistics for Covariate Variables

<table>
<thead>
<tr>
<th>Factor Category</th>
<th>Covariate Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic Background</td>
<td>Secondary school GPA</td>
<td>74</td>
<td>417</td>
<td>316.62</td>
<td>49.367</td>
</tr>
<tr>
<td></td>
<td>SAT Math</td>
<td>1</td>
<td>6</td>
<td>4.00</td>
<td>1.092</td>
</tr>
<tr>
<td></td>
<td>SAT Verbal</td>
<td>1</td>
<td>6</td>
<td>3.97</td>
<td>1.057</td>
</tr>
<tr>
<td></td>
<td>ACT</td>
<td>2</td>
<td>6</td>
<td>4.23</td>
<td>.823</td>
</tr>
<tr>
<td>Social Background</td>
<td>Teacher-student relationship</td>
<td>1.00</td>
<td>4.00</td>
<td>2.65</td>
<td>.499</td>
</tr>
<tr>
<td></td>
<td>Learning environments</td>
<td>1.00</td>
<td>4.00</td>
<td>3.16</td>
<td>.490</td>
</tr>
<tr>
<td></td>
<td>Peer environments</td>
<td>0</td>
<td>46.66</td>
<td>.38</td>
<td>1.689</td>
</tr>
<tr>
<td>Cultural Background</td>
<td>Parental higher education expectations</td>
<td>0</td>
<td>100</td>
<td>88.63</td>
<td>18.970</td>
</tr>
<tr>
<td></td>
<td>Parental educational attainment</td>
<td>2</td>
<td>20</td>
<td>13.90</td>
<td>2.789</td>
</tr>
<tr>
<td>Economic Background</td>
<td>Income during higher education period</td>
<td>-1.34</td>
<td>5.13</td>
<td>.01</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Income during secondary education period</td>
<td>-1.53</td>
<td>7.44</td>
<td>.01</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Academic Background

Respondents' academic preparation and achievement were measured in terms of their secondary school GPA, SAT, and ACT scores. Each of these variables is discussed in more detail below.
Secondary school GPA. Data on this variable was collected in 1999. The variable reflects a credit-weighted overall GPA. This variable indicates a respondent’s grade-point average across all of his or her courses, as computed on a four-point grading scale. For each course, the quality grade (TRANS_CRS_GRADE.xxx) was weighted in terms of Carnegie credits (TRANS_CRS_CARNEGIE_CREDIT.xxx). Quality grades were re-coded. A higher value indicates a higher level GPA in secondary education.

SAT scores. The SAT variables in Table 3.4 comprise SAT Verbal and SAT Math scores. These variables were created for all respondents in 2007 (Round 11 of the NLSY97), regardless of their survey status at the time, and reflect each respondent’s highest score from all previous rounds. The scale for this variable is 1 (200 – 300), 2 (301 – 400), 3 (401 – 500), 4 (501 – 600), 5 (601 – 700), and 6 (701 – 800).

ACT scores. This variable represents each respondent’s highest ACT score. The variable was created for all respondents in 2007 (Round 11), regardless of their survey status at the time. The scale is 1 (0 – 6), 2 (7 – 12), 3 (13 – 18), 4 (19 – 24), 5 (25 – 30), and 6 (31 – 36).

Co-enrollment. The co-enrollment variable indicates for how many years a respondent was involved in any form of co-enrollment, which was not reflected credit earned in community colleges. I began by determining enrollment for each year. For example, an individual enrolled at one institution for the 2002-2003 academic year was coded as 1, whereas an individual enrolled at two institutions was coded as 2. I then recoded this variable using dummy coding, so that an individual enrolled at more than one institution would not be coded 1, indicating co-enrollment status. Thus, an individual coded as 0 did not have co-enrollment
during that year. Finally, I added all ten-year period dummy variables together in order to create the co-enrollment variable.

Social Background

**Secondary educational environments.** The In terms of social factors, I considered the secondary educational environment, taking into account respondents’ teacher-student relationships and learning and peer environments. Data regarding respondents’ secondary educational environments were collected in 1997.

*Teacher-student relationship.* The NLSY97 survey included items reflecting respondents’ teacher-student relationships. Specifically, respondents were required to indicate their degree of agreement with two statements on a five-point scale (in which 5 = strongly agree and 1 = strongly disagree), namely “The teachers are good” and “The teachers are interested in the students.” To calculate this variable for each respondent, I averaged their responses to these two items, and a high score reflects a good teacher-student relationship. Thus, this teacher-student relationship variable can be considered as operating along a continuous scale.

*Learning environment.* Respondents’ learning environments were measured by the NLSY97 in 1997 by means of the following items, requiring an indication of level of agreement (in which 1 = strongly agree and 4 = strongly disagree): “Disruptions by other students [get/gets] in the way of my learning;” “Students are graded fairly;” “There is a lot of cheating on tests and assignments;” and “Discipline is fair.” Note that a high score for the second and fourth items would indicate unfavorable learning environments. Therefore, I reverse-recoded these two items and averaged the scores for all four items, for which a high score reflects a favorable
learning environment. Thus, the learning environment variable can be considered as operating along a continuous scale.

**Peer environment.** The nature of NLSY97 respondents’ peer environments was measured in 1997, requiring them to indicate their level of agreement with items on a scale of 0 (minimum) to 99 (maximum). These items were: “I had something of value stolen from me at school;” “Someone threatened to hurt me at school;”; and “I got into a physical fight at school.” I averaged the scores, and a high score represents a relatively unfavorable peer environment.

**Ethnic identity.** In terms of ethnicity, the respondents were separated into two groups, namely underrepresented racial minorities (URM), which included black, Latina/o, and American Indian respondents (Hurtado et al., 2008), and the remainder, being Asian and white. This categorization was based on literature that reports URM students not graduating at the same rate as white and Asian American students. In terms of coding, I recorded URM respondents as 1 and white and Asian respondents as 0.

**Cultural Background**

**Parental educational attainment.** In the original NLSY97 survey, the parental educational attainment variable was drawn from questions about the highest grade level completed by each respondent’s resident father and mother (including both biological and non-biological fathers and mothers). The scale was 1 to 20, with higher numbers indicating higher educational attainment.

**Parental higher education expectations.** The data reflecting parental higher education expectations were collected in 1997. Respondents’ parents were asked to respond to the question: “Now think ahead to when [your son or daughter] turns 30 years old. What is the
percent chance that [he or she] will have a four-year college degree by the time [he or she] turns 30?"

**Economic Background**

**Income during secondary education period.** The data for this variable were drawn from the surveys of 1997 to 2003 (Rounds 1 to 7), and reflected respondents’ total household income during each preceding calendar year. Responses to several items were combined to create this income variable, namely those related to non-farm and farm wages, wages of a respondent’s spouse/partner, child support, interest and dividends from stocks or mutual funds, rental income, retirement pension/alimony/social security payments, parents’ income if the respondent resided with them, monetary gifts (other than an allowance) from parents, public support sources, and other sources of income.

**Income during higher education period.** The data for this variable were drawn from the surveys of 2004 to 2011 (Rounds 8 to 15), and reflected respondents’ total family income during each preceding calendar year. Like the income during secondary education variable, this variable was calculated using a combination of response to several income-related questions. However, there is a difference between this and the former variable: in Rounds 1 to 7, items in the income section asked the NLSY97 respondents about the income of each current household member aged 14 and over, yielding the total household income for a particular year. Starting in Round 8, the wording of some income questions changed, and the total household income could no longer be calculated. This necessitated the creation of a different total income variable, which reflects the total family income rather than the total household income.
Statistical Analyses

To better understand how social behaviors unfold over time, many researchers in the fields of education, sociology, and psychology currently employ longitudinal developmental trajectory modeling, particularly latent growth mixture modeling (LGMM) approaches (Jung & Wickrama, 2008). With a similar context, the present study applied LGMM in exploring the variability in the data concerning credits earned. In this way, discrete growth trajectories (classes) were identified, and predictors of membership of those classes were gauged (Muthen, 2004; Muthen & Muthen, 2000).

For the population examined here, the LGMM differed in terms of growth parameters, such as intercept and slope, and such parameters stemmed from a number of indicators (i.e., repeated measures of an outcome). Because the LGMM does not base its findings on the presence of a single population, it has the capacity to examine individuals from numerous groups or populations, as long as those individuals come from normally distributed multivariate populations. The respondents in the present study were examined in terms of both continuous latent variables (such as slope and intercept, which function as a means of charting and categorizing growth patterns) and categorical latent variables.

The LGMM approach benefitted this study in several ways. While traditional latent growth modeling techniques assume both that a single growth trajectory can approximate a homogeneous population and that covariates (predictors) can affect growth factors to influence each individual in the same way, in reality a number of other theoretical frameworks suggest the significant presence of distinct sub-categories of individuals (e.g., in this case, those that vary in terms of credits earned each semester, college entry timing, college experiences, or graduation age). For present purposes, I applied in this study a theoretical frame cognizant of different
enrollment patterns in the higher education experience. Thus, this study applied a latent growth model, which allowed me to measure variations both between and within various individuals, while also recognizing the heterogeneity of different groups among the broader population. The LGMM approach therefore provided a framework through which the study could note the heterogeneity within the wider body of respondents.

The goal of this study was to identify differences in respondents’ experiences of higher education at the individual level. Using LGMM accomplished this purpose, as it focused on each individual person, which is the primary distinction between this type of method and variable-centric models (Muthen & Muthen, 2000). In order to categorize single individuals in a population, such person-centric models explore connections between individuals rather than variables. This allows researchers to sort respondents into groups centered around similarities in response patterns, so that the members of each group are more alike than they are like members of other groups. Variable-centric approaches, in contrast, aim to reveal outcome predictors and the links between variables.

The GMM Process

To identify latent classes in terms of credits earned, I used the Mplus version 6.12 statistics package. The default estimator of GMM was the robust standard errors maximum likelihood (MLR). Wang and Wang (2012) described the fundamental steps of LGMM as follows: a) latent growth factors, namely intercept and slope (linear) or quadratic (non-linear) forms with repeated main outcome variables (in this case, representative credits earned at ages 18 to 27); b) a categorical variable representing class; and c) covariates.
The first step of the LGMM was to fit the single-class growth model. In this study, there were 10 outcome variables, namely age 18 to age 27. I specified the factor loadings (intercept and slope) as corresponding to equidistant time intervals (0 to 9), and added the quadratic (non-linear) slope. By specifying the simple latent growth curve model, I could check whether the overall pattern of cumulative credits earned across the ten-year period of the sample followed a linear or quadratic trend. Chi square, root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker-Lewis Index (TLI), and standardized root-mean-square residual (SRMR) were reported (Muthen & Muthen, 2009). I considered RMSEA and SRMR values less than 0.06 to be ideal, and values less than 0.08 to be acceptable (e.g., Hu & Bentler, 1998, 1999). I also used CFI and TLI values greater than 0.95, but considered values greater than 0.90 acceptable (e.g., Hu & Bentler, 1998, 1999). If the simple latent curve model (both linear and quadratic) demonstrated a poor trend over the 10 years, then I could establish a rationale for attempting to analyze the LGMM. This is because the result from the general growth curve model showed no overall trend across the sample but remained diverse in terms of the cumulative patterns of credits earned.

The second step of the LGMM was to specify the unconditional model (no predictor). This study examined 2- to 7-class models. I specified the same latent growth curve model (with linear or quadratic slope) and free estimated across all classes. Crucially, I did not hold equal the intercepts of growth factors across classes, but did hold equal across classes both residual variance and residual covariance of the growth factors. This allowed me to estimate the unique variance of intercept and slope for each class. In other words, the GMM model allowed the free estimation of within-class variance rather than fixing to zero as occurs in the Latent Class
Growth Analysis (LCGA) model. This is the main difference between LCGA, which assumes no within-class variance, and LGMM, which estimates the within-class variance.

One of most important parts of the LGMM process was to determine the number of classes. To do so, a researcher must not only consider statistical fit indices, but also the research questions, theoretical background, and the interpretability of the data. It is useful, however, for several model fit indices to assist in identifying the best number of classes in the initial exploratory step (Tofighi & Enders, 2008). Nylund et al. (2007) conducted a number of simulations, and suggested that a bootstrap likelihood ratio test (BLRT; McLachlan, 1987; McLachlan & Peel, 2000) be performed to determine the most appropriate number of classes. Nylund et al. (2007) also pointed out that the BLRT requires the longest computing time, and recommended that researchers compare the combination of other model fit indices, such as the Akaike information criterion (AIC; Akaike, 1973, 1983), the Bayesian information criterion (BIC; Schwarz, 1978), sample-size adjusted BIC (saBIC), entropy value, and the Lo-Mendell-Rubin likelihood ratio test (LRT; Lo, Mendell & Rubin, 2001), rather than including the BLRT in the initial exploratory steps. After the initial stages, if the researcher has identified a few plausible class model solutions, then these models can be compared through the BLRT.

Thus, this study first compared the combination of model fit indices. Following Nylund et al.’s (2007) recommendation, the combination of indices (lower saBIC value, higher entropy value [near 1.0], no less than 1% of the total count in a class, and higher posterior probabilities [near 1.0]) proved the relatively best fitting model solution. Although there were no specific cut-off criteria in terms of entropy value and posterior probabilities, an entropy value above 0.8
(Clark, 2010) and a probability of correct class membership assignment of 0.70 or greater (Nagin, 2005) are generally considered reasonably acceptable levels.

In addition, in the manner of determining the number class solution, the researcher should consider the global maximum of the likelihood. Hence, in order to ensure global maximum likelihood optimization, when more than two classes were specified in the mixture models, a larger number of random sets of starting values are needed. Therefore, I specified 1000 random starting value sets for the initial stage optimizations, 250 random starting value sets for the final stage optimizations, and the maximum number of iterations in optimization as 20.

As a result of these steps, I identified a few plausible model solutions and then analyzed these models through BLRT. If the results from the BLRT were statistically significant between the 2-class and 3-class models, then the 3-class model fit significantly better than the 2-class model. In such a case, I then compared the 3-class model to the 4-class model, and so on until the results showed no significance.

After determining the number of classes, I visualized estimated means trajectories for each class using graphs. In addition, once a set of latent classes for each pattern of credits earned was determined in this model, each latent class was defined in a meaningful and interpretable manner. The definition of a latent class was based on the patterns of credits earned across the 10 years in that class.

The final step in the analysis was to add the time-invariant covariates. This required a type of multinomial logistic regression of the categorical latent variable (class) on the time-invariant covariates when comparing class 1 to the other classes. This multinomial regression
with latent variable (class) assigned each individual fractionally to all classes using the posterior probabilities.

**Missing Data**

A number of researchers have recommended determining missing data type before performing remediation of that data (e.g., Graham, 2012; Little, 2013; Tabachnick & Fidell, 2013). The missing data mechanism indicates one of three categories, namely missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR) (Graham, 2012; Little, 2013; Tabachnick & Fidell, 2013). Tabachnick and Fidell (2011) suggested that the SPSS Missing Value Analysis (MVA) Expectation Maximization (EM; Little’s MCAR test) can be used for confirming MCAR data. I applied the MVA menu option of SPSS to a total of 3,282 responses to determine the pattern of missing values and to check whether the missingness in the data set was MCAR. A chi-square significance of greater than .05 indicates that the data are MCAR. The results of Little’s MCAR test ($\chi^2 (df = 1113) = 3700.419, p < .05$) confirmed that the data in this study were not MCAR.

According to Graham (2012), when data are not MCAR, the researcher should apply a complete case analysis, also known as listwise or pairwise deletion. However, such deletion removes cases with missing values, thereby biasing parameter estimates, as complete cases are not representative of the whole sample. Schafer and Graham (2002) have therefore pointed out the advantages of imputing missing values, which reduces the problems resulting from a small sample size, such as power and generalizability, and retains a full dataset for a complete analysis. A number of other researchers have also noted the advantages of multiple imputation over other traditional methods, such as mean substitution (Graham, 2012; Little, 2013; Tabachnick &
According to Graham (2012), the goals of the multiple imputation method are to maintain significant characteristics of the entire dataset, to produce unbiased estimates of parameters, and to allow examination of the variability around estimates. Tabachnick and Fidell (2013) have insisted that multiple imputation is the most effective strategy for dealing with missing data, and that it may be used for data which is not MCAR. Although multiple imputation is based on the MAR assumption, Schafer and Graham (2012) have emphasized the difficulty in determining whether missing data is MAR or NMAR. Graham (2012) therefore noted that multiple imputation is at least as good as or better than other methods for treating missing data, even data that is not MAR. Therefore, in this analysis, I applied multiple imputation in Mplus to remediate the missing data. Through Mplus, multiple imputation for a set of variables with missing values was carried out using Bayesian analysis (Rubin, 1987; Schafer, 1997).
CHAPTER 4

Results

In this chapter, I present the results of the above analyses. I begin by reporting on the analysis examining credits earned patterns in terms of age. I then repeat the analysis of credits earned trajectories by examining credits earned since high school graduation. Following this, I report on the investigation of how these credits earned patterns are related to individual respondent characteristics.

Analysis on the Basis of the Age Variable

As described above, the first model aimed to analyze the credits earned patterns in terms of age. Thus, the data were arranged from age 18 to age 27 in the GMM. Figure 1 depicts this first structural model.

![Figure 1. Structural Model for Age Based GMM](image)
Comparison of Simple Linear and Quadratic Growth Models

At the beginning of the analysis, I developed a model solution by estimating a simple growth model. Table 4.1 displays the results of this simple growth model. I specified factor loadings for the time points during the first step. By using both the likelihood ratio chi-square test as the absolute fit, and CFI, TLI, RMSEA, and SRMR as the relative model fit to determine a better model, I examined the models in terms of intercept and slope parameters (linear growth), and intercept, slope, and quadratic parameters (nonlinear growth).

Table 4.1

*Simple Comparison of Linear and Quadratic Growth Models*

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>X2/df</td>
<td>14345.856/50(P&lt;.000)</td>
<td>4634.447/46 (P&lt;.000)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.630</td>
<td>0.881</td>
</tr>
<tr>
<td>TLI</td>
<td>0.667</td>
<td>0.884</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.295</td>
<td>0.174</td>
</tr>
<tr>
<td>SRMR</td>
<td>4.396</td>
<td>0.208</td>
</tr>
</tbody>
</table>

The quadratic model solution showed a significant improvement in fit over the linear model for credits earned ($x2/df = 9711.409/4df, p < .05$), and this result indicated an overall change in credits earned across the 10 years of the sample. Both simple linear and non-linear
growth models, however, showed a poor fit, which implies that the overall pattern of credits earned over the 10 years cannot be demonstrated by a simple trajectory. This implies that the data require further analysis through a multi-class approach, and that, although the quadratic growth model offered a better fit, the linear growth model nevertheless demonstrated potential for fitting a multi-class approach, which suggests that a multi-class model could reveal linear effects as well.

**Determining Class Solution**

Following the recommendations of the above model testing, I compared 2- to 7-class unconditional models (i.e., no covariates) for both linear and quadratic forms of credits earned. To determine the appropriate class solution, I examined the log likelihood value, the saBIC indices, entropy values, the LRT, and the BLRT. I sought a model with lower values for the log likelihood and saBIC criterion indices, higher entropy values, and significant \( p \) values for both the LRT and BLRT. Nylund et al. (2007) have recommended the use of fit indices, such as log likelihood, saBIC, and entropy, during the beginning phase because of the increased amount of computing time for the LRT and BLRT. Otherwise, it would be equally possible to use fit indices to reach possible solutions that could then be reanalyzed by requesting the LRT and BLRT. Table 4.2 displays the fit indices of 2- to 7-class mixture model.
Table 4.2

*Fit Indices for 2- to 7-Class GMMs for Credits Earned (Unconditional)*

<table>
<thead>
<tr>
<th></th>
<th>2 Classes</th>
<th>3 Classes</th>
<th>4 Classes</th>
<th>5 Classes</th>
<th>6 Classes</th>
<th>7 Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-98311.271</td>
<td>-97531.545</td>
<td>-97531.545</td>
<td>-97063.161</td>
<td>-96581.889</td>
<td>-96472.882</td>
</tr>
<tr>
<td>saBIC</td>
<td>196711.079</td>
<td>195166.383</td>
<td>195181.140</td>
<td>194259.129</td>
<td>193311.342</td>
<td>193108.082</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.942</td>
<td>0.942</td>
<td>0.617</td>
<td>0.821</td>
<td>0.959</td>
<td>0.779</td>
</tr>
<tr>
<td>LRT p value</td>
<td>0.0000</td>
<td>0.1045</td>
<td>0.6061</td>
<td>0.4452</td>
<td>0.4272</td>
<td>0.5185</td>
</tr>
<tr>
<td>BLRT p value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td># people/class</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2428(73.98)</td>
<td>236(7.19)</td>
<td>840(25.59)</td>
<td>529(16.12)</td>
<td>359(10.94)</td>
<td>103(3.14)</td>
</tr>
<tr>
<td>2</td>
<td>854(26.02)</td>
<td>820(24.98)</td>
<td>2198(66.97)</td>
<td>529(16.12)</td>
<td>1966(59.9)</td>
<td>0(0)</td>
</tr>
<tr>
<td>3</td>
<td>2226(67.82)</td>
<td>244(7.43)</td>
<td>2024(61.67)</td>
<td>399(12.16)</td>
<td>1814(55.27)</td>
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</tr>
<tr>
<td>4</td>
<td>0(0)</td>
<td>0(0)</td>
<td>174(5.3)</td>
<td>377(11.49)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>200(6.09)</td>
<td>19(0.58)</td>
<td>364(11.09)</td>
<td></td>
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</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td>365(11.12)</td>
<td>207(6.31)</td>
<td>417(12.71)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quadratic</td>
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<td></td>
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<tr>
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<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Log</td>
<td>-93302.256</td>
<td>-92154.407</td>
<td>-91632.603</td>
<td>-90966.650</td>
<td>-90553.776</td>
<td>-90010.123</td>
</tr>
<tr>
<td>saBIC</td>
<td>186717.643</td>
<td>184441.620</td>
<td>183417.687</td>
<td>182105.457</td>
<td>181299.384</td>
<td>180231.753</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.982</td>
<td>0.961</td>
<td>0.956</td>
<td>0.970</td>
<td>0.963</td>
<td>0.958</td>
</tr>
<tr>
<td>LRT p value</td>
<td>0.1432</td>
<td>0.0067</td>
<td>0.0010</td>
<td>0.0006</td>
<td>0.3787</td>
<td>0.5655</td>
</tr>
<tr>
<td>BLRT p value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th># people/class (% of total sample)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>186(5.67)</td>
<td>186(5.67)</td>
<td>2091(63.71)</td>
<td>2271(69.19)</td>
<td>2080(63.38)</td>
<td>37(1.13)</td>
</tr>
<tr>
<td>2</td>
<td>3096(94.33)</td>
<td>2285(69.64)</td>
<td>523(15.93)</td>
<td>761(23.19)</td>
<td>474(14.44)</td>
<td>117(3.57)</td>
</tr>
<tr>
<td>3</td>
<td>811(24.7)</td>
<td>493(15.02)</td>
<td>29(0.88)</td>
<td>29(0.88)</td>
<td>158(4.81)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>175(55.33)</td>
<td>169(5.15)</td>
<td>490(14.93)</td>
<td>489(14.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>52(1.58)</td>
<td>50(1.52)</td>
<td>23(0.7)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>159(4.85)</td>
<td>2000(60.93)</td>
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<tr>
<td>7</td>
<td>458(13.96)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note:* saBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.
As illustrated in Table 4.2, the information criterion indices showed lower values for each additional class ranging from two to seven classes for both linear and quadratic forms of credits earned. This finding suggests that the 7-class linear (saBIC = 193108.082) and the 7-class quadratic (saBIC = 180231.753) solutions should prove optimal.

However, for some of classes in the linear solution model, there is no specified class membership, as reflected by 0% of class membership. Thus, I disregarded the linear model for further analysis. Furthermore, each of the 5-, 6-, and 7-class solution quadratic models had less than 1% of the total sample in a class. As mentioned in Chapter 3, small proportions of class membership can be problematic. Thus, I disregarded the 5- to 7-class solution models and considered only the 2- to 4-class solution models in the further analysis. The LRT tends to detect the number of class solutions more easily than the BLRT, and Nylund et al. (2007) have suggested that the p value of the BLRT is more reliable in determining the number of classes. Thus, the model with a low saBIC value (quadratic 4-class) and a significant BLRT p value, when comparing the k and the k-1 class models, should suggest the statistically best solution. In other words, comparing the current model (4-classes solution) against the model with 1 less class (3-classes solution) should give a BLRT p value of less than 0.05. In this study, the BLRT showed a statistically significant difference \( P = 0.0000 \) between the 4-class and 3-class models. This suggests that 4-class model demonstrated a significantly better fit than did the 3-class model.

In determining the number of classes, it is crucial to rely not merely on statistical factors such as fit indices, but also to take into account issues of research question, parsimony, theoretical justification, and interpretability. The totality of these indices, combined with the
interpretability and theoretical coherence of a given class solution, should guide the final model selection (Muthen, 2003; Wang & Wang, 2012). As previously mentioned, this study aimed to thoroughly explain different class types. The quadratic 4-class solution had the lowest values for log likelihood and saBIC, and appropriate entropy value (> 0.8) and BLRT p value. Furthermore, each trajectory of the quadratic 7-class solution had greater than 0.70 posterior probabilities: class 1 was 0.989, class 2 was 0.959, class 3 was 0.930, and class 4 was 0.966.

Furthermore, I tested the global maximum of model estimation for the 4-class quadratic solution. By specifying 1000 initial and 250 final random starts, I established the global maximum of model estimation. I specified the 250 sets of random starting values for final stage optimizations, and found that -91632.603 (the best log-likelihood value) related to the 716th set of the initial random starting values, and that the corresponding random seed was 573096. The best log likelihood value should be yielded multiple times in the most frequent solution for successful model convergence (Wang & Wang, 2012). In this case, the best log likelihood (i.e., -91632.603) was replicated many times, indicating good model convergence. Lastly, to ensure the global maximum of model estimation, I tested two different random seeds models. This test indicated that the two different random seeds estimated by the models’ parameters were identical, implying that the model estimation had established the global maximum of likelihood.

The quadratic 4-class solution divided the majority of the present sample into two groups: the first group represented traditional college completers (class 1; 63.7%), while the second represented several non-traditional trajectories of credits earned. Of particular note is that the quadratic 4-class solution revealed the classes of traditional and non-traditional trajectories of credits earned, but also showed three classes with different non-traditional trajectories, namely a)
an early drop-out class (class 2; 15.7%); b) a late drop-out class (class 3; 15.3%); and c) a change of major or lateral transfer class (class 4; 5.3%). Figure 2 depicts the estimated mean of each trajectory for the quadratic 4-class solution. Table 4.3 shows information about the mean of intercept, linear slope, and quadratic slope for the 4-class quadratic model.

Figure 2. Estimated Mean of Each Trajectory for the Quadratic 4-class Solution (Based on Age)

Table 4.3

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>Intercept</th>
<th>Linear Slope</th>
<th>Quadratic Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early drop-out trajectory</td>
<td>15.502</td>
<td>2.187</td>
<td>-0.180</td>
</tr>
<tr>
<td>Change major or lateral transfer trajectory</td>
<td>31.628</td>
<td>-7.968</td>
<td>1.606</td>
</tr>
<tr>
<td>Late drop-out trajectory</td>
<td>18.722</td>
<td>10.083</td>
<td>-0.647</td>
</tr>
<tr>
<td>Traditional trajectory</td>
<td>6.280</td>
<td>24.247</td>
<td>-1.565</td>
</tr>
</tbody>
</table>
Analysis on the Basis of the High School Graduation Variable

In the second stage of the data analysis, focusing on timing of college entry, I analyzed the credits earned variable with high school graduation timing as the starting point. As described in the chapter 3, the high school graduation variable reflects the number of years after an individual had graduated high school. Thus, if an individual had graduated high school at age 18, the baseline outcome variable was coded as 0 at age 18. Alternatively, if an individual had graduated high school at age 19, he or she was recoded with the outcome variable as 0 at age 19. As a result of this rearrangement, the overall outcome variable had nine time points (0 to 8). The structural model is displayed in Figure 3.

Figure 3. Structural Model for High School Graduation Based GMM
Comparison of Simple Linear and Quadratic Growth Models

As reported above for the age based credits earned pattern, I tested a simple growth model. Table 4.4 displays the simple growth model results. Both simple linear and non-linear growth models showed a poor fit, which implies that the overall pattern of credits earned over the nine years cannot be demonstrated by a simple growth model. Therefore, I analyzed the data further through a multi-class approach.

Table 4.4

*Simple Comparison of Linear and Quadratic Growth Models*

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>X2/df</td>
<td>13274.433/40 (P&lt;.000)</td>
<td>3212.757/36 (P&lt;.000)</td>
</tr>
<tr>
<td>CFI</td>
<td>0.579</td>
<td>0.899</td>
</tr>
<tr>
<td>TLI</td>
<td>0.621</td>
<td>0.899</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.322</td>
<td>0.166</td>
</tr>
<tr>
<td>SRMR</td>
<td>3.215</td>
<td>0.114</td>
</tr>
</tbody>
</table>

Determining Class Solution

As with the age based analysis above, I compared the 2- to 7-class unconditional models. Table 4.5 displays the results for fit indices.
Table 4.5

*Fit Indices for 2- to 7-Class GMMs for Credits Earned (Unconditional)*

<table>
<thead>
<tr>
<th></th>
<th>2 Classes</th>
<th>3 Classes</th>
<th>4 Classes</th>
<th>5 Classes</th>
<th>6 Classes</th>
<th>7 Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Linear</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-88730.671</td>
<td>-88730.671</td>
<td>-88730.671</td>
<td>-88730.671</td>
<td>-88730.671</td>
<td>-88730.671</td>
</tr>
<tr>
<td>saBIC</td>
<td>177544.446</td>
<td>177549.334</td>
<td>177554.223</td>
<td>177559.111</td>
<td>177563.999</td>
<td>177568.888</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.936</td>
<td>0.495</td>
<td>0.576</td>
<td>0.884</td>
<td>0.852</td>
<td>0.823</td>
</tr>
<tr>
<td>LRT p value</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>BLRT p value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td># people/class (%% of total sample)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2359(74.08)</td>
<td>850(26.69)</td>
<td>849(26.66)</td>
<td>826(25.94)</td>
<td>826(25.94)</td>
<td>826(25.94)</td>
</tr>
<tr>
<td>2</td>
<td>825(25.91)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
</tr>
<tr>
<td>3</td>
<td>2334(73.30)</td>
<td>0(00.00)</td>
<td>2358(74.05)</td>
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<td>2358(74.05)</td>
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</tr>
<tr>
<td>4</td>
<td></td>
<td>2335(73.33)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td>0(00.00)</td>
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<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td>0(00.00)</td>
<td>0(00.00)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0(00.00)</td>
<td></td>
</tr>
<tr>
<td>Quadratic Log</td>
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<td>-82591.336</td>
<td>-82113.217</td>
<td>-81462.188</td>
<td>-81079.357</td>
<td>-80665.122</td>
</tr>
<tr>
<td>---------------</td>
<td>------------</td>
<td>------------</td>
<td>------------</td>
<td>------------</td>
<td>------------</td>
<td>------------</td>
</tr>
<tr>
<td>saBIC</td>
<td>167370.858</td>
<td>165309.772</td>
<td>164373.088</td>
<td>163090.584</td>
<td>162344.475</td>
<td>161535.559</td>
</tr>
<tr>
<td>Entropy</td>
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<td>0.951</td>
<td>0.954</td>
<td>0.961</td>
<td>0.953</td>
<td>0.955</td>
</tr>
<tr>
<td>LRT p value</td>
<td>0.0000</td>
<td>0.1868</td>
<td>0.7248</td>
<td>0.4520</td>
<td>0.4796</td>
<td>0.0965</td>
</tr>
<tr>
<td>BLRT p value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
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</tr>
<tr>
<td>(total sample)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>792(24.87)</td>
<td>766(24.05)</td>
<td>755(23.71)</td>
<td>76(02.38)</td>
<td>157(04.93)</td>
<td>471(14.79)</td>
</tr>
<tr>
<td>2</td>
<td>2392(75.12)</td>
<td>2223(69.81)</td>
<td>75(02.35)</td>
<td>173(05.43)</td>
<td>435(13.66)</td>
<td>33(01.03)</td>
</tr>
<tr>
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<td>195(06.12)</td>
<td>171(05.37)</td>
<td>731(22.95)</td>
<td>21(00.66)</td>
<td>77(02.41)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2183(68.56)</td>
<td>20(00.62)</td>
<td>60(01.88)</td>
<td>2025(63.59)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2184(68.59)</td>
<td>2043(64.16)</td>
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</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>127(03.98)</td>
</tr>
</tbody>
</table>

Note: saBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.

As illustrated in Table 4.5, the information criterion indices showed lower values for each additional class ranging from two to seven classes for both linear and quadratic models of credits.
earned. This finding suggests that the 7-class linear (saBIC = 177568.888) and 7-class quadratic (saBIC = 161535.559) solutions would prove optimal. Interestingly, in the linear 7-class individual classification based on most likely membership, the second, fourth, fifth, fourth, and last classes unrealistically have no members. Thus, I disregarded the 7-class linear solution in the further analysis. Furthermore, each of the 5-, 6-, and 7-class quadratic solutions has less than 1% of total sample in a class. As mentioned above, small proportions of class membership can be problematic; thus, I disregarded the 5- to 7-class solution models and consider only the 2- to 4-class solution models in the further analysis. Comparing the 4-class to the 3-class model revealed a statistically significant difference ($P = 0.0000$). This suggests that the 4-class model demonstrated significantly better fit than the 3-class model. The quadratic 4-class model solution had the lowest log likelihood and saBIC values, and appropriate entropy (> 0.8) and BLRT $p$ values. Furthermore, each trajectory of the quadratic 7-class solution had greater than 0.70 posterior probabilities: class 1 was 0.966, class 2 was 0.938, class 3 was 0.935, and class 4 was 0.982. In addition, good model convergence and global maximum of model estimation were established for this model.

Several reasons emerge as to why the graphical representations of credits earned trajectories by the age and high school graduation variables differed. First, the greatest difference between the age based and high school graduation based models was that the age model did not show a prolonged degree completion trajectory (class 3). Rather, the age model suggested late drop-out (class 3) rather than a prolonged pattern. This may be because an age based model cannot precisely reflect the population who has delayed entry and late graduation.
As mentioned above, more and more students are choosing not to enter college immediately, or to prolong the time before obtaining a degree.

Second, the model based on high school graduation timing may have more significant and meaningful implications, in that it focused on different patterns by which credits were earned in higher education, rather than in a secondary education. In other words, the age based model could not exclude the effect of credits having been earned during secondary education, because high school graduation timing was not considered. Recall the dual enrollment trend reported in Chapter 3, by which college credits may be earned by individuals still attending high school, influencing their higher education trajectories. The credits earned model based on high school graduation can eliminate the effects of this dual enrollment trend. Thus, the credits earned patterns within higher education can be captured in isolation through the model that considers high school graduation timing.

As mentioned above, another reason for preferring the model based on high school graduation timing is that its 4-class solution is particularly useful in providing details to classify and explain the groups. For example, with the theoretical backgrounds, the majority of the college-going population could be divided into two groups: the first represented the traditional college completers, and the second represented several non-traditional trajectories of credits earned. Specifically, these results divided the sample into traditional college completers (class 4; 68.2%) and non-traditional college completers, the latter comprising completely separated groups with different non-traditional trajectories, namely a) a drop-out class (class1; 23.7%); b) a change of major or lateral transfer class (class 2; 2.4%); and c) a prolonged degree completion class (class 3; 6.7%). This allowed a more thorough empirical interpretation of the credits
earned patterns using the quadratic 4-class solution. Figure 4 depicts the estimated mean of each trajectory for the quadratic 4-class solution. Table 4.6 presents information about the mean of intercept, linear slope, and quadratic slope for the quadratic 4-class model.

![Credit Earned Trajectories](image)

**Figure 4.** Estimated Mean of Each Trajectory for the Quadratic 4-class Solution (Based on High School Graduation)

**Table 4.6**

*Mean of Intercept, Linear Slope, and Quadratic Slope for Each Trajectory (Based on High School Graduation)*

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>Intercept</th>
<th>Linear Slope</th>
<th>Quadratic Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out trajectory</td>
<td>15.902</td>
<td>5.397</td>
<td>-0.432</td>
</tr>
<tr>
<td>Change major or lateral transfer trajectory</td>
<td>49.488</td>
<td>-24.510</td>
<td>3.652</td>
</tr>
<tr>
<td>Prolonged degree completion trajectory</td>
<td>9.589</td>
<td>7.563</td>
<td>0.263</td>
</tr>
<tr>
<td>Traditional trajectory</td>
<td>10.907</td>
<td>25.334</td>
<td>-1.841</td>
</tr>
</tbody>
</table>
Several aspects of the theoretical background for this study bolster the validity and relevance of my use of the high school graduation-based model rather than the age-based model. Traditional developmental theories (e.g., Chickering, & Gamson, 1991; Erikson, 1968) may suggest that individual development occurs in a sequence influenced by age-based biological change; however, the principle of these developmental theories implies not only an age-based sequence, but also the view that the individuals interact with their environment, including higher education institutions, which shapes their particular character and extent. In particular, according to Erikson (1968), development occurs through a series of crises, when biological and psychological changes interact with sociocultural demands to present the distinctive challenges or threat characteristics of a given stage. For Erikson, a crisis does not mean a physical or psychological emergency, but rather a time for decision requiring significant choices among alternative courses of action. In this context, high school graduation could be a significant crisis for an individual in terms of developmental stages. At the same time, entering college could be drastically challenging as an individual adjusts to a totally new environment. For example, early theory in higher education decision-making processes consisted of general steps in order to demonstrate the sequential decision-making process for college enrollment and highlighted high school graduation as one of the critical events (Behrman, Kletzer, McPherson, & Schapiro, 1998; Fuller, Manski, & Wise, 1982; Hossler, Smith, & Vesper, 1999). Also, as previously mentioned, the measurement of delayed entry timing has been assessed by the time between high school graduation and college enrollment.

I therefore chose this quadratic form of the 4-class solution as the optimal model and empirically defined each class. According to the above findings, the majority of college
students in the present sample (n = 2183, 68.2%) demonstrated a traditional enrollment trajectory, a finding consistent with those of previous research (e.g., Goldrick-Rab, 2006). Choy (2002) has defined such a traditional route as enrolling in a four-year college program immediately following high school, attending that institution continuously on a full-time basis, and completing a degree within a span of four to six years. In addition to the traditional enrollment pattern, three classes showed various manifestations of a non-traditional trajectory, as have been reported by many studies in the past, namely class 1 showing a drop-out trajectory (23.7% of the sample), class 2 showing a change of major or lateral transfer (2.4% of the sample, and class 3 showing prolonged degree completion (3; 6.7% of the sample). Each of these groups is discussed in more detail below.

**Drop-outs or non-completers.** Table 4.7 showed characteristics of each nontraditional trajectory. Bean and Metzner (1985) defined a “drop-out” as a student who withdraws following a semester of coursework and does not complete his or her formally declared program of study. According to Kember (1995), there are three possibilities for a students’ status during an academic program, namely a) non-starters, who informally withdraw from the course; b) formal withdrawals, who complete an official withdrawal procedure or fail academically; and c) non-continuers, who may never have intended to complete a full program of study. Similarly, Yorke (1999) defined a “non-completer” as a person who disappeared from the student record system. Mahmodi and Ebrahimzade (2015) have drawn attention to the high drop-out rate in higher education courses, which results in students’ academic failure. Furthermore, reflecting the concern for persistence vs. attrition in higher education, several studies have examined the factors that influence students’ decisions to drop out. Note that the 4-class solution modelled
here did not identify a class with delayed entry. This result may be because the population with delayed entry was integrated in the class of dropped-out non-completers. In this regard, many prior studies have suggested that delayed entry negatively affects the likelihood of degree completion (e.g., Adelman, 2004; Bozick & DeLuca, 2005).

**Change of major or lateral transfer.** These days, the college student experience is complex (Ingels et al., 2002). Recent patterns of attendance show that individuals increasingly put off college entrance, enrollment, transfer, and withdrawal. Furthermore, the proportion of students simultaneously enrolled at more than one college has increased from 51% to 57% between the 1970s and 1990s (Adelman, 1999; Adelman, Daniel, & Berkovits, 2003). Goldrick-Rab and Pfeffer (2009) noted two types of student mobility at four-year colleges, namely lateral transfer, which occurs between two similar colleges (e.g., between two four-year colleges), and reverse transfer, which occurs between different types of college, such as moving from a four-year college to a community college. Goldrick-Rab and Pfeffer (2009) also have shown that at least 19.5% of students transfer laterally between four-year institutions, and approximately 15.5% reverse transfer. Although a significant number of students transfer laterally, there has been limited research in this area, with most studies focusing on students at community colleges (e.g., Dougherty, 1987; Lee & Frank, 1990; Velez & Javalgi, 1987). Furthermore, research on reverse transfer is equally scarce, with most studies focusing on limited sample populations (e.g., Bach et al., 2000; Winter & Harris, 1999). Such limitations may create barriers to understanding how and why students decide to transfer (Townsend & Dever, 1999). In the present study, 2.4% of the sample of students followed the trajectory of a change of major or lateral transfer.
**Prolonged degree completion.** Research has demonstrated that continued engagement in nontraditional pathways may negatively impact the likelihood of degree completion. In other words, students who interrupt their studies or move between institutions are less likely to complete their degrees in a timely fashion. However, this does not mean that college students who enroll discontinuously never complete their degrees. Past research has shown that pathways do exist enabling the delayed attainment of a degree (e.g., Elman & O’Rand, 2004; Goldrick-Rab, 2006).

Also, the linking high school graduation showed whether or not an individual started earning college credits within one year of his/her high school graduation. This might be another possible reason why this analysis does not uncover the “delayed enrollment” group. For example, if someone graduated from high school at the beginning of 18 years old and enrolled in college at the end of 19 years old, he delayed college enrollment for almost 2 years. But according to coding used in the present study, this student does not delay the college enrollment at all. Besides, if a student delayed entry just only a semester, then the analysis could not capture this pattern even though a semester delayed entry is one of most prevalent delay entry patterns.
Table 4.7

Summary of each nontraditional trajectory

<table>
<thead>
<tr>
<th>Trajectories</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out trajectory</td>
<td>The percentage of credits earned stagnated as of a particular year (e.g., if an individual stopped earning credits at 40% and did not graduate for some reason, his/her credits-earned trajectory was indicated as 40% in the end).</td>
</tr>
<tr>
<td>Change of major or lateral transfer trajectory</td>
<td>In the case of an individual transferring permanently from a primary institution to a second institution, the second institution became the primary institution once the individual enrolled there. If the respondent transferred certain credits from a previous institution to a new institution, then he/she may not have been able to transfer every credit earned from a previous institution. Thus, credits earned might decrease at a specific point, and the student would transfer. The individual would not begin with zero credits at the new institution.</td>
</tr>
<tr>
<td>Prolonged degree completion trajectory</td>
<td>If an individual was discontinuously enrolled over one or more academic years, the credits-earned variable was coded as being the same throughout that period (e.g., if an individual did not enroll at a school for 2 years due to a full-time job, the pattern of his or her credits-earned trajectory may have been flat in those years).</td>
</tr>
</tbody>
</table>

Finally, in order to check cross validation of the BA degree completion rate within each trajectory, I compared that rate with the variable CVC_BA_DEGREE, which referred to the date when a bachelor’s degree was received in a continuous month scheme. As a result of this cross check, most of the trajectory membership populations were found to be over 95% correctly assigned. Otherwise, in the case of degree completion trajectory, over 95% of the population reported that they completed the degree. Also, in the case of the non-degree completion
trajectory almost all of the population was categorized as not completing a BA degree.

Therefore, this classification established cross validity.

Table 4.8

Validation of classification

<table>
<thead>
<tr>
<th></th>
<th>N of BA Degree no completion (%)</th>
<th>N of BA Degree completion (%)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out trajectory</td>
<td>747 (98.94)</td>
<td>8 (1.06)</td>
<td>755</td>
</tr>
<tr>
<td>Change of major or</td>
<td>2</td>
<td>73</td>
<td>75</td>
</tr>
<tr>
<td>lateral transfer trajectory</td>
<td>2.67</td>
<td>(97.33)</td>
<td></td>
</tr>
<tr>
<td>Prolonged degree</td>
<td>4</td>
<td>167</td>
<td>171</td>
</tr>
<tr>
<td>completion trajectory</td>
<td>2.34</td>
<td>(97.66)</td>
<td></td>
</tr>
<tr>
<td>Traditional trajectory</td>
<td>9</td>
<td>2174</td>
<td>2183</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(99.59)</td>
<td></td>
</tr>
</tbody>
</table>

Analysis in Terms of Covariate Variables

Testing Assumptions

In the first step of analyzing the effects of covariate variables, I tested assumptions for multinomial logistic regression. I designated the traditional trajectory as the reference group in the multinomial logistic regression analyses. As I had several continuous variables, I had to check that each was linearly related to the logit of the outcome variable. To test this assumption, I ran the multinomial logistic regression but included predictors that were the interaction between each predictor and the log of itself (Hosmer & Lemeshow, 1989). In the new model, if the interaction terms were significant, this indicated that the main effect violated the assumption of the linearity of the logit. For example, in the academic background factor model, all interactions were statistically insignificant, indicating that the assumption of linearity of the logit was met. Following this, to test the multicollinearity assumption, I checked the
tolerance value and variance inflation factor (VIF) for each variable. Tolerance values less than 0.1 (Menard, 1995) and VIF values greater than 10 (Myers, 1990) were taken to indicate a problem. Table 4.7 presents the correlation matrix, tolerance values, and VIFs for this academic background factor model. In this model, there were no issues for the multicollinearity assumption for any predictor.
Table 4.9

Correlation Matrix, Tolerance Values, and VIFs for the Academic Background Factor Model

<table>
<thead>
<tr>
<th></th>
<th>GPA</th>
<th>SATM</th>
<th>SATV</th>
<th>ACT</th>
<th>COEN</th>
<th>TSR</th>
<th>PE</th>
<th>LE</th>
<th>EM</th>
<th>PHE</th>
<th>MEAL</th>
<th>FEAL</th>
<th>ILHE</th>
<th>ILSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPA</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>SATM</td>
<td>.314*</td>
<td>-</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SATV</td>
<td>.266**</td>
<td>.614**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ACT</td>
<td>.397**</td>
<td>.527**</td>
<td>.566**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COEN</td>
<td>.012</td>
<td>-.013</td>
<td>-.002</td>
<td>-.015</td>
<td>-</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TSR</td>
<td>.114**</td>
<td>.062**</td>
<td>.071**</td>
<td>.095**</td>
<td>-.011</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>.119**</td>
<td>.102**</td>
<td>.071**</td>
<td>.129**</td>
<td>-.017</td>
<td>.414**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LE</td>
<td>-.082**</td>
<td>-.062*</td>
<td>-.034</td>
<td>-.086**</td>
<td>-.011</td>
<td>-.061**</td>
<td>-.106**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>EM</td>
<td>-.282**</td>
<td>-.273**</td>
<td>-.287**</td>
<td>-.353**</td>
<td>-.013</td>
<td>-.083**</td>
<td>-.119**</td>
<td>-.024</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>PHE</td>
<td>.227**</td>
<td>.198**</td>
<td>.164**</td>
<td>.187**</td>
<td>.021</td>
<td>.113**</td>
<td>.105**</td>
<td>-.017</td>
<td>-.003</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEAL</td>
<td>.145**</td>
<td>.191**</td>
<td>.204**</td>
<td>.148**</td>
<td>.062**</td>
<td>.039*</td>
<td>.039*</td>
<td>-.033</td>
<td>-.250**</td>
<td>.109**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FEAL</td>
<td>.230**</td>
<td>.220**</td>
<td>.222**</td>
<td>.250**</td>
<td>.017</td>
<td>.070**</td>
<td>.087**</td>
<td>-.029</td>
<td>-.350**</td>
<td>.099**</td>
<td>.273**</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ILHE</td>
<td>.082**</td>
<td>.173**</td>
<td>.149**</td>
<td>.124**</td>
<td>.018</td>
<td>.056**</td>
<td>.066**</td>
<td>.005</td>
<td>-.271**</td>
<td>.147**</td>
<td>.299**</td>
<td>.406**</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>ILSE</td>
<td>.042*</td>
<td>.061*</td>
<td>.027</td>
<td>.080**</td>
<td>.010</td>
<td>.048**</td>
<td>.033</td>
<td>-.006</td>
<td>-.123**</td>
<td>.062</td>
<td>.115**</td>
<td>.191**</td>
<td>.397**</td>
<td>-</td>
</tr>
<tr>
<td>Tolerance</td>
<td>.736</td>
<td>.516</td>
<td>.530</td>
<td>.565</td>
<td>.910</td>
<td>.662</td>
<td>.706</td>
<td>.842</td>
<td>.595</td>
<td>.774</td>
<td>.656</td>
<td>.855</td>
<td>.583</td>
<td>.778</td>
</tr>
</tbody>
</table>

Academic Background Factors

As described earlier, I analyzed one regression model, but reported each result in separate tables. Table 4.8 displays the results of the academic background covariate variables in the model. As the table shows, in comparison to the traditional trajectory, a higher GPA in secondary education was associated with a significantly decreased probability of membership of any class of non-traditional trajectory. That is, as a respondent’s GPA increased, the probability of him or her being a member of a non-traditional trajectory class decreased, for the dropped out non-completing class (odds ratio (OR) = .973, \(p < .01\)), the change of major or lateral transfer class (OR = .990, \(p < .01\)), and the prolonged degree completion class (OR = .984, \(p < .01\)). The second covariate amongst the academic background factors was the SAT Math score. In comparison to the traditional trajectory, a higher SAT Math score was also associated with a significantly decreased probability of membership of any non-traditional trajectories. In other words, a respondent with a higher SAT Math score had progressively less chance of being a member of the dropped out non-completing class (OR = .776, \(p < .01\)), the change of major or lateral transfer class (OR = .648, \(p < .01\)), or the prolonged degree completion class (OR = .724, \(p < .01\)). The third covariate of the academic background factors was the SAT Verbal score. When compared to the traditional trajectory, a higher SAT Verbal score was once again associated with a significantly decreased probability of membership of any non-traditional trajectory. If a respondent had a higher SAT Verbal score, the probability decreased for membership of the dropped out non-completing class (OR = .733, \(p < .01\)), the change of major or lateral transfer class (OR = .655, \(p < .01\)), and the prolonged degree completion class (OR = .694, \(p < .01\)). The fourth covariate among the academic background factors was the ACT score. When compared with the traditional trajectory, a higher ACT score
was again associated with a significantly decreased probability of membership of any non-traditional trajectory. If a respondent had a higher ACT score, the probability decreased for membership of the dropped out non-completing class (OR = .688, \( p < .01 \)), the change of major or lateral transfer class (OR = .526, \( p < .05 \)), and the prolonged degree completion class (OR = .534, \( p < .01 \)). Finally, the last covariate among the academic background factors co-enrollment status. In comparison to the traditional trajectory, co-enrollment status was significantly associated with probability of membership of the dropped out non-completing class (OR = .644, \( p < .05 \)) and the prolonged degree completion class (OR = 2.071, \( p < .05 \)). However, co-enrollment status was not associated with membership of the change of major or lateral transfer class, when compared to the traditional trajectory.

Table 4.10

*Prediction of Credits Earned Trajectory on the Basis of Academic Background Factors*

<table>
<thead>
<tr>
<th>Class trajectory</th>
<th>Covariate</th>
<th>B</th>
<th>Std. Error</th>
<th>Wald</th>
<th>Sig.</th>
<th>OR</th>
<th>95% Confidence Interval for OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop-out trajectory</td>
<td>GPA</td>
<td>-.019</td>
<td>.004</td>
<td>180.210</td>
<td>.000</td>
<td>.973</td>
<td>.964 to .988</td>
</tr>
<tr>
<td></td>
<td>SATM</td>
<td>-.321</td>
<td>.042</td>
<td>26.615</td>
<td>.000</td>
<td>.776</td>
<td>.608 to .854</td>
</tr>
<tr>
<td></td>
<td>SATV</td>
<td>-.228</td>
<td>.032</td>
<td>14.188</td>
<td>.000</td>
<td>.721</td>
<td>.625 to .845</td>
</tr>
<tr>
<td></td>
<td>ACT</td>
<td>-.373</td>
<td>.085</td>
<td>19.491</td>
<td>.000</td>
<td>.688</td>
<td>.583 to .813</td>
</tr>
<tr>
<td></td>
<td>COEN</td>
<td>-.441</td>
<td>.207</td>
<td>4.541</td>
<td>.033</td>
<td>.644</td>
<td>.429 to .965</td>
</tr>
<tr>
<td>Change major or</td>
<td>GPA</td>
<td>-.010</td>
<td>.002</td>
<td>32.354</td>
<td>.000</td>
<td>.990</td>
<td>.986 to .993</td>
</tr>
</tbody>
</table>
Table 4.9 presents the results of analyzing credits earned trajectories in terms of social background factors that may influence these. The first covariate among the social background factors was a respondent’s teacher-student relationship during secondary education. In comparison to the traditional trajectory, a relatively favorable teacher-student relationship was associated with a significant decrease in probability of membership of the dropped out non-completing class (OR = .729, p < .01). However, the teacher-student relationship during secondary education, when compared to traditional trajectory, was not significantly associated with membership of either of the other non-traditional trajectories. The second covariate among the social background factors was a respondent’s learning environment during secondary
education. When compared to the traditional trajectory, a more favorable learning environment (e.g., reported to have fair grading and discipline, and little disruption or cheating) was associated with a significant decrease in the probability of membership of the dropped out non-completing class (OR = .779, \( p < .01 \)). However, the secondary education learning environment, when compared to the traditional trajectory, was not significantly associated with either of the other two non-traditional trajectories. The third covariate among the social background factors was a respondent’s peer environment. When compared to the traditional trajectory, a relatively unfavorable peer environment (e.g., reports of having had something stolen by a peer, having fought with a peer, or having been threatened by a peer) was associated with a significantly increased probability of membership of the dropped out non-completing class (OR = 1.091, \( p < .01 \)). However, an unfavorable secondary education peer environment was not statistically significant in relation to either of the remaining non-traditional trajectories. The final covariate among the social background factors concerned ethnicity and minority status. When compared to the traditional trajectory, minority status was significantly associated with an increased probability of membership of every non-traditional trajectory. If a respondent was a member of a minority group, he or she had a greater probability of membership of the dropped out non-completing class (OR = 2.222, \( p < .01 \)), the change of major or lateral transfer class (OR = 2.024, \( p < .01 \)), and the prolonged degree completion class (OR = 1.850, \( p < .01 \)).
Table 4.11

Prediction of Credits Earned Trajectory on the Basis of Social Background Factors

<table>
<thead>
<tr>
<th>Class</th>
<th>Covariates</th>
<th>B</th>
<th>Std. Error</th>
<th>Wald</th>
<th>Sig.</th>
<th>OR</th>
<th>95% Confidence Interval for OR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>Drop-out trajectory</td>
<td>TSR</td>
<td>-.316</td>
<td>.095</td>
<td>11.068</td>
<td>.001</td>
<td>.729</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LE</td>
<td>-.250</td>
<td>.087</td>
<td>8.315</td>
<td>.004</td>
<td>.779</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PE</td>
<td>.087</td>
<td>.028</td>
<td>9.557</td>
<td>.002</td>
<td>1.091</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EM</td>
<td>.799</td>
<td>.086</td>
<td>85.340</td>
<td>.000</td>
<td>2.222</td>
<td></td>
</tr>
<tr>
<td>Change of major or lateral transfer trajectory</td>
<td>TSR</td>
<td>-.416</td>
<td>1.028</td>
<td>.164</td>
<td>.685</td>
<td>.659</td>
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</tr>
<tr>
<td></td>
<td>LE</td>
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<td>.980</td>
<td>.090</td>
<td>.764</td>
<td>.745</td>
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<tr>
<td></td>
<td>PE</td>
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<td>.061</td>
<td>.805</td>
<td>1.669</td>
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</tr>
<tr>
<td></td>
<td>EM</td>
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<td>8.912</td>
<td>.003</td>
<td>2.024</td>
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</tr>
<tr>
<td>Prolonged degree completion trajectory</td>
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<td>.008</td>
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<tr>
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<td>.615</td>
<td>.161</td>
<td>14.638</td>
<td>.000</td>
<td>1.850</td>
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</table>


Cultural Background Factors

As shown in Table 4.10, when compared to the traditional trajectory, a higher level of educational attainment by a respondent’s mother was associated with a significantly decreased probability of membership of the dropped out non-completing class (OR = .912, p < .01) and the prolonged degree completion class (OR = .918, p < .01). However, a mother’s level of education was not statistically significantly related to the probability of membership of the change of major or lateral transfer class. A higher level of educational attainment of a respondent’s father was also associated with a significantly decreased probability of membership of the dropped out non-completing class (OR = .938, p < .01) and the prolonged degree
completion class (OR = .968, p < .01). As for mothers, the level of a father’s education was not statistically significant in relation to the probability of membership of the change of major or lateral transfer class. The third covariate among the cultural background factors was parental higher education expectation. When compared to the traditional trajectory, parental expectation of higher education was significantly associated with a decreased probability of membership of the dropped out non-completing class (OR = .982, p < .01). However, compared to the traditional trajectory, parental higher education expectation was not statistically significant in relation to either of the remaining non-traditional trajectories.

Table 4.12

*Prediction of Credits Earned Trajectory on the Basis of Cultural Background Factors*

<table>
<thead>
<tr>
<th>Class</th>
<th>Covariates</th>
<th>B</th>
<th>Std. Error</th>
<th>Wald</th>
<th>Sig.</th>
<th>OR</th>
<th>95% Confidence Interval for OR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>Drop-out trajectory</td>
<td>Parental Higher Education Expectation</td>
<td>-.018</td>
<td>.004</td>
<td>24.438</td>
<td>.000</td>
<td>.982</td>
<td>.975</td>
</tr>
<tr>
<td></td>
<td>Mothers’ Educational Attainment</td>
<td>-.092</td>
<td>.010</td>
<td>81.905</td>
<td>.000</td>
<td>.912</td>
<td>.894</td>
</tr>
<tr>
<td></td>
<td>Fathers’ Educational Attainment</td>
<td>-.064</td>
<td>.006</td>
<td>101.882</td>
<td>.000</td>
<td>.938</td>
<td>.926</td>
</tr>
<tr>
<td>Change of major or</td>
<td>Parental Higher Education Expectation</td>
<td>-.017</td>
<td>.009</td>
<td>3.872</td>
<td>.052</td>
<td>.983</td>
<td>.967</td>
</tr>
<tr>
<td>lateral transfer</td>
<td>Parental Educational Attainment</td>
<td>-.052</td>
<td>.028</td>
<td>3.355</td>
<td>.067</td>
<td>.949</td>
<td>.898</td>
</tr>
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<td>Economic Background Factors</td>
<td></td>
<td></td>
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</tbody>
</table>

As shown in Table 4.11, when compared to the traditional trajectory, income level during secondary education was significantly associated with the probability of membership of both the dropped out non-completing class (OR = .770, \( p < .01 \)) and the prolonged degree completion class (OR = .830, \( p < .05 \)). However, secondary education income level was not significantly associated with membership of the change of major or lateral transfer class, in comparison to the traditional trajectory. Similarly, when compared to the traditional trajectory, income during higher education was significantly associated with the probability of being a member of the dropped out non-completing class (OR = .694, \( p < .01 \)), the change of major or lateral transfer class (OR = .740, \( p < .05 \)), and the prolonged degree completion class (OR = .676, \( p < .01 \)).
Lastly, in much of the literature, significant interaction effects have been reported among background variables for enrollment patterns of higher education such as academic background with economic background (e.g., An 2010; Charles et al., 2007) and cultural background with economic background (Gamoran & Mare, 1989; Lareau & Weiningher, 2008; Lucas 2001; Lucas & Berends 2002). As shown in Table 4.14, I specified several interaction effects from the
literature and tested them. As a result of the tests, most of the interaction effects were found to be significantly associated with nontraditional class membership.

Table 4.14

*Prediction of Credits-Earned Trajectory on the Basis of Interaction Effects*

<table>
<thead>
<tr>
<th>Class</th>
<th>Covariate</th>
<th>B</th>
<th>Std. Error</th>
<th>Wald</th>
<th>Sig.</th>
<th>OR</th>
<th>95% Confidence Interval for OR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Lower Bound</td>
</tr>
<tr>
<td>Drop-out trajectory</td>
<td>GPA*FEAL</td>
<td>.000</td>
<td>.000</td>
<td>128.585</td>
<td>.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>SATM* FEAL</td>
<td>-.021</td>
<td>.002</td>
<td>126.201</td>
<td>.000</td>
<td>.980</td>
<td>.976</td>
</tr>
<tr>
<td></td>
<td>SATV* FEAL</td>
<td>-.020</td>
<td>.002</td>
<td>117.402</td>
<td>.000</td>
<td>.980</td>
<td>.977</td>
</tr>
<tr>
<td></td>
<td>ACT* FEAL</td>
<td>-.016</td>
<td>.002</td>
<td>83.502</td>
<td>.000</td>
<td>.984</td>
<td>.981</td>
</tr>
<tr>
<td></td>
<td>GPA*MEAL</td>
<td>.000</td>
<td>.000</td>
<td>163.097</td>
<td>.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>SATM*MEAL</td>
<td>-.025</td>
<td>.003</td>
<td>99.518</td>
<td>.000</td>
<td>.975</td>
<td>.970</td>
</tr>
<tr>
<td></td>
<td>SATV*MEAL</td>
<td>-.023</td>
<td>.003</td>
<td>83.943</td>
<td>.000</td>
<td>.977</td>
<td>.972</td>
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<tr>
<td></td>
<td>ACT* MEAL</td>
<td>-.022</td>
<td>.003</td>
<td>67.961</td>
<td>.000</td>
<td>.979</td>
<td>.973</td>
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<tr>
<td></td>
<td>ACT* ILSE</td>
<td>-.092</td>
<td>.020</td>
<td>20.415</td>
<td>.000</td>
<td>.912</td>
<td>.877</td>
</tr>
<tr>
<td></td>
<td>ACT* ILHE</td>
<td>-.092</td>
<td>.020</td>
<td>20.415</td>
<td>.000</td>
<td>.912</td>
<td>.877</td>
</tr>
<tr>
<td>Change in major or lateral transfer trajectory</td>
<td>GPA*FEAL</td>
<td>.000</td>
<td>.000</td>
<td>6.428</td>
<td>.011</td>
<td>1.000</td>
<td>1.000</td>
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<tr>
<td></td>
<td>SATM*FEAL</td>
<td>-.011</td>
<td>.004</td>
<td>6.689</td>
<td>.010</td>
<td>.989</td>
<td>.980</td>
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<tr>
<td></td>
<td>SATV*FEAL</td>
<td>-.011</td>
<td>.004</td>
<td>5.667</td>
<td>.017</td>
<td>.989</td>
<td>.981</td>
</tr>
<tr>
<td></td>
<td>ACT*FEAL</td>
<td>-.015</td>
<td>.006</td>
<td>7.191</td>
<td>.007</td>
<td>.985</td>
<td>.974</td>
</tr>
<tr>
<td></td>
<td>GPA*MEAL</td>
<td>.000</td>
<td>.000</td>
<td>15.264</td>
<td>.000</td>
<td>1.000</td>
<td>1.000</td>
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<tr>
<td></td>
<td>SATM*MEAL</td>
<td>-.016</td>
<td>.006</td>
<td>6.506</td>
<td>.011</td>
<td>.984</td>
<td>.971</td>
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<td>SATV*MEAL</td>
<td>-.014</td>
<td>.006</td>
<td>4.914</td>
<td>.027</td>
<td>.986</td>
<td>.973</td>
<td>.998</td>
</tr>
<tr>
<td>ACT*MEAL</td>
<td>-.015</td>
<td>.009</td>
<td>2.796</td>
<td>.094</td>
<td>.985</td>
<td>.967</td>
<td>1.003</td>
</tr>
<tr>
<td>GPA*ILHE</td>
<td>-.001</td>
<td>.000</td>
<td>2.263</td>
<td>.132</td>
<td>.999</td>
<td>.998</td>
<td>1.000</td>
</tr>
<tr>
<td>SATM*ILHE</td>
<td>-.087</td>
<td>.045</td>
<td>3.771</td>
<td>.052</td>
<td>.916</td>
<td>.839</td>
<td>1.001</td>
</tr>
<tr>
<td>SATV*ILHE</td>
<td>-.071</td>
<td>.043</td>
<td>2.659</td>
<td>.103</td>
<td>.932</td>
<td>.855</td>
<td>1.014</td>
</tr>
<tr>
<td>ACT*ILHE</td>
<td>-.106</td>
<td>.075</td>
<td>2.024</td>
<td>.155</td>
<td>.899</td>
<td>.777</td>
<td>1.041</td>
</tr>
</tbody>
</table>

| GPA*FEAL  | .000 | .000 | 9.931 | .002 | 1.000 | 1.000 | 1.000 |
| SATM*FEAL | -.013 | .003 | 17.036 | .000 | .987 | .981 | .993 |
| SATV*FEAL | -.013 | .003 | 15.268 | .000 | .988 | .981 | .994 |
| ACT*FEAL  | -.012 | .003 | 13.121 | .000 | .988 | .982 | .995 |
| GPA*MEAL  | .000 | .000 | 31.242 | .000 | 1.000 | 1.000 | 1.000 |
| SATM*MEAL | -.022 | .005 | 23.755 | .000 | .978 | .969 | .987 |
| SATV*MEAL | -.023 | .005 | 24.151 | .000 | .978 | .969 | .987 |
| ACT*MEAL  | -.022 | .005 | 21.540 | .000 | .979 | .970 | .988 |
| GPA*ILHE  | -.001 | .000 | 10.622 | .001 | .999 | .998 | 1.000 |
| SATM*ILHE | -.110 | .035 | 10.065 | .002 | .896 | .837 | .959 |
| SATV*ILHE | -.111 | .035 | 9.917 | .002 | .895 | .835 | .959 |
| ACT*ILHE  | -.095 | .039 | 5.919 | .015 | .909 | .842 | .982 |
| SATM*ILHE | -.110 | .035 | 10.065 | .002 | .896 | .837 | .959 |
| SATM*ILHE | -.110 | .035 | 10.065 | .002 | .896 | .837 | .959 |

Thus, in summary, the data analysis described in this chapter showed that 4 classes of enrollment pattern (i.e., a traditional class, a drop-out class, a change of major or lateral transfer class; and a prolonged degree completion class) were the statistically best solution. The overall patterns and relationships within these findings will be discussed in relation to the research aims in Chapter 5.
CHAPTER 5
Discussion

Enrollment Patterns in Higher Education

The current study sought to establish the best fitting trajectories reflecting actual enrollment patterns of college students, and also to examine covariate predictors of such trajectories within the same semiparametric model. The findings indicate that a quadratic 4-class model based on the high school graduation timing variable, which included traditional and non-traditional trajectories of credits earned, best explained variations in enrollment patterns in higher education in the present sample. The majority of the respondents in the present sample of college students demonstrated a traditional enrollment trajectory (class 4), a finding consistent with previous research (e.g., Goldrick-Rab, 2006). As mentioned above, Choy (2002) defined such a traditional route as enrolling for a four-year college program immediately following high school, and attending that institution continuously on a full-time basis to complete a degree within four to six years. More than half of the present respondents followed this traditional pattern. In addition to this traditional enrollment pattern, three classes showed different manifestations of a non-traditional trajectory, namely the non-completing drop-out class, the change of major or lateral transfer class, and the prolonged degree completion class. An advantage of the GMM approach applied here was that it could extend to include theoretically relevant covariates that potentially improved model fit and illuminated predictors of trajectory class membership. Thus, I also investigated covariates of interest (namely academic, social, cultural, and economic background factors) that further informed respondents’ enrollment trajectories when considered within the same GMM, revealing how these covariates influenced
the four credits earned patterns (i.e., the traditional trajectory, the non-completing drop-out trajectory, the change of major or lateral transfer trajectory, and the prolonged degree completion trajectory). The influence of each of these covariates is discussed in more detail below.

**Academic background.** This study investigated whether higher education enrollment patterns could be differentiated on the basis of academic background factors. The hypothesis was that respondents with lower levels of certain supportive academic factors (i.e., academically underprepared respondents) would be more likely to be members of a delayed entrance sub-group, a discontinuous sub-group, or a non-completing sub-group, due to college deferral or failure to acquire the necessary credits for graduation by age 27. Conversely, it was hypothesized that academically well-prepared respondents, as well as multiple enrollment respondents, would have a higher chance of being members of a sub-group that began earning credits on time at age 18 and completed their BA degree within four to six years (i.e., following the traditional pathway). In testing these hypotheses, this study found that respondents with higher levels of academic achievement in secondary education (namely, a higher GPA, higher SAT Math and Verbal scores, and a higher ACT score) were indeed more likely to follow the traditional credits earned pathway (timely entrance and graduation within four to six years), and were less likely to follow non-traditional enrollment patterns (prolonged degree completion, interrupted enrollment, or non-completion). These results are consistent with those of past studies (e.g., ACT, 2007; Adelman, 2006; Eckland & Henderson, 1981; Kirst & Venezia, 2004; Reason, 2009; Rowan-Kenyon, 2007), and demonstrate the relationship between academic background and higher education enrollment patterns. Conversely, the present findings indicated that under-prepared respondents were more likely to display patterns of enrollment
characterized by disruption, prolongation of degree completion, or non-completion. This negative impact of academic under-preparedness also supports the findings of previous researchers (e.g., ACT, 2007; Adelman, 2006; Reason, 2009).

A further interesting aspect of the present results is that the enrollment pattern involving a change of major or lateral transfer was related to a respondent’s level of academic preparedness. This finding is not consistent with those of Goldrick-Rab’s (2009) study, which showed that lateral transfer was not related to reduced degree completion rates, leading to the hypothesis that lateral transfer relates more to individual preferences than to poor academic performance at a previous institution. Although I had hypothesized that lateral transfer patterns may not be associated with academic under-preparedness, the present findings suggest that the change of major or lateral transfer patterns relate to academic preparation in a more complex manner.

There are several possible explanations as to why respondents with lower levels of academic preparation showed a higher possibility of following a non-traditional credits earned trajectory, i.e., a change of major or lateral transfer. First, although the changing major and lateral transfer patterns of enrollment are qualitatively different and represent separate sub-populations, these two groups in this sample appeared similar in terms of decreasing credits earned and in other aspects of their overall patterns. Thus, even though these qualitatively different groups were categorized as a single sub-population in this study, the change of major and the lateral transfer populations may actually constitute two distinct two groups. The first may comprise students underprepared in terms of college-level prerequisites (e.g., Math and Science in STEM major); members of such a sub-group might decide to change their major to a field that demands less in terms of those prerequisites. The second group may comprise students who do not feel they fit
well with their previous major, regardless of academic preparation; such students would become members of the lateral transfer group, in which students might transfer to another new school based on preference rather than level of preparation (Goldrick-Rab, 2009).

The final variable within academic background factors was co-enrollment status. The present results indicated that non-completion enrollment patterns, when compared to the traditional enrollment pattern, were negatively associated with co-enrollment (i.e., simultaneous enrollment at more than an institution). In other words, if a respondent was enrolled at more than one institution, he or she was more likely to complete the degree. These findings imply that co-enrollment might remain prevalent regardless of the diversification of contemporary enrollment patterns (Wang & Wickersham, 2014). According to Peter and Forrest Cataldi (2005), approximately 11% of college students enroll at more than one institution simultaneously, and this percentage has grown as students continue to take diverse pathways throughout higher education. Wang and Wickersham (2014) posited several explanations for why students enroll at more than one institution simultaneously. First, co-enrollment expands course availability by affording students a larger pool of institutions and classes to choose from; this may lead to an increase in the attainment of a BA degree within the four-year time frame if required courses are consistently offered across institutions. Moreover, as college tuition fees continue to rise, co-enrollment options allow students to attend multiple institutions and select courses based on affordability. Furthermore, institutions in close proximity to one another may consider strategically the number of students who co-enroll and the types of courses they take. On this basis, such institutions can determine whether it is worthwhile to offer the same courses at both institutions, or to offer certain courses at only one of the two. Thus, a student’s decision
to co-enroll may allow more efficient allocation of financial resources toward other curricular or co-curricular areas. Finally, note that this enrollment pattern necessitates the articulation of agreements to ensure that students who choose to co-enroll complete the required credits and courses, and this in turn may ensure more efficient degree progression and completion.

**Social background.** Regarding the social background covariate, it was hypothesized that respondents with more favorable and supportive social backgrounds (i.e., a better secondary education environment) would more likely follow the traditional pathway, beginning to earn credits on time at age 18 and completing their BA within four to six years. It was also hypothesized that respondents with less favorable social backgrounds (e.g., minority populations) would be more likely to delay college entry, to engage in a discontinuous enrollment patterns, or to not complete a degree.

The results of this study indicated that respondents who reported a less favorable secondary education environment were indeed more likely to follow a non-completion pattern in terms of credits earned. This finding implies that a superior educational environment during secondary school (e.g., a better learning environment and peer atmosphere) positively impacts higher education patterns as reflected by credits earned (Orfield & Lee, 2005; McDonough, 2005). However, the present analysis showed that the teacher-student relationship was not related to non-completion among the respondents, suggesting that the teacher-student relationship might have only an indirect effect on the pattern of credits earned in higher education. In other words, other variables, such as the academic background covariates, which have a direct impact, may mediate the relationship between teacher-student relationships and patterns of credits earned. For example, an unfavorable teacher-student relationship may...
influence academic performance in high school, leading a student to delay college entry, to have trouble studying in college, or finding it difficult to complete a degree.

In addition, ethnic minority status was found amongst the present respondents to be directly related to an increased probability of following each non-traditional pattern of earning credits (either interrupted enrollment or non-completion). From a social background perspective, minority populations have long been considered as being among a relatively small percentage of underrepresented groups attending college. Students in such groups may therefore face challenges stemming from the lack of a social network on campus. Furthermore, many studies have suggested that historically under-represented groups (such as ethnic minorities) are more likely to have difficulties entering the higher education system, and are less likely to participate fully on campus or to complete a degree (e.g., Feagin, Vera, & Imani, 1996; Flowers, 2002; Flowers & Pascarella, 1999; Outcalt & Skewes-Cox, 2002; Pascarella & Terenzini, 2005; Patton, Bridges, & Flowers, 2011; Rankin & Reason, 2005).

**Cultural background.** With regard to cultural background factors, it was hypothesized that respondents with higher parental educational attainment and expectations for higher education would be more likely to follow the traditional credits earned pathway, entering higher education around age 18 and completing their BA degree within a continuous four- to six-year timeframe. It was also hypothesized that respondents with lower levels of parental educational attainment and parental higher education expectations would be more likely to fall in the one of the sub-groups with delayed college entry, discontinuous enrollment, or failure to complete a degree by age 27. With regard to parental education, the present findings showed that a lower level was significantly related to non-completion among the respondents. In other words, a
respondent with higher level of parental education was more likely to follow a traditional enrollment pattern (i.e., timely college entrance, consistently accumulating credits until graduation). This result was consistent with a number of previous studies that have reported on the effects of parent educational level on their offspring’s college experience. Regarding college entry, enrollment pattern, and time to complete a degree, most previous studies have suggested a negative impact of lower levels of parental education attainment (e.g., Cabrera & La Nasa, 2001; Goldrick-Rab & Han, 2011; Ishitani, 2006; Perna, 2000; Rowan-Kenyon, 2007; Wells & Lynch, 2012). The present results likewise imply that students with a lower level of parental education may face a barrier that prevents them from fully engaging in a traditional college enrollment pattern. Such barriers may stem from discomfort arising during the college transition period (Gupton, Castelo-Rodriguez, Martinez, & Quintanar, 2009; Hsiao, 1992; Thayer, 2000), as such students are more likely to be unfamiliar with a campus environment (Pascarella, Edison, Hagedorn, Nora, & Terenzini, 1996), as their parents could not provide them with first-hand accounts (Saufley, Cowan, & Blake, 1983).

The other covariate among the cultural background factors was parental higher education expectation. The results indicated that a relatively higher level of parental expectation was positively associated with timely degree completion among the present respondents. Thus, a respondent with a higher level of parental expectation for college education was less likely to drop out of college.

**Economic background.** Regarding economic background factors, it was hypothesized that respondents with more favorable economic factors (i.e., higher income levels) would be more likely to follow a traditional higher education trajectory, while respondents with lower
income levels would be more likely to delay college entry, interrupt enrollment, or not complete a degree. The results indicated that most of the non-completion credits earned patterns did indeed relate to income level as a factor. Respondents with lower levels of income in the higher education period were more inclined to drop out, change their major, transfer, or prolong their degree completion, rather than following the traditional pattern of earning credits. On the other hand, respondents with higher levels of income were more likely to follow the traditional pattern of credits earned, as has been found in previous research (Bozick & DeLuca, 2005; Goldrick-Rab & Han, 2011; Hearn, 1992; Horn, Cataldi, & Sikora, 2005; Rowan-Kenyon, 2007). These findings support the notion that students from poorer economic backgrounds are more likely to face challenges related to completing high school, meeting college admission requirements, receiving family support, and understanding college application and financial aid processes (Cabrera & La Nasa, 2001; Fitzgerald, 2004). Furthermore, the present results imply that lower income students are more likely to interrupt their enrollment or to fail to complete their degree. In addition, the results revealed economic background to be one of the most powerful variables in reflecting the enrollment issues discussed here (i.e., dropping out, interrupting, retention, persistence, and non-completion), and this is consistent with the findings of other researchers (e.g., ACT, 2004; Bozick & DeLuca, 2005; Pascarella & Terenzini, 2005; Rowan-Kenyon, 2007; Walpole; 2003). These results imply that students from poorer economic backgrounds may face both visible and invisible barriers with regard to college enrollment patterns, which continue to influence on their credits earned pattern after entering college (Gupton, Castelo-Rodriguez, Martinez, & Quintanar, 2009). According to Corrigan (2003), such findings are linked to the inclination of lower income students to work longer hours at paying jobs, reducing the time spent
studying or participating in on- and off-campus activities, thereby reducing their academic and social integration, respectively (Walpole, 2003).

**Practical Implications**

This study has shown, once again, that historical risk factors (namely academic under-preparedness, ethnic minority group membership, lower parental education level, and lower economic status) negatively impact college enrollment in terms of students’ credits earned trajectories. These results support the notion that student engagement on a college campus should be prioritized, so as to assist all students to achieve their academic goals. Students’ level of engagement depends on the time and effort they devote to activities related to their college aspirations, as well as depending on what institutions do to promote student participation in such activities (Kuh, 2009). Students with higher levels of engagement both on and off campus tend to persist to graduation at a higher rate than do those with lower levels of engagement (Kuh, 2009). Evidence supporting this assertion has been consistently documented by numerous empirical studies conducted by higher education researchers (e.g., Astin, 1975, 1993; Bean, 1990, 2005; Berger & Milem, 1999; Braxton, Milem, & Sullivan, 2000; Bridges, Cambridge, Kuh, & Leegwater, 2005; Pascarella & Terenzini, 2005; Peltier, Laden, & Matranga, 1999; Tinto, 1993, 2000, 2005). Devotion to studying and academic preparation is a measure of student engagement, as well as being a significant predictor of student persistence (Astin, 1993). In fact, research has shown that high levels of engagement in college may compensate for students’ under-preparedness at college entry, as it serves as a buffer, preventing the negative effects on grades and persistence (Kuh, 2009; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008; National Survey of Student Engagement [NSSE], 2007)
Thus, interestingly, this positive effect of engagement appears to apply to all students, regardless of their academic, social, cultural, and economic background. Even disadvantaged groups, such as low-income, first-generation, or academically underprepared students, may expect to achieve more positive performance outcomes as their level of engagement increases (Greene, Marti, & McClenneney, 2008; Kuh, 2003; Pace, 1990). Therefore, in the context of the present findings, which indicated that a historically disadvantaged background may have a negative impact on credits earned trajectories, it is ever more important for higher education institutions to seek ways to increase student involvement in educationally purposeful activities, particularly encouraging those who manifest risk factors.

The theory and literature on student engagement have indicated that encouraging students to become more involved can have strong positive outcomes, regardless of their background. The AAC&U’s LEAP project (2007) delineated ten potentially “high-impact practices” that help direct students toward activities that promote their engagement (Kuh, 2009). These practices include first-year seminars (FYS), learning communities, common intellectual experiences, writing-intensive courses, service learning, student-faculty research, diversity experiences, study abroad, senior capstone experiences, and internships or field placements. Among these, typical contemporary students, diversified in terms of enrollment patterns, may benefit most from FYSs and learning communities. By utilizing such resources, students may have better access to the university community and in turn experience more positive academic outcomes, particularly in the form of stable credits earned.

**First-year seminars.** The present research and that reviewed above suggest that FYS ought to be offered in the form of a mandatory course for incoming college students. In fact,
one of the main objectives of FYS is to help students acquire effective academic skills and strategies (Hunter & Linder, 2005). Thus, LHU can expect compulsory FYS to have a positive influence on credits earned patterns, as well as other positive academic outcomes. Moreover, FYS would be particularly helpful for students with poorer academic preparedness and lower income backgrounds, as the diversity across the student body may be somewhat leveled, thereby ensuring that all students have equal opportunities to succeed academically. For contemporary higher education institutions in particular, which house students from a wide variety of backgrounds, FYS may be expected to foster student engagement, as well as offering academic support. Studies have shown that students who have participated in FYS are more likely to persist and graduate from college (Hunter & Linder, 2005). Furthermore, in an experimental study carried out by Strumpf and Hunt (1993), students who took FYS (the experimental group) tended to have higher retention rates through their second year of college than students who did not (the control group). The results of the study advocate that FYS be adopted as a mandatory program in the present context of more diverse credits-earned trajectories in the contemporary higher education context.

**Learning communities.** A learning community is defined as “some formal program where groups of students take two or more classes together” (Tinto, 2000). Put differently, a learning community “links two or more courses during an academic term and enrolls a common cohort of students” (Lattuca & Stark, 2009, p.222). Students who are part of a learning community students tend to interact with a more diverse range of faculty and peers, to study more, and to engage in learning activities more frequently than their counterparts who do not participate in a learning community (Rocconi, 2010; Zhao & Kuh, 2004). Thus, it is important
for institutions to intentionally create learning communities for incoming freshmen. Tinto (n.d.) argues that learning communities can be especially useful for retention in a student’s first year, as the student’s relationship to the campus is only just being formed. In addition, first-year participants who living on campus and participating in a learning community have reported a more positive perspective on the quality of their social lives, and experienced more contact with faculty (NSSE, 2007). Most students participate in learning communities in their first year in college, but its positive impact appears to last throughout their college years. Thus, it is important for institutions to create and maintain such learning communities, embedded within the system. As a result of such learning communities, students with high risk backgrounds, who may have been more likely to interrupt or not complete their degrees, might be prevented from following a non-traditional credits earned trajectory. For example, Szelenyi et al. (2007) reported evidence that suggested that the positive relationship between learning community participation and a successful transition to college was stronger for low-SES students.

**Limitations**

This study has several limitations. First, I analyzed only respondents who had earned at least a credit toward a bachelor’s degree. Thus respondents who had earned credit from a community college were not considered, even though in reality many students begin with credits earned for an associate degree and then transfer to a four-year school for a BA degree. In other words, in this study I could not reflect the trajectories of students who began at a two-year college rather than a four-year degree granting institution, although many lower SES students begin their postsecondary studies at 2-year institutions (Light & Strayer 2000; Schneider et al. 2006; Velez 1985). The second limitation is that the data do not allow exploration beyond a
ten-year trajectory due to unbalanced data by birth year even though some of the population (i.e., birth years 80, 81, 82, and 83) has over ten years of data for earning credits (outcome variable). In other words, different enrollment patterns of higher education trajectories are evident in nationally representative data. While the NLS 97 is frequently used to address educational development as well as other issues in terms of a longitudinal perspective, this study model cannot capture the degree attainment of students who completed a degree after a ten-year period. Finally, it is difficult to generalize the findings of this study to different cultures or nations because the participants in this study were members of the population of the United States.

Because the atmosphere or situation of a higher education environment can differ by type of cultural background or national context, the higher education context of the United States can be differentiated from other nations. Therefore, it is hard to say that these findings in the United States inform us generally about students in global higher education. Thus, studying students with more diverse cultural backgrounds or national contexts, including those from a multicultural and world-wide sample, is needed to test and generalize these findings in future research.

Conclusion

This study investigated whether the credits earned trajectories within higher education could be differentiated in terms of academic, social, cultural, or economic background factors, using an advanced research method, namely GMM. The results support the contention that historically disadvantaged students are likely to follow different college enrollment patterns than do their advantaged counterparts. Therefore, while existing research has focused on the significant influence of academic, social, cultural, and economic background, this study provided evidence that students follow notably different credits earned patterns once they have entered the
higher education system. According to Goldrick-Rab (2006), the original system in higher education institutions and policies were mainly designed with traditional students in mind, who followed traditional, linear, credits earned trajectories. However, it may now be time to restructure higher education systems and policies in order to focus on students with more complicated, non-traditional, non-linear, credit earning dynamics. In this complex contemporary higher education context, it is crucial that policy makers, faculties, university administrators, and higher education researchers attempt to work toward the advancement of diversification in higher education.
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