Impact of Individual and Institutional Characteristics on Transfer from Two-Year to Four-Year Public Institutions in Ohio

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This dissertation titled
Impact of Individual and Institutional Characteristics on Transfer from Two-year to Four-
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ABSTRACT

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Impact of Individual and Institutional Characteristics on Transfer From Two-year to Four-year Public Institutions in Ohio (198 pp.)

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One of the core missions of community colleges is to prepare students to transfer to a four-year institution. Yet, out of all students attending public two-year institutions in 1995-96 with an intent of transferring to attain a baccalaureate degree, only 23% actually achieved their goal of by 2001, and another 14% were still enrolled at four-year institutions (National Center for Education Statistics, 2002). In addition, the rate of transfer differs from one institution to another, and students from different demographic backgrounds and with different levels of academic preparation transfer at different rates. The differential rate of transfer suggests that individual characteristics and institutional policies matter with respect to transfer. This study tracks all students enrolled in public two-year institutions in Ohio in 2001 for three years, and based on their transfer behavior, measures the relationship between individual and institutional factors, and transfer. Using hierarchical linear modeling, this study also analyzes how the impact of individual factors changes with changing institutional factors. Self-declared intent and completion of relatively high numbers of credits in the first year is found to have the greatest positive relationship with transfer. Holding other factors constant, positive intent increases the probability of transfer by over 8%. For an additional 12 credits completed beyond the average of 25 credits in the first year, the probability of transfer increases by 5%.

Academic factors such as GPA and attending full-time also have a positive effect on
transfer. Females and African Americans enrolled in two-year institutions in Ohio in 2001 had a lower probability of transferring within three years than whites or males respectively. Of all variables included in the model to describe the individual characteristics, such as gender, race, age, intent of transferring, enrollment status, number of credit hours completed in first year, and GPA, age has the greatest negative impact on transfer. However, the negative relationship between age and probability of transferring is mitigated to a large extent by the positive intent of the student. Based on the findings, two recommendations are made to improve the probability of transfer. First, at the institutional level, introducing transfer advising centers, using students who transferred successfully as “transfer champions”, and including transfer training in “introduction to college courses” may help increase the number of students who express an intention to transfer. Such activities serve the purpose of bridging the information gap as well as motivating students. Second, the state could offer financial rewards to the students to increase completion of a higher number of credits in the first year.

Approved: _____________________________________________________________

Valerie Martin Conley
Associate Professor of Counseling and Higher Education
DEDICATION

“Don't walk in front of me, I may not follow.
Don't walk behind me, I may not lead.
Just walk beside me and be my friend”-- Albert Camus

To all my friends who helped me reach where I stand today.
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CHAPTER ONE: INTRODUCTION

Two-year institutions of higher learning serve many functions, one of which is to prepare students to transfer to four-year institutions in pursuit of baccalaureate degrees (Cohen & Brawer, 1987). In Ohio, the demand for workers with a baccalaureate degree or above is projected to increase by 15% during the period 2002-2012 (Ohio Labor Market Information, 2007). State policy-makers are actively looking for ways to increase the number of baccalaureate degree holders. One strategy is to help students transfer from two-year to four-year institutions of postsecondary education. Creating a seamless structure that will allow students to transfer credits from one institution to another is one prerequisite to facilitate transfer. Another prerequisite is informing and encouraging students aspiring to transfer to use the infrastructure created (Ginzer & Simmons, 2008). The leaders at community colleges play a critical role in developing a culture of transfer that motivates students to aspire to attain a baccalaureate degree. Understanding the student characteristics and institutional factors that are associated with successful transfer could help campus leaders allocate resources to activities that encourage transfer. The main purpose of this research is to measure how the demographic and academic background of the students, and the variables that describe the institution that they attend, are related to the observed difference in their probability of transferring from two-year to four-year public institutions in Ohio. Most of the research conducted on transfer from two-year to four-year institutions focused on transfer rate from a single institution (Dougherty & Kienzl, 2006). The multi-institution studies that were conducted used datasets that are at least ten years old and the findings are not consistent about the effect
of individual and institutional characteristics on transfer (Dougherty & Kienzl, 2006; Grubb, 1991; Lee & Frank, 1990; Velez & Javalgi, 1987;). Although the research conducted at four-year institutions suggests strong relationships exist among background characteristics, institutional factors, and student success (Braxton, McClendon, & Hirschy, 2004; Goenner & Snaith, 2003), insights obtained from these research studies may not necessarily hold true for two-year institutions with large numbers of part-time, working, and adult students. As the proportion of students delaying entry into postsecondary education after graduating from high school increases, the role of factors such as academic preparation in high school may weaken and possibly, be substituted for by life experience and motivation of the students. The insights gained from this study may help academic and student service professionals, and policy makers develop appropriate interventions to help students transfer successfully and to help the campus leadership develop a culture that supports transfer.

Background of the Study

Despite making progress in baccalaureate degree attainment over the last two decades, Ohio still ranks poorly compared to other states and the nation. An estimated 23% of Ohio’s adult population age 25 years or above held a baccalaureate degree or higher in 2005, compared to the national average of 27% (The Performance Report for Ohio’s Colleges and Universities, 2006). Although the percentage of baccalaureate degree holders increased from 17% to 23% between 1990 and 2005, Ohio’s national ranking only improved from 39 to 38 (Ginzer & Simmons, 2008). Students leaving the state after completing high school or college, lower percentages of students enrolling in college, or lower percentages of students transferring from two-year to four-year
institutions can all potentially reduce the number of adults holding a baccalaureate degree in the state. In 2005, 1,641 more students left the state than those who entered to attend college (Measuring Up, 2006). Evidence suggests that the net number of students going out of state is relatively small compared to the total postsecondary enrollment of over 450,000; the lower proportion of baccalaureate degree attainment in Ohio, in all likelihood, is not because students go out of state to pursue their postsecondary education.

Between 1998 and 2005, the Fall headcount enrollments at university main campuses in Ohio grew by 3%, while the community and technical college enrollments grew by 26%. Growth in university regional campuses was 13% (The Performance Report for Ohio’s Colleges and Universities, 2006). The enrollment growth at community and technical colleges can help increase baccalaureate degree attainment if students transfer to four-year institutions in pursuit of a baccalaureate degree. Despite increases in enrollments in two-year institutions, baccalaureate degree attainment has not improved. One strategy for increasing the baccalaureate degree attainment of Ohio’s population is to help more students beginning at two-year institutions transfer to four-year institutions and complete baccalaureate degrees.

The gap between the number of students aspiring to transfer and the number of students actually transferring is quite wide. According to the Community College Survey of Student Engagement [CCSSE] (2006), 50% of community college students across the nation indicated that transferring to a four-year college or university was one of their primary goals. This self-declared primary goal has remained stable at over 50% for the past four years as reflected in the annual surveys (CCSSE, 2006). Research on national
data has consistently shown that the transfer rate from community colleges to four-year colleges and universities hovers between 20% and 25% (Dougherty, 1992; Ford Foundation, 1998; Hagedorn, Moon, Cypers, Maxwell, & Lester, 2006; Tinto, 1998). Among 2005 baccalaureate degree recipients at the public universities in Ohio, 17% transferred from a two-year college (The Performance Report for Ohio’s Colleges and Universities, 2006). It appears that only about half of the students intending to transfer actually end up doing so. This has remained unchanged over the past fifteen years.

With very little rigorous research available on institutional effectiveness in community colleges, the reasons for non-attainment of desired levels of transfer are not clearly identified (Jenkins, 2006). Although several researchers explored the relationship between individual and institutional characteristics and transfer using both single-institution and multi-institution datasets, the findings from these studies often do not agree with each other. On a broader context of student success, there is strong evidence that student background and institutional factors have influence on overall success in college (Braxton, Hirschy, & McClendon, 2004; Tinto, 1975).

Student Background, Institutional Factors, Success and Transfer

Several researchers have studied the relationship between student background characteristics, institutional factors and student success for four-year institutions (Astin, 1997; Braxton, Hirschy, & McClendon, 2004; Goenner & Snaith, 2003; Kroc, Howard, & Hull, 1995; Smith, Edminster & Sullivan, 2001). Alexander Astin’s research (1991, 1993, 1997) focused on the effects of students’ backgrounds on their potential to be successful in college. The studies found that individual characteristics have an important influence on students’ success, where success is measured by the institution’s graduation
rate. Braxton, Hirschy, and McClendon (2004) adopted Tinto’s (1975) interactionalist model of student persistence to show the relationship between student entry characteristics and persistence; their model also explored how institutional factors reinforce student goal commitment. In addition to students’ backgrounds, the characteristics of the institution, such as student-to-faculty ratios, percentage of full-time faculty, and total expenditures, all play a significant role in explaining student success parameters such as graduation rate (Goenner & Snaith, 2003; Kroc, Howard, & Hull, 1995). Although it is likely that student background characteristics and institutional factors will have a relationship with graduation rate as well as other outcomes of students enrolled in two-year institutions, not much research has explored this area. Between 1990 and 2003, only 8% of the articles published in five major referred journals of higher education even mentioned community colleges (Townsend, Donaldson, and Wilson, 2005).

Student success and transfer are not synonymous for those enrolled at two-year institutions. Many students enroll at two-year institutions with an intention to acquire short-term training or a certificate. Yet, transfer remains one of the major goals of students enrolled in two-year institutions. Hoachlander, Sikora, and Horn (2003) observed in their analysis of National Educational Longitudinal Study:1988 (NELS:88) data that out of all high school graduates of 1992 who enrolled in a community college within two years, 63% stated their aim was to complete at least a baccalaureate degree. In a more recent analysis of Beginning Postsecondary Students (BPS:96) data, 78% of first-time college students entering public two-year colleges in 1995-96 had a goal to complete at least a baccalaureate degree (Kojaku & Nunez, 1998). It is not possible to
determine how firm or realistic the self-declared goals are; however, they cannot simply be dismissed. Transfer to a four-year institution is one of the critical success factors for students attending two-year institutions.

The research findings from four-year institutions cannot be assumed to hold true in two-year institutions in their entirety because the student population that attends two-year institutions differs in many ways from those who enroll in four-year institutions. A higher proportion of community college students attend part-time, and work for a significant number of hours (Achieving the Dream, 2005). The problem is further complicated by the rapid changes in the student population enrolling in community and technical colleges in the last ten years (American Association of Community Colleges [AACC], 2006).

Research literature on transfer is dominated by institutional studies that focused on transfer rate for one specific two-year college. The multi-institution studies conducted on national datasets such as Velez and Javalgi’s 1987 analysis of the National Longitudinal Survey of the High School Class of 1972 (NLS-72), Lee and Frank’s 1990 study of High School and Beyond (HS&B), Hoachlander, Shikora, and Horn’s 2003 analysis of National Educational Longitudinal Study (NELS:88), and Grubb’s 1991 study of both NLS-72 and HS&B are at least ten years old. During this period, the student population attending two-year institutions has changed considerably. The changed student demographic emphasizes the need to conduct current analyses on single as well as multi-institution datasets to validate or refute earlier findings between student background, institutional factors and transfer.
Research on transfer conducted over the last two decades on multi-institutional datasets shows that the role of factors such as race and age on transfer has changed over time. Not much is mentioned about the changing role of gender on transfer (Dougherty & Kienzl, 2006). The surveys used by studies conducted a decade ago focused on students entering college right out of high school. The selection disallowed the examination of transfer rates of students who delayed their college entry by a year or two. As more students who delayed their college entry enter community colleges, it is important to know how the life experience gained by the student: (a) influences performance at the community college, and (b) relates to the probability of transferring.

Few studies have examined the effect of individual factors on student success after controlling for the institutional effects (Bailey, Calcagno, Jenkins, Kienzl, & Leinbach, 2005; Wassmer, Moore, & Shulock, 2004). Studies typically either aggregate the individual factors to the institutional level, or disaggregate the institutional factors to the individual level. If institutional factors are distributed uniformly to all students in an institution, it assumes relationships observed in groups hold true for individuals (Freedman, 2001). Aggregating student data to draw inference about institutional factors leads to the reverse problem, where it is assumed that all individuals behave the same way in an institution (Hox, 2002). Also, the studies using national datasets have not controlled for the influence of individual state policies on transfer (Jenkins, 2006).

This study is significant because it determines how the individual and institutional factors are related to the probability of transfer and how the relationship changes with the changing demographics of students in Ohio. The shortage of trained workforce is identified as a critical issue in Ohio. In order to develop a workforce ready for the jobs of
the future, Ohio needs to increase the number of baccalaureate degree holders. In his strategic plan, the Chancellor of the University System of Ohio has set a goal of increasing baccalaureate degree awards from 37,816 to 52,000 from 2006 to 2017 (Ohio Board of Regents, 2008). The findings from this study will help identify potential solutions to increase the number of students transferring from two-year to four-year institutions, and contribute to developing a trained workforce in Ohio.

Research Questions

An understanding of student background characteristics and institutional factors associated with successful transfer is necessary for developing an institutional culture of transfer, and student centered transfer advising policies. This study examines the relationship between selected individual and institutional factors and the probability of transfer and how the relationship changes when institutional factors change. The research questions are as follows:

1. Do the academic indicators -- full-time attendance, number of credits completed in the first year, and GPA at the time of transfer -- increase the probability of transfer in Ohio?

2. Do African American, Hispanic, female, or older students have a lower probability of transfer in Ohio compared to their white, male, and younger counterparts? Does positive self-declared intent to transfer improve the probability of transfer?

3. Do increases in size, retention rate, graduation rate, a higher ratio of full-time to part-time faculty, less distance between start and transfer institutions, lower percentage of students receiving need-based financial aid, higher percentage of full-time students,
and higher number of credits accepted by transfer institutions increase the probability of transfer?

4. By what percentage does the probability of transfer increase (or decrease) if any of the individual and institutional factors included in Questions 1, 2, and 3 are allowed to vary?

5. Does the probability of transfer for two students with similar background attending two institutions with different characteristics change with changes in the institutional variables mentioned in Question 3? If the probability does change, what are the institutional factors associated with the change and what is the magnitude of the change?

Purpose of the Study

This study has three purposes. The first purpose is to determine how and to what extent do individual and institutional factors affect the likelihood of transfer from two-year to four-year public institutions in Ohio between 2002 and 2004. The intended outcome of the study is to determine: (a) if the explanatory variables of interest are positively related with transfer; and (b) to what extent probability of transfer changes for change in the explanatory variable.

The second purpose of the study is to measure how changes in individual characteristics affect transfer in different institutional contexts. Institutional context is determined by selected institutional factors such as size, percentage of full-time students, percentage of male students, percentage of students over 24 years old, retention rate, graduation rate, ratio of full-time to part-time faculty, the distance between start and transfer institutions, the number of transfer credits accepted by the transfer institution,
and percentage of students receiving need-based financial aid at the start institution. Two students with similar individual backgrounds studying at different institutions may have different probabilities of transfer depending on the institutional variables. Such differences in outcome are attributed to student-institution fit (Banning & McKinley, 1980; Painter & Painter, 1982; Pascarella & Terenzini, 1991, 2005). Theory of student-institution fit posits that congruence of individual characteristics and institutional factors result in higher performance and lower stress (Pervin, 1968). A positive fit may increase the probability of success of a student, while a negative fit may work otherwise. The strength of relationship will be measured by the increase or decrease in the probability of transfer for every unit change in the institutional factors, when student background is controlled.

The third purpose of this study is to advance the literature pertaining to transfer, with particular emphasis on community and technical colleges in Ohio. Empirical research exploring the relationship among student background, institutional factors, and transfer is often inconclusive (Bailey et. al., 2005; Bailey & Weininger, 2002; Dougherty & Kienzl, 2006; Lee & Frank, 1990, Wassmer et al., 2004). The difference in findings may stem from variation in state policies when national datasets were used to model the relationships. Also, the findings of multi-institutional studies on transfer conducted in the 1980s and 1990s may not hold true in the present context, as the student population has changed over the last ten years (AACC, 2006; Achieving the Dream, 2005). By confining the dataset to all community college in Ohio, this study will ensure that the effect of state policies on transfer is uniform for all the institutions and allow exploration of the relationship between student background, institutional factors and transfer.
Significance of the Study

Three of the key stakeholders in the transfer process include: students, two-year institutions, and four-year institutions. Most state policies focus on creating an infrastructure that facilitates transfer of credits from one institution to another. Developing transfer articulation guidelines and creating common course numbering systems are examples of establishing a transfer infrastructure. Pursuant to passage of House Bill 95 in 2004, the public institutions in Ohio have undertaken major curriculum reform. Aligning the curriculum between two-year and four-year institutions, and creating an infrastructure to facilitate credit transfer are all positive steps taken by the state of Ohio. The Course Applicability System (CAS) directly supports student advising functions by providing course equivalencies and identifying the courses that can be transferred (Ohio Board of Regents, 2008). However, mere existence of a transfer infrastructure may not increase the transfer rate. Encouraging students to use the available infrastructure should complement the infrastructure development and curriculum alignment process and help increase the transfer rate. This study is significant because it seeks to help institutions develop student centered transfer advising strategies based on an understanding of the role of student background and institutional factors on the probability of transferring.

Most of the existing studies explored the relationship between factors such as academic preparation in high school, race and transfer. In the last ten years, a higher proportion of students are delayed enrollment in two-year institutions for a few years after graduating from high school (Achieving the Dream, 2005; Dougherty & Kienzl,
2006; Wellman, 2002). As more non-traditional or older students enter postsecondary education several years after graduating from high school, the effect of academic preparation in high school may be expected to be a weaker predictor of success in college. In addition, the motivation of the student to succeed may play an important role in student success. A study conducted by Jack Kent Cooke Foundation found that community college students who did not do well in high school could make up for the lack of preparation and transfer to prestigious institutions to pursue their baccalaureate degree aspirations (Dowd, Bensimon, Gabbard, Singleton, Macias, Dee, Melguizo, Cheslock, & Giles, 2006). Intent to succeed and a demonstrated ability to achieve success by completing a large number of credits may all be positively related to transfer. As more non-traditional students enter community colleges, it is important to understand the relationship among age, motivation, and transfer behavior. This study will contribute to understanding this relatively unexplored area.

Scope of the Study

Students were selected for the study based on the following criteria:

1. Enrolled in a postsecondary institution for the first time in or after 2000.
4. Have accumulated at least 12 semester credits in their first year.

The age is restricted between 15 and 50 in order to exclude the outliers that may skew the results. In the absence of any universally accepted definition of transfer, Cohen’s (1991) framework for defining transfer is adopted with some modifications. The modifications are made keeping in mind the purpose and scope of the study. Cohen
introduced the idea of 12 credits as the common denominator to calculate transfer rate. Cohen defines transfer rate as “all students entering the community college in a given year who have no prior college experience and who complete at least twelve college units [at the community college] divided into the number of that group who take one or more classes at an in-state, public university within four years” (Cohen, 1991, p 3). More than 15 years have passed since Cohen proposed this definition and student demographics have changed significantly in this period. For example, several students now enroll at two institutions simultaneously, adding another complexity to defining transfer rate.

Students who have been enrolled in postsecondary institutions for two years are included in this study in order to capture students who may have stopped out of postsecondary education after graduating from high school. Students who stop out are different from those who drop out. The stop outs leave because of temporary problems of continuing in college; their focus remains on returning to college. As working adults enroll in community colleges in higher proportions, the number of students who may need to stop out because of different life situation also increases. Therefore, an attempt is made to include the students who may stop out. While Cohen’s definition allows for inclusion of students who have transferred within four years, this study restricts the upper limit to three years. Since students who may have been enrolled in a postsecondary institution for two years are included, this study tracks transfer behavior of students for five years after initial enrollment, instead of four years suggested by Cohen. Transfer behavior is tracked for a longer period because the adult students that enroll in community colleges are more likely to stop out than the students ten years ago.
The choice of dataset has confined the scope of this study to only students transferring from two-year public institutions to four-year public institutions in Ohio. Students transferring to private institutions or those moving to another two-year institution are not captured in this study. However, 35% of students transfer from two-year to four-year public institutions (Government Accountability Office [GAO], 2005). Therefore, this research covers the largest group of transfer students.

Limitations of the Study

Every research study using secondary data sources, such as this one, shares some important advantages and disadvantages. The rigorous process followed to compile the data is one of the advantages of a secondary dataset. In contrast to randomized controlled experiments that are designed to attribute causality to specific interventions, but often have limited scope to generalize the findings, large-scale secondary datasets are designed to enhance generalizability. Large-scale datasets also allow for predictive analysis and tentative causal inference (Schneider, Carnoy, Kilpatrick, Schmidt, & Shavelson, 2007). The student dataset used for this study is collected by The Ohio Board of Regents as a part of its Higher Education Information (HEI) data collection system. Thus, the data are expected to be consistent. One disadvantage of using secondary data is it restricts the choice of variables.

The independent variables have been selected on the basis of existing research literature. However, the absence of a large volume of research on multi-institutional datasets of community colleges and transfer, and changing demographics of the community college students influenced the selection of variables. One variable not included in the study is academic preparation in high school. Studies conducted on
datasets from the 1990s explored the relationship between high school performance and transfer (Bailey & Weininger, 2002; Lee & Frank, 1990); however, this study does not include high school preparation as an independent variable because academic preparation in high school is not expected to have a strong relationship with transfer for students who enroll in postsecondary institutions a few years after graduating from high school. Although this study does not focus only on students who delayed entry or stopped out, the average age of students in the study is 24 years. This is discussed in detail in the “Significance of the study” section. Performance in the two-year institution and motivation to succeed may have a stronger relationship with transfer for older students. Variables that represent academic ability are included in the model, however. For example, grade point average (GPA) and number of credits completed in the first year are used to represent the academic performance and commitment of the students respectively. The study focuses on the academic performance in community colleges rather than in high school.

The intention code recorded in the dataset is self-reported by the students at the time of enrolling in a postsecondary institution. It is not clear how firm or realistic these goals are. Also, any changes in the intention of the student subsequent to enrollment are not updated in the dataset. However, several studies found that a large percentage of students declaring a positive intent of transferring do not end up transferring (Hoachlander, Sikora, & Horn 2003; Kokaju & Nunej, 1998).

Allocation of financial resources by an institution is a measure of its commitment to achieve specific objectives. Few studies have modeled the relationship between institutional factors and transfer in the recent past. Therefore, the factors that may have a
positive relationship with transfer are not identified clearly. In the absence of an understanding of the factors that may have a positive relationship with transfer, the allocation of fiscal resources to promote transfer is difficult to define. An exception to this is direct investment in transfer training courses or centers. The information on institutional investment in transfer-specific activities is not available from the existing data sources.

This study excludes the students who have gone out of state, enrolled in for-profit institutions, or enrolled in not-for-profit private institutions after beginning their postsecondary education at a community college. In 2005, a net of 1,641 postsecondary students left Ohio to pursue higher education elsewhere. The number of students leaving the state is small enough to not significantly affect the results. The effect of state policy on transfer is uniform for all institutions in Ohio. Therefore, by confining the selection of institutions to Ohio only, the effects of state policy on transfer has been eliminated.

Academic and social integration are integral aspects of student success (Braxton, 2000; Tinto, 1993). The dataset used for this study did not include variables that measure conditions one would expect to be consistent with a commitment to academic life. Talking to faculty outside of class, number of hours spent on homework, talking to academic advisors, visiting the career and placement office, are all consistent with a commitment to academic life. Data on these parameters are not available at the state level. Surveys such as CCSSE collect information associated with academic integration. Two difficulties associated with the use of CCSSE data are: (1) CCSSE data are not available for all institutions in Ohio because the surveys are not mandatory, and (2) the data collected in CCSSE surveys are self-reported by the students. Although year-to-year
comparison of CCSSE results can indicate important trends, such data may not be
extrapolated to the institutions that have not used CCSSE. Also, at least one study found
that factors such as the number of contacts with faculty outside the classroom, attending
career oriented lectures, or talking to academic advisors did not have a significant
relationship with transfer (Dougherty & Kienzl, 2006). The dataset selected for this study
includes information of nearly all students attending all but one public institution in Ohio.

Finally, the dataset made available by the Ohio Board of Regents did not include
students from Zane State College, where the researcher is currently employed, to ensure
confidentiality of the students. This institution only enrolls approximately 350 students
every fall; therefore, the omission of the students from this institution should not skew
the results significantly. There are other institutions in the geographic area where Zane
State College is located. Thus, there will not be an issue of non-representation of a
region. Any student record so specific that the individual can be identified is not included
in the dataset to protect the confidentiality of the student.

Definition of Terms

Delayed entry students: Students who did not enroll in college in the fall term following
high school graduation, irrespective of their age.

Individual characteristics: Attributes associated with an individual student such as race,
gender, age, intent to transfer, grade point average, number of credits completed in
the first year, attendance pattern (full-time or part-time).

Institutional characteristics: Attributes associated with an institution, such as size,
gradiuation rate, ratio of full-time to part-time faculty, percentage of full-time to part-
time students.
Late bloomers: Students who discover their academic potential or capacity after leaving primary education (Pak, Bensimon, Malcom, Marquez, & Park, 2006).

Level-1 variables: All individual characteristics.

Level-2 variables: All institutional characteristics.

Start institution: Postsecondary institution where the student was enrolled in 2001. This may or may not be the first postsecondary institution attended by the student.

Student background: Individual characteristics associated with a student.

Student success: Accomplishing the stated or implied goal of the student, such as completion of a degree or certificate, persisting from one year to another, transferring to a four-year institution in pursuit of a baccalaureate degree.

Traditional student: A student under the age of 19 who enrolls directly into college on a full-time basis in the fall term following high school graduation.

Transfer infrastructure: Systems and procedures created by the state governing body to facilitate transfer, such as transfer articulation agreements and a common course numbering system.

Transfer institution: Four-year institution where the student transferred between 2002 and 2004.

Organization of the Study

This research is organized in five chapters. The first chapter provides an introduction to the problem associated with transfer from two-year to four-year public institutions in Ohio, discusses why it is important to study this problem, introduces the research questions, and explains the purpose, significance, scope, and limitations of the study. The second chapter explores the research literature pertaining to transfer, and the
role of student background and institutional factors on student outcomes. Student outcomes include attaining a degree, transferring to another institution, persisting from one term to another, and successfully completing credit courses. The third chapter explains the conceptual framework and research methodology, including an explanation of datasets and variables. The results are presented in chapter four. The fifth and final chapter includes the conclusions of the research, as well as a discussion of the implications for policy formulation and future research directions.
CHAPTER TWO: REVIEW OF THE LITERATURE

Organization of the Chapter

Review of the literature begins with a discussion of the changing role of transfer in the mission of community colleges during the last century. This section is followed by a synopsis of the changing relationship between student background, institutional factors, and transfer during the last twenty years. Comparison of results from different studies on transfer is complicated by the absence of a universally accepted definition of transfer (Cohen, 2005). The problems associated with transfer rate are presented in the next section titled “The complexity of transfer rate”. While using a widely accepted definition of transfer to calculate transfer rate, researchers observed that transfer rate varies across states, institutions, and student groups. The differential rate of transfer points to a probable relationship between state policies, institutional factors, student background and transfer. The literature pertaining to the relationship between individual characteristics, institutional factors, student-institution fit, and transfer is presented in the section “Three strands of Research on Transfer”. A discussion of the theoretical perspectives of Astin and Pace related to student involvement, and quality of effort, and how the theories relate to transfer precedes the chapter summary.

Community College and Transfer

One of the fundamental missions of community colleges is to facilitate baccalaureate degree attainment by providing initial years of college education and aiding transfer from two-year to four-year institutions (Brint & Karabel, 1989; Cohen & Brawer, 2003; Dougherty, 1994; Dougherty & Kienzl, 2006; Romano & Wisniewski, 2003). The
initial argument to create public junior colleges in the 1890s was to provide an alternative option for the first two years of instruction of a four-year degree (Brint & Karabel, 1989). During the first five decades of their existence, community colleges helped to reduce the demand on universities by offering lower-division work (Cohen & Brawer, 2003). Between 1900 and 1930, democratization of public schools, rapid industrialization, and establishment of research universities influenced the functioning of community colleges (Deegan, Tillery & Associates, 1985). The scope of operation of the community colleges expanded during this period. However, preparing the liberal arts students to transfer to a four-year institution remained a main focus (Brint & Karabel, 1989).

After World War II, a paradigm shift took place in the operation of community colleges in the United States. A large number of students took advantage of the GI Bill and started attending institutions of postsecondary education. New courses in technical, professional, and remedial education began to emerge (Cohen & Brawer, 2003; Deegan, et al., 1985). The scope of operation of community colleges changed further when the legislation in most states established an open-door admissions policy for community colleges (Deegan, et al., 1985). The open-door legislation required that community colleges admit all applying high school graduates (Roueche & Hurlburt, 1968).

In order to support the increasing enrollment as a consequence of the open door policy, community colleges began making technical, vocational, occupational, and community education a higher priority than transfer (Cohen & Brawer, 2003). Among students entering community college right after high school, the rate of transfer to a four-year college dropped from 29% in 1972 to 20% in 1980 (Grubb, 1991). Eaton (1994) argued that less emphasis on transfer during the 1960s and 1970s, change of emphasis on
programs of study, and changing enrollment patterns limited the social mobility of community college students.

The decrease in the transfer rate from community colleges to four-year institutions gave birth to a contentious debate over the last several decades (Brint & Karabel, 1989; Clark, 1960; Christie & Hutchinson, 2003; Cohen & Brawer, 2003; Dougherty, 1987, 1994). Although as early as in the 1930's, a large number of students entering junior colleges were unable to transfer to four-year institutions due to lack of academic rigor or lack of transfer articulation agreements (Deegan, et al., 1985), the long standing debate on the academic preparation of students enrolling in community colleges gained momentum following the enactment of open door admissions policies. Scholars have argued that community colleges actually created a class structure among postsecondary education in the United States (Bowles & Gintis, 1976; Dougherty, 1987; Karabel, 1972). According to Pascarella and Terenzini (1991, 2005), attending a community college lessened the chances for a student to attain a baccalaureate degree. Critics contended that instead of providing access, the community colleges protected universities from the economically and academically under-prepared students, thereby creating class inequality and channeling students into the same lower class positions of their parents (Brint & Karabel, 1989; Clark, 1960).

Advocates for community colleges argued that the open door admissions policies and the transfer function of community colleges allowed students from academically and economically challenged classes an option to acquire postsecondary education (Cohen & Brawer, 2003). In a meta-analysis of the literature on this controversy, Dougherty (1987) noted that both arguments have some merit, but concluded that evidence points somewhat
in favor of supporting the argument that community colleges enforce class structures. In a more recent study, Melguizo and Dowd (2006) found that community college students from lower socio-economic backgrounds who transfer to selective four-year institutions are more likely to graduate than students with similar backgrounds that started their postsecondary education in four-year institutions.

In the last decade, there has been a renewed interest in transfer by researchers and practitioners. State governments encouraged students to start their postsecondary education at community colleges and transfer to four-year institutions in order to make postsecondary education more cost-effective for both the state and the student (Ignash & Townsend, 2001; Wellman, 2002). The average cost of attendance, measured by in-state tuition and fees, at a two-year public institution in Ohio for academic year 2006-07 was $3,505 compared to $8,553 at a four-year public university (The Performance Report for Ohio’s Colleges and Universities, 2006). Therefore, beginning postsecondary education at community colleges and transferring to universities helps reduce the overall cost of higher education. In Ohio, community college enrollment has grown by 26% compared to 3% at universities between 1998 and 2005 (The Performance Report for Ohio’s Colleges and Universities, 2006).

Although interest in transfer from two-year to four-year institutions has been renewed recently, researchers are divided in their findings on how individual student background and institutional factors are related to the probability of transfer. The problem is further complicated because the demographics of students that are enrolling in two-year institutions are changing rapidly, calling for re-evaluation of the relationship between student background, institutional factors, and transfer. Few research studies have
explored how the change in student demographics has affected transfer in the recent past. In the following section, the datasets and variables used in the research studies on transfer, and how the factors that are related to transfer have changed during the last two decades are summarized.

Student Background, Institutional Factors, and Transfer

While much of the research on transfer comes from single institution studies (Romano & Wisniewski, 2003), some researchers have used national datasets such as the National Longitudinal Survey of the High School Class of 1972 (NLS-72), High School & Beyond 1990 (HS&B), the National Longitudinal Survey of Youth (NLSY), and the National Educational Longitudinal Study: 1988 (NELS:1988), and the Beginning Postsecondary Students Longitudinal Studies (BPS:90 & BPS:96) (Dougherty & Kienzl, 2006). Studies of the NLS-72, HS&B, and NLSY found that race, socio-economic status, and gender all were significantly related to transfer (Lee & Frank, 1990; Surette, 2001; Velez & Javalgi, 1987).

None of these studies used age as an independent variable to determine its relationship with transfer behavior (Dougherty & Kienzl, 2006). This is probably due to the fact that community college students in the 1970s and 1980s were not much different from traditional students in terms of age. Over the last decade, attendance patterns in community colleges have changed drastically. The so-called “traditional” full-time undergraduate under age 19 and residing on campus now account for just 16% of the U.S. postsecondary student population. Instead, the majority of today’s postsecondary students are working adults attending community colleges and other institutions of postsecondary education (National Community College Symposium, 2007). The changing population
attending community colleges necessitates re-evaluation of the demographic factors that affect transfer (Dougherty & Kienzl, 2006).

Research on transfer for traditional age students also emphasizes the importance of prior high school achievement and degree aspirations for college success and persistence (Adelman, 1999; Bailey et al., 2005; Bailey & Weininger, 2002; Ehrenberg & Smith, 2004; Lee & Frank, 1990; Wassmer et al., 2004). Adelman (1999, 2006) has identified the inability to maintain continuous enrollment; withdrawing, dropping, or not completing courses; not completing an AA degree before transferring; and external demands such as work and family as some of the key factors that impede student success and persistence. Hall (1990) found that self-motivation is one of the most important factors in student success. In an analysis of successful student transitions from two-year to four-year institutions in the state of New York, Ehrenberg & Smith (2004) suggested that information on academic background such as grade point average, number of credit hours transferred, number of credit hours completed, and scores on standardized tests should be taken into consideration as factors that affect transfer. However, not many two-year institutions require students to submit scores on standardized tests due to their open admissions policy.

Existing research on transfer has focused on students who enrolled in college immediately after high school, and has explored the relationship among academic performance in high school, race, socio-economic status, and transfer. In the last ten years, more students are delaying entry into two-year colleges and are gaining life experience between high school graduation and postsecondary education (Achieving the Dream, 2005). The role of factors such as preparation in high school may be less relevant
for these students and life experience may play a greater role in contributing to their success in two-year institutions. Moreover, as the students delay their entry into postsecondary education, they lose touch with academic institutions. The non-traditional students need more advising and institutional support to reestablish their connection with the institutions (Achieving the Dream, 2005). However, the level of support services available to transfer students varies from one institution to another.

Although the overall transfer rate has declined slightly in the last three decades, there is variance in transfer rates between institutions. A study initiated by the American Association of Community Colleges found that institutional bureaucracy, lack of collaboration/communication between institutions and inadequate student advising are some of the major barriers to transfer (Improving access to baccalaureate, 2004). Transfer students often face socio-cultural adjustment issues when they leave a closely knit community college environment to embark on a more independent lifestyle in a university (Braxton, 2000; Davies & Casey, 1999). Transfer-oriented advising can help students adjust to such transitions. The need for such advising is expected to increase as more students delay their entry into community colleges. The effectiveness of two-year institutions in preparing students for transfer has not been explored rigorously (Jenkins, 2006).

Apart from advising and inter-institutional collaboration, mission, size, wealth, complexity, productivity and selectivity are among the institutional factors that affect student success (Pascarella, 1985). The studies conducted on institutional factors and their relationship with transfer either aggregated the factors at the institutional level (Bailey et. al., 2005) or disaggregated them using the student as the unit of analysis
(Wassmer et al., 2004). None of these studies focused on how the individuals with similar backgrounds studying at different institutions are affected by institutional factors.

Efforts to understand the issue of community college transfer are further complicated by the variety of transfer patterns (Adelman, 2006; Townsend, 2001; Townsend & Dever, 1999). In the traditional sense, transfer refers to students going from a two-year institution to a four-year institution. Some students move back to a two-year institution from a four-year institution, a phenomenon referred to as reverse transfer. Many students move between two-year or four-year institutions. Several students enroll at multiple institutions simultaneously. There is also a trend of “swirling” students, who move back and forth between institutions (Adelman, 2006).

The comparison of results from one study to another is further complicated by the lack of a standard definition of transfer. Although scholars in general agree that it is important to calculate the extent to which community colleges contribute to the educational progress of students en route to the baccalaureate degree, there is no universally accepted methodology for calculating transfer rates (Bradburn, Hurst & Peng, 2001). The following section summarizes the issues pertaining to developing a common definition of transfer.

The Complexity of “Transfer Rate”

Theoretically, there are four possible transfer situations between two-year and four-year institutions: from a community college to a baccalaureate degree granting institution (2/4 transfer) and vice versa (4/2 transfer) as well as transfer from one two-year institution to another (2/2 transfer) or between two four-year institutions (4/4 transfer). The type of institution, public or private, provides another dimension of
categorization, and this does not take into consideration the “swirling” students who shift from one institution to another (Adelman, 2006). Data collected by the Beginning Postsecondary Students (BPS) Survey show that students do seek transfer in numerous directions.

Out of all first-time transfer students between 1995 and 2001, nearly 35% transferred from public two-year to public four-year institutions, followed by 16% each from four-year to four-year and two-year to two-year institutions. 11% of students reverse transfer, going from four-year to two-year institutions. Only 4% of students transferred from for-profit institutions to public or private not-for-profit institutions. The remaining 18% of transfer students are categorized under “all other” (GAO, 2005). The 2/4 transfer is not only the largest segment of transferring students, but also the most significant in terms of policy implications because “its success (or failure) is central to many dimensions of state higher education performance, including access, equity, affordability, cost effectiveness, degree productivity, and quality” (Wellman, 2002; pp. 3). Minority students and students from low income families are more likely to begin their postsecondary education in two-year institutions. In order to bridge the gap in educational attainment, it is critical for this group to be able to transfer successfully and complete their baccalaureate degrees (Achieving the Dream, 2005; Long, 2005; Wellman, 2002). Measurement of the flow of 2/4 student transfer is often used as an indicator of the community college's ability to accomplish its transfer goals and is a critical part of the community college mission although community colleges do not have complete control over the process of transfer.
Transfer rate is a ratio of students transferring from a two-year to a four-year institution to the total number of students eligible to transfer. The numerator, the number of students transferring, is more easily quantifiable, although capturing that information may present some challenges. For swirling students or students with concurrent enrollment at two campuses, the number of students transferring is difficult to define. When a student transfers to an out-of-state institution, the data capture process becomes even more complex.

The denominator is the potential number of students eligible to transfer and is difficult to define primarily because there are several parameters that can be used to define a transfer cohort. Factors commonly used to define transfer cohorts include number of credits completed before transfer, length of time attended, and progress towards degree completion (Bradburn, Hurst & Peng, 2001; Laanan & Sanchez, 1996, Wellman, 2002). The transfer rate indicator should give a performance benchmark that is understood by a broad audience and is feasible to compile in terms of time, cost and expertise (Choy & Carroll, 1998; Cohen, 1988; Spicer & Armstrong, 1996). However, agreeing on a valid definition is one of the most problematic aspects plaguing researchers (Brawer, 1991; Clagett & Huntington, 1992; Cohen, 2005).

From a policy perspective, lawmakers, journalists and researchers alike want to know the contribution of community colleges to the baccalaureate degree achievement of postsecondary students. Cohen (1996) contends that though the question is consistent, the answer may vary depending upon how the rate is calculated. Using different criteria for the denominator, the transfer rate for community colleges in California varied from 3.7% to 17.7%. The lack of agreement on the denominator has led researchers to compute
several transfer rates. As the denominator becomes more restrictive, the rate increases. Spicer & Armstrong (1996) compiled the following eleven possible denominators for calculating transfer rates:

1. All students new to the institution.
2. All first time college students.
3. All first time college students with a degree (AA, AS, certificate, baccalaureate) goal.
4. All first time college students who earned at least twelve units in a four-year period.
5. All first time college students with a transfer goal.
6. All first time college students with a transfer goal and who earned more than zero units.
7. All first time college students with a transfer goal and who earned twelve or more units.
8. All first time college students with a degree goal who attempted full-time units in their first term.
9. All first time college students who are transfer ready (completing freshmen English composition & mathematics courses transferable to four-year colleges and universities).
10. All first time college students with a transfer goal and who are transfer-ready.
11. All first time college students with a transfer goal who are transfer ready and who have completed at least fifty-six units.
Over the years, education researchers have defined transfer rate for themselves, thus making comparison of results from one study to another difficult (Wassmer et al., 2004). Transfer rates are perceived to be manipulated by researchers to fit the political, financial, and educational agendas (Cohen, 2005).

In their study of how different transfer rates highlight student characteristics, Bradburn, Hurst and Peng (2001) compiled transfer rates according to several definitions based on data from the Beginning Postsecondary Education Longitudinal Study (1990/94). Rates varied from 25% to 52%, depending on the denominator. It is necessary to have a uniform definition of transfer rate to compare results from one study to another. In the calculation of transfer rate, the denominator represents a level of commitment to transfer from the student perspective. The more committed the student, the more restrictive the denominator and consequently, the higher the rate.

The debate over the calculation of rate has continued because each measure takes into account specific factor(s) that impact transfer. For example, students who expressed interest in transferring are pre-disposed and to some extent, self-motivated to transfer. The challenges they face may differ from those faced by students who did not consider pursuing a baccalaureate degree at all. Essentially, the criteria applied to arrive at the denominator represent the location of the student along the educational pipeline. All students entering postsecondary education represents the beginning of the journey; every milestone, such as expressing an intention to transfer, earning at least 12 credits, earning fifty-six credits with a GPA of 2.0, represents the movement of the student towards the goal of transferring. The closer the student is to the goal, the higher the probability of transferring successfully.
To introduce uniformity in measurement of transfer rates, a common point needs to be identified along the transfer readiness pipeline. The Transfer Assembly Project, based at the Center for the Study of Community Colleges at the University of California at Los Angeles and headed by Arthur Cohen, is the longest standing initiative of analyzing transfer data. Cohen (1991) introduced the idea of completion of twelve credits as the criterion to calculate transfer rate. According to Cohen, a transfer rate can be most accurately calculated by including in it only those students who are beginning their postsecondary studies in a community college and who stay there long enough to complete at least four courses (12 credits). Cohen defined transfer rate as “all students entering the community college in a given year who have no prior college experience and who complete at least twelve college units [at the community college] divided into the number of that group who take one or more classes at an in-state, public university within four years” (Cohen, 1991; pp3).

Applying this formula, the average transfer rate was calculated as 22% for first-time students entering community colleges in 1990. The variation between states ranged from 11% to 40%; there were substantial variations within a state between individual community colleges. For example, California colleges experienced transfer rates ranging from 3% to 32% (Cohen, 1996). The difference in transfer rates between ethnic groups was also noticeable: 24% for Asians, 23% for Caucasians, 13% for African-Americans, and 12% for Hispanics (Bender, 1991; Cohen, 1996). In a different study, the Illinois Community College Board found a positive relationship between student intention and transfer. The Illinois study calculated a 22% percent transfer rate for all students, a 29% transfer rate for students enrolled in baccalaureate/transfer programs, and a 34% transfer
rate for students who enrolled in baccalaureate/transfer programs and who entered the community college with the stated intent of transferring in the year 1990 (Palmer, n.d.).

The variation of transfer rate within state, between state, and between student groups indicates that state policies, institutional factors, and individual student background all are related to transfer. The studies on single-institution datasets could not control for the relationship between state policies, institutional factors, and transfer. The single-institution studies, therefore, could not illuminate how individual background, institutional factors, and state policies are related to the probability of transferring. The studies involving national datasets that explored the relationship between individual background and institutional factors with transfer often came up with findings that were contradictory to one another. In the following section, findings from these studies are presented.

Three Strands of Research on Transfer

The findings of the studies exploring the relationship between individual student background and transfer often differ from one another. While some studies found race was related to transfer, other studies did not corroborate this finding (Bailey & Weininger, 2002; Lee & Frank, 1990). In a recent study, blacks were found to have a significantly lower probability of transfer than whites from similar socioeconomic background only when educational aspirations were controlled. The researchers controlled for educational aspirations because they argued that blacks have higher educational aspirations than whites from the same socio-economic background (Dougherty & Kienzl, 2006). Gender was found to affect transfer significantly in a study using the National Longitudinal Survey of Youth (NLSY) (Surette, 2001). A more recent
study found that although women have lower transfer rates than men, the difference was not statistically significant (Dougherty & Kienzl, 2006). The independent variables selected for the studies have also changed over the last twenty years. The earlier studies did not use age as an independent variable (Dougherty & Kienzl, 2006). Similarly, the findings from studies on the relationship between institutional factors and transfer do not always corroborate each other. Two studies that used the percentage of full-time faculty as an independent variable came up with two different observations: one study found a positive relationship between the percentage of full-time faculty and transfer while the other did not observe any relationship (Bailey et al., 2005; Ehrenberg & Zhang, 2004).

The research on individual background, institutional characteristics and transfer is divided in three areas: (a) individual student characteristics and transfer; (b) Institutional influence on transfer; and (c) Student-institution fit and its impact on transfer. These three strands of literature provide complementary theories and evidence about factors that influence student success in general, and transfer in particular.

Individual Student Characteristics and Transfer

A rich body of research literature focuses on the relationship between individual student background and academic outcomes. Research on nationally representative datasets such as the Beginning Postsecondary Students Longitudinal Study (BPS) and the National Educational Longitudinal Study (NELS) of 1988 have shown that input factors such as maintaining good high school records, coming from high income families, attending full time, and attending college immediately after high school all contribute to student success (Adelman, 1999, 2006; Astin, 1975, 1984; Bailey et al., 2005; Hungar and Lieberman, 2001; Lee & Frank, 1990; Wassmer et al., 2004). Most of these studies
explored the relationship between academic preparation in high school, and performance in college.

Lee and Frank (1990) studied the relative importance of social and academic background on the probability of transferring to a four-year institution. The study was conducted on a sample of 2,500 randomly chosen students who entered community college within two years of graduation from high school in 1980. Four years after graduation from high school, 24% of these students had transferred to a four-year college. The study found that factors describing the students’ academic performance in community college were the strongest predictors of transfer. The study drew data from the High School and Beyond (HS&B) database, a multipurpose nationally representative longitudinal study of American high school graduates. The HS&B study tracked 30,000 randomly selected high school seniors from 1,000 randomly selected high schools. The researchers selected a sample of 10,815 students from the HS&B dataset. The dataset also provided information on the sample at two additional points in time: two years and four years after they graduated from high school. The proportion of minority students in the population was relatively small. The researchers over-sampled the minority students to compensate for the low representation in the original data. The researchers identified a “transfer group” of 2,500 students. To qualify as a member of the transfer group, the subjects had to fulfill the following two criteria: (a) have enrolled in a four-year college full-time or part-time during any semester or quarter during 1982 to 1984 and (b) have attended community college before that time (Lee & Frank, 1990).

Lee and Frank (1990) developed the structural model with the assumption that performance in secondary education has a strong positive relationship with performance
in postsecondary education. According to the researchers, “the structural model was formed from more general theoretical and practical knowledge of the sociological relationships in the secondary and postsecondary educational domains” (p 181). Social background and high school performance influenced behavior and academic attainment in college and indirectly influenced the probability of transferring. Using a path analysis model, the researchers first evaluated the effect of student background on the students’ academically related high school behavior. The set of variables used to measure student background included social class, race and gender. The variables used to measure students' academically related behavior in high school included curricular track, attendance at a Catholic high school, homework done, number of academic mathematics courses taken, tenth-grade educational aspirations, and parents' interest in academically related activities. The combined effect of student background and high school behavior on high school outcomes was determined. High school outcomes were measured by academic achievement, GPA and whether the student applied for college while in high school. The effects of background, high school behavior and high school outcome on community college behavior was determined next. Factors that determined community college behavior included semester-hours of credit earned, semesters of full time attendance, college grades, the number of semesters in which mathematics and science courses were taken. Finally, the effect of all four constructs: background, high school behavior, high school outcomes and community college behavior on the probability of transfer was evaluated. The study found that the students who transferred were of a higher social class, were less likely to be minority or female, were more academically oriented, were more successful in both high school and community college and were less
likely to be working while attending college. Academic behavior in community college showed the “strongest direct effects on transfer” (Lee & Frank, 1990, p186). The direct effects of background factors on probability of transfer were found to be relatively weak. Also, academic behavior in high school exhibited a weak relationship with the probability of transfer. The results from this study show that even for students enrolling in postsecondary education immediately after high school, the relationship between academic performance in high school and probability of transfer is weak.

Bailey and Weininger (2002) provided contradictory evidence to the conclusion of Lee and Frank’s (1990) study, which held that ethnic minority students have lower transfer rates. Bailey & Weininger (2002) concluded that the presence of a high percentage of immigrant minority students in New York may have contributed to the different finding. For immigrant students who are otherwise academically well prepared, language is a barrier to success. Such deficiency is different from the inherent lack of academic preparation. African Americans were the only students more likely than white students to enroll in a community college once other factors were controlled. Also, immigrants who went to a U.S. high school were more likely than native-born two-year entrants to transfer to a bachelor's program, as were male immigrants who attended high school abroad. But immigrant students who enrolled in two-year institutions appeared to have higher levels of educational achievement than natives who were enrolled in the same programs. Irrespective of where they attended high school, immigrants earned more credits and were more likely to complete an associate degree. The researchers explained that the standardized test scores for the foreign-born students were not reflective of their academic ability because of their lack of English language skills. Once they acquired
proficiency in the English language, these students performed better than the natives who entered the same program. Race and ethnicity appeared to have a relatively small impact on the measures of educational success such as credit accumulation, completion of associate degree, or transfer. However, once the students had transferred to a four-year institution, race and ethnicity were found to be powerfully associated with graduation: both blacks and Hispanics were subject to a large reduction in the probability of degree completion. These factors remained significant even after controlling for cumulative pre-transfer GPA or receipt of associate degree. The research results indicate that the reduced odds of graduation by Hispanics and blacks cannot be attributed to either poorer preparation at the associate level or completion of associate degree (Bailey & Weininger, 2002). It is not clear why race does not play a role in performance in community college but becomes significant in a four-year institution.

Another study explored the impact of individual factors on transfer students in the late nineties using two national datasets, the National Education Longitudinal Study: 1988 (NELS: 88), and Beginning Postsecondary Students Longitudinal Study (BPS: 90) (Dougherty & Kienzl, 2006). The findings of this research were different from both the earlier studies conducted on the students transferring in the 1980s and early 1990s. Race was found not to have any statistically significant relationship with transfer. However, there was an important caveat to this finding in the case of blacks. When blacks and whites with similar educational aspirations and high school academic preparation were compared, “the black-white gap in transfer rates grows sharply, becoming statistically significant in the analysis of the BPS: 90 dataset” (Dougherty & Kienzl, 2006, pp 474).
This study found a significant impact of parental socioeconomic status (SES) on transfer. Another variable found to have an impact on transfer was age. Controlling for other variables, the researchers found that students entering community college between ages 21 and 30 were 15% less likely to transfer, and students 30 and above were 20% less likely to transfer than students entering college before turning 19. Given the fact that a large percentage of students entering community college in the last ten years are over 19, the relationship between age and transfer needs to be re-evaluated. Factors that indicate academic and social integration, such as, the number of contacts with faculty outside the classroom, attending career oriented lectures, or talking to academic advisors did not have a significant relationship with transfer.

A study of first time freshmen students from California community colleges who started their undergraduate education in 1996 and 1997 found that the race/ethnic composition of the student body had an impact on transfer (Wassmer et al., 2004). In the absence of unit level data, the researchers developed an institution-level model of factors on aggregate student characteristics and community characteristics. Transfer rate was defined as the ratio of transfers from a cohort to the total number of first time freshmen in the cohort. This definition restricted the scope of the analysis, but provided a uniform criterion to compare transfer rates across 108 campuses in California. The researchers used several regression models to estimate the impact of student cohort characteristics, college characteristics, and community characteristics on transfer rates. The student characteristics were percentage of enrolled students below 25 years of age, percentage female, percentage African American, percentage Asian American, percentage Latino, percentage Filipino/Pacific Islander, percentage temporary resident, percentage
uninformed transfer desire. The school characteristics included miles to nearest California State University (CSU) campus, number of students, academic performance index for recent freshmen, percentage degrees awarded in general studies or liberal arts/sciences. The community characteristics included county population density, county unemployment rate, percentage county high school students receiving reduced price meals, and percentage county high school students English language learners (Wassmer et al, 2004). Results showed that colleges with a high percentage of black or Latino students had a lower rate of transfer, even after controlling for academic preparation and socioeconomic status.

The studies discussed above use background characteristics of the student as input variables and predicted the output, transfer, or academic success based on the inputs. The results were hardly uniform. Academic preparation of the student in high school, and race were two variables used extensively in these studies. However, as the gap between high school graduation, and enrollment in postsecondary institution increases, the relationship between academic preparation in high school and probability of transfer may weaken. One of the studies found that older college entrants are less likely to transfer partly because of their lower educational aspirations. The proportion of older students enrolling in community colleges has increased steadily in the last decade. The relationship between variables such as age, educational aspiration, and transfer is likely to change with the transformation of student demographics. Not much research has explored how the changing student demographics are affecting the relationship between individual student background and transfer.
A second set of models explain the effect of institutional factors such as mission, size, wealth, complexity, productivity and selectivity on a variety of student outcomes including aspiration, educational attainment, career attainment and transfer. Astin conceptualized college outcomes along two dimensions: cognitive and affective. Cognitive outcomes refer to the measures having to do with utilization of higher order intellectual processes such as analysis, synthesis, reasoning, logic, and knowledge comprehension. Astin contends that students’ cognitive outcomes are most closely associated with the educational objectives of not only the student, but also of faculty, administrators, trustees, parents, and other constituents (Astin, 1973; Cueso, 2001; Pascarella, 1985). The faculty, administrators, and trustees collectively define and develop an institutional approach to educational objectives. The academic outcome of a student, therefore, is closely linked to the way an institution defines its educational objectives.

Extensive research exists on institutional determinants of educational outcomes for four-year institutions. However, few studies have been conducted on community college student performance (Townsend, Donaldson, and Wilson, 2005). Integrating individual student data from the National Educational Longitudinal Study: 1988 (NELS:1988) and institutional data from the Integrated Postsecondary Education Data System (IPEDS), scholars from Teachers’ College, Columbia University analyzed the probability of a student completing a certificate or associate degree, or transferring to a baccalaureate institution (Bailey et al., 2005). The approach of taking both institutional
and individual data into consideration helped the researchers estimate the institutional
effect while controlling for the individual factors. An initial sample of 2,438 students
from 686 community colleges was selected from the NELS: 88 dataset. Two statistical
models, pooled probit and random effect probit were used to analyze the data. The pooled
probit model assumes that the heterogeneity of students’ probability to graduate is only
affected by observable institutional variables. A limitation of this assumption is that the
effect of unobservable institutional variables such as leadership, faculty relations, and
local political environment are not taken into consideration at all. This is a problem area
for considering institutional factors in a quantitative model.

Several qualitative factors are hypothesized to have a significant role in student
outcomes, but these factors are hard to measure. To overcome this difficulty, the
researchers also estimated a random effects probit model; this model took into
consideration the institution-level unobserved factors that may affect the individual’s
propensity to graduate. Neither of these two models recognized the impact of multiple
institutions on student outcome, although it was observed that 40% of the NELS: 88
survey respondents attended multiple institutions. To account for the impact of multiple
institutions, a third model was created that assigned an index value for each institutional
factor as a weighted average of all the institutions attended.

Four categories of institutional variables were selected for the study: general
institutional, compositional, financial, and fixed location (Bailey et al., 2005). The
variables that could be controlled by the institutions directly were defined as general
institutional variables. Institutional size, proportion of part-time to full-time faculty, and
number of associate degrees and certificates conferred per year all belonged to this
category. Student composition factors considered in this study were measures of overall household income, percent of part-time, female and minority students. Other factors such as residential versus commuter students were not considered. Financial variables taken into consideration for the study were average federal aid per FTE, average undergraduate in-state tuition, average expenditures per FTE in instruction, academic support, student services, and administration. Fixed location factors described whether the school was in a rural, semi-urban, or urban area; the socio-economic level of the student body attending the institution also represented location factors. In general, the impact of institutional factors was more difficult to measure and the institutional characteristics were not as strongly related to the student outcome as the individual factors.

Factors describing individual backgrounds were used as control variables. A measure of socioeconomic status was derived from parental education, parental occupation, and total household income as available from the NELS: 88 dataset. Academic readiness was captured by using tenth-grade test scores. Gender, race, ethnicity, and declared major were used as measures of fixed control.

The study results showed that as school size -- measured by enrollment -- increased, graduation rates decreased (Bailey et al., 2005). This conclusion appears somewhat straightforward, as large size comes with the associated difficulty in creating a socially and academically engaging environment (Cejda, 1994; Pascarella & Terenzini, 1991, 2005; Toutkoushian & Smart, 2001). However, studies on size and engagement of four-year institutions have found that large institutions have a significant positive impact on persistence (Titus, 2004). This is explained by the belief that larger institutions have stronger institutional socialization capabilities and offer degrees possessing higher status.
The contradictory results of the two studies may partly be explained by the student-institution fit.

A second finding from the study was the negative relationship between a high percentage of part-time faculty and graduation rate (Bailey et al., 2005). Using part-time faculty is a cost-saving strategy often used in community colleges. However, findings on the impact of part-time faculty differed from one study to another. A study conducted by Ehrenberg and Zhang (2004) found that the percentage of part-time faculty had no effect on graduation rates. Stronger emphasis on occupational training or workforce development is also observed to reduce graduation rates in community colleges. Some researchers have argued that emphasis on direct occupational preparation can lower graduation and transfer rates (Brint & Karabel, 1989; Dougherty, 1994). The effect of financial factors was not found to significantly influence graduation and transfer rates (Bailey et al., 2005). Overall, the researchers found that individual factors are more strongly related to completion probabilities than institutional ones. They advanced the argument that individual factors may create barriers that are difficult to be scaled by effective institutional policies; however, the interaction of these two issues is difficult to quantify (Bailey et al., 2005). Also, individual factors are measured with a higher level of precision than institutional factors. How institutional variables may impact individuals with similar backgrounds attending different institutions is not clear from this research.

McDonough (1997) explored the influence of social background in shaping educational aspirations and college destinations of female high school students. She conducted a qualitative study to investigate whether social class limits the aspirations and outcomes of students. In general, students from lower social classes were expected to
defer their college preparation, apply to fewer colleges and restrict their choice set of colleges. U.S. Secretary of Education, Margaret Spellings’ Commission on the Future of Higher Education noted that escalating tuition and anti-Affirmative action campaigns have turned many elite schools into the domains of wealthy and white (Pluviose, 2007). There is an effort from elite institutions now to counter the trend by encouraging students from low income families to attend by providing additional tuition scholarships. A grant from the Jack Kent Cooke Foundation helped defray the cost of attending elite institutions for students from poor families. This grant, called Pathways to Success, places particular emphasis on community college students obtaining four-year degrees. One out of four undergraduates at Cornell University is expected to be a transfer student. Of the total number of transfer students, 33% came from community colleges (Pluviose, 2007). The success of community college students at prestigious institution such as Cornell University contradicts the theory that community colleges create a class structure among postsecondary students and contradicts the findings of McDonough that social class limits the educational outcomes (Dowd et al., 2006).

The relationship between social background and access to postsecondary education opportunities has been studied by a number of researchers (Dougherty & Kienzl, 2006; Hearn, 1984, 1991; Karen, 2002,). Hearn used data from the University of California’s Cooperative Institutional Research Program (CIRP) to study the college destination patterns of high school students. While factors such as socioeconomic class and race played a role in college choice, Hearn also found a strong relationship among institutional quality, academic programs, tested ability and the selectivity of college destinations (Hearn, 1984). In a follow up study conducted on the data from HS&B,
Hearn (1991) found that academic experience is the primary determinant of attending a more selective institution. Hearn used standard regression coefficients to estimate the relationship between a student's tested ability and the selectivity of institution attended. The model developed by Hearn was tested by Karen (2002) almost a decade later. Using data from the National Educational Longitudinal Survey (88:94), Karen (2002) confirmed that academic ability plays a critical role in student’s choice of college; factors such as race, potential income, and parental education are also very important.

A new perspective on distance between start and transfer institutions was propounded by McDonough (1997). She investigated how the institution shapes or lowers the expectation of its students using a qualitative research methodology involving high school students. High school districts serving students from lower socio-economic status guided students to community colleges, or regional universities rather than more selective universities, even though the students had adequate academic preparation. This lowering of expectations is demonstrated by the difference between the concept of "distance" among students from varying socio-economic background. Students from upper socio-economic background defined distant locations as more than two hours by air. The students from lower socio-economic background viewed these distances as inaccessible by car (McDonough, 1997). The self-concept attributed to socio-economic class is reinforced by institutional behavior at high school. Building on these findings, it makes sense to suggest that the community colleges play a critical role in developing the self concept of its students. The role of physical distance between start and destination institutions and transfer needs to be explored.
Most of the studies that explored the relationship between institutional factors and transfer were conducted on datasets collected in the 1980s and 1990s. The researchers explored the relationships between institutional variables such as size, selectivity, graduation rate, percentage of full-time faculty, percentage of minority students, percentage of students above 24 years, and transfer. The student composition in community college has changed since these studies were conducted. It is not known if the conclusions reached by these researchers are still valid.

*Student-Institution Fit and its Impact on Transfer*

A third group of literature developed models targeted at explaining the impact of student-institution fit on student outcomes (Banning & McKinley, 1980; Painter & Painter, 1982; Pascarella & Terenzini, 1991, 2005). How a fit between the student and the institution can increase probability of transfer is not explored specifically in these models, although transfer is one of the major outcome measures of community college students. Perhaps this is because not much research exists on student-institutional commitment in the two-year sector (Strauss & Volkwein, 2004). A review of these models shows that institutional commitment plays an important role in student goal accomplishment (Painter & Painter, 1982; Williams, 1985). Although these models focus more on student retention than on transfer as an outcome measure, they illuminate how institutions can help students get involved to increase the possibility of success in general. An understanding of these models is helpful to know how student-institution fit can help transfer also.

This research stream postulates that colleges and universities establish conditions to attract, and retain students and challenge them to develop the qualities of an educated
person. Educational environments exert an influence before the students enter an institution. Such influence is recognized in the degree of attraction or repulsion felt by a student towards a particular environment (Strange & Banning, 2001). Educational institutions that recognize human dynamics and take into consideration the impact of the human environment on learning are expected to have higher impact on learning outcomes of the students (Dewey, 1933). Providing the right kind of match between the student and the institution maximizes the chances of personal satisfaction and safety. Student persistence and growth depends on the degree of successful integration into the academic and social cultures of the institution (Braxton, 2000; Diaz, 1992; Graham & Hughes, 1994; Spady, 1970, 1971; Strange & Banning, 2001; Tinto, 1993). Creating environments that identify and support the need of the students is an important step towards engaging the student.

Prior to 1980s, institutions focused their attention on matching demographic characteristics of entering students with the students who persisted to graduation (Williams, 1985). The demographic characteristics were often limited to high school grade point average and standardized test scores, and to a lesser extent, parent’s income and occupation. Such an approach of matching student characteristics with the institution assumed that students who do not match the profile of previously successful students are deficient in some manner (Banning & McKinley, 1980). The inherent flaw in this approach is when the student body changes from its predecessors, not many entering students are expected to match demographic characteristics of the previously successful students. Empirical evidence also contradicts the validity of this approach. When departing students were surveyed, most commonly cited reasons for departure were: “(a)
lack of fit between expectations regarding campus life and their experience at the institution; (b) few opportunities to develop friendships; (c) lack of fit between ability and academic expectations; and (d) unavailability of student support services” (Painter & Painter, 1982; pp. 88-92). The reasons cited by the students identify student-institution fit issues that can be addressed by targeted interventions (Williams, 1985). The observations suggest that institutions should focus on developing interventions aimed at increasing the probability of student-institution fit.

If institutions assume that students are unable to pursue their academic goals because of a lack of adjustment and not due to some inherent deficiency, the institutional efforts can be aimed at helping the student adjust to the campus environment (Banning & Kaiser, 1974). This approach shifts the focus away from providing an environment that encourages traditional students to developing an institutional atmosphere that supports non-traditional students with different needs. This student-centered way of thinking does not suggest that every student issue can be attributed to campus environment. However, with careful assessment, some of the student problems can be linked to the campus environment. Unless a significant portion of the student body experiences the problem, institutions need not invest their resources to intervene and solve such problems (Williams, 1985). Pace’s (1980) work provides an understanding of the issues that need to be considered to develop interventions aimed at increasing student-institution fit.

Pace (1980) attempted to explain the underlying reasons of dissatisfied students in terms of student-institution fit: (1) “students entering college with unrealistic expectations about the environment are more likely to have problems adjusting and are more likely to withdraw; (2) students who perceive campus environment as friendly are more likely to
be satisfied with college; (3) when congruency or fit exists between student personality characteristics and institutional characteristics, student objectives are more likely to be achieved" (pp. 91-92). When both institutional and student expectations are aligned appropriately, student-institution fit is at its best. Older, non-traditional students may find it easier to integrate on a campus with a higher percentage of non-traditional students.

Institutions can help students via interventions aimed at matching students with appropriate groups. At a large institution, the initiatives may be present, but a match may not take place because of size. A smaller, closely-knit institution may be better at assessing individual needs, but the ability to fulfill those needs may be restricted by size. In a large institution, the possibility of fit would increase because of the presence of different student groups. However, finding the appropriate group may become more challenging in such a situation. Size can play either a positive or a negative role in student success. In any case, specific efforts from the institution to advise students about the institutional climate and manage student expectations may be necessary to ensure students persist in the institution and achieve their academic goals. Student advising is expected to play an important role in increasing the probability of student-institution fit; however, quantifying the factors that identify the fit is difficult.

Using institutional characteristics that may align student expectations with institutional environments is expected to increase probability of student-institution fit. In order to accomplish such a fit, total campus environment should be carefully and systematically defined and assessed. Thereafter, data must be used as the basis to advise students as well as redesign the campus environment (Williams, 1985). Systematic
assessment of a campus environment is best approached through the theoretical concept known as person-environment interaction.

The conceptual framework of person-environment interaction models developed by Kantor (1924), Lewin (1935), and Murray (1938) suggests that individual and environment shape each other. When individuals and their environments are congruent with their self-perceived personality characteristics, higher performance, greater satisfaction, and reduced stress occurs (Pervin, 1968). This approach is based on the assumption that major discrepancies between perceived and actual self is unpleasant to an individual and the individuals become negatively disposed to the environmental factors that distance them from their perceived self. Institutions should encourage students to consider how they view themselves in a number of different dimensions, such as physical, social, and intellectual. An assessment of campus environment may reveal that the campus may not hold much potential for success for specific students (Williams, 1985). The criteria used to measure campus environment may include factors such as population of students over a certain age, proportion of minority students, or proportion of students receiving need-based financial aid. However, quantifying factors that measure social, and intellectual dimensions of students and establishing the positive impact of student-institution fit may be challenging, as is evidenced by existing research.

Nichols (1964) attempted to align student academic growth in college with campus environment. National Merit Scholarship Qualifying Test (NMSQT) score was used to control for academic ability of 356 students who attended 91 different institutions. The scores of the students on the Graduate Records Examination (GRE) were used to measure academic aptitude of the student after attending the institutions. The
results indicated little relationship between institutional characteristics and academic achievement. The findings of this study seem to suggest that institutional atmosphere, and student-institute fit did not influence academic outcome, unless it is assumed that student-institute fit was uniform in all the cases. A limitation of this study was the low number of participants from each institution: 356 students attending 91 institutions averages out to less than four students per institution.

Astin (1968) conducted a similar study on 669 students attending 38 colleges. Astin also used the score in NMSTQ to control for academic ability prior to attending college. However, he used the score in GRE Area Tests as the output measure. The areas tested were social sciences, humanities, and natural sciences. Astin concluded that “traditional measures of institutional quality do not appear to contribute to student achievement” (pp. 661).

Centra, Rock and Linn (1970) built upon the studies of Astin and Nichols to measure how campus environments influence learning. They sampled a larger population of students, used several measures of academic ability, and most importantly, used the institution instead of the student as the unit of analysis. One of their research objectives was to measure if “input quality of student ability was held constant, will identifiable groups of colleges have graduates with higher average achievement than others?” (pp.111). The researchers used seven measures to define the campus atmosphere:

1. Number of books in the library
2. Library books per student
3. College income per student
4. Faculty to student ratio
5. Proportion of faculty with doctorate degrees

6. Full time equivalent enrollment

7. Expenditure per student

Using data from 6,855 students attending 95 small institutions, the researchers concluded that a high proportion of differences between colleges were predictable from academic aptitude of the students at entrance. However, two factors that contribute to campus environment were found to have a significant positive relationship with student learning: (1) college income per student and (2) the proportion of faculty with a doctorate degree. The findings from this study do not illuminate if student-institute fit or institutional characteristics caused the improved student performance.

A model developed by Chickering (1969) suggested that interactions with major socialization agents on campus, e.g. faculty and peers, are particularly important sources of student development. DeCoste (1966, 1968) conducted two experiments addressing the influence of student peer culture on achievement. The studies found that high aptitude students living in proximity of other high aptitude students had significantly higher cumulative achievement than their counterparts living in close proximity with students of varied aptitude. This result illuminates the positive impact of high aptitude students. The positive impact of peer-group influence was confirmed by studies conducted later (Duncan & Stoner, 1977; Pascarella & Terenzini, 1982).

More recent studies by Dowd & Cheslock (2006) have found some evidence to suggest that low SES community college students who transfer to elite institutions are more likely to graduate than the low SES students who started their postsecondary education at four-year institutions. This study found that the environment of community
colleges did not appear to be a barrier to these students. Students from low SES background who started their postsecondary education in four-year institutions did not benefit from the traditional academic environment as their graduation rate was lower than their counterparts who transferred from two-year institutions. The study does not explain what specific factors may contribute to the superior performance of community college students.

Another important construct of socialization on campus is the interaction between student and faculty. Pascarella and Terenzini’s (1978, 1980) student-faculty informal contact model emphasizes the importance of informal contact between faculty and student. The model suggests that student background characteristics interact with institutional factors. The interactions between student and the faculty impact satisfaction with the university, educational aspirations, intellectual development, and academic achievement. Environmental factors such as finances, opportunity to transfer, and socialization with friends also leads to institutional commitment or dropout. A more recent study conducted by Dougherty and Kienzl (2006) did find a weak negative relationship between academic integration factors such as contact with faculty members and transfer.

Although theoretical models indicate that student-institution fit increases student retention and other measures of success, variables that define institutional climate are hard to quantify. The problem has been complicated by the fact that when improvement in student performance is noticed, it remained unclear if such improvement was due to institutional characteristics, student-institution fit, or some other unobserved characteristic. Non-availability of consistent and comparable information across multiple
institutions required to conduct student-institution fit studies imposes another barrier to conducting such studies. Unless performance of similar students attending different institutions is compared, the impact of student-institution fit on student success may remain unknown. However, an understanding of student-institution fit reinforces the importance of advising to create a bonding between the student and the institution. Overall, the models on student-institution fit suggest that managing physical, social, and intellectual expectations of the students and aligning these expectations with the campus climate can improve the probability of student success, and transfer. Theoretical works of Astin (1975, 1984) and Pace (1980) provide a framework for connecting the students with the campus environment to aid student development.

Theoretical Background of Student Involvement and Quality of Effort

Astin’s (1975, 1984) theory of student involvement is concerned with behavioral mechanisms that facilitate student development. The three cornerstones of Astin's theory are as follows:

1. The psychological and physical time and energy of students are finite.
2. The time devoted to a goal is proportionate to involvement
3. The state of "involvement" is different from motivation. While motivation represents a psychological state, involvement signifies the behavioral manifestation of that state.

A longitudinal study of college dropouts serves as the foundation of the theory (Astin, 1975). Astin found that students who: (a) devote considerable energy to studying, (b) spend much time on campus, (c) participate actively in student organizations, and (d) interact frequently with faculty members, and other students are likely to remain in college. Conversely, (a) a student who neglects studies, (b) spends little time on campus,
(c) abstains from extracurricular activities, and (d) has infrequent contact with faculty members or other students is more prone to drop out of college. Student involvement refers to the amount of physical and psychological energy that the student devotes to the academic experience. Astin claimed that “it is not so much what the individual thinks or feels, but what the individual does, how he or she behaves, that defines and identifies involvement” (1984, pp. 298). This theory “can explain most of the empirical knowledge about environmental influences on student development that researchers have gained over the years” (Astin, 1984, pp. 297).

Lanaan (2004) used Astin’s theory of student involvement to explain the role of adjustments to a new environment for students transferring from two-year to four-year institutions. Upon transferring, the students are required to adopt to a changing social, psychological, financial and academic environment quickly in order to be involved in academic endeavors and to be successful. If the students are actively engaged in the academic process and campus life immediately after transfer, they are more likely to succeed. From this perspective, community colleges should involve the students in several activities before they transfer. In other words, the community colleges should begin with an element of "transfer training." Such training is aimed at orienting the aspiring transfer student to the environment of the four-year institution (Lanaan, 2004).

The positive impact of transfer training centers was observed in an initiative funded by the Illinois Board of Higher Education (IBHE). Twenty-five community colleges were funded to set up minority transfer centers that served nearly 25,000 students annually. The efforts of these centers increased the transfer rate for African Americans and Hispanics by 12.7% and 38.6% respectively between 1990 and 1994.
While these large percentage increases may be a result of a low base to begin with, the centers reported an overall increase of 3.4% in total community college student transfers during this period (Zamani, 2001). Other researchers have found a positive effect of participation in study groups and transfer (Dougherty & Kienzl, 2006). Zamani (2001) found students who had high levels of involvement at the community college and who are prepared beforehand to accept the challenges at the four-year campus will likely continue their involvement after transferring. From a measurability standpoint, Astin's theory suggests that independent variables such as social demographics and community college involvement will influence or explain the academic and social adjustment process of the transferring students (Laanan, 2004, Zamani, 2001).

Astin’s theory of student involvement illuminates how community colleges can train the students to be successful in a four-year campus after transfer. However, such institutional initiatives can realize their full potential when complemented by the student initiative. Pace (1992) argued that “accountability for achievement and related student outcomes must consider what the institution offers and what the students do with those offerings” (pp.4). Pace’s (1980, 1984) concept of “Quality of Effort” (QE) is grounded in the belief that the quality and extent of effort that students put into academic experiences determines what they get out of an institution. Two students with different levels of preparation, socioeconomic background, attitude towards education and family support may be exposed to the same educational institution and yet perform at different levels. This is because the learning ability as well as effort put towards learning differ from one student to another. Essentially, this approach recognizes that fulfillment of academic goals depends as much on the institutional context as on the individual
characteristics of the student. Pace’s approach shifts the responsibility of learning from
the institution and makes the students accountable for their actions.

For transfer students, the extent to which they are involved and spend quality time
in various activities should impact outcomes that include satisfaction, involvement, and
adjustment. It is important, however, to take into account the unique environment of the
community college and the extent to which it differs from a four-year university. Several
researchers contend that four-year institutions expect a higher level of academic
commitment from the students and attending community colleges reduces the possibility
of baccalaureate degree attainment of the students (Dougherty, 1987; Bowles & Gintis,
higher expectation levels and involving them in institutional activities from community
colleges will likely facilitate a smooth transition to four-year institutions (Lanaan, 2004).

Summary and Conclusion

Existing research indicates that factors that describe student background such as
age, gender, race, intent to transfer, attendance pattern (full-time or part-time), number of
credits transferred, and GPA all have an effect on transfer (Bailey & Weininger, 2002;
Lee & Frank, 1990; Dougherty & Kienzl, 2006). The results are often contradictory about
the relationship between the factor and its effect. Since these studies are conducted over a
period of nearly two decades, and on populations from different parts of the country, it is
difficult to determine if the differences in findings are due to inherent variations among
the population characteristics or if the relationships evolved over a period of time. Studies
that explored the relationship between institutional factors such as size, selectivity,
retention rate, graduation rate, ratio of part-time to full-time faculty, percentage of
students receiving need-based financial aid, and transfer did not concur with one another (Bailey et. Al., 2005; Ehrenberg & Zhang, 2004; Wassmer et. al., 2003). Few studies quantified the extent of the effect or compared the magnitude of the effects of different factors.

Studies conducted over the last two decades indicate that the relationship between individual factors and transfer has changed over time. The changing mission of community colleges and renewed interest in two-year to four-year transfer in the recent past may also have contributed to the differences in findings. While the majority of studies were conducted on data from a single institution, most of the multi-institution studies were conducted on datasets in the 1990s. As community college student demographics have changed over the last ten years, the relationship between individual characteristics, institutional factors, and probability of transfer needs to be re-assessed.

Most of the multi-institution studies used national datasets such as the National Educational Longitudinal Survey, the Beginning Postsecondary Student Survey, or High School & Beyond. All these datasets include institutions from several states. Every state has its own policies that affect transfer. The studies on national datasets did not control for the variations due to the state policies. Studies conducted on a dataset from a single state can eliminate the effect of state policy and focus on the relationship between individual characteristics, institutional factors, and transfer.

The impact of institutional policies on all students is not necessarily uniform. Institutional factors are aggregated in several studies for the purpose of analysis. This approach assumes that all students attending an institution are similarly affected by institutional policies. No study has observed the effect of individual factors with change
in institutional variables. For example, one of the studies found that the probability of transfer is related inversely to the age of the student; older students are less likely to transfer than their younger counterparts, holding all other individual factors constant (Dougherty & Kienzl, 2006). The researchers did not explore if this behavior was consistent across all institutions. There is a possibility that specific institutional factors may mitigate the effect of age on transfer. In order to observe the institutional effect, transfer behavior of students of the same age studying in different institutions need to be considered. This can be done by treating individual and institutional variables separately (Ehrenberg & Smith, 2004).

In the next chapter, a model to assess the relationship between individual characteristics, institutional factors and probability of transferring from two-year to four-year public institutions in Ohio is developed and the research methodology is elaborated.
CHAPTER THREE: METHOD

Research Questions

The purpose of this research is to identify the individual and institutional factors that are correlated with student transfer from two-year to four-year public institutions in Ohio and to determine the degree to which these factors are related to transfer. Existing research suggests that both individual background and institutional factors affect student transfer. Although all students attending an institution have an opportunity to be exposed to the same institutional factors, the impact of institutional factors on the individual students from different backgrounds and with different levels of academic preparation may not be the same. The issue of student-institution match plays an important role in shaping the outcome. In Ohio, the transfer rate from two-year to four-year institutions varies by institution type (The Performance Report for Ohio’s Colleges and Universities, 2006), giving rise to the possibility that the inter-relationship between individual and institutional factors is not uniform for all students. This research is intended to answer the following five questions:

1. Do academic indicators -- full-time attendance, higher number of credits completed in the first year, and higher GPA at the time of transfer -- increase the probability of transfer in Ohio?

2. Do African American, Hispanic, female, or older students have a lower probability of transfer in Ohio compared to their white, male, and younger counterparts? Does positive self-declared intent to transfer improve the probability of transfer?
3. Do increase in size, retention rate, graduation rate, a higher ratio of full time to part time faculty, less distance between start and transfer institutions, lower percentage of students receiving need-based financial aid, higher percentage of full time students, and higher number of credits accepted by transfer institutions increase the probability of transfer?

4. By what percentage does the probability of transfer increase (or decrease) if any of the individual and institutional factors included in Questions 1, 2, and 3 are allowed to vary?

5. Does the probability of two students with similar backgrounds attending two different institutions change with changes in the institutional variables such as size, retention rate, graduation rate, a higher ratio of full time to part time faculty, less distance between start and transfer institutions, lower percentage of students receiving need-based financial aid, higher percentage of full time students, and higher number of credits accepted by transfer institutions? If the probability does change, what are the institutional factors associated with the change and what is the magnitude of the change?

By disaggregating the probability of transferring for different student groups, this study will help institutional leaders develop student centered advising strategies.

Conceptual Framework

Individual and institutional characteristics contribute to the initial commitment of students towards transfer. An understanding of the relationships between individual characteristics and the probability of transfer will help the transfer training staff develop specific advising strategies that increase the goal commitment of the student and
simultaneously help the student find appropriate destination institutions. For example, the transfer advising staff may encourage a first generation minority student to transfer to an institution with a high proportion of minorities, if it is known that such an institutional choice will help the minority student adjust to the new environment relatively easily. However, if the probability of transferring does not depend on the race of the student, the transfer advising centers may not consider the racial composition of the student population at the destination institution as a selection criterion. Similarly, if students with specific characteristics are not known to have a high probability of transferring, the transfer advising center can work more closely with those students to help them overcome the barriers they may face.

The individual student background, institutional characteristics, and student-institution fit determine the initial goal commitment of the student towards transfer. Involving the student in the academic activities in the campus will contribute to improving academic performance of the student. The relationship between improved academic performance and transfer will be measured by the model. The institutional initiative to involve the student in academic activities is complemented by the effort put in by the student. Active advising and transfer training is expected to increase the aspiration of the student to attain a baccalaureate degree. The relationship between increased aspiration and probability of transfer will be determined by the model.

Transfer aspirations of the students cannot be fulfilled without adequate infrastructure that facilitates transfer of credits and identification of transfer destinations. The state of Ohio has been investing in developing an infrastructure that facilitates transfer. Although it is necessary to have the infrastructure to transfer successfully,
creating an infrastructure will not improve transfer unless students take advantage of the infrastructure created. The students will have to be made aware of the existing infrastructure for transfer. The more student-centered the guidance, the higher the probability of successfully using the transfer infrastructure. The theory of student-institution fit emphasizes the importance of student-centered advising.

The conceptual model for this study is shown in Figure 1.

Figure 1: Conceptual model of transfer.
In order to develop student-centered advising strategies, it is necessary to understand how student background and institutional factors are related with transfer. By estimating the probability of transferring with the variables that describe the student background and institutional characteristics, this model will help develop a framework for improving transfer. For example, if it is known that completing higher number of credits in the first year increase probability of transferring, students can be given incentives to attain a minimum number of credits in the first year.

This model departs from the earlier studies in two ways. First, it explores the relationship between individual variables and transfer, while taking into consideration that individuals with similar characteristics enrolled in different institutions may have different probabilities of transfer. This estimation is done using hierarchical linear modeling (Bryk & Raudenbush, 2002). Second, this model does not use the performance in high school as one of the explanatory variables for transfer. Earlier studies have found that high school preparation does not have a strong correlation with transfer (Dowd et al., 2006; Lee & Frank, 1990). As students delay their enrollment in a postsecondary institution after graduating from high school, the relationship between high school preparation and transfer is expected to weaken. The model explores, among other variables, the relationship between performance in community college, and transfer. The relationship between age and transfer is also explored in this model.

The existing research on transfer used varied methodology to explore the relationship among individual characteristics, institutional factors, and transfer. In general, the studies were inductive in nature, attempting to relate student background and institutional effects with transfer. The factors that make up student background and
institutional effect differed from one study to another and the factors changed over the period of the last twenty years. Based on the findings, the studies formed some tentative hypotheses about relationships between the factors and transfer and ended up with general conclusions. The current study builds on the previous research by using some of the variables that were not included before and by separating the relationships of individual and institutional effects on transfer.

Four analytical models are used for this study to examine the relationships between individual characteristics, institutional characteristics, and transfer. The first model, also known as the null model, does not include any independent variables and explores if probability of transfer indeed varies from one institution to another. The level-1 and level-2 models include individual and institutional variables, respectively, to determine which of these variables are significantly correlated with transfer. Finally, the fourth model includes all the variables that are found to have a significant relationship with the probability of transfer. The fourth model allows both individual and institutional characteristics to vary and determines how the probability of transfer changes with each independent variable, when all other independent variables are controlled.

Data Source and Population

The original dataset (n=463,950) included information on every student who was enrolled at a public institution in Ohio in 2001, irrespective of when they started their postsecondary education. Out of the entire student population, 202,789 students, nearly 43%, were enrolled at two-year institutions. The percentage of students enrolled at the two-year institutions is similar to the national student statistics. During Fall 2001, 45% of all U.S. undergraduates were enrolled in community colleges (National Center for
Education Statistics [NCES], 2003). According to the scope of the study, students who satisfied the following three criteria were selected:

1. First-time enrolled in a postsecondary institution in or after 2000
4. Completed at least 12 semester credits in their first year.

Seven percent of the total number of students enrolled in postsecondary institutions in Ohio fulfilled all three selection criteria. The final population of 32,922 students was selected for the study. The selection method and number of students satisfying each of the three selection criteria is shown in Table 1.

Table 1
Student selection

<table>
<thead>
<tr>
<th>Selection criteria</th>
<th>No. of students</th>
<th>% of students</th>
</tr>
</thead>
<tbody>
<tr>
<td>All students enrolled in public institutions in Ohio in 2001</td>
<td>463,950</td>
<td>100%</td>
</tr>
<tr>
<td>All students enrolled in 2-year public institutions in 2001</td>
<td>202,789</td>
<td>43%</td>
</tr>
<tr>
<td>All students enrolled in a 2-year public institution in 2001 who started postsecondary education in or after 2000</td>
<td>79,242</td>
<td>17%</td>
</tr>
<tr>
<td>All students enrolled in a 2-year public institution in 2001 who started postsecondary education on or after 2000, completed at least 12 credits in the first year, and were above 15 years and below 50 years of age</td>
<td>32,922</td>
<td>7%</td>
</tr>
</tbody>
</table>

The number of students from this group transferring to public four-year universities and branch campuses during 2002, 2003, and 2004 is shown in Table 2. Out of the 32,922 students selected, 4,870 transferred to a four-year institution, 10,010 did not
transfer, and 18,042 were not enrolled in 2004. Among the students who transferred, 42% transferred in the first year, another 36% transferred in the second year, and the remaining 22% transferred in the third year. The student data file consisting of 32,922 records is used as the level-1 data file for hierarchical linear modeling (HLM).

The institutional data were collected from The Performance Report for Ohio’s Colleges and Universities (2002) and validated based on the data available from the National Center for Education Statistics website (NCES, 2007). All variables were continuous. The file consisting of the variables of 22 two-year institutions is referred to as the level-2 data file. Student data for one institution in southeastern Ohio where the researcher works are not included in the study.

Table 2
Transfer and enrollment pattern of students selected for the study

<table>
<thead>
<tr>
<th>Selection criteria</th>
<th>Frequency</th>
<th>Valid %</th>
<th>Cumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cohort studied: Enrolled in a 2-year institution in 2001, between 15 &amp; 50 years of age, completed at least 12 credits in first year</td>
<td>32,922</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Out of the cohort, following students:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transferred in 2002</td>
<td>2,036</td>
<td>6.2</td>
<td>6.2</td>
</tr>
<tr>
<td>Transferred in 2003</td>
<td>1,754</td>
<td>5.3</td>
<td>11.5</td>
</tr>
<tr>
<td>Transferred in 2004</td>
<td>1,080</td>
<td>3.3</td>
<td>14.8</td>
</tr>
<tr>
<td>Remained enrolled in same institution in 2004</td>
<td>10,010</td>
<td>30.4</td>
<td>45.2</td>
</tr>
<tr>
<td>Not enrolled in 2004</td>
<td>18,042</td>
<td>54.8</td>
<td>100.0</td>
</tr>
</tbody>
</table>

The data for this study are collected from three sources. Variables describing individual students are obtained from the Ohio Board of Regents Higher Education
Information data file. The records of students from Zane State College, the institution where the researcher works, were excluded from the dataset to protect confidentiality of the students. Also, any observation where the number of students belonging to a particular demographic description was so low that their individual identity could be traced was eliminated from the dataset to keep the student information confidential.

The institutional characteristics were obtained from performance reports published by the Ohio Board of Regents and the National Center for Education Statistics (NCES). All public institutions report aggregate level institutional information to NCES through the Integrated Postsecondary Education Data System (IPEDS). Data are collected by NCES three times during the year and are available to the public through its website. The institutional information was retrieved from IPEDS Institutional Characteristics Survey (IPEDS, 2007). The Ohio Board of Regents collects individual student data for all students enrolled in public postsecondary education institutions in the state. The Annual Performance Report is prepared from the individual student data by Ohio Board of Regents staff. This report provides institutional information such as the percentage of full-time faculty, percentage of students receiving Pell grants for all public institutions. The report is available from the Ohio Board of Regents website (The Performance Report for Ohio’s Colleges and Universities, 2002). The institutional data for the year 2001 were collected to align the individual and institutional data at the same time frame.

Variable Selection

Based on the review of literature, independent variables were selected to describe demographic background, academic preparation and institutional factors. While selecting the variables, particular attention was given to factors such as age that are associated with
the changing demographics of students enrolling in community colleges. Existing studies are inconclusive about the effect of race or gender on transfer; some studies concluded that females have a lower probability of transferring. Intent has been found to have a significant impact on transfer. As students are delaying enrollment in community colleges for a few years after graduating from high school, number of credit hours completed in the first year and GPA are selected as indicators of academic performance instead of academic preparation in high school, a variable used in earlier studies.

Among the institutional variables, existing research is inconclusive about the relationship between size and percentage of full-time students with transfer. The proportion of students receiving need-based financial aid is included as a proxy measure of socioeconomic status. Institutional variables such as the percentage of full-time faculty, percentage of students receiving need-based financial aid, size, retention rate, and graduation rate are included.

**Dependent Variable**

The dependent variable for this study is the binary outcome of transfer: a student who has transferred is coded as 1. For all students who have not transferred, the outcome on transfer is coded as 0. The reason for not transferring can be completion of academic objectives, drop out, stop out, or continuation at the start institution. The two-year institution attended in 2001 is referred to as the start institution and the four-year institution where the student subsequently transferred is called the transfer institution. Since a binary, dichotomous variable rarely follows a normal distribution, a transformation function was used to convert the binary outcome to a continuous probability distribution (Bryk & Raudenbush, 2002).
**Independent Variables**

_Demographic variables:_ Individual factors are measured at the student level. For the purpose of this study, individual factors are divided into two classes, one based on demographic information, and the other based on academic preparation. Variables categorized under demographic information include _gender, race, age_, and self-declared _intent_ of transferring. All of the variables except _age_ are binary variables. _Age_ is coded as a continuous variable.

The dataset contained information on five races: white, black, Hispanic, all other - not including Hispanic, all other - including Hispanic. In this study, three variables are used to indicate race: white, black, Hispanic. Each of the races is defined as a binary variable, with values of zero or one, depending on whether the student belonged to a particular race. For example, a binary variable called _black_ is set equal to 1, while all other race variables are set equal to 0 when the student is African American. _Gender_ is coded as a binary variable, with the values of 0 for male and 1 for female.

Transfer _intent_ is recorded in ten different ways in the original dataset given by the Board of Regents. The codes are as shown in Table 3.

Table 3 (continued on p. 84)

<table>
<thead>
<tr>
<th>Intent Code</th>
<th>Original Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>04</td>
<td>To transfer before completing a degree or certificate.</td>
</tr>
<tr>
<td>1</td>
<td>06</td>
<td>To obtain an associate degree for transfer.</td>
</tr>
<tr>
<td>1</td>
<td>08</td>
<td>To obtain a bachelor's degree.</td>
</tr>
<tr>
<td>0</td>
<td>01</td>
<td>To obtain knowledge for personal interest.</td>
</tr>
<tr>
<td>0</td>
<td>02</td>
<td>To upgrade skills for current job by taking only selected courses.</td>
</tr>
</tbody>
</table>
These ten codes were organized into two categories. The students coded 04, 06 and, 08 indicated a clear intent to transfer. The intent of students coded 01, 02, 03, 07, and UK is not clear; they may or may not have the intent to transfer. The responses 04, 06, and 08 are coded as 1 and all other responses are coded as 0.

In the original data, intent is recorded at the time the student enrolls at an institution. Fewer than 12% of the responses on intent were reported “UK” or unknown. In the remaining 88% of the cases, student intent was recorded in the dataset. Therefore, missing response is not a problem in using this variable.

*Academic preparation:* The independent variables used to determine academic preparation included *enrollment status (full-time or part-time), the number of credit hours completed in first year*, and *GPA* at the time of transfer. The determination of enrollment status (part-time or full-time) is based on the number of student credit hours attempted at the start institution. The National Center for Education Statistics defines a full-time student as one enrolled for at least 12 quarter or semester credit hours; the same definition is maintained to determine student enrollment status. Enrollment status is coded as binary, with 0 indicating part-time and 1 indicating full-time. The other two variables, student GPA and *number of credit hours completed during the first year* are continuous.
Institutional factors: The variables in this group are associated with the start institution. The impact of size, percentage of full-time students, percentage of male students, percentage of students over 24 years old, retention rate, graduation rate, ratio of full-time to part-time faculty, the distance between start and transfer institutions, the number of transfer credits accepted by the transfer institution, and percentage of students receiving need-based financial aid at the start institution are used as independent institutional variables to determine how they affect transfer. Size is a continuous variable measured by the headcount at the start institution during the year 2001.

Selection of Statistical Method for Data Analysis

The independent variables that are included in the model are collected at two levels. All independent variables that describe the individual student are called level-1 variables and all variables that describe the institution are called level-2 variables. Since each student attends an institution, all level-1 variables are nested into the level-2 variables. In the case of students with concurrent enrollment at two campuses, the campus where the student takes the most number of courses is considered as primary.

There are two approaches to analyzing multi-level data using regression analysis. Either all higher level variables are disaggregated uniformly to the lower level unit or all lower level variables are aggregated to the higher level unit (Bryk and Raudenbush, 2002; Luke, 2004). Both of these approaches impose limitations on the ability to analyze the data. Standard regression analysis is limited in its ability to provide reliable results for multi-level data for several reasons.

First, the approach to disaggregate the data presupposes that relationships observed in the higher level uniformly hold for the lower level uniformly. For example, if
an institutional variable such as the percentage of full-time faculty helps students transfer, the impact is assumed to be the same for all students attending that institution. This may not necessarily be the case. There is a possibility that having a higher percentage of full-time faculty members helps full-time students to transfer but does not affect the part-time students. Such generalizations about the uniform impact of a higher level variable on a lower level one are known as ecological fallacies (Freedman, 2001) and is a shortcoming of the approach to distribute the higher level variables uniformly. The lower level variable is assumed to hold a uniform relationship even when the context defined by the higher level variable changes (Luke, 2004).

Second, aggregating the lower level variables to the higher level poses the reverse problem. In this case, an individual behavior is expected to hold true for a group. The influence of the group on the individual behavior is not taken into consideration. For example, the probability of transfer for female students may depend upon the overall percentage of female students attending an institution. Therefore, for institutions with a higher percentage of females, the probability of transfer will go up for all individual females. Two female students attending two different institutions with different percentage of females in the student population may have different probabilities of transfer. Individual characteristics tend to be lost when data are aggregated because of grouping effects and make observations less precise (Bryk & Raudenbush, 2002). Such generalizations are known as atomistic fallacies (Hox, 2002).

Disaggregating group level data leads to two statistical problems. First, the group level factors provide a background to any analysis. In any statistical model, part of the variance of the outcome variable is not attributed to any input factor. The part that is not
modeled is captured in the error term. By disaggregating the group level data, all un-modeled information gets pooled into the error term (Duncan, Jones & Moon, 1998). Individuals belonging to the same sample are expected to have correlated errors: for example, students belonging to a particular race may face similar difficulties in transferring. The un-modeled part of this behavior will get pooled into the error term. Pooling of correlated errors violates one of the basic assumptions of multiple regression analysis. The second problem is that the aggregation approach does not recognize the context and the regression coefficients are applied equally to all contexts. This in effect implies that all individuals behave in the same way in different contexts. The contextual effects are sacrificed in such a situation (Luke, 2004).

Multi-level data are best analyzed using Hierarchical Linear Modeling (HLM) or Multi-level Modeling (Bryk & Raudenbush, 2002; Luke, 2004). The goal of HLM is to predict the values of the dependent variable based on a function of predictor variables at more than one level. Three basic differences between multi-level modeling and ordinary least square analysis are as follows (Bryk & Raudenbush, 2002):

1. Improved estimation of individual effects; e.g., developing an improved estimation of a regression model for an institution by comparing whether similar estimates exist for other institutions.
2. Modeling the cross-level effect; e.g., how an institutional factor such as size might affect the relationship between individual factor and transfer.
3. Partitioning the variance-covariance components; e.g., decomposing the covariance components among a set of student-level variables into within- and between-institution effects for a more straightforward attribution of causality.
In the following section, the need of a multi-level model from empirical, statistical, and theoretical perspectives is presented.

*Empirical Evidence for HLM*

The existing literature on transfer is not unanimous in explaining the effects of individual variables such as race or academic performance on transfer. Some researchers have found academic preparation to be a key criterion for transfer (Lee & Frank, 1990) while others argued that academic preparation does not play any significant role in transfer (Bailey & Weininger, 2002). There is a possibility that the specific population of students selected for these studies came from different demographic backgrounds. The difference in demographic background and interaction between different factors may explain the differences observed in the studies. In other words, even if the academic performance of two students is the same, their ability to transfer may vary depending on their demographic identity or the way they integrate themselves in different institutions.

The relationship between the ratio of part-time to full-time faculty and student success was not found to be uniform in the existing studies. While Ehrenberg and Zhang (2004) found the percentage of part-time faculty was not significantly related to student success, other researchers (Bailey et al., 2005) found the relationship was significant. Separating the effect of the institutional and individual variables may help explain the conflicting results of the two studies. The percentage of part-time faculty, an institutional characteristic, may have a different impact on two different groups of students. Multi-level models can de-compose the error term and split up the variance-covariance components to further explain the impact of each of the levels of variables separately.
Statistical Rationale for HLM

The second rationale for use of HLM is statistical. The ordinary least square (OLS) model assumes that the error terms are independent of each other. Whenever there is a nested data structure, there is a high possibility of dependence between error terms. For example, students belonging to a particular race are expected to face similar obstacles while transferring. Similarly, students coming from a large institution may have characteristics that differ considerably from those coming from a small one. A group of students belonging to the same demographic background, therefore, is expected to have closely related error components in the model. The independence condition of OLS models demand that error-terms must not be correlated with each other. In nested data, the likelihood is high that the independent error term assumption is violated. For multi-level models, the estimation of the individual effects is improved by comparing the observations of similar individuals across different institutions. Independence of error-terms is not a prerequisite for multi-level models. The statistical treatment accommodates correlated error structures (Duncan, Jones, & Moon, 1998; Luke, 2004).

Theoretical Approach to HLM

Finally, the third justification for using a multi-level model is theoretical. If a data structure is nested, the appropriate treatment should be multi-level (Bryk & Raudenbush, 2002; Luke, 2004). In the present study, there are two clear foci of the data: the student and the institution. The student data are captured in the first level and the institution, the second level. Each student attends an institution. While the individual level variables are directly attributed to the student, the institutional variables provide the background for
the student behavior. A multi-level model will help separate out the background effects of
an institution on individual student behavior.

Based on the data structure, and empirical, statistical, and theoretical perspectives,
hierarchical linear modeling is selected as the statistical technique for the data analysis.
The software, HLM version 6.04 is used for analysis of the data.

Creating the Multivariate Data Matrix

Four HLM models were developed to evaluate the relationship between the
individual characteristics, institutional factors, and transfer. A fifth model was created to
determine if the rate of change of probability of transfer changes from one institution to
another depending on the change in institutional variables (slopes-as-outcomes model).
For all the models, the level-1 and level-2 files are used as input to create the multivariate
data matrix (mdm file). All analysis performed by the HLM software is based on the
.mdm file. After the file is created and variables at levels 1 and 2 are defined, an output is
generated to verify if all data are accurately read by the software. The descriptive
statistics for the level-1 variables is shown in Table 4.

Three variables, number of credits completed in first year (First-Year_Credits),
age, and GPA are continuous while the other seven variables are binary. The outcome of
interest, expressed as the dependent variable Transfer Code is binary. It is to be noted
that although 32,922 students were initially selected based on the criteria of transfer, for
most of the variables, the number of observations is 31,245. For the variables age and
full-time, the number of observations is 31,195 and 30,336 respectively. This is because
HLM software eliminates the records with missing values while making the .mdm file.
As the number of observations available after eliminating the missing data are large and proportion of missing data are less than 5%, no imputation technique was used.

Table 4 shows that one half of the students were attending full time, 32% expressed intent to transfer, and the average GPA was 2.31. Of this group, 15% of the students actually transferred. Over 80% of the students were white, 11% were black and only about 2% were Hispanic. The average age was 24 years, and the average number of credits completed in the first year, 25.76. The number of credits completed in the first year is high because only those with at least 12 credit hours completed in the first year were taken in this dataset. Few students completed over 50 credit hours in the first year. For a discussion on students completing over 50 credit hours in the first year, please refer to Appendix 1.

Table 4
Descriptive statistics for student data

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean (μ)</th>
<th>S.D. (σ)</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Minimum</td>
</tr>
<tr>
<td>First_Year_Credits</td>
<td>31,245</td>
<td>25.76</td>
<td>11.82</td>
<td>12.00</td>
</tr>
<tr>
<td>Transfer_Code</td>
<td>31,245</td>
<td>15%</td>
<td>0.36</td>
<td>0.00</td>
</tr>
<tr>
<td>Full-Time</td>
<td>30,336</td>
<td>50%</td>
<td>0.50</td>
<td>0.00</td>
</tr>
<tr>
<td>GPA</td>
<td>31,245</td>
<td>2.31</td>
<td>1.41</td>
<td>0.00</td>
</tr>
<tr>
<td>Age</td>
<td>31,195</td>
<td>24.02</td>
<td>7.07</td>
<td>15.00</td>
</tr>
<tr>
<td>Female</td>
<td>31,245</td>
<td>55%</td>
<td>0.50</td>
<td>0.00</td>
</tr>
<tr>
<td>Intent</td>
<td>31,245</td>
<td>32%</td>
<td>0.47</td>
<td>0.00</td>
</tr>
<tr>
<td>White</td>
<td>31,245</td>
<td>81%</td>
<td>0.40</td>
<td>0.00</td>
</tr>
<tr>
<td>Black</td>
<td>31,245</td>
<td>11%</td>
<td>0.32</td>
<td>0.00</td>
</tr>
<tr>
<td>Hispanic</td>
<td>31,245</td>
<td>2%</td>
<td>0.13</td>
<td>0.00</td>
</tr>
</tbody>
</table>

For one institution in level-2, the data on percentage of full-time faculty and percentage of students receiving need based financial aid were missing. The average of
other 21 institutions is used as an approximation for these two missing values (Allison, 2001). All other data were from the original source without any imputation or estimation of missing values. The institutional variables, also referred to as level-2 variables, are summarized in Table 5. The data indicates 42% of the students studying in all of the institutions combined were full-time, 41% were male, and 62% persisted from one fall to another. The overall graduation rate was 30%, and 41% of the students received need-based financial aid or Pell grant.

The difference in the percentage of full-time or the percentage of males between the level-1 and level-2 data is due to the change in the unit of measurement. The institutional data represent all students in the institution, irrespective of when they joined or the number of credits they completed. The individual data are more restrictive in terms of number of credits completed and when the student started postsecondary education, as detailed in the scope of the study.

Table 5
Descriptive statistics for institutional variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean (µ)</th>
<th>Standard deviation (σ)</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headcount</td>
<td>22</td>
<td>6861.55</td>
<td>7549.70</td>
<td>1409</td>
<td>24711</td>
</tr>
<tr>
<td>% Full Time</td>
<td>22</td>
<td>42%</td>
<td>0.14</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>% Age&gt;24</td>
<td>22</td>
<td>47%</td>
<td>0.06</td>
<td>0.33</td>
<td>0.55</td>
</tr>
<tr>
<td>% Male</td>
<td>22</td>
<td>41%</td>
<td>0.07</td>
<td>0.28</td>
<td>0.54</td>
</tr>
<tr>
<td>Persistence Rate</td>
<td>22</td>
<td>62%</td>
<td>0.07</td>
<td>0.54</td>
<td>0.88</td>
</tr>
<tr>
<td>% Full time faculty</td>
<td>22</td>
<td>49%</td>
<td>0.11</td>
<td>0.28</td>
<td>0.76</td>
</tr>
<tr>
<td>% Pell</td>
<td>22</td>
<td>41%</td>
<td>0.11</td>
<td>0.20</td>
<td>0.59</td>
</tr>
<tr>
<td>Graduation Rate</td>
<td>22</td>
<td>30%</td>
<td>0.13</td>
<td>0.10</td>
<td>0.65</td>
</tr>
</tbody>
</table>
Developing HLM models

Four separate models were created to evaluate the data. The first one was a null or unconditional model that had no variables. Subsequent models included level-1, level-2, and both level-1 and 2 variables to determine the effect of variables on the outcome individually and collectively. The models were differentiated by the levels of independent variables that were included. Models with the level-1 and level-2 variables only were created to identify the variables that have a statistically significant impact on the probability of transfer. The final model included only those variables that had a significant impact on probability of transfer.

Hierarchical linear models assume that the dependent variable is normally distributed. The dependent variable in this case is binary, assuming a value of 1 if a student transferred and, 0 otherwise. A transformation function was used to convert the binary outcome into a variable with a normal distribution (Bryk & Raudenbush, 2002). The standard logit model was used as a link function to transform the binary variable. The link function is as follows:

$$ \eta_{ij} = \log \left( \frac{\varphi_{ij}}{1 - \varphi_{ij}} \right) $$

where $\eta_{ij}$ is the log of the odds of success. If the probability of successful transfer, $\varphi_{ij}$ is 0.5, the odds of success is $\varphi_{ij} / (1 - \varphi_{ij}) = (0.5 / 0.5) = 1.0$ and log-odds or logit is $\log (1) = 0$. If the probability of success is less than 0.5, the odds are less than 1 and the logit is negative. When the probability is greater than 0.5, the logit is positive. The value of $\varphi_{ij}$ is bound by (0, 1) while $\eta_{ij}$ can assume any value.

Using the logit link function, the system of equations for the models is as follows:

Level-1 model:
\[ \eta_{ij} = \beta_0 + r. \]

Level-2 model:

\[ \beta_0 = \gamma_{00} + u_0. \]

The equations above establish a link between the level-1 and level-2 variables. The outcomes of the level-2 equations are used as intercepts of level-1 equations. The result of such an analysis allows us to determine if the probability of transfer of two students, who are similar in all respects but studying in different institutions, varies depending on institutional variables, and if yes, the extent of such variances.

Each model provides four sets of outputs of final estimation of fixed effects for: (1) the unit specific model, (2) population average model (3) unit specific model with robust standard errors and (4) population average model with robust standard errors. The detailed outputs obtained from the HLM software are produced in Appendix 2. The proximity of values attained through all four tests is another non-confirmatory indication that the data fit the models appropriately (Bryk & Raudenbush, 2002). The intra-class correlation, a measure of the variability of the dependent variable that is accounted for by each level of independent variable, is calculated for each of the models using the level-1 and level-2 variances.

*The Unconditional (Null) Model*

The purpose of creating the unconditional model is to estimate the variation in the probability of transfer among the start institutions. The null model did not include any of the level-1 or level-2 variables. Table 6 summarizes the key parameters from the detailed output. The reliability estimate of 0.959 indicates the sample means are reliable indicators of true institutional means (Bryk & Raudenbush, 2002).
Table 6
Variance and reliability estimates for the unconditional model

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>S.E.</th>
<th>t-ratio</th>
<th>Approx d.f.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma^2$ (level-1 variance)</td>
<td>0.996</td>
<td>0.008</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau$ (level-2 variance)</td>
<td>0.301</td>
<td>0.095</td>
<td>21</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Reliability estimate</td>
<td>0.959</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept $\gamma_{00}$</td>
<td>-1.906</td>
<td>0.119</td>
<td>-15.961</td>
<td>21</td>
<td>0.001</td>
</tr>
</tbody>
</table>

The intra-class correlation coefficient (ICC), measured by the ratio of level-2 variance, $\tau$, to the total variance, $(\sigma^2 + \tau)$, measures the proportion of variance in the dependent variable, probability of transfer, that is accounted for by the level-2 groups, i.e. institutions. In this case, ICC is computed as follows:

$$
ICC = \frac{\tau}{\tau + \sigma^2} = \frac{0.301}{1.297} = 0.232.
$$

The ICC indicates that 23.2% of the variance is accounted for by the institutions.

The prediction based on the ICC assumes that the variance at level-1 is uniform, or homoscedastic. However, as a non-linear link function was used to transform the binary outcome, the level-1 variance is expected to be non-uniform, or heteroscedastic (Bryk & Raudenbush, 2002; Snijders & Bosker, 1999). The level-1 variance will equal $\varphi_{ij}(1-\varphi_{ij})$, where $\varphi_{ij}$ is the predicted probability according to the model. The heteroscedasticity of level-1 variance reduces the predictive power of calculated ICC.

The intercept $\gamma_{00}$ is the average log-odds of transfer across all two-year institutions, while $\tau$ is the variance between the institutions in institutional average log-odds of transfer. The model estimates the probability of transfer for a “typical institution” by holding all independent variables at their mean value. Thus, for the “typical” institution, the log-odd of transfer is calculated as:
\[ \eta_{ij} = \log\left(\frac{\varphi_{ij}}{1 - \varphi_{ij}}\right) = \beta_0 = \gamma_0 = -1.906489. \]

Simplifying,
\[ \frac{\varphi_{ij}}{1 - \varphi_{ij}} = e^{\log(\varphi_{ij})} = e^{-1.906489} = 1/ e^{1.906489}. \]

Therefore,
\[ \varphi_{ij} = 1/ (1 + e^{1.906489} ) = 1/7.729420 = 0.129376. \]

This typical probability is less than the observed mean, 0.15, of transfer data (per Table 4). The mean is calculated from the dataset used for the study. This difference is attributed to the non-linear relationship between \( \eta_{ij} \), the log-odds of transfer and \( \varphi_{ij} \), the probability of transfer.

The estimated probability of transfer by the unconditional model is close to the empirical observation. Both level-1 and level-2 variables have an impact on transfer, as indicated by the intra-class correlation coefficient. In the next model, only level-1 variables are included to determine which of the variables has a significant relationship with the probability of transfer and the magnitude of the relationship.

**Model with level-1 Variables Only**

This model includes all level-1 variables but no level-2 variables. All the level-1 variables were selected based on previous research findings. It is not known whether all these variables influence the probability of transfer or not.

The purpose this model is to explore which level-1 variables are significantly related to the probability of transfer and the direction and extent of the relationship for students attending public institutions in Ohio in 2001. Level-2 variables are held unchanged for this model. The detailed output is included in Appendix 2.
The equation for level-1 only model is as follows:

\[ \eta_{ij} = \gamma_0 + \gamma_{10} (\text{First\_Year\_Cr}) + \gamma_{20} (\text{FT}) + \gamma_{30} (\text{GPA}) + \gamma_{40} (\text{Age}) + \gamma_{50} (\text{Gender}) + \gamma_{60} (\text{Intent}) + \gamma_{70} (\text{White}) + \gamma_{80} (\text{Black}) + \gamma_{90} (\text{Hispanic}) + \tau + \sigma^2. \]

The output for the unit-specific model is given in Table 7. The p-values show that all level-1 variables except white and Hispanic have a significant impact on log-odds of transfer. Completing more credit hours in the first year, attending full-time, high GPA, and, intent to transfer, all increases the log-odds of transfer. On the contrary, females, blacks, and older students are negatively related to the probability of transfer.

The model output gives the intercept, the coefficients of each of the independent variables, standard error, degrees of freedom, and significance. The t-ratio is calculated by dividing the coefficient by the standard error. For all the independent variables with binary outcomes, such as gender, intent, whether attending full-time, or race, the change in log-odds of probability is calculated by substituting the value of the independent variable for a specific case. For example, the variable value for gender is zero for a male and one for a female. The unit change in the case of continuous variables, such as the number of credits completed in the first year or age is measured by its standard deviation. Table 8 shows the values of coefficients for the unit-specific model with level-1 variables only for the logit link function. Keeping all the variables at zero, the log-odds of transfer is calculated as:

\[ \eta_{ij} = \log(\frac{\text{P}(\text{transfer})}{1 - \text{P}(\text{transfer})}) = \gamma_0 + \gamma_{10} (\text{First\_Year\_Cr}) + \gamma_{20} (\text{FT}) + \gamma_{30} (\text{GPA}) + \gamma_{40} (\text{Age}) + \gamma_{50} (\text{Gender}) + \gamma_{60} (\text{Intent}) + \gamma_{70} (\text{White}) + \gamma_{80} (\text{Black}) + \gamma_{90} (\text{Hispanic}) + \tau + \sigma^2. \]

Substituting the values,
\[ \log\left(\frac{\phi_{ij}}{1 - \phi_{ij}}\right) = \gamma_0 = -1.564729. \]

Or \( \phi_{ij} = 0.172969. \)

Table 7
Output for the unit specific model for logit link function with level-1 variables only

<table>
<thead>
<tr>
<th>Level-1 variables</th>
<th>Level-2 Fixed effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-ratio</th>
<th>Approx. d.f.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, ( \beta_0 )</td>
<td>Intercept, ( \gamma_{00} )</td>
<td>-1.565***</td>
<td>0.198</td>
<td>-7.89</td>
<td>21</td>
</tr>
<tr>
<td>First_Year_Credit slope, ( \beta_1 )</td>
<td>Intercept, ( \gamma_{10} )</td>
<td>0.037***</td>
<td>0.002</td>
<td>16.37</td>
<td>30276</td>
</tr>
<tr>
<td>Full_Time, slope ( \beta_2 )</td>
<td>Intercept, ( \gamma_{20} )</td>
<td>0.163***</td>
<td>0.050</td>
<td>3.23</td>
<td>30276</td>
</tr>
<tr>
<td>GPA slope, ( \beta_3 )</td>
<td>Intercept, ( \gamma_{30} )</td>
<td>0.068***</td>
<td>0.014</td>
<td>4.48</td>
<td>30276</td>
</tr>
<tr>
<td>Age slope, ( \beta_4 )</td>
<td>Intercept, ( \gamma_{40} )</td>
<td>-0.078***</td>
<td>0.004</td>
<td>-17.82</td>
<td>30276</td>
</tr>
<tr>
<td>Gender slope, ( \beta_5 )</td>
<td>Intercept, ( \gamma_{50} )</td>
<td>-0.315***</td>
<td>0.036</td>
<td>-8.82</td>
<td>30276</td>
</tr>
<tr>
<td>Intent slope, ( \beta_6 )</td>
<td>Intercept, ( \gamma_{60} )</td>
<td>0.821***</td>
<td>0.034</td>
<td>21.00</td>
<td>30276</td>
</tr>
<tr>
<td>White slope, ( \beta_7 )</td>
<td>Intercept, ( \gamma_{70} )</td>
<td>0.008</td>
<td>+</td>
<td>0.11</td>
<td>30276</td>
</tr>
<tr>
<td>Black slope, ( \beta_8 )</td>
<td>Intercept, ( \gamma_{80} )</td>
<td>-0.283 **</td>
<td>0.095</td>
<td>-2.96</td>
<td>30276</td>
</tr>
<tr>
<td>Hispanic slope, ( \beta_9 )</td>
<td>Intercept, ( \gamma_{90} )</td>
<td>-0.175</td>
<td>+</td>
<td>-1.07</td>
<td>30276</td>
</tr>
</tbody>
</table>

* \( p < .05. \)  ** \( p < .01. \)  *** \( p < .001. \)  + \( p > .05 \)

The change in the probability of transfer corresponding to a change in the value of a variable is calculated by computing two probabilities with the two values of the variables and measuring the difference in the probabilities. All other variables are held constant at their mean value as given in Table 4 and Table 5.

The variances and reliability estimate of the level-1 only model is summarized in Table 8.
Table 8

The variance and reliability estimates for model with Level-1 variables only

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>S.E.</th>
<th>Approx d.f.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma^2 ) (level-1 variance)</td>
<td>1.098</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \tau ) (level-2 variance)</td>
<td>0.420</td>
<td>0.131</td>
<td>21</td>
<td>0.001</td>
</tr>
<tr>
<td>Reliability estimate</td>
<td>0.964</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Model with Level-2 Variables Only

This model explores how the probability of transfer changes with change in institutional variables. The equation for the model is as follows:

\[
\eta_{ij} = \log\left( \frac{\varphi}{1 - \varphi} \right) = \gamma_0 + \gamma_{01} (\text{Headcount}) + \gamma_{02} (\text{FT\_Student}) + \gamma_{03} (\text{Age\_Over}) + \gamma_{04} (\text{Male}) + \gamma_{05} (\text{Persistence}) + \gamma_{06} (\text{FT\_Faculty}) + \gamma_{07} (\text{Pell\_Percent}) + \gamma_{08} (\text{Grad\_Rate}) + \tau + \sigma^2.
\]

All level-2 variables were centered around their grand mean. Centering in a multi-level model is used if a predictor variable does not have a meaningful zero points. None of the level-2 variables can have a possible zero value - all the variables except size represent percentage of students or faculty belonging to a particular category, such as full-time, male, or Pell-recipient. Therefore, the deviance from the grand mean is a better indicator of the impact of the variable than their un-centered values. When variables are centered around their grand mean, all values are expressed as deviations from the centered value. Thus, the continuous variables with values below the grand mean are expressed as negative. Though the concept of grand mean is used for data analysis, the results are shown in absolute percentage terms for ease of interpretation.
The detailed output for the model is given in Appendix 2. The output for the unit-specific model is reproduced in Table 9. The coefficients on this output are closely comparable to the population average model. From the output, it is evident that the only statistically significant institutional variable that affects the probability of transfer is the percentage of students receiving Pell Grant.

Table 9
Output for unit specific model with logit link function for level-2 variables only model

<table>
<thead>
<tr>
<th>Level-2 variables</th>
<th>Fixed effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-ratio</th>
<th>Approx. d.f.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\gamma_{00}$</td>
<td>-1.910***</td>
<td>0.077</td>
<td>-24.781</td>
<td>13</td>
</tr>
<tr>
<td>Headcount</td>
<td>$\gamma_{01}$</td>
<td>0.001*</td>
<td>0.001</td>
<td>1.881</td>
<td>13</td>
</tr>
<tr>
<td>FT_Student</td>
<td>$\gamma_{02}$</td>
<td>-1.092+</td>
<td>1.282</td>
<td>-0.852</td>
<td>13</td>
</tr>
<tr>
<td>Age_Over</td>
<td>$\gamma_{03}$</td>
<td>-1.798+</td>
<td>3.047</td>
<td>-0.590</td>
<td>13</td>
</tr>
<tr>
<td>Male</td>
<td>$\gamma_{04}$</td>
<td>-1.006+</td>
<td>1.116</td>
<td>-0.902</td>
<td>13</td>
</tr>
<tr>
<td>Persistence</td>
<td>$\gamma_{05}$</td>
<td>-0.876+</td>
<td>2.000</td>
<td>-0.438</td>
<td>13</td>
</tr>
<tr>
<td>FT_Faculty</td>
<td>$\gamma_{06}$</td>
<td>-1.191+</td>
<td>1.027</td>
<td>-1.160</td>
<td>13</td>
</tr>
<tr>
<td>Pell_Prcnt</td>
<td>$\gamma_{07}$</td>
<td>-3.039*</td>
<td>1.143</td>
<td>-2.659</td>
<td>13</td>
</tr>
<tr>
<td>Grad_Rate</td>
<td>$\gamma_{08}$</td>
<td>0.708+</td>
<td>0.814</td>
<td>0.869</td>
<td>13</td>
</tr>
</tbody>
</table>

* $p < .05$. ** $p < .01$. *** $p < .001$. + $p > .05$

In order to determine if grand centering reduced the significance of the variables, the same model was run without centering. The results of the un-centered model are very similar to this one (centered around grand mean) and the un-centered model did not reflect any different pattern of significance.

Reliability estimates and variance of fixed effects for the model is given in the Table 10.
Table 10
The variance and reliability estimates for model with Level-2 variables only

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>S.E.</th>
<th>Approx d.f</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma^2$ (level-1 variance)</td>
<td>0.996</td>
<td>0.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau$ ((level-2 variance)</td>
<td>0.118</td>
<td>0.0398</td>
<td>13</td>
<td>0.001</td>
</tr>
<tr>
<td>Reliability estimate</td>
<td>0.904</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Final Model with both Level-1 and Level-2 Variables**

Based on the analysis of the three models (null, level-1 variables only, and level-2 variables only), only those variables that have a statistically significant impact on the outcome variable, transfer, is selected for inclusion in the final model. Thereafter, one level-2 variable is introduced at a time to determine if the significance of the impact of the variable changes when it interacts with other level-2 variables. The variable in addition to the percentage of students receiving a Pell grant that had a significant impact on transfer was the percentage of full-time students attending the institution.

Unlike the model with level-1 or level-2 variables only, the final model includes variables from both levels 1 and 2. Inclusion of variables from both levels allows for an exploration of the change in probability of transfer by varying the institutional factors only, while controlling for the individual factors, and vice versa. This model helps estimate whether two students with similar backgrounds attending two different institutions have different probabilities of transferring. The objective of the model is to determine how the level-2 variables, the percent of students receiving Pell grants or the percentage of full-time students at an institution influences the impact of individual, or level-1 factors on transfer. The final model includes two institutional variables, percentage of full-time students and percentage of students receiving Pell grants, that
were found to impact the probability of transfer of students from a two-year institution to a four-year institution, holding all other individual variables constant. The model includes two level-2 or institutional variables and seven level-1 or individual variables. The equation for the model is:

\[
\eta_{ij} = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \gamma_{00} + \gamma_{01} (Pell\_Prcnt) + \gamma_{02} (FT\_Students) + \gamma_{20} (First\_Year\_Cr) + \gamma_{30} (Full\_time) + \gamma_{40} (GPA) + \gamma_{50} (Age) + \gamma_{60} (Gender) + \gamma_{70} (Intent) + \gamma_{80} (Black) + \tau + \sigma^{2}.
\]

The results from the model show that having a positive intent to transfer, attending full-time, completing higher number of credits in the first year, and maintaining higher GPA, all significantly increase the probability of transfer. Females, blacks, and older students have a significantly lower probability of transfer. The percentage of students receiving Pell grants at an institution is an indicator of the financial need of the students attending that institution. The probability of transfer decreases for all students in an institution with an increase in percentage of Pell grant recipients in that institution, irrespective of Pell recipient status of the individual student.

The model outputs are given for both identity link function, and logit link function. The unit specific model calculates the coefficients for a unit increase in the predictor, holding constant the other predictors and assuming that the level-1 variance, \(\sigma^{2}\), remains the same across all institutions. The population average estimates, in contrast, calculates the coefficients for a unit increase in the predictor, holding constant all other predictors but distributing the level-1 variance, \(\sigma^{2}\), across all level-2 institutions. Table 11 shows that population average model coefficients are in close proximity of the unit specific model. The coefficients are presented in Table 11.
The coefficients for both unit specific and population average models are all in the same direction and are of similar magnitude. As noted in model selection, although the inferences based on the models are often quite similar, the choice of one model over the other is determined by the research aims. The unit specific model relies on the level-1 or individual student coefficients to describe the process that is occurring across the institutions. In this study, the difference among the institutions is in the intercepts: two level-2 institutional variables, the percentage of students receiving Pell grant and the percentage of full-time students are used to calculate the intercept. Therefore, the unit-specific model is more appropriate for use in this case.

Table 11
Coefficients for the final model with level-1 and level-2 variables

<table>
<thead>
<tr>
<th>Level-1 variables</th>
<th>Level-2 Fixed effect</th>
<th>Identity link</th>
<th>Logit link: Unit specific</th>
<th>Logit link: Population average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept, $\beta_0$</td>
<td>Intercept, $\gamma_{00}$</td>
<td>0.121</td>
<td>-1.561***</td>
<td>-1.499***</td>
</tr>
<tr>
<td>Pell percent, $\gamma_{01}$</td>
<td>-0.278</td>
<td>-2.700***</td>
<td>-2.656 **</td>
<td></td>
</tr>
<tr>
<td>FT_Student, $\gamma_{02}$</td>
<td>-0.299</td>
<td>-2.821 *</td>
<td>-2.668 **</td>
<td></td>
</tr>
<tr>
<td>First-Year_Credit slope, $\beta_1$</td>
<td>Intercept, $\gamma_{10}$</td>
<td>0.004</td>
<td>0.037***</td>
<td>0.036***</td>
</tr>
<tr>
<td>Full_Time, slope $\beta_2$</td>
<td>Intercept, $\gamma_{20}$</td>
<td>0.030</td>
<td>0.164 **</td>
<td>0.167***</td>
</tr>
<tr>
<td>GPA slope, $\beta_3$</td>
<td>Intercept, $\gamma_{30}$</td>
<td>0.007</td>
<td>0.068***</td>
<td>0.066***</td>
</tr>
<tr>
<td>Age slope, $\beta_4$</td>
<td>Intercept, $\gamma_{40}$</td>
<td>-0.005</td>
<td>-0.079***</td>
<td>-0.077***</td>
</tr>
<tr>
<td>Gender slope, $\beta_5$</td>
<td>Intercept, $\gamma_{50}$</td>
<td>-0.377</td>
<td>-0.316***</td>
<td>-0.309***</td>
</tr>
<tr>
<td>Intent slope, $\beta_6$</td>
<td>Intercept, $\gamma_{60}$</td>
<td>0.118</td>
<td>0.819***</td>
<td>0.803***</td>
</tr>
<tr>
<td>Black slope, $\beta_8$</td>
<td>Intercept, $\gamma_{80}$</td>
<td>-0.035</td>
<td>-0.288***</td>
<td>-0.278***</td>
</tr>
</tbody>
</table>

* $p < .05$. ** $p < .01$. *** $p < .001$. + $p > .05$.

Institutional (level-2) variables are used to model the intercept of individual (level-1) variables only; the slopes of the level-1 variables are not calculated from the
level-2 variables. The underlying assumption is the intercept of the equation for transfer probability changes with a change in institutional variables, the *percentage of full-time students* and the *percentage of students receiving Pell grants*. The slope of the probability equation is assumed to be the same for all institutions. In reality, the slope of the equation may also vary with a change in an institutional variable. For example, the slope of the probability equation may change with a change in *percentage of students receiving Pell grant*. In that case, as the *percentage of students receiving Pell grant* in an institution increases, the probability of students transferring decreases at an increasing rate. The impact of the two institutional variables, *percentage of full-time students* and *percentage of students receiving Pell grants*, on the slope of the probability of transfer equation was tested by including the variables (percentage of full time students and percentage of students receiving Pell grants) in the intercepts $\gamma_{10}$ to $\gamma_{80}$. The level-2 equation in this case was:

$$\beta_1 = \gamma_{10} + \gamma_{11} \times \text{(Percentage of full-time students)} + \gamma_{12} \times \text{(Percentage receiving Pell grant)}.$$ 

All level-1 intercepts, $\beta_1$ to $\beta_8$, are modeled similarly allowing the two level-2 variables to have an impact on the slope. The model output shows that the effect on the slope is not statistically significant in any of the cases. The model output is given in Appendix 2. Based on this finding, the impact of institutional variables on the slope of the outcome was not included in the final model. The variances and reliability parameters from the final model including both level-1 and level-2 variables are shown in Table 12.
Table 12

The variance and reliability estimates for the final model including both level-1 and level-2 variables

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>S.E.</th>
<th>Approx d.f.</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma^2 ) (level-1 variance)</td>
<td>1.095</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \tau ) (level-2 variance)</td>
<td>0.183</td>
<td>0.056</td>
<td>19</td>
<td>0.001</td>
</tr>
<tr>
<td>Reliability estimate</td>
<td>0.924</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Reliability of the Models

Reliability is a measure of consistency of a model. The goal of a model is to predict the value of the dependent variable based on the independent variables. However, if a variable is measured twice under similar conditions, it is expected that the two values will differ from each other. This is because the observed value of a variable is an additive composite of two parts: the true score and the random error. While all independent variables aim at estimating the true score of the dependent variable, the random error term associated with the dependent variable cannot be measured by a model. The reliability of a model is estimated by the ratio of true scores or parameter variance, relative to the observed score, or total variance of the sample mean. Reliability of the hierarchical linear models is measured by the formula:

\[
\lambda_j = \frac{\tau_{00}}{\tau_{00} + \sigma^2/n_j}
\]

where \( \tau_{00} \) is the variance between institutions (level-2), \( \sigma^2 \) is the variation within institutions (level-1) and \( n_j \) is number of students from institution j. The reliability of the model tends to be large if \( n_j \) is large across all the institutions.

The reliabilities of the four models created above are summarized in Table 13.
Table 13

Reliability estimates for the four models

<table>
<thead>
<tr>
<th>Model</th>
<th>Reliability estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unconditional or null</td>
<td>0.959</td>
</tr>
<tr>
<td>Level-1 variables only</td>
<td>0.964</td>
</tr>
<tr>
<td>Level-2 variables only</td>
<td>0.904</td>
</tr>
<tr>
<td>Both level-1 and level-2 variables (final model)</td>
<td>0.924</td>
</tr>
</tbody>
</table>

The value of reliability can range from 0 to 1, where a value closer to 1 indicates a higher reliability. For example, a reliability of 0.9 means 90% of the variance of the measure is inherent to the variable and 10% is attributed to random error. The HLM software averages reliability across all institutions to arrive at the overall reliability of the model.

Validity of the Models

The validity of a model is an assessment of how well the concepts used in the theoretical framework of the model have been operationalized and how effectively the variables measure the outcome of interest. In simple terms, validity determines if the model translated the concepts or constructs into a functioning and operating reality (Trochim, 2006). If the validity of a model is high, the data used for the model should support the theoretical view of relations among the constructs. All statistical models assume that the data satisfy certain conditions. If the data do not fit the model assumptions, the robustness of the results decline. Determining the adequacy of the data to meet the model criteria is an important aspect of validity.

Two of the most important assumptions of multi-level models are (a) the level one (within group) errors are independent and are normally distributed with a mean of zero
and (b) the random effects are normally distributed with a mean zero and are independent across the groups.

One of the methods to determine the validity of the data is creating the normal quantile-quantile plot, or the q-q plot. A q-q plot is a graphical technique to determine if two datasets come from the populations with a similar distribution. The quintiles of the first dataset are plotted against the quintiles of the second dataset. The fraction or percent of points below a given value is defined as the quintile. Thus, 30th quintile is the point where 30% of the data fall below and 70% fall above. The expected logistic values of the level-1 residuals are plotted against the observed values. Higher linearity of the q-q plot suggests greater normality of level-1 errors.

The q-q plot is shown in Figure 2. The deviation from the straight line is the highest for the lower and upper extremes of the observed values. This suggests that the errors associated with extreme values of observations are not normally distributed. The non-normality of the errors at level-1 does not bias the estimation of level-2 effects, but it will introduce bias into standard errors at both levels and therefore into the computation of confidence intervals and hypothesis tests. Not much is known at this time regarding the direction or severity of such effects (Bryk and Raudenbush, 2002).
Figure 2: Q-Q plot of expected logistic values and level-1 residues

The descriptive statistics for the data and results from the four models are presented in chapter four.
CHAPTER FOUR: RESULTS

Four hierarchical linear models were created to test the relationship between individual student background, institutional factors, and probability of transfer. The demographic background and academic preparation were measured at the individual level (level-1). The institutional factors were measured at an aggregate level (level-2). The null model did not include any predictor variables; it was used to determine if probability of transfer differs from one institution to another. Every model progressively added a new level of variables. The four models constructed were as follows:

1. Null model
2. Model with level-1 variables only
3. Model with level-2 variables only
4. Final model with both level-1 and level-2 variables

Self-declared intent and number of credits completed in the first year were found to have the largest positive relationship with probability of transfer, while age had the largest negative relationship. At the institutional level, an institutional factor of large percentage of students receiving need-based financial aid (Pell grants) was observed to reduce probability of transfer of all students attending the institution. The decrease in probability of transfer with increase in percentage of full-time students at the institution is another finding from the final model.

Descriptive Statistics

Out of the 463,950 enrolled students in 2001, nearly 43% were enrolled in two-year institutions. The proportion of students enrolled in two-year institutions is
comparable with the existing literature that indicates nearly 45% of undergraduate students start their education (AACC, 2006) at community colleges. The transfer rate of 14.8% is comparable to the transfer rate in Ohio. Out of all students attaining a baccalaureate degree from public institutions in Ohio in 2005, nearly 17% transferred from a two-year campus (The Performance Report for Ohio’s Colleges and Universities, 2006).

The average age of the students was 24 years. Fifty-four percent of the students were 20 years or older and 40% of the students were older than 21 years. Ten percent of the students were older than 35 years.

The distance between start and transfer institutions was calculated from the zip code of the address of the institutions. A matrix of start and transfer institution was compiled, and the number of students transferring as well as distance between the institutional pairs were computed. The variable indicating distance between start and transfer institution could not be included in the hierarchical linear models. If a student had not transferred, the distance between start and transfer institution was zero and corresponding probability of transfer was also zero. The largest proportion of students transferred when distance between start and transfer institution was less than five miles. This was observed when a student transferred from a community college to a branch campus located within the same zip code. For bigger cities such as Columbus, Dayton, Cincinnati, or Cleveland, often the distance between start and transfer institution was less than five miles. Thereafter, the probability of transfer decreased with increasing distance. A positive transfer outcome always corresponded to a non-zero distance. The HLM software could not run the analysis with distance as a level-1 predictor because the
probability to transfer is always zero if distance is zero. Therefore, the relationship between distance and transfer is evaluated using descriptive statistics.

Another level-1 variable, number of credits accepted by transfer institution, could not be used because of similar reason. The number of credits accepted by transfer institution is non-zero only if a transfer takes place. Therefore, for the binary outcome transfer, a value of zero (this is nearly 85% of the cases) corresponds to a zero value of number of credits accepted by transfer institution. The descriptive statistics for number of credits accepted in case of successful transfer could not be included in the inferential model. The results from the four models as well as the summary of descriptive statistics for distance and number of credits transferred are summarized in the following sections.

Results from Model with Level-1 Variables Only

Seven variables at the individual level were found to have a statistically significant relationship with probability of transfer. The change in probability of transfer associated with a change in the independent variables is given in Table 14. For calculation of change of probability, only one independent variable is changed at a time, keeping all other variables at their mean value. The mean value of each variable is given in Table 4. The unit change is measured in two ways: for continuous variables, one unit is equivalent to one standard deviation from the mean. The binary variables take the value of 0 or 1. For example, attending full-time is coded as 1, while attending part-time is coded as 0. If probability of transferring is calculated for two students with the same individual characteristics except for attendance status, the probability is calculated using the values of 0 and 1 respectively for the variable, full-time, and then the difference in the two probabilities is measured. This difference is attributed to attendance status.
According to the data summarized in Table 14, attending full-time increases the probability of transfer by 1.4%.

It is evident from Table 14 that the self-declared intent has the largest positive relationship with transfer, while age had the largest negative relationship. Females are 3% less likely than males to transfer. Both GPA and attending full time increases probability of transfer, but the effect is not as strong as completing number of credits in first year or having a self-declared intent to transfer.

Table 14
Change in probability of transfer for unit change in independent student background

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Value(s)</th>
<th>Change in probability</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of credits completed in first year</td>
<td>S.D.</td>
<td>11.82</td>
<td>+0.047</td>
<td>+ 4.7%</td>
</tr>
<tr>
<td>Full time</td>
<td>Binary</td>
<td>FT = 1, PT = 0</td>
<td>+0.014</td>
<td>+ 1.4%</td>
</tr>
<tr>
<td>GPA</td>
<td>S.D.</td>
<td>1.41</td>
<td>+0.008</td>
<td>+ 0.8%</td>
</tr>
<tr>
<td>Age</td>
<td>S.D.</td>
<td>7.07</td>
<td>- 0.040</td>
<td>- 4.0%</td>
</tr>
<tr>
<td>Gender</td>
<td>Binary</td>
<td>M = 0, F = 1</td>
<td>- 0.028</td>
<td>- 2.8%</td>
</tr>
<tr>
<td>Intent</td>
<td>Binary</td>
<td>No = 0, Yes = 1</td>
<td>+0.084</td>
<td>+ 8.4%</td>
</tr>
<tr>
<td>Black</td>
<td>Binary</td>
<td>No = 0, Yes = 1</td>
<td>- 0.023</td>
<td>- 2.3%</td>
</tr>
</tbody>
</table>

Existing research on the relationship between race and transfer produced contradictory evidence. While some studies found race to have a negative impact, others did not find the relationship to be significant. The students in this model were tested for their membership in three races: white, black, and Hispanic. Only blacks were found to
have a 2.3% lower probability of transfer, when all other factors were controlled. No effect was noticed for either whites or Hispanics.

The variable column in Table 14 shows all seven variables that were found to have a significant relationship with probability of transfer. Three variables, *number of credits completed in the first year*, *GPA*, and *age* are continuous while the other four variables are binary. The column for values denotes the codes for binary variables, and standard deviation for the continuous variables. The fourth column, $\Delta \phi$, shows the change in probability of transfer for a change of one unit in the value of a corresponding independent variable, holding all other independent variables at their mean value. For example, if the *number of credits completed in the first year* increases by 11.82 controlling all other variables, the probability of transfer will increase by 4.7%. Instead of changing the value of one variable at a time while controlling all other variables, multiple variables can be allowed to vary at the same time, and the consequent change of probability of transferring can be estimated.

The relationship between the level-1 variables and probability of transfer is depicted with a series of figures. For continuous variables such as *number of credits completed in first year*, the slope indicates the relationship of the variable on the outcome. For dichotomous variables such as gender, the difference between two categories (male and female) is an indicator of how the relationship differs from one gender to another.

Figure 3 shows the difference in probability of transfer for two students, one with *intent* to transfer and the other without any self-declared intent. The difference in probability is over 8% when all other variables are controlled. The relationship is
consistent with the observations of earlier researchers (Illinois Community College Board [ICCB], 1998; Hall, 1990). Earlier research findings calculated a 5% change of probability of transfer associated with positive intent (ICCB, 1998).

Figure 3: Relationship between intent and probability of transfer

The change in probability of transfer with increasing number of credit completion in the first year is shown in Figure 4. The slope of the line in Figure 4 increases with increasing number of credits in the first year, indicating a higher probability of transfer associated with a higher number of credits completed in the first year. The changes are not uniform with increase in number of credits completed. The rate of change increases with over thirty credits at a higher rate.

It is apparent from Figure 4 that the slope of the graph keeps increasing towards the right, indicating a faster rate of increase with increasing number of credit completion.
in the first year. Intuitively, this suggests students who complete more credits in the first year have a higher chance of transferring.

![Graph showing the relationship between probability of transfer and number of credits completed in first year.](image)

Figure 4: Relationship between probability of transfer and number of credits completed in first year

Figure 5 shows the combined effect of positive *intent* and higher *number of credits completed in the first year* on probability of transfer. The increase is not simply the sum of probability of transfer corresponding to a change in each of the individual variables. Students with a positive intent and who have completed 25 credit hours in the first year have a 8.4% higher probability of transfer than those with equal *number of credits completed in first year* but no positive *intent* to transfer. The probability increases to 11% for students with 36 credit hours completed during first year. However, positive *intent*
increases probability of transfer by 8.4%, and completing 12 more credit hours (than the average of 24) increase probability by 4.7%. The sum of these two probabilities is 13.1%, which is more than the difference of 11% derived from Figure 5. The change in probability of transfer when more than one independent variable is allowed to vary is an important result obtained from the model with level-1 variables only.

![Diagram]

Figure 5: Change in probability to transfer with increasing number of first year credits and intent to transfer

Figure 6 combines the effect of two level-1 variables, gender and attendance pattern, on probability of transfer. Full time students have a higher probability to transfer, but the difference is only 1.4%. Males have a higher probability of transfer than females. The relationship between probability of transferring and attendance pattern is not the same for males and females. Full-time female students have nearly 3% less chance of
transferring than full-time male students. Among part-time students, females have a 2.7% lower probability of transferring than males. The gap in probability of transferring between males attending full-time and part-time is nearly 1.7%, while for females, the gap is 1.3%.

![Graph showing gender, attendance pattern, and probability of transfer](image)

Figure 6: Gender, attendance pattern and probability of transfer.

The relationship between GPA and probability of transfer is not very strong, although it is significant. The mean GPA for the student population was 2.31 with a standard deviation of 1.41. Figure 7 illustrates that the probability of transfer increased by nearly 1% for an increase of one standard deviation, or 1.41 in GPA. The weak influence of GPA on transfer supports the theory of late bloomers (Dowd et al., 2006). A study of community college students transferring to elite institutions reported that some
community college students start working hard once they are actively engaged in the academic process.

Figure 7: Relationship between GPA and probability of transfer

However, for these students, a weak start does not necessarily work to the detriment of their success. Although this finding emphasizes the importance of the role of student aspiration in accomplishing the goal of transfer, further research is necessary to validate such an observation. The role of factors such as selectivity, the admissions process, course equivalency structure at the destination institution needs to be taken into consideration to assess the consistency of this finding among various institutions.
Figure 8 combines the relationship between age, intent, and probability of transfer. Probability of transfer goes down as age increases and the decline is rather rapid until age 25. Thereafter, the decline continues at a lesser rate.

![Graph showing the relationship between age, intent, and probability of transfer](image)

**Figure 8: Relationship between age, intent and probability of transfer**

This suggests that perhaps students above 25 years of age have family as well as work commitments that restrict their mobility and transferability. Existing research has identified that probability of transfer goes down by 15% for students above 20 years of age; the probability decreases by 20% for students above the age of 30 years (Dougherty & Kienzl, 2006). The results from this study show that the probability decreases by 8% when age increases from 20 to 29 for the students with positive intent to transfer. For the same change of age, the probability decreases from 10% to 7% for students with no
positive intent (to transfer). The results from this study show that a positive intent can mitigate the negative effect of age on probability of transfer to a large degree.

The difference in probability of transfer between those with a declared intent to transfer and those without any such intent is quite pronounced in Figure 8. For a 15 year old student, the probability of transfer increases by 8.3% if the self-declared intent to transfer is positive. For a 25-year old student, the probability of transfer changes by 4.7% with the change of self-declared intent to transfer. Though the difference exists for all age groups, the degree of difference diminishes with age.

Other factors being equal, a black student has a 2.3% lesser chance of transfer. This is shown in Figure 9.

Figure 9: Relationship between race (black) and probability of transfer
No significant relationship was found between white, or Hispanics, and the probability of transfer. The population of students had nearly 85% white students. Therefore, it is not unusual that the relationship between white and probability of transfer is not significant: the probability of transfer of whites dominates the overall probability of transfer of any student because of their overwhelming majority in the population.

The results from the model with level-1 variables only illustrate the relationship between individual student background and probability of transfer. The results show the relationship of each variable individually as well as two or more variables collectively with the probability of transfer. The effect of multiple variables is not simply the cumulative effect of the individual variables. Overall, intent and number of credits completed in the first year have the highest positive relationship with the probability of transfer while age has the largest negative relationship.

Results from Model with Level-2 Variables Only

The second model determined which of the institutional variables had a statistically significant impact on probability of transfer. Out of the nine variables used to define the institutional factors, only the percentage of students receiving need-based financial aid had a statistically significant impact on probability of transfer ($p=0.02$). Existing research indicates that there is a high level of correlation between SES and student success. Researchers have used different approaches to measure SES. Some researchers have used percentage of county high school students receiving reduced-price meals, and percentage of county unemployment rates as a measure of SES (Wassmer et al., 2004), while some others have used social class (Lee & Frank, 1990). In this study,
percentage of students receiving Pell grants, a federal grant program aimed at helping students from low-income families pay for college, is used as measure of SES.

This study suggests that high percentages of low-SES students attending an institution, identified by their Pell grant recipient status, decreases the probability of transfer of all students attending the institution, irrespective of their individual status with respect to need-based financial aid. The negative relationship between the percentage of students receiving need-based financial aid and probability of transfer corroborates the earlier findings that low-SES is a barrier to transfer (Dougherty & Kienzl, 2006).

Figure 10: Relationship between percentage of students receiving Pell Grant and probability of transfer

The percentage of students receiving Pell grants is centered around the grand mean in this model. The change in Pell recipients is denoted by the relative distance of
the institution from the grand mean and not the absolute percentage of students receiving Pell grants. A negative value of this variable refers to an institution where a less than average percentage of students receive Pell grants and a positive value indicates an institution where greater than average students receive Pell grants. The change in probability of transfer because of this variable (\textit{percent of students receiving Pell grants}) is attributed to the institutional context and does not depend on whether the student is receiving a Pell grant.

The models with level-1 and level-2 variables identified the independent variables that have a significant relationship with probability of transfer. In the final model, independent variables from both levels were combined to explore how the relationship with transfer changes when all explanatory variables are present.

**Final Model with Both Level-1 and Level-2 Variables**

The variables that were found to have a statistically significant relationship with probability of transfer in the previous two models were included in the final model. One institutional variable was introduced at a time to determine if the significance of institutional context changes when all individual parameters are allowed to vary. The only institutional variable found to have a significant impact other than \textit{percentage receiving Pell grants} was \textit{percentage of students attending full-time}. Somewhat surprisingly, the probability of transfer decreases for institutions with higher percentage of students attending full time.

The change in probability for all the variables included in the model is presented in Table 15. The changes are calculated by taking two values of the variable under consideration, holding all other values at their mean. The difference in two values is used
to calculate the probability to transfer. For continuous variables, one standard deviation is considered equivalent to change in one unit of that variable. The change in probability of transfer for the change in values of level-1 variable is the same as the model with level-1 variables only.

It follows from Table 15 that increasing percentage of students receiving Pell grant from 0% to 25% decreases probability of transfer by 4.6% for all students attending the institution. Institutions with higher percentages of full-time students do not have a positive relationship with probability of transfer, though individually, a student increases his/her chances of transfer by attending full-time. Figures 11 and 12 illustrate the relationship between probability of transfer and percentage of students receiving Pell grant.

Table 15
Change in probability of transfer for change in independent variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit specific coefficients</th>
<th>Mean</th>
<th>Change</th>
<th>Change in probability of transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pell percent, γ₀₁</td>
<td>-2.699172</td>
<td>0.0</td>
<td>.25</td>
<td>- 4.6%</td>
</tr>
<tr>
<td>FT_Student, γ₀₂</td>
<td>-2.821548</td>
<td>0.0</td>
<td>.25</td>
<td>- 4.8%</td>
</tr>
<tr>
<td>First_Year_Credit slope, β₁</td>
<td>0.03751</td>
<td>25.76</td>
<td>σ = 11.82</td>
<td>4.7%</td>
</tr>
<tr>
<td>Full_Time, slope β₂</td>
<td>0.163564</td>
<td>0.50</td>
<td>FT = 1; PT = 0</td>
<td>1.4%</td>
</tr>
<tr>
<td>GPA slope, β₃</td>
<td>0.067724</td>
<td>2.31</td>
<td>σ = 1.41</td>
<td>0.8%</td>
</tr>
<tr>
<td>Age slope, β₄</td>
<td>-0.078721</td>
<td>24.02</td>
<td>σ = 7.07</td>
<td>- 4.0%</td>
</tr>
<tr>
<td>Gender slope, β₅</td>
<td>-0.316028</td>
<td>0.55</td>
<td>M = 0; F = 1</td>
<td>- 2.9%</td>
</tr>
<tr>
<td>Intent slope, β₆</td>
<td>0.819875</td>
<td>0.32</td>
<td>No = 0; Yes = 1</td>
<td>8.4%</td>
</tr>
<tr>
<td>Black slope, β₈</td>
<td>-0.287735</td>
<td>0.11</td>
<td>No = 0; Yes = 1</td>
<td>- 2.3%</td>
</tr>
</tbody>
</table>
Figure 11 shows the probability of transfer for institutions in the 25th, 50th, and 75th quartile categorized by the percentage of Pell recipients. If all institutions are ranked by percentage of students receiving Pell grants, the 25th percentile will represent those institutions that belong to the bottom 25% of the rankings. These are institutions where fewer percentage of students receive Pell grants. The percentile ranks do not represent the actual percentage of students receiving Pell grants in these institutions, but indicates their relative position with respect to other institutions. The probability of transfer goes down from 11% for institutions in the 25th percentile to 8% in the 75th percentile. This indicates that a higher percentage of Pell grant recipients reduce the probability of transfer of all students attending the institution.
In Figure 12, the change in the probability of transfer with a change in percentage of students receiving Pell grants is illustrated. The probability of transfer decreases by 4.7% for all students attending an institution when the percentage of students receiving Pell grants (in that institution) increases from 0% to 25%. When the percentage of students receiving Pell grant increases from 25% to 50%, the probability of transfer decreases by 2.5%. The decline continues for institutions with higher percentages of students receiving a Pell grant.
Figure 12: Relationship between percentage of students receiving Pell grant and probability of transfer

Figure 13 shows the relationship of the probability of transferring with two variables: one of the variables, \textit{age}, is measured at an individual level, and the other variable, \textit{percentage of students receiving Pell grants}, is measured at an institutional level. Each institution is represented by a separate line in Figure 13. Age is represented along the X-axis and probability of transfer, on the Y-axis. This figure explores how the percentage of students receiving Pell grants at an institution affects the probability of transfer of two students of the same age attending two different institutions. The percentage of students receiving Pell grants is used as a measure of institutional environment.
Figure 12 shows that if percentage of students receiving Pell grant at an institution goes up, it reduces the probability of transfer of all students attending that institution, irrespective of their individual status with respect to Pell grant. The probability of transfer for a student of age 23.75 years, for example, depends upon the institution the student attends. The probability varies from less than 0.09 to nearly 0.25. The slopes are steeper at a younger age and tend to even out over time. This indicates that the impact on the probability of transfer goes down as age increases. This is expected because the probability of transfer decreases with increasing age.

Figure 13: Relationship among age, percentage of students receiving Pell grant and probability of transfer
The second institutional level variable found to have an impact on transfer is percentage of full-time students attending the institution. As the percentage of full-time students attending the institution increases, the probability of transfer goes down. This is illustrated in Figure 14.

![Figure 14: Relationship between percentage of students attending full-time and the probability of transfer](image)

The finding is intuitively difficult to explain. Existing research indicates that the probability of student success increases for individual students attending full-time (Adelman, 2006). Therefore, a higher percentage of students attending an institution full-time is expected to increase the potential for success. Contrary to the expectation, this
study finds that if the percentage of students attending full-time increases, the probability of transfer for all students attending the institution decreases.

The contradictory finding may come from the fact that several small technical colleges in Ohio have a higher percentage of students attending full-time and the transfer rate from these institutions is lower than that of the large campuses having a higher percentage of part-time students. Since all institutions were given equal weight, the lower transfer rate from institutions with higher percentage of full-time students has probably skewed the results. Further research is necessary to substantiate this explanation.

Figure 15 shows the relationship between the number of students attending full-time, number of credits completed in the first year, and probability of transfer. Students who completed the same number of credits in the first year and were attending different institutions had a different probability of transfer.
Figure 15: Relationship among number of credits completed in the first year, percentage of students attending full-time and probability of transfer

The difference is attributed to the percentage of students attending full-time at the institution. Higher percentages of full-time students attending the institution mitigate the positive relationship between completing higher numbers of credits in the first year and the probability of transferring. Figure 15 also shows that the probability of transfer curves for all institutions belonging to any particular quintile do not necessarily remain in close proximity with one another. For example, the institutions with percentages of full-time students in the lower quintile are found to be distributed over the entire range. Two institutions are towards the top end, while others are more towards the middle of the
distribution of the set of probability curves. Further research is necessary to identify what causes the dispersion.

Effect of Distance and Number of Credits Transferred

Distance between start and transfer institution and number of credit hours accepted at transfer institution were two variables that could not be included in the models constructed. These variables assumed non-zero values only if the student transferred from one institution to another. The cases where the student was unable to transfer were always associated with a value of zero for distance between the institutions. Also, for those who did not transfer, number of credits transferred is always zero. One of the models that included these variables did not converge even after 1,200 iterations, suggesting the possibility that correlation between transfer and non-zero values sets up an infinite loop. Since these two variables could not be included in the model, the relationship between these two variables and transfer were explored separately.

In order to explore the relationship between distance and transfer, all students who transferred were selected and the distance between their start and transfer institutions was calculated. For all the cases where the student did not transfer, the distance between start and transfer institution was zero (because those two institutions were the same). If a student transferred successfully but both start and transfer institutions were located in the same zip code area, the distance was coded as 1 instead of zero. In all other cases, the distance was designated by the geographical distance in miles between the start and transfer institution. Intuitively, it is expected that the largest number of transfers will take place when the distance is low, and the number of transfers will decline with increasing distance. The data are presented in figure 16.
It is evident that students tend to transfer to institutions within 5 miles of their start institution. The number of transfers involving institutions separated by a distance exceeding 150 miles is low. In general, number of transfers decline as the distance grows more than 50 miles. However, there are distances beyond the 50 miles that accounted for a large number of transfers. There is a possibility that students drawn to a leading institution irrespective of distance may have caused the spike.

The fact that most of the transfers involve institutions separated by not more than 50 miles is probably driven by economic and cultural reasons. Another possible reason for students not to go far away may involve lack of availability of information. While
students gain familiarity about institutions closer to home from a variety of sources, getting information about institutions located over 100 miles away may become difficult. The role of inter-institutional cooperative agreements is another potential factor that may affect the popularity of a destination institution. The large number of institutions offering baccalaureate degrees in Ohio is another possible reason why students do not have to travel too far to transfer.

Figure 17 shows the number of credits transferred by students. The largest number of students did not transfer in any credit. This observation requires further exploration because Ohio is aligning curriculum among institutions to facilitate transfer of credits. Non-awareness of credit transfer opportunities is a possible explanation why so many students failed to transfer credits.

![Frequency distribution of number of credits transferred and transfer](image)

Mean = 44  
Std. Dev. = 28  
N = 4,810

Figure 17: Frequency distribution of number of credits transferred and transfer
Future studies may illuminate the potential reason why a large number of students did not transfer any credits. Barring this group, the number of credits transferred seems to follow a normal distribution with a mode towards transferring greater than average number of credit hours. Students transferring sixty to seventy credits are the groups with highest frequency.

Summary of Results

The four models explore the relationships between individual and institutional factors with probability of transfer. The results indicate that academic performance in community college is not strongly related to the probability of transferring. Factors that measure motivation, such as \textit{intent} to transfer, are found to have the strongest positive relationship with transfer. Academic accomplishment measured by \textit{number of credits completed in the first year} is also found to have a strong relationship with probability of transferring. \textit{Older} students have significantly lower probability to transfer, as do \textit{females} and \textit{blacks}. Although attending \textit{full-time} and maintaining higher \textit{GPA} contributes to higher probability of transfer, the positive relationship is not found to be strong. The number of students not transferring any credit to their destination institution is relatively high. At the institutional level, probability to transfer is decreases at institutions where: (a) higher \textit{percentage of students receives Pell grants}, and (b) higher \textit{percentage of students attends full-time}.

Overall, the findings from this study improve the understanding of the relationship between student background, institutional characteristics, and probability of transfer. The implications of the findings are considered in detail in chapter five.
CHAPTER FIVE: DISCUSSION AND CONCLUSIONS

The largest and fastest growing sector of American higher education, the community college, has witnessed unprecedented growth in the last few decades. Community colleges have followed an open-access policy to provide educational opportunities to a large population who did not previously participate in postsecondary education. Their comprehensive missions, range of program offerings, and open-access policies ensure that people from different socio-economic backgrounds, from new immigrants to laid-off workers, have access to the education they seek (AACC, 2006).

For a number of entering college students, it is often a difficult challenge to continue their education beyond community colleges in order to complete a baccalaureate degree. Several state policies, such as transfer articulation guides, and common course numbering systems, are aimed at making the process of transfer easier for these students.

Creating an infrastructure that helps students to transfer credits is not sufficient to increase the transfer rate. The students need to be informed of the available resources at the appropriate time and they should have the ability to use the resources when necessary. Committed students who seek out and utilize the resources available for transfer successfully transition to the four-year campuses and matriculate to four-year institutions (Flaga, 2006). However, fewer than 18% students from two-year institutions in Ohio are able to successfully use resources available for transfer (The Performance Report for Ohio’s Colleges and Universities, 2006).

Existing research suggests demographic background and academic preparation play critical roles in helping students transfer successfully. However, researchers are not
unanimous in their view about how different factors affect transfer. The ever-changing demographics of students entering community colleges render interpretation and application of study results more difficult.

To this end, this study, based on the dataset of students attending community colleges in Ohio, examines individual and institutional factors that may explain the probability of transferring from a two-year to a four-year public institution in the state. By identifying the characteristics of these students, this study contributes to the body of knowledge necessary to develop a student-centered advising strategy. The knowledge of institutional factors that increase probability of transfer is expected to help institutional leaders develop a culture of transfer at their institutions.

Summary of Research Findings

The goal of this study was, (a) to examine the direction and magnitude of the relationship among individual characteristics, institutional factors and transfer, and (b) to determine how the relationship of individual factors changes when the institutional factors are allowed to vary. The individual factors were clustered into two areas: (1) factors that describe demographic background and (2) factors that relate to academic endeavors. Overall, the study results showed that having a positive intent and completing a higher number of credits in the first year have the largest positive correlation with the probability of transfer, while age has the largest negative relationship. The following sections summarize the findings, and contextualize them with existing literature.

Intent and Transfer

Having a positive intent to transfer is used as a factor to indicate the motivation of a student. In organization research, variables that denote the intent to accomplish a task is
often used as a surrogate to the actual variable of interest (Dalton, Johnson, & Daily, 1999). For example, intent to leave an organization may be used as a surrogate to the variable, actual turnover in an organization. It is assumed that a high degree of correlation exists between intent to leave and actually leaving an organization. This may not necessarily be true. Many students may record a positive intent to transfer as a primary objective without giving it much thought. The possibility of students developing an intent to transfer upon joining college cannot be ruled out. There is some evidence that positive intent is a strong predictor of success (Hall, 1990), however, the study focused on overall student success and transfer was only a part of the outcome. Since research literature suggests that although nearly 42% of community college students intend to transfer, only a fourth of them actually end up doing so (U.S. Department of Education, 2007), an empirical study is necessary to determine the relationship between intent and transfer.

The results obtained from the final model indicate that self-declared intent has the strongest positive relationship with transfer. When all other factors are controlled, change in intent increases probability of transfer by 8.4%. The result also indicates that for two students with similar backgrounds and studying at similar institutions, not having intent (to transfer) may reduce the probability of transfer by 8.4%. Research conducted at Illinois in the late nineties corroborates the positive relationship between intent and transfer (Palmer, n.d.).

The Illinois Community College Board (1998) analyzed the transfer rates for entering students. Their study showed a 22% transfer rate for all students, a 29% transfer rate for students enrolled in baccalaureate/transfer programs, and a 34% transfer rate for students enrolled in baccalaureate/transfer programs and entered community colleges
with a stated intent to transfer. While the Illinois study, conducted nearly ten years ago, attributed an increase of 5% transfer rate for students with a positive intent, this study estimated the increase in probability to transfer due to positive intent to be 8.4%. The positive relationship between intent and transfer is also supported from the theoretical perspectives of education researchers (Palmer, n.d.).

From a theoretical perspective, Tinto’s interactionalist theory posits that the student background is positively related to initial goal commitment. It is likely that institutional initiatives help re-inforce the initial goal commitment of the student (Braxton, Hirschy, & McClendon, 2004). The conceptual framework of this study is based on reinforcing the initial goal commitment of the student by targeted advising activity at the institution. The positive relationship between intent and transfer indicates that if institutions can help increase student goal commitment, their probability of transfer may increase.

*First-year Credits and Transfer*

The results from this research confirm that the probability of transfer increases by more than 4% when the number of credit hours completed in the first year increases from 25 to 37. Although the positive relationship between number of credits completed in the first year and academic success has been documented, (Adelman, 2006), the study did not explore the correlation between number of credits completed in the first year and transfers. A combination of intent of transfer and completion of a higher number of credits helped students increase the probability of transferring by up to 11%.

Completion of a higher number of credits in the first year is an indication of a student’s progress towards fulfilling his or her academic goal. If enrolling in a
postsecondary institution indicates the beginning of an academic journey, every milestone such as expressing intent to transfer, earning a minimum number of credits in the first year, or completing a minimum number of credits with a GPA of 2.5, indicates how well the student is progressing towards the academic goal. The closer the student gets to the goal, the higher the possibility of accomplishing it. Thus, completion of higher number of credits in the first year may enhance the goal commitment of the student. A higher goal commitment may result in a higher probability of transferring.

The implication of this finding on policy formulation is rather straightforward. Encouraging students to complete a higher number of credits in the first year should correspond to a higher transfer rate. Setting a threshold for completing a certain number of credits in the first year may bring about a positive change in student success. Targeted financial aid for students who complete a certain number of credit hours in the first year may also bring about the desired positive effect on transfer. Such policies may be implemented either at the state or institutional level. A combination of policies aimed at increasing first year credit completion and enhancing student intent through transfer advising centers may increase the probability of transfer significantly.

Age, Gender, Race and Transfer

In the last decade, the proportion of students of non-traditional age entering community colleges has increased significantly (AACC, 2006). As the gap between high school graduation and enrolling in college increases, the relevance of age in determining success at community colleges becomes more critical. In this study, age is found to have the largest negative impact on probability of transfer. However, the negative effect of age may be mitigated to a large extent by positive intent to transfer.
Females are less likely to transfer than their male counterparts. The impact of age and gender on probability to transfer is somewhat intuitive. Increases in age changes life situation, increasing family commitments and decreases available time for academic pursuits. This is likely to result in lower probability of transfer. Being female may also result in increasing family commitments, and decreasing mobility, and eventually reducing the probability of transfer. However, an older student with a positive intent to transfer increases the probability of transfer substantially. The understanding of the relationship among age, intent and probability of transfer can be used by advisors to effectively increase transfer rates. The fact that most of the students transfer to institutions within 50 miles from their start institution can also help the older students with family commitments look at the possibility of transfer more favorably.

Dougherty and Kienzl (2006) noted that lower educational aspiration is one of the major factors that contribute to the low transfer rate of older students. The lower transfer rate of the older students is not because they lack academic preparation: aspiration is a motivational state rather than a representation of academic preparation. Lower aspiration of older students is possibly rooted in the belief that transferring to another institution will upset their job and family life. Institutional initiatives aimed at informing the older students of various transfer opportunities may help reduce some of the potential barriers. The fact that it is possible to find a transfer institution not too far away from home can encourage older students to transfer. The findings from the model suggest that the probability of transfer of a 21-year old student without intent to transfer is the same as that of a 28-year old student with a positive intent. Such information and availability of
institutions not too far from home can help motivate older students to transfer and aspire to attain a baccalaureate degree.

Among students from different races, only African American students are found to be at a disadvantage when it comes to transfer. There is no relationship between Whites or Hispanic and probability to transfer. Previous studies were inconclusive on the impact of race on transfer. The findings from this research do not add much clarity to the previous findings.

**GPA, Attending Full-time, and Transfer**

The relationship between GPA and transfer is positive; however, the rate of increase of probability of transfer is low. The weak influence of GPA on transfer (0.8% increase in probability for an increase of 1.4 in GPA) is perhaps best explained from the perspective of late bloomers (Dowd et al., 2006). Community college students often come from backgrounds where they were not encouraged to attend institutions of higher education (Achieving the Dream, 2005). The lack of encouragement may result in their lower academic achievement, which should not be confused with lower ability or potential. Once these students come into contact with appropriate change agents, whether by design or by accident, they tend to overcome their lower achievement relatively quickly. Success of community college students at elite institutions, such as Cornell University is showcased as evidence of academic accomplishment of the late bloomers (Dowd et al., 2006).

Another possible explanation of the weak relationship between GPA and probability of transfer is that older community colleges students take their studies more seriously, and therefore have better GPAs. However, older students are less likely to
transfer because of lower aspiration and potential disturbance to their job and family life. The lower transfer rate of older students with a high grade point average can potentially have a mitigating effect on the relationship between GPA and transfer. GPA in community college is used as a measure of academic performance in this study, instead of academic preparation in high school. This was done to accommodate for the life experience of students who do not enroll in colleges immediately after graduating from high school. The weak association between GPA and transfer suggest that life experience and goal commitment helps students overcome limitations in prior academic preparation. However, life experience impacts students in several ways: academic pursuit is only one of them. Other areas significantly affected by life experience are job and family life. The relationship between these complex set of factors and academic aspiration of the student is beyond the scope of this study.

Students attending full-time are likely to have a greater probability to transfer than their counterparts attending part-time. This is corroborated by a study that linked full-time attendance with academic success (Adelman, 2006). However, the decrease in probability of transfer for attending part-time is higher for males than for females. The reason for this difference is not answered by this study.

**Distance, Number of Credits Accepted, and Transfer**

The relationship between distance and transfer indicates that most of the students transfer to an institution within 50 miles of their start institution. There are several possible explanations for this observation. Availability of institutions within a close proximity may contribute to the transfer students not going far from their home. Availability of information from institutions from institutions located close to their home
is another possible reason for such institutions being a preferred destination. The existence of inter-institutional co-operative agreements is the third possibility of choosing institutions that are located nearby. The information that most of the students find a transfer institution within fifty miles of their start institution may encourage older students who do not transfer because of problems associated with relocation.

The largest number of students transferred did not transfer any credit from the start institution. This finding raises questions about awareness of credit transfer policies among the students that intend to transfer. Repeating credits not only affects the student but also costs the state. Developing transfer advising centers with trained advisors who are aware of state policies and transfer articulation agreements may help increase the number of credits transferred.

Institutional Factors and Transfer

Two institutional factors found to have an impact on transfer are the percentage of students receiving Pell grants and the percentage of full-time students studying at the institution. In both cases, the probability of transfer goes down with an increase in the value of the variables. If the percentage of students receiving a Pell grant is higher in one institution than another, the probability of transfer from that institution will be lower (than the other institution). While this is intuitively not difficult to understand, the finding that higher percentage of full-time students reduces overall probability of transfer for the institution goes against conventional wisdom.

Recent studies have found a positive correlation between attending full-time and student success (Adelman, 2006; Dougherty & Kienzl, 2006). This research found that at an individual level, attending full-time increases probability of transfer. However, at the
institutional level, a higher percentage of full-time students results in a lower probability of transfer.

This aberration is probably because the dataset included several technical colleges in Ohio with enrollment less than 5,000 that have a high percentage of full-time students. The institutional data used for the research shows that 47% of technical college students attend full-time, compared to 40% of community colleges. Fewer students tend to transfer from technical colleges for a variety of reasons, academic objective being one of them. A lower transfer rate from a number of institutions with higher percentage of full-time students may have contributed to the finding that probability to transfer goes down with an increase in percentage of full-time students.

Scope of Future Research

The institutional leadership plays a critical role in developing the culture of an institution. Tinto’s (1975) interactionalist theory posits that social integration reflects the student’s perception of his/her degree of congruence with institutional beliefs and values. Thus, the institutional leadership plays a crucial role in shaping student expectation. Although the impact of leaders on institutional effectiveness has a strong effect on student success, measuring such impact in quantitative terms can be challenging. This study did not include any variable to model the impact of leadership. The role of institutional initiatives in developing student expectations on transfer is an area for future studies.

The findings from this study indicate that financial need negatively effects the probability of transfer at an institutional level. It is not known if there is any relationship between such institutional characteristics and amount of resources the institution allocates
to serve the students from low SES backgrounds. Including institutional financial information, such as percentage of educational and general expenses allocated to student support outside the classroom can shed some light in this area. Students with lower SES are perceived to have lower aspirations and less information (Achieving the Dream, 2005). If institutions allocate resources to address these gaps, student achievement may improve. Allocation of resources not only helps support activities in a particular area, but also indicates an institutional philosophy to student support. Future studies can explore the relationship between institutional allocation of fiscal resources and the probability of transfer.

Self-declared intent is captured when a student joins an institution. This variable represents a state of aspiration and ambition of a student. It is possible that such aspirations change after the student joins an institution. The interaction with student advisors or faculty can result in either increasing or decreasing the aspiration and ambition. How the intent changes after enrolling in the institution and the potential impact of such change of intent remains unknown. Future research involving students and campuses with advising centers focused on transfer encouragement can help us understand how student centered advising contributes to subsequent goal commitment by the student.

Several studies established strong correlation between SES and academic success (Wellman, 2002; Long, 2004). In the present study, no individual level variable was included in the model to account for SES of the student. It is generally perceived that students from lower SES face more barriers than others. The finding that a higher percentage of students receiving Pell grants at an institution lower the institutional
probability of transfer is a vindication of the fact that lower SES has a negative impact on transfer. Future research may reveal the impact of this factor at an individual level.

The grade point average of the student was used to model the academic achievement level of the student. Other academic variables, such as high school GPA, scores in ACT or SAT examinations, placement into developmental classes were not considered either at individual or at institutional levels. How academic factors such as standardized test scores, high school GPA, or placement into developmental education affects transfer remains unknown.

One of the findings from this study is a negative relationship between percentage of full-time students attending an institution and probability of transferring. It is possible that small technical colleges having a higher proportion of full-time students who do not aspire to pursue a baccalaureate degree has contributed to this finding. Future research could draw a clear distinction between technical and community colleges.

Involving students in activities outside the classroom are known to increase student engagement with the institution (Astin, 1984). Studies such as Community College Survey of Student Engagement (CCSSE) do track parameters such as talking to faculty outside of class, number of hours spent on homework, talking to academic advisors, visiting the career and placement office as measures of involvement. No such parameter was used for this study because all institutions do not implement CCSSE and therefore, data for all institutions are not available. Also, at least one study concluded that factors such as the number of contacts with faculty outside the classroom, attending career oriented lectures, or talking to academic advisors did not have a significant relationship with transfer (Dougherty & Kienzl, 2006).
Though some studies found students from community colleges went on to do well at premier institutions (Dowd, et. al., 2006), there is a general notion that weak academic background negatively impacts future academic endeavors. Lee and Frank (1990) found academic preparation to be a strong predictor of success in community colleges while Bailey and Weininger (2002) did not observe any such effect. Findings from this research tend to indicate that strong academic preparation does have a positive relationship with transfer, but the magnitude of the relationship is not found to be large. Including more academic variables may provide more insight on this issue.

Policy Recommendations and Conclusion

The two factors that have the highest positive relationship with the probability of transfer are student intent and number of credits completed in the first year. Both of these findings can be used to form effective policy at both the state and institutional level. Specific policies may target improving intent through institutional initiatives, such as transfer advising centers, and involving students as transfer champions. Rewarding first year credit completion can provide the much needed motivation for students to set their aspirations higher. Another state initiative could be fiscal rewards to the group of students who demonstrate higher potential to transfer.

Institutional Initiatives

Although the state of Ohio has considerable resources to develop transfer of credit among institutions, one of the findings of this study is several students in who successfully transferred to a four-year institution between 2002 and 2004 did not transfer credits. One possible reason for the inability to transfer courses is lack of information available on credit transfer procedures. The informational gap can be attributed to a host
of possibilities, including first generation college students and coming from low SES background (Dowd et al., 2006). Holding transfer orientation courses, inviting students who transferred successfully, developing a formal peer mentor program to facilitate use of available resources, disseminating information about advantages of baccalaureate degree: all of these can help bridge the information gap.

The lower probability of transferring among older students is another finding from this study. Existing research suggests that older students do not transfer because of lower motivation (Dougherty & Kienzl, 2006). Older students may not lack the academic preparation necessary for the transfer students. If the older students develop a positive intent to transfer, they can potentially improve their probability of transferring. The understanding of how a positive intent can help mitigate the negative effect of age can be used for student advising.

Astin (1984) advocated involvement in campus activities as a way to connect and feel a part of the institution. Setting up student advising centers to provide information about transfer possibilities is a good point to start the process of involving the student. However, success of such advising centers will depend on the students seeking support. If a student gets to know about it early, he or she will benefit from such institutional services. Mandating dissemination of transfer information in the “first-year experience” courses can help reach out to the students further. Creating role models from the pool of students who have successfully transferred can act as a strong encouragement to the “late bloomers”. Including students who have successfully transferred, curricula specifically targeted to increase transfer, as well as promotional materials about transfer can help
improve transfer rates as well. Such actions intended at actively engaging students in the transfer conversation could result in student involvement, and an active intent to transfer.

Apart from financial support, all these policies require a positive intent on part of the institution. State policymakers can help by providing financial support for targeted activities at the institutional level. The change in number of students transferring can be measured fairly accurately through the existing data reporting mechanisms. Rewarding schools that achieve higher transfer rates can also be considered by policymakers. Policymakers need to focus on institutional and systemic initiatives to help improve student intent. Over the years, the actions that help maximum number of students may be identified and such activities may be scaled up at the state level across all institutions.

*State Initiatives*

The other important positive influence of transfer comes from completing a higher number of credits in the first year. Although completing a higher number of credits in the first year may not necessarily have a causal relationship with the probability of transfer, encouraging and rewarding students to complete a higher number of courses in the first year can help involve the student in the campus. The institutional goal of transferring to a four-year institution can help students increase their probability of transferring.

Establishing a threshold for number of credits to be completed in the first year and rewarding the students who successfully complete the threshold credit hours can bring about the desired change in transfer. Further evidence should be collected to link transfer success with types of courses completed in the first year. Initiatives such as transfer
articulation guideline and common course numbering can be combined with this initiative to ensure that interested students do not need to repeat the courses after transfer.

This recommendation has associated problems also. The lure of reward may encourage more students to enroll for courses, and eventually dropping them, thus creating avoidable pressure on the faculty. Also, this study identifies that completing a higher number of credits in the first year helps to increase the probability of transfer; the type of courses that help students transfer is not identified. If there is indeed any specific category of courses that help students transfer, that need to be identified. Otherwise, many students may take a number of courses without achieving intended benefits. A good place to start may be to require completion of general education courses in the first year (at least beyond the threshold).

A combination of encouragement to achieve more, providing structured channels of information dissemination, and rewarding those taking positive steps to transfer can help improve the transfer rate. Policymakers and institutions need to ensure that the resources reach the students who need them the most.
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*Journal of College Student Personnel, 25,* 297-308.


Melguizo, T., & Dowd, A. C. (2006). National estimates of transfer access and bachelor’s degree attainment at four-year colleges and universities. Los Angeles, CA and Boston, MA: University of Southern California and University of Massachusetts Boston.


APPENDIX 1

Analysis of High Credit Completion

The highest number of credits completed in first year is 126. The percentile frequency distribution for the variable, number of credits completed in first year is shown in Table 21. It is evident from Table 21 that 90% of the students completed up to 43 credits in the first year and half the students completed up to 23 credits in the first year. Upon further scrutiny of the data, it was found that only 51 students completed over 70 credits in their first year. It is possible that some of the students with a high number of credits completed part of the credits while in high school. If that is the case, they would still qualify as having registered in the postsecondary institution for the first time and yet have a large number of credits completed in the first year, including those completed while in high school. Authenticity of this assumption could not be validated. However, the number of students with very high credit completion is so few in relation to the entire dataset that they will not bias the analysis.

Table 21

Percentile distribution for number of credits completed in first year

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<th>31245</th>
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<td>59.000</td>
</tr>
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APPENDIX 2

Output of the Unconditional (Null) Model

Program: HLM 6 Hierarchical Linear and Nonlinear Modeling
Authors: Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher: Scientific Software International, Inc. (c) 2000
techsupport@ssicentral.com
www.ssicentral.com

------------------------------
Module: HLM2.EXE (6.04.27107.1)
Date: 26 January 2008, Saturday
Time: 13:21:35
------------------------------

SPECIFICATIONS FOR THIS NONLINEAR HLM2 RUN

The data source for this run = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\Transfer_12.mdm
The command file for this run = whlmtemp.hlm
Output file name = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\hlm2.txt
The maximum number of level-1 units = 31245
The maximum number of level-2 units = 22
The maximum number of micro iterations = 50
Method of estimation: full PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

Weighting Specification

--------------------------------------
Weight Variable
Weighting? Name Normalized?
Level-1 no
Level-2 no
Precision no
--------------------------------------

The outcome variable is TFR_CODE
The model specified for the fixed effects was:

--------------------------------------
Level-1 Level-2
Coefficients Predictors
--------------------------------------
The model specified for the covariance components was:

**Tau dimensions**

**INTRCPT1**

Summary of the model specified (in equation format)

---

**Level-1 Model**

\begin{equation}
\text{Prob}(Y=1|B) = P
\end{equation}

\begin{equation}
\log\frac{P}{1-P} = B0
\end{equation}

**Level-2 Model**

\begin{equation}
B0 = G00 + U0
\end{equation}

Level-1 variance = \(\sigma^2/[P(1-P)]\)

The value of the likelihood function at iteration 4 = -1.211174E+004

---

**RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION: Unit-Specific Model**

(macro iteration 3)

Sigma\_squared = 0.99570

Standard Error of Sigma\_squared = 0.00797

Tau

**INTRCPT1,B0** 0.30100

Standard Errors of Tau

**INTRCPT1,B0** 0.09458

Tau (as correlations)

**INTRCPT1,B0** 1.000

---

The value of the likelihood function at iteration 2 = -4.430579E+004

The outcome variable is TFR\_CODE

Final estimation of fixed effects: (Unit-specific model)

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<th>Fixed Effect</th>
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<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx d.f.</th>
<th>P-value</th>
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<table>
<thead>
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<th>Odds Ratio</th>
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<tr>
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</table>
The outcome variable is TFR\_CODE

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

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<tr>
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<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx d.f.</th>
<th>P-value</th>
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<td>(0.116, 0.190)</td>
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</table>

Final estimation of variance components:

<table>
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<tr>
<th>Random Effect</th>
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</tbody>
</table>

RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION:
Population Average Model
The value of the likelihood function at iteration 3 = -4.519192E+004
The outcome variable is TFR\_CODE

Final estimation of fixed effects: (Population-average model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, B0</td>
<td>-1.805015</td>
<td>0.118901</td>
<td>-15.181</td>
<td>21</td>
<td>0.000</td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.805015</td>
<td>0.164472</td>
<td>(0.128, 0.211)</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>
Output of Model with Level-1 Variables only

Program: HLM 6 Hierarchical Linear and Nonlinear Modeling
Authors: Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher: Scientific Software International, Inc. (c) 2000
techsupport@ssicentral.com
www.ssicentral.com

-------------------------------------------------------------------------------
Module: HLM2.EXE (6.04.27107.1)
Date: 26 January 2008, Saturday
Time: 13:17:6
-------------------------------------------------------------------------------

SPECIFICATIONS FOR THIS NONLINEAR HLM2 RUN

The data source for this run = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\Transfer_12.mdm
The command file for this run = whlmtemp.hlm
Output file name = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\hlm2.txt
The maximum number of level-1 units = 31245
The maximum number of level-2 units = 22
The maximum number of micro iterations = 50
Method of estimation: full PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli
Weighting Specification

<table>
<thead>
<tr>
<th>Level-1</th>
<th>Level-2</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>no</td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>

The outcome variable is TFR_CODE
The model specified for the fixed effects was:

<table>
<thead>
<tr>
<th>Level-1 Coefficients</th>
<th>Level-2 Predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, B0</td>
<td>INTRCPT2, G00</td>
</tr>
<tr>
<td># FIRST_YE slope, B1</td>
<td>INTRCPT2, G10</td>
</tr>
<tr>
<td># FT slope, B2</td>
<td>INTRCPT2, G20</td>
</tr>
<tr>
<td># GPA slope, B3</td>
<td>INTRCPT2, G30</td>
</tr>
<tr>
<td># AGE slope, B4</td>
<td>INTRCPT2, G40</td>
</tr>
<tr>
<td># GENDER slope, B5</td>
<td>INTRCPT2, G50</td>
</tr>
<tr>
<td># INTENT slope, B6</td>
<td>INTRCPT2, G60</td>
</tr>
<tr>
<td># WHITE slope, B7</td>
<td>INTRCPT2, G70</td>
</tr>
<tr>
<td># BLACK slope, B8</td>
<td>INTRCPT2, G80</td>
</tr>
<tr>
<td># HISPANIC slope, B9</td>
<td>INTRCPT2, G90</td>
</tr>
</tbody>
</table>

'#' - The residual parameter variance for this level-1 coefficient has been set to zero.

The model specified for the covariance components was:

<table>
<thead>
<tr>
<th>Tau dimensions</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1</td>
</tr>
</tbody>
</table>

Summary of the model specified (in equation format)

Level-1 Model

\[
\text{Prob}(Y=1|B) = P \\
\log[P/(1-P)] = B0 + B1*(FIRST_YE) + B2*(FT) + B3*(GPA) + B4*(AGE) + B5*(GENDER) + B6*(INTENT) + B7*(WHITE) + B8*(BLACK) + B9*(HISPANIC)
\]

Level-2 Model

\[
B0 = G00 + U0 \\
B1 = G10 \\
B2 = G20 \\
B3 = G30 \\
B4 = G40 \\
B5 = G50 \\
B6 = G60 \\
B7 = G70 \\
B8 = G80 \\
B9 = G90
\]

Level-1 variance = \( \sigma^2 / [P(1-P)] \)
Run-time deletion has reduced the number of level-1 records to 30286
The value of the likelihood function at iteration 6 = -1.059765E+004
RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION: Unit-Specific Model
(macro iteration 6)
Sigma squared = 1.09378
Standard Error of Sigma squared = 0.00889
Tau
INTERCPT1,B0  0.42011
Standard Errors of Tau
INTERCPT1,B0  0.13128
Tau (as correlations)
INTERCPT1,B0  1.000

Random level-1 coefficient Reliability estimate

The value of the likelihood function at iteration 2 = -4.437209E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Unit-specific model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td>-1.564729</td>
<td>0.198287</td>
<td>-7.891</td>
<td>21</td>
<td>0.000</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1</td>
<td>0.037397</td>
<td>0.002284</td>
<td>16.375</td>
<td>30,276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td>0.163148</td>
<td>0.050509</td>
<td>3.23</td>
<td>30,276</td>
<td>0.002</td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td>0.067648</td>
<td>0.013975</td>
<td>4.841</td>
<td>30,276</td>
<td>0.000</td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td>-0.07857</td>
<td>0.004409</td>
<td>-17.822</td>
<td>30,276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope, B5</td>
<td>-0.315401</td>
<td>0.035757</td>
<td>-8.821</td>
<td>30,276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td>0.820676</td>
<td>0.039078</td>
<td>21.001</td>
<td>30,276</td>
<td>0.000</td>
</tr>
<tr>
<td>For WHITE slope, B7</td>
<td>0.008113</td>
<td>0.075644</td>
<td>0.107</td>
<td>30,276</td>
<td>0.915</td>
</tr>
<tr>
<td>For BLACK slope, B8</td>
<td>-0.282736</td>
<td>0.095499</td>
<td>-2.961</td>
<td>30,276</td>
<td>0.004</td>
</tr>
</tbody>
</table>
The outcome variable is TFR_CODE
Final estimation of fixed effects
(Unit-specific model with robust standard errors)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0, INTRCPT2, G00</td>
<td>-1.564729</td>
<td>0.17133</td>
<td>-9.133</td>
<td>21</td>
<td>0.000</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1, INTRCPT2, G10</td>
<td>0.037397</td>
<td>0.005463</td>
<td>6.846</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2, INTRCPT2, G20</td>
<td>0.163148</td>
<td>0.054129</td>
<td>3.014</td>
<td>30276</td>
<td>0.003</td>
</tr>
<tr>
<td>For GPA slope, B3, INTRCPT2, G30</td>
<td>0.067648</td>
<td>0.026025</td>
<td>2.599</td>
<td>30276</td>
<td>0.010</td>
</tr>
<tr>
<td>For AGE slope, B4, INTRCPT2, G40</td>
<td>-0.07857</td>
<td>0.006993</td>
<td>-11.236</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope, B5, INTRCPT2, G50</td>
<td>-0.315401</td>
<td>0.052387</td>
<td>-6.021</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6, INTRCPT2, G60</td>
<td>0.820676</td>
<td>0.062015</td>
<td>13.234</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For WHITE slope, B7, INTRCPT2, G70</td>
<td>0.008113</td>
<td>0.106421</td>
<td>0.076</td>
<td>30276</td>
<td>0.940</td>
</tr>
<tr>
<td>For BLACK slope, B8, INTRCPT2, G80</td>
<td>-0.282736</td>
<td>0.120472</td>
<td>-2.347</td>
<td>30276</td>
<td>0.019</td>
</tr>
<tr>
<td>For HISPANIC slope, B9, INTRCPT2, G90</td>
<td>-0.175378</td>
<td>0.164438</td>
<td>-1.067</td>
<td>30.276</td>
<td>0.287</td>
</tr>
<tr>
<td>Fixed Effect</td>
<td>Coefficient</td>
<td>Odds Ratio</td>
<td>Confidence Interval</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------</td>
<td>-------------</td>
<td>------------</td>
<td>---------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>For INTRCPT1, B0</td>
<td>-1.564729</td>
<td>0.209145</td>
<td>(0.147, 0.299)</td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>For FIRST_YE slope, B1</td>
<td>0.037397</td>
<td>1.038105</td>
<td>(1.027, 1.049)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td>0.163148</td>
<td>1.177211</td>
<td>(1.059, 1.309)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td>0.067648</td>
<td>1.069988</td>
<td>(1.017, 1.126)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td>-0.07857</td>
<td>0.924437</td>
<td>(0.912, 0.937)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>For GENDER slope, B5</td>
<td>-0.315401</td>
<td>0.729496</td>
<td>(0.658, 0.808)</td>
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</tr>
<tr>
<td>INTRCPT2, G50</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td>0.820676</td>
<td>2.272036</td>
<td>(2.012, 2.566)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G60</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For WHITE slope, B7</td>
<td>0.008113</td>
<td>1.008146</td>
<td>(0.869, 1.169)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G70</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For BLACK slope, B8</td>
<td>-0.282736</td>
<td>0.753719</td>
<td>(0.818, 1.242)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For HISPANIC slope, B9</td>
<td>-0.175378</td>
<td>0.83914</td>
<td>(0.669, 1.053)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G90</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Final estimation of variance components:

<table>
<thead>
<tr>
<th>Random Effect</th>
<th>Standard Deviation</th>
<th>Variance Component</th>
<th>Degrees of freedom</th>
<th>Chi-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, U0</td>
<td>0.64816</td>
<td>0.42011</td>
<td>21</td>
<td>1290.19186</td>
<td>0.000</td>
</tr>
<tr>
<td>level-1, R</td>
<td>1.04584</td>
<td>1.09378</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION:
Population Average Model
The value of the likelihood function at iteration 3 = -4.404025E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Population-average model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0 INTRCPT2, G00</td>
<td>-1.425347</td>
<td>0.195417</td>
<td>-7.294</td>
<td>21</td>
<td>0.000</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1 INTRCPT2, G10</td>
<td>0.035663</td>
<td>0.002169</td>
<td>16.446</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2 INTRCPT2, G20</td>
<td>0.162216</td>
<td>0.05198</td>
<td>3.121</td>
<td>30276</td>
<td>0.002</td>
</tr>
<tr>
<td>For GPA slope, B3 INTRCPT2, G30</td>
<td>0.064173</td>
<td>0.01397</td>
<td>4.594</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For AGE slope, B4 INTRCPT2, G40</td>
<td>-0.076189</td>
<td>0.004241</td>
<td>17.966</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope, B5 INTRCPT2, G50</td>
<td>-0.301437</td>
<td>0.036051</td>
<td>-8.361</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6 INTRCPT2, G60</td>
<td>0.785912</td>
<td>0.040068</td>
<td>19.614</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For WHITE slope, B7 INTRCPT2, G70</td>
<td>0.003136</td>
<td>0.077144</td>
<td>0.041</td>
<td>30276</td>
<td>0.968</td>
</tr>
<tr>
<td>For BLACK slope, B8 INTRCPT2, G80</td>
<td>-0.274712</td>
<td>0.09776</td>
<td>-2.81</td>
<td>30276</td>
<td>0.005</td>
</tr>
<tr>
<td>For HISPANIC slope, B9 INTRCPT2, G90</td>
<td>-0.171732</td>
<td>0.17498</td>
<td>-0.981</td>
<td>30276</td>
<td>0.327</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0, INTRCPT2, G00</td>
<td>-1.425347</td>
<td>0.240425</td>
<td>(0.160,0.361)</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1, INTRCPT2, G10</td>
<td>0.035663</td>
<td>1.036307</td>
<td>(1.032,1.041)</td>
</tr>
<tr>
<td>For FT slope, B2, INTRCPT2, G20</td>
<td>0.162216</td>
<td>1.176114</td>
<td>(1.062,1.302)</td>
</tr>
<tr>
<td>For GPA slope, B3, INTRCPT2, G30</td>
<td>0.064173</td>
<td>1.066276</td>
<td>(1.037,1.096)</td>
</tr>
<tr>
<td>For AGE slope, B4, INTRCPT2, G40</td>
<td>-0.076189</td>
<td>0.926641</td>
<td>(0.919,0.934)</td>
</tr>
<tr>
<td>For GENDER slope, B5, INTRCPT2, G50</td>
<td>-0.301437</td>
<td>0.739754</td>
<td>(0.689,0.794)</td>
</tr>
</tbody>
</table>
For INTENT slope, B6, INTRCPT2, G60 0.785912 2.194408 (2.029,2.374)
For WHITE slope, B7, INTRCPT2, G70 0.003136 1.00314 (0.862,1.167)
For BLACK slope, B8, INTRCPT2, G80 -0.274712 0.759791 (0.627,0.920)
For HISPANIC slope, B9, INTRCPT2, G90 -0.171732 0.842205 (0.598,1.187)

The outcome variable is TFR_CODE
Final estimation of fixed effects
(Population-average model with robust standard errors)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0, INTRCPT2, G00</td>
<td>-1.425347</td>
<td>0.151693</td>
<td>-9.396</td>
<td>21</td>
<td>0.000</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1, INTRCPT2, G10</td>
<td>0.035663</td>
<td>0.004966</td>
<td>7.182</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2, INTRCPT2, G20</td>
<td>0.162216</td>
<td>0.055581</td>
<td>2.919</td>
<td>30276</td>
<td>0.004</td>
</tr>
<tr>
<td>For GPA slope, B3, INTRCPT2, G30</td>
<td>0.064173</td>
<td>0.026091</td>
<td>2.46</td>
<td>30276</td>
<td>0.014</td>
</tr>
<tr>
<td>For AGE slope, B4, INTRCPT2, G40</td>
<td>-0.076189</td>
<td>0.006645</td>
<td>-11.465</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope, B5, INTRCPT2, G50</td>
<td>-0.301437</td>
<td>0.051916</td>
<td>-5.806</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6, INTRCPT2, G60</td>
<td>0.785912</td>
<td>0.069656</td>
<td>11.283</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For WHITE slope, B7, INTRCPT2, G70</td>
<td>0.003136</td>
<td>0.108784</td>
<td>-0.029</td>
<td>30276</td>
<td>0.977</td>
</tr>
<tr>
<td>For BLACK slope, B8, INTRCPT2, G80</td>
<td>-0.274712</td>
<td>0.129484</td>
<td>-2.122</td>
<td>30276</td>
<td>0.034</td>
</tr>
<tr>
<td>For HISPANIC slope, B9, INTRCPT2, G90</td>
<td>-0.171732</td>
<td>0.129104</td>
<td>-1.33</td>
<td>30276</td>
<td>0.184</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0, INTRCPT2, G00</td>
<td>-1.425347</td>
<td>0.240425</td>
<td>(0.175,0.329)</td>
</tr>
<tr>
<td>For FIRST_YE slope, B1, INTRCPT2, G10</td>
<td>0.035663</td>
<td>1.036307</td>
<td>(1.026,1.046)</td>
</tr>
<tr>
<td>For FT slope, B2, INTRCPT2, G20</td>
<td>0.162216</td>
<td>1.176114</td>
<td>(1.055,1.311)</td>
</tr>
<tr>
<td>For GPA slope, B3, INTRCPT2, G30</td>
<td>0.064173</td>
<td>1.066276</td>
<td>(1.013,1.122)</td>
</tr>
<tr>
<td>For AGE slope, B4, INTRCPT2, G40</td>
<td>-0.076189</td>
<td>0.926641</td>
<td>(0.891,0.960)</td>
</tr>
<tr>
<td>For GENDER slope, B5, INTRCPT2, G50</td>
<td>-0.301437</td>
<td>0.739754</td>
<td>(0.668,0.819)</td>
</tr>
</tbody>
</table>
For INTENT slope, B6, INTRCPT2, G60  0.785912  2.194408  (1.914,2.515)
For WHITE slope, B7, INTRCPT2, G70  0.003136  1.00314  (0.811,1.242)
For BLACK slope, B8, INTRCPT2, G80  -0.274712  0.759791  (0.589,0.979)
For HISPANIC slope, B9, INTRCPT2, G90  -0.171732  0.842205  (0.654,1.085)

Output of Model with Level-2 Variables only

Program: HLM 6 Hierarchical Linear and Nonlinear Modeling
Authors: Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher: Scientific Software International, Inc. (c) 2000
techsupport@ssicentral.com
www.ssicentral.com

-------------------------------------------------------------------------------
Module:    HLM2.EXE (6.04.27107.1)
Date:      26 January 2008, Saturday
Time:      13:19:33
-------------------------------------------------------------------------------
SPECIFICATIONS FOR THIS NONLINEAR HLM2 RUN

The data source for this run = C:\Documents and Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New Folder\HLM\Transfer_12.mdm
The command file for this run = whlmtemp.hlm
Output file name = C:\Documents and Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New Folder\HLM\hlm2.txt
The maximum number of level-1 units = 31245
The maximum number of level-2 units = 22
The maximum number of micro iterations = 50
Method of estimation: full PQL
Maximum number of macro PQL iterations = 100

Distribution at Level-1: Bernoulli

Weighting Specification

<table>
<thead>
<tr>
<th>Weight Variable</th>
<th>Weighting?</th>
<th>Name</th>
<th>Normalized?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level-1</td>
<td>no</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level-2</td>
<td>no</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Precision</td>
<td>no</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The outcome variable is TFR_CODE
The model specified for the fixed effects was:

Level-1                  Level-2
Coefficients             Predictors
----------------------   ---------------
INTRCPT1, B0      INTRCPT2, G00
$                          HEADCOUN, G01
$                          FT_STUDE, G02
$                          AGE_OVER, G03
$                          MALE, G04
$                          PERSISTE, G05
$                          FT_FACUL, G06
$                          PELL_PRC, G07
$                          GRAD_RAT, G08

'S' - This level-2 predictor has been centered around its grand mean.

The model specified for the covariance components was:

Tau dimensions
INTRCPT1

Summary of the model specified (in equation format)

Level-1 Model
    Prob(Y=1|B) = P
    log[P/(1-P)] = B0
Level-2 Model
    B0 = G00 + G01*(HEADCOUN) + G02*(FT_STUDE) + G03*(AGE_OVER) +
    G08*(GRAD_RAT) + U0

Level-1 variance = sigma_squared/[P(1-P)]

The value of the likelihood function at iteration 5 = -1.210226E+004
RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION: Unit-Specific Model
(macro iteration 4)
Sigma_squared = 0.99594
Standard Error of Sigma_squared = 0.00797
Tau
INTRCPT1,B0  0.11770

Standard Errors of Tau
INTRCPT1,B0  0.03912
Tau (as correlations)
INTRCPT1,B0  1.000
Random level-1 coefficient  Reliability estimate

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, B0</td>
<td></td>
<td>0.904</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The value of the likelihood function at iteration 2 = - 4.429980E+004

The outcome variable is TFR_CODE

Final estimation of fixed effects: (Unit-specific model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2,G00</td>
<td>-1.91012</td>
<td>0.07708</td>
<td>-24.781</td>
<td>13</td>
<td>0.000</td>
</tr>
<tr>
<td>HEADCOUN,G01</td>
<td>0.000023</td>
<td>0.000012</td>
<td>1.881</td>
<td>13</td>
<td>0.082</td>
</tr>
<tr>
<td>FT_STUDE,G02</td>
<td>-1.09249</td>
<td>1.281583</td>
<td>-0.852</td>
<td>13</td>
<td>0.410</td>
</tr>
<tr>
<td>AGE_OVER,G03</td>
<td>-1.79838</td>
<td>3.047892</td>
<td>-0.59</td>
<td>13</td>
<td>0.565</td>
</tr>
<tr>
<td>MALE,G04</td>
<td>-1.00616</td>
<td>1.115893</td>
<td>-0.902</td>
<td>13</td>
<td>0.384</td>
</tr>
<tr>
<td>PERSISTE,G05</td>
<td>-0.8765</td>
<td>2.000259</td>
<td>-0.438</td>
<td>13</td>
<td>0.668</td>
</tr>
<tr>
<td>FT_FACUL,G06</td>
<td>-1.19154</td>
<td>1.027002</td>
<td>-1.16</td>
<td>13</td>
<td>0.267</td>
</tr>
<tr>
<td>PELL_PRC,G07</td>
<td>-3.03922</td>
<td>1.143112</td>
<td>-2.659</td>
<td>13</td>
<td>0.020</td>
</tr>
<tr>
<td>GRAD_RAT,G08</td>
<td>0.707709</td>
<td>0.814445</td>
<td>0.869</td>
<td>13</td>
<td>0.401</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2,G00</td>
<td>-1.910116</td>
<td>0.148063</td>
<td>(0.125,0.175)</td>
</tr>
<tr>
<td>HEADCOUN,G01</td>
<td>0.000023</td>
<td>1.000023</td>
<td>(1.000,1.000)</td>
</tr>
<tr>
<td>FT_STUDE,G02</td>
<td>-1.09249</td>
<td>0.33538</td>
<td>(0.021,5.329)</td>
</tr>
<tr>
<td>AGE_OVER,G03</td>
<td>-1.798382</td>
<td>0.165566</td>
<td>(0.000,118.982)</td>
</tr>
<tr>
<td>MALE,G04</td>
<td>-1.006163</td>
<td>0.365619</td>
<td>(0.033,4.063)</td>
</tr>
<tr>
<td>PERSISTE,G05</td>
<td>-0.876495</td>
<td>0.416239</td>
<td>(0.006,31.189)</td>
</tr>
<tr>
<td>FT_FACUL,G06</td>
<td>-1.191537</td>
<td>0.303754</td>
<td>(0.033,2.786)</td>
</tr>
<tr>
<td>PELL_PRC,G07</td>
<td>-3.039224</td>
<td>0.047872</td>
<td>(0.004,0.564)</td>
</tr>
<tr>
<td>GRAD_RAT,G08</td>
<td>0.707709</td>
<td>2.029337</td>
<td>(0.350,11.767)</td>
</tr>
</tbody>
</table>

The outcome variable is TFR_CODE

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.910116</td>
<td>0.07796</td>
<td>-24.501</td>
<td>13</td>
<td>0.000</td>
</tr>
<tr>
<td>0.000023</td>
<td>0.000012</td>
<td>1.906</td>
<td>13</td>
<td>0.079</td>
</tr>
<tr>
<td>-1.09249</td>
<td>1.414518</td>
<td>-0.772</td>
<td>13</td>
<td>0.454</td>
</tr>
</tbody>
</table>
### Fixed Effects

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2,G00</td>
<td>-1.910116</td>
<td>0.148063</td>
<td>(0.125, 0.175)</td>
</tr>
<tr>
<td>HEADCOUN,G01</td>
<td>0.000023</td>
<td>1.000023</td>
<td>(1.000, 1.000)</td>
</tr>
<tr>
<td>FT_STUDE,G02</td>
<td>-1.09249</td>
<td>0.33538</td>
<td>(0.016, 7.100)</td>
</tr>
<tr>
<td>AGE_OVER,G03</td>
<td>-1.798382</td>
<td>0.165566</td>
<td>(0.000, 68.912)</td>
</tr>
<tr>
<td>MALE,G04</td>
<td>-1.006163</td>
<td>0.365619</td>
<td>(0.025, 5.278)</td>
</tr>
<tr>
<td>PERSISTE,G05</td>
<td>-0.876495</td>
<td>0.416239</td>
<td>(0.005, 36.830)</td>
</tr>
<tr>
<td>FT_FACUL,G06</td>
<td>-1.191537</td>
<td>0.303754</td>
<td>(0.036, 2.570)</td>
</tr>
<tr>
<td>PELL_PRC,G07</td>
<td>-3.039224</td>
<td>0.047872</td>
<td>(0.006, 0.415)</td>
</tr>
<tr>
<td>GRAD_RAT,G08</td>
<td>0.707709</td>
<td>2.029337</td>
<td>(0.326, 12.621)</td>
</tr>
</tbody>
</table>

The robust standard errors are appropriate for datasets having a moderate to large number of level-2 units. These data do not meet this criterion.

Final estimation of variance components:

<table>
<thead>
<tr>
<th>Random Effect</th>
<th>Standard Deviation</th>
<th>Variance Component</th>
<th>Degrees of freedom</th>
<th>Chi-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, U0</td>
<td>0.34307</td>
<td>0.11770</td>
<td>13</td>
<td>494.16358</td>
<td>0.000</td>
</tr>
<tr>
<td>level-1, R</td>
<td>0.99797</td>
<td>0.99594</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION:

Population Average Model

The value of the likelihood function at iteration 3 = -4.402077E+004

The outcome variable is TFR_CODE

Final estimation of fixed effects: (Population-average model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2,G00</td>
<td>-1.871951</td>
<td>0.07681</td>
<td>-24.371</td>
<td>13</td>
<td>0.000</td>
</tr>
<tr>
<td>HEADCOUN,G01</td>
<td>0.0000024</td>
<td>0.000012</td>
<td>1.934</td>
<td>13</td>
<td>0.075</td>
</tr>
<tr>
<td>FT_STUDE,G02</td>
<td>-0.968404</td>
<td>1.275619</td>
<td>-0.759</td>
<td>13</td>
<td>0.461</td>
</tr>
</tbody>
</table>
AGE_OVER,G03 -1.685668 3.027459 -0.557 13 0.587
MALE,G04 -1.340865 1.118341 -1.199 13 0.252
PERSISTE,G05 -1.005091 1.991185 -0.505 13 0.622
FT_FACUL,G06 -1.249669 1.024718 -1.22 13 0.245
PELL_PRC,G07 -3.088322 1.139125 -2.711 13 0.018
GRAD_RAT,G08 0.795533 0.815107 0.976 13 0.347

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2,G00</td>
<td>-1.871951</td>
<td>0.153823</td>
<td>(0.130,0.182)</td>
</tr>
<tr>
<td>HEADCOUN,G01</td>
<td>0.000024</td>
<td>1.000024</td>
<td>(1.000,1.000)</td>
</tr>
<tr>
<td>FT_STUDE,G02</td>
<td>-0.968404</td>
<td>0.379689</td>
<td>(0.024,5.956)</td>
</tr>
<tr>
<td>AGE_OVER,G03</td>
<td>-1.685668</td>
<td>0.185321</td>
<td>(0.000,1.27433)</td>
</tr>
<tr>
<td>MALE,G04</td>
<td>-1.340865</td>
<td>0.261619</td>
<td>(0.023,2.923)</td>
</tr>
<tr>
<td>PERSISTE,G05</td>
<td>-1.005091</td>
<td>0.366011</td>
<td>(0.005,26.894)</td>
</tr>
<tr>
<td>FT_FACUL,G06</td>
<td>-1.249669</td>
<td>0.2866</td>
<td>(0.031,2.616)</td>
</tr>
<tr>
<td>PELL_PRC,G07</td>
<td>-3.088322</td>
<td>0.045578</td>
<td>(0.004,0.533)</td>
</tr>
<tr>
<td>GRAD_RAT,G08</td>
<td>0.795533</td>
<td>2.215622</td>
<td>(0.382,12.865)</td>
</tr>
</tbody>
</table>

The robust standard errors are appropriate for datasets having a moderate to large number of level-2 units. These data do not meet this criterion.
Output of the Final Model with both Level-1 and Level-2 Variables

Program: HLM 6 Hierarchical Linear and Nonlinear Modeling
Authors: Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher: Scientific Software International, Inc. (c) 2000
techsupport@ssicentral.com
www.ssicentral.com

Module: HLM2.EXE (6.04.27107.1)
Date: 26 January 2008, Saturday
Time: 13: 8:33

SPECIFICATIONS FOR THIS NONLINEAR HLM2 RUN
The data source for this run = C:\Documents and Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New Folder\HLM\Transfer_12.mdm
The command file for this run = whlmtemp.hlm
Output file name = C:\Documents and Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New Folder\HLM\hlm2.txt
The maximum number of level-1 units = 31245
The maximum number of level-2 units = 22
The maximum number of micro iterations = 50
Method of estimation: full PQL
Maximum number of macro iterations = 100
Distribution at Level-1: Bernoulli
Weighting Specification

---------------------------------------------
Weight
Variable
Weighting? Name Normalized?
Level-1 no
Level-2 no
Precision no

The outcome variable is TFR_CODE
The model specified for the fixed effects was:

---------------------------------------------
Level-1 Level-2
Coefficients Predictors
---------------------------------------------
INTRCPT1, B0 INTRCPT2, G00
$ FT_STUDE, G01
$ PELL_PRC, G02
# FIRST_YE slope, B1 INTRCPT2, G10
# FT slope, B2 INTRCPT2, G20
# GPA slope, B3 INTRCPT2, G30
# AGE slope, B4 INTRCPT2, G40
# GENDER slope, B5 INTRCPT2, G50
# INTENT slope, B6 INTRCPT2, G60
# BLACK slope, B7 INTRCPT2, G70

'#' - The residual parameter variance for this level-1 coefficient has been set to zero.
'S' - This level-2 predictor has been centered around its grand mean.

The model specified for the covariance components was:

```
Tau dimensions
INTRCPT1
```

Summary of the model specified (in equation format)

```
Level-1 Model
Prob(Y=1|B) = P
log[P/(1-P)] = B0 + B1*(FIRST_YE) + B2*(FT) + B3*(GPA) + B4*(AGE) +
B5*(GENDER) + B6*(INTENT) + B7*(BLACK)

Level-2 Model
B0 = G00 + G01*(FT_STUDE) + G02*(PELL_PRC) + U0
B1 = G10
B2 = G20
B3 = G30
B4 = G40
B5 = G50
B6 = G60
B7 = G70
```

Level-1 variance = sigma_squared/[P(1-P)]

Run-time deletion has reduced the number of level-1 records to 30286

The value of the likelihood function at iteration 6 = -1.059000E+004

RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION: Unit-Specific Model

(macro iteration 6)

Sigma_squared = 1.09488
Standard Error of Sigma_squared = 0.00890

Tau
INTRCPT1,B0 0.18303
Standard Errors of Tau
INTRCPT1,B0 0.05962

Tau (as correlations)
INTRCPT1,B0 1.000

Random level-1 coefficient Reliability estimate
The value of the likelihood function at iteration 2 = -4.437865E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Unit-specific model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td>0.924</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.56091</td>
<td>0.15119</td>
<td>10.324</td>
<td>19</td>
<td>0.000</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.69917</td>
<td>0.70905</td>
<td>3.807</td>
<td>19</td>
<td>0.001</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-2.82155</td>
<td>0.89052</td>
<td>3.168</td>
<td>19</td>
<td>0.006</td>
</tr>
<tr>
<td>For FIRST_YE, slope, B1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td>0.03751</td>
<td>0.00228</td>
<td>16.442</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
<td>0.16356</td>
<td>0.05044</td>
<td>3.243</td>
<td>30276</td>
<td>0.002</td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td>0.067724</td>
<td>0.01397</td>
<td>4.845</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.07872</td>
<td>0.00440</td>
<td>17.859</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope, B5</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>INTRCPT2, G50</td>
<td>-0.31603</td>
<td>0.03574</td>
<td>-8.84</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G60</td>
<td>0.819875</td>
<td>0.03896</td>
<td>21.04</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For BLACK slope, B7</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G70</td>
<td>-0.28774</td>
<td>0.06662</td>
<td>-4.319</td>
<td>30276</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td>0.924</td>
<td>0.209944</td>
<td>(0.153, 0.288)</td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.560914</td>
<td>0.067261</td>
<td>(0.015, 0.296)</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.699172</td>
<td>0.059514</td>
<td>(0.009, 0.383)</td>
</tr>
</tbody>
</table>
The outcome variable is TFR_CODE
Final estimation of fixed effects
(Unit-specific model with robust standard errors)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td>-1.560914</td>
<td>0.145647</td>
<td>-10.717</td>
<td>19</td>
<td>0.000</td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-2.699172</td>
<td>0.733208</td>
<td>-3.681</td>
<td>19</td>
<td>0.001</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.821548</td>
<td>0.676956</td>
<td>-4.168</td>
<td>19</td>
<td>0.006</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>0.03751</td>
<td>0.005595</td>
<td>6.704</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FIRST_YE, slope, B1</td>
<td>0.163564</td>
<td>0.055572</td>
<td>2.943</td>
<td>30276</td>
<td>0.004</td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td>0.067724</td>
<td>0.026115</td>
<td>2.593</td>
<td>30276</td>
<td>0.010</td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td>-0.078721</td>
<td>0.006957</td>
<td>-11.316</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.316028</td>
<td>0.052197</td>
<td>-6.055</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td>0.819875</td>
<td>0.061506</td>
<td>13.33</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>INTRCPT2, G60</td>
<td>-0.287735</td>
<td>0.101053</td>
<td>-2.847</td>
<td>30276</td>
<td>0.005</td>
</tr>
<tr>
<td>For BLACK slope, B7</td>
<td>-1.560914</td>
<td>0.209944</td>
<td>(0.155,0.285)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
FT_STUDE, G01  | -2.699172 | 0.067261 | (0.015,0.312)  
PELL_PRC, G02  | -2.821548 | 0.059514 | (0.014,0.245)  

For FIRST_YE, slope, B1, INTRCPT2, G10 | 0.03751 | 1.038222 | (1.027,1.050)  
For FT slope, B2, INTRCPT2, G20   | 0.163564 | 1.177701 | (1.056,1.131)  
For GPA slope, B3, INTRCPT2, G30   | 0.067724 | 1.07007  | (1.017,1.126) 
For AGE slope, B4, INTRCPT2, G40   | -0.078721 | 0.924297 | (0.912,0.937)  
For GENDER slope, B5, INTRCPT2, G50 | -0.316028 | 0.729039 | (0.658,0.808)  
For INTENT slope, B6, INTRCPT2, G60 | 0.819875 | 2.270216 | (2.012,2.561)  
For BLACK slope, B7, INTRCPT2, G70 | -0.287735 | 0.74996  | (0.615,0.914) 

The robust standard errors are appropriate for datasets having a moderate to large number of level-2 units. These data do not meet this criterion.

Final estimation of variance components:

<table>
<thead>
<tr>
<th>Random Effect</th>
<th>Standard Deviation</th>
<th>Variance Component</th>
<th>Degrees of freedom</th>
<th>Chi-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, U0</td>
<td>0.42782</td>
<td>0.18303</td>
<td>19</td>
<td>485.93724</td>
<td>0.000</td>
</tr>
<tr>
<td>level-1, R</td>
<td>1.04637</td>
<td>1.09488</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION:
Population Average Model
The value of the likelihood function at iteration 3 = -4.403231E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Population-average model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.499478</td>
<td>0.148383</td>
<td>-10.105</td>
<td>19</td>
<td>0.000</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.655838</td>
<td>0.706745</td>
<td>-3.758</td>
<td>19</td>
<td>0.002</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-2.668194</td>
<td>0.888629</td>
<td>-3.003</td>
<td>19</td>
<td>0.008</td>
</tr>
<tr>
<td>For FIRST_YE, slope, B1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td>0.03631</td>
<td>0.002216</td>
<td>16.386</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
<td>0.166724</td>
<td>0.050645</td>
<td>3.292</td>
<td>30276</td>
<td>0.001</td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td>0.066375</td>
<td>0.013907</td>
<td>4.773</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.077372</td>
<td>0.00429</td>
<td>-18.035</td>
<td>30276</td>
<td>0.000</td>
</tr>
<tr>
<td>For GENDER slope,</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B5</td>
<td>INTRCPT2, G50</td>
<td>-0.308992</td>
<td>0.035583</td>
<td>-8.684</td>
<td>30276</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------------</td>
<td>-----------</td>
<td>----------</td>
<td>--------</td>
<td>-------</td>
</tr>
</tbody>
</table>
For INTENT slope, B6  | INTRCPT2, G60 | 0.802869 | 0.038792 | 20.697 | 30276 | 0.000 |
For BLACK slope, B7   | INTRCPT2, G70 | -0.27863 | 0.066088 | -4.216 | 30276 | 0.000 |

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.499478</td>
<td>0.223247</td>
<td>(0.164,0.304)</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.655838</td>
<td>0.07024</td>
<td>(0.016,0.308)</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-2.668194</td>
<td>0.069377</td>
<td>(0.011,0.445)</td>
</tr>
</tbody>
</table>
For FIRST_YE, slope, B1| INTRCPT2, G10 | 0.03631   | 1.036977           | (1.032,1.041) |
For FT slope, B2, INTRCPT2, G20 | 0.166724 | 1.181428   | (1.070,1.305)       |
For GPA slope, B3, INTRCPT2, G30 | 0.066375 | 1.068628   | (1.040,1.098)       |
For AGE slope, B4, INTRCPT2, G40 | -0.077372 | 0.925546   | (0.918,0.933)       |
For GENDER slope, B5, INTRCPT2, G50 | -0.308992 | 0.734187   | (0.685,0.787)       |
For INTENT slope, B6, INTRCPT2, G60 | 0.802869 | 2.231934   | (2.069,2.408)       |
For BLACK slope, B7, INTRCPT2, G70 | -0.27863 | 0.75682    | (0.665,0.861)       |

The outcome variable is TFR_CODE
Final estimation of fixed effects
(Population-average model with robust standard errors)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.499478</td>
<td>0.141958</td>
<td>-10.563</td>
<td>19</td>
<td>0.000</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-2.655838</td>
<td>0.695224</td>
<td>-3.82</td>
<td>19</td>
<td>0.001</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-2.668194</td>
<td>0.639181</td>
<td>-4.174</td>
<td>19</td>
<td>0.001</td>
</tr>
</tbody>
</table>
For FIRST_YE, slope, B1| INTRCPT2, G10 | 0.03631       | 0.005634 | 6.445 | 30276 | 0.000 |
For FT slope, B2, INTRCPT2, G20 | 0.166724 | 0.057153       | 2.917   | 30276 | 0.004 |
For GPA slope, B3, INTRCPT2, G30 | 0.066375 | 0.025911       | 2.562   | 30276 | 0.011 |
<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1, B0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.499478</td>
<td>0.223247</td>
<td>(0.166,0.300)</td>
</tr>
<tr>
<td>FT.STUDE, G01</td>
<td>-2.655838</td>
<td>0.07024</td>
<td>(0.016,0.301)</td>
</tr>
<tr>
<td>PELL.PRC, G02</td>
<td>-2.668194</td>
<td>0.069377</td>
<td>(0.018,0.264)</td>
</tr>
<tr>
<td>For FIRST_YE, B1</td>
<td>0.03631</td>
<td>1.036977</td>
<td>(1.026,1.048)</td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td>0.166724</td>
<td>1.181428</td>
<td>(1.056,1.321)</td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td>0.066375</td>
<td>1.068628</td>
<td>(1.016,1.124)</td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For AGE slope, B4</td>
<td>-0.077372</td>
<td>0.925546</td>
<td>(0.914,0.938)</td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For GENDER slope, B5</td>
<td>-0.308992</td>
<td>0.734187</td>
<td>(0.664,0.812)</td>
</tr>
<tr>
<td>INTRCPT2, G50</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td>0.802869</td>
<td>2.231934</td>
<td>(1.958,2.544)</td>
</tr>
<tr>
<td>INTRCPT2, G60</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For BLACK slope, B7</td>
<td>-0.27863</td>
<td>0.75682</td>
<td>(0.619,0.925)</td>
</tr>
<tr>
<td>INTRCPT2, G70</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The robust standard errors are appropriate for datasets having a moderate to large number of level-2 units. These data do not meet this criterion.
Output of the Model with Changing Slopes and Intercept

Program: HLM 6 Hierarchical Linear and Nonlinear Modeling
Authors: Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher: Scientific Software International, Inc. (c) 2000
technical@ssicentral.com
www.ssicentral.com

-------------------------------------------------------------------------------
Module: HLM2.EXE (6.04.27107.1)
Date: 26 January 2008, Saturday
Time: 13:27:15
-------------------------------------------------------------------------------

SPECIFICATIONS FOR THIS NONLINEAR HLM2 RUN
The data source for this run = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\Transfer_12.mdm
The command file for this run = whlmttemp.hlm
Output file name = C:\Documents and
Settings\Sbandyopadhyay\Desktop\Santanu\Dissertation\Data File\New
Folder\HLM\hlm2.txt
The maximum number of level-1 units = 31245
The maximum number of level-2 units = 22
The maximum number of micro iterations = 50
Method of estimation: full PQL
Maximum number of macro iterations = 100
Distribution at Level-1: Bernoulli
Weighting Specification

<table>
<thead>
<tr>
<th>Weight</th>
<th>Variable</th>
<th>Weighting?</th>
<th>Name</th>
<th>Normalized?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level-1</td>
<td>no</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level-2</td>
<td>no</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Precision</td>
<td>no</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The outcome variable is TFR_CODE
The model specified for the fixed effects was:

<table>
<thead>
<tr>
<th>Level-1</th>
<th>Level-2</th>
<th>Predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, B0</td>
<td>INTRCPT2, G00</td>
<td></td>
</tr>
<tr>
<td>$</td>
<td>FT_STUDE, G01</td>
<td></td>
</tr>
</tbody>
</table>
$ \text{PELL_PRC, G02} \\
# \text{FIRST_YE slope, B1} \quad \text{INTRCPT2, G10} \\
$ \text{FT_STUDE, G11} \\
$ \text{PELL_PRC, G12} \\
# \text{FT slope, B2} \quad \text{INTRCPT2, G20} \\
$ \text{FT_STUDE, G21} \\
$ \text{PELL_PRC, G22} \\
# \text{GPA slope, B3} \quad \text{INTRCPT2, G30} \\
$ \text{FT_STUDE, G31} \\
$ \text{PELL_PRC, G32} \\
# \text{AGE slope, B4} \quad \text{INTRCPT2, G40} \\
$ \text{FT_STUDE, G41} \\
$ \text{PELL_PRC, G42} \\
# \text{GENDER slope, B5} \quad \text{INTRCPT2, G50} \\
$ \text{FT_STUDE, G51} \\
$ \text{PELL_PRC, G52} \\
# \text{INTENT slope, B6} \quad \text{INTRCPT2, G60} \\
$ \text{FT_STUDE, G61} \\
$ \text{PELL_PRC, G62} \\
# \text{BLACK slope, B7} \quad \text{INTRCPT2, G70} \\
$ \text{FT_STUDE, G71} \\
$ \text{PELL_PRC, G72} \\

'#$ - The residual parameter variance for this level-1 coefficient has been set to zero. 
'S' - This level-2 predictor has been centered around its grand mean.

The model specified for the covariance components was:

\begin{verbatim}
---------------------------------------------------------
 Tau dimensions 
 INTRCPT1 
---------------------------------------------------------
Summary of the model specified (in equation format)

Level-1 Model
 Prob(Y=1|B) = P 
 log[P/(1-P)] = B0 + B1*(FIRST_YE) + B2*(FT) + B3*(GPA) + B4*(AGE) + 
 B5*(GENDER) + B6*(INTENT) + B7*(BLACK)

Level-2 Model
 B0 = G00 + G01*(FT_STUDE) + G02*(PELL_PRC) + U0 
 B1 = G10 + G11*(FT_STUDE) + G12*(PELL_PRC) 
 B2 = G20 + G21*(FT_STUDE) + G22*(PELL_PRC) 
 B3 = G30 + G31*(FT_STUDE) + G32*(PELL_PRC) 
 B4 = G40 + G41*(FT_STUDE) + G42*(PELL_PRC) 
 B5 = G50 + G51*(FT_STUDE) + G52*(PELL_PRC) 
 B6 = G60 + G61*(FT_STUDE) + G62*(PELL_PRC) 
 B7 = G70 + G71*(FT_STUDE) + G72*(PELL_PRC)
\end{verbatim}
Level-1 variance = \( \sigma^2 / [P(1-P)] \)
Run-time deletion has reduced the number of level-1 records to 30286
The value of the likelihood function at iteration 6 = -1.048158E+004
RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION: Unit-Specific Model
(macro iteration 6)
Sigma_squared = 1.06136
Standard Error of Sigma_squared = 0.00863
Tau
INTRCPT1, B0 0.19936
Standard Errors of Tau
INTRCPT1, B0 0.06443
Tau (as correlations)
INTRCPT1, B0 1.000
----------------------------------------------------
Random level-1 coefficient  Reliability estimate
----------------------------------------------------
INTCRCPT1, B0 0.932
----------------------------------------------------
The value of the likelihood function at iteration 2 = -4.390896E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Unit-specific model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>For INTRCPT1,B0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.47337</td>
<td>0.157055</td>
<td>-9.381</td>
<td>19</td>
<td>0.000</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-0.68542</td>
<td>1.160878</td>
<td>-0.59</td>
<td>19</td>
<td>0.561</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-0.46321</td>
<td>1.632216</td>
<td>-0.284</td>
<td>19</td>
<td>0.780</td>
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<tr>
<td>For FIRST_YE slope, B1</td>
<td></td>
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<tr>
<td>INTRCPT2, G10</td>
<td>0.038622</td>
<td>0.002362</td>
<td>16.353</td>
<td>30262</td>
<td>0.000</td>
</tr>
<tr>
<td>FT_STUDE, G11</td>
<td>-0.0667</td>
<td>0.017261</td>
<td>-3.864</td>
<td>30262</td>
<td>0.000</td>
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<tr>
<td>PELL_PRC, G12</td>
<td>-0.0539</td>
<td>0.028894</td>
<td>-1.865</td>
<td>30262</td>
<td>0.062</td>
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<tr>
<td>For FT slope,B2</td>
<td></td>
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</tr>
<tr>
<td>INTRCPT2, G20</td>
<td>0.05126</td>
<td>0.060174</td>
<td>0.852</td>
<td>30262</td>
<td>0.395</td>
</tr>
<tr>
<td>FT_STUDE, G21</td>
<td>-0.78041</td>
<td>0.455373</td>
<td>-1.714</td>
<td>30262</td>
<td>0.086</td>
</tr>
<tr>
<td>PELL_PRC, G22</td>
<td>0.24839</td>
<td>0.597979</td>
<td>0.415</td>
<td>30262</td>
<td>0.677</td>
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<tr>
<td>For GPA slope, B3</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td>0.047556</td>
<td>0.014817</td>
<td>3.21</td>
<td>30262</td>
<td>0.002</td>
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<tr>
<td>FT_STUDE, G31</td>
<td>-0.36907</td>
<td>0.108574</td>
<td>-3.399</td>
<td>30262</td>
<td>0.001</td>
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<tr>
<td>PELL_PRC, G32</td>
<td>-0.19481</td>
<td>0.159221</td>
<td>-1.224</td>
<td>30262</td>
<td>0.221</td>
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</table>
For AGE slope, B4

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.07647</td>
<td>0.926381</td>
<td>(0.918, 0.935)</td>
</tr>
<tr>
<td>FT_STUDE, G41</td>
<td>0.073566</td>
<td>1.052596</td>
<td>(0.935, 1.184)</td>
</tr>
<tr>
<td>PELL_PRC, G42</td>
<td>-0.04347</td>
<td>0.94753</td>
<td>(0.895, 1.003)</td>
</tr>
</tbody>
</table>

For GENDER slope, B5

<table>
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<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
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</thead>
<tbody>
<tr>
<td>INTRCPT2, G50</td>
<td>-0.31969</td>
<td>0.729152</td>
<td>(0.629, 0.845)</td>
</tr>
<tr>
<td>FT_STUDE, G51</td>
<td>-0.16667</td>
<td>0.835849</td>
<td>(0.715, 0.976)</td>
</tr>
<tr>
<td>PELL_PRC, G52</td>
<td>0.570127</td>
<td>1.785845</td>
<td>(1.207, 2.681)</td>
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</tbody>
</table>

For INTENT slope, B6

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G60</td>
<td>0.853661</td>
<td>2.329165</td>
<td>(1.915, 2.836)</td>
</tr>
<tr>
<td>FT_STUDE, G61</td>
<td>0.492854</td>
<td>1.617172</td>
<td>(1.321, 1.981)</td>
</tr>
<tr>
<td>PELL_PRC, G62</td>
<td>0.188536</td>
<td>1.190693</td>
<td>(0.995, 1.407)</td>
</tr>
</tbody>
</table>

For BLACK slope, B7

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G70</td>
<td>-0.31312</td>
<td>0.729152</td>
<td>(0.629, 0.845)</td>
</tr>
<tr>
<td>FT_STUDE, G71</td>
<td>-0.67384</td>
<td>0.503881</td>
<td>(0.444, 0.579)</td>
</tr>
<tr>
<td>PELL_PRC, G72</td>
<td>0.24839</td>
<td>1.28196</td>
<td>(0.397, 1.439)</td>
</tr>
</tbody>
</table>

Fixed Effect | Coefficient | Odds Ratio | Confidence Interval |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.473371</td>
<td>0.229152</td>
<td>(0.165, 0.318)</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-0.685415</td>
<td>0.503881</td>
<td>(0.444, 0.579)</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-0.463205</td>
<td>0.629263</td>
<td>(0.021, 0.191)</td>
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</table>

For FIRST_YE slope, B1

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G10</td>
<td>0.038622</td>
<td>1.039377</td>
<td>(1.035, 1.044)</td>
</tr>
<tr>
<td>FT_STUDE, G11</td>
<td>-0.066702</td>
<td>0.935474</td>
<td>(0.904, 0.968)</td>
</tr>
<tr>
<td>PELL_PRC, G12</td>
<td>-0.053897</td>
<td>0.94753</td>
<td>(0.895, 1.003)</td>
</tr>
</tbody>
</table>

For FT slope, B2

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G20</td>
<td>0.05126</td>
<td>1.052596</td>
<td>(0.935, 1.184)</td>
</tr>
<tr>
<td>FT_STUDE, G21</td>
<td>-0.780408</td>
<td>0.458219</td>
<td>(0.188, 1.119)</td>
</tr>
<tr>
<td>PELL_PRC, G22</td>
<td>0.24839</td>
<td>1.28196</td>
<td>(0.397, 1.439)</td>
</tr>
</tbody>
</table>

For GPA slope, B3

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G30</td>
<td>0.047556</td>
<td>1.048705</td>
<td>(1.019, 1.080)</td>
</tr>
<tr>
<td>FT_STUDE, G31</td>
<td>-0.369072</td>
<td>0.691375</td>
<td>(0.559, 0.855)</td>
</tr>
<tr>
<td>PELL_PRC, G32</td>
<td>-0.194808</td>
<td>0.822992</td>
<td>(0.602, 1.124)</td>
</tr>
</tbody>
</table>

For AGE slope, B4

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.07647</td>
<td>0.926381</td>
<td>(0.918, 0.935)</td>
</tr>
</tbody>
</table>
FT_STUDE, G41 | 0.073566 | 1.076339 | (1.010,1.147)
PELL_PRC, G42 | -0.043469 | 0.957463 | (0.868,1.056)
For GENDER slope, B5
INTRCPT2, G50 | -0.319693 | 0.726372 | (0.672,0.786)
FT_STUDE, G51 | -0.166666 | 0.846482 | (0.469,1.529)
PELL_PRC, G52 | 0.570127 | 1.768491 | (0.797,3.922)
For INTENT slope, B6
INTRCPT2, G60 | 0.853661 | 2.348228 | (2.150,2.565)
FT_STUDE, G61 | 0.492854 | 1.636982 | (0.836,3.204)
PELL_PRC, G62 | 0.188536 | 1.20748 | (0.507,2.876)
For BLACK slope, B7
INTRCPT2, G70 | -0.313123 | 0.73116 | (0.616,0.868)
FT_STUDE, G71 | -0.673843 | 0.509746 | (0.141,1.843)
PELL_PRC, G72 | -2.768532 | 0.062754 | (0.008,0.470)

The robust standard errors cannot be computed for this model.

Final estimation of variance components:

<table>
<thead>
<tr>
<th>Random Effect</th>
<th>Standard Deviation</th>
<th>Variance Component</th>
<th>Degrees of freedom</th>
<th>Chi-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRCPT1, U0</td>
<td>0.44649</td>
<td>0.19936</td>
<td>19</td>
<td>617.35064</td>
<td>0.000</td>
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<tr>
<td>level-1, R</td>
<td>1.03022</td>
<td>1.06136</td>
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</tbody>
</table>

RESULTS FOR NON-LINEAR MODEL WITH THE LOGIT LINK FUNCTION:
Population Average Model
The value of the likelihood function at iteration 3 = -4.354785E+004
The outcome variable is TFR_CODE
Final estimation of fixed effects: (Population-average model)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-ratio</th>
<th>Approx. d.f.</th>
<th>P-value</th>
</tr>
</thead>
</table>
| For INTRCPT1,B0
| INTRCPT2, G00 | -1.409204 | 0.154207 | -9.138 | 19 | 0.000 |
| FT_STUDE, G01 | -0.76871 | 1.167206 | -0.659 | 19 | 0.518 |
| PELL_PRC, G02 | -0.474747 | 1.59952 | -0.297 | 19 | 0.770 |
| For FIRST_YE slope, B1
| INTRCPT2, G10 | 0.037044 | 0.002301 | 16.097 | 30262 | 0.000 |
### Fixed Effects

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
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<tbody>
<tr>
<td><strong>For INTRCPT1,B0</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-1.409204</td>
<td>0.244338</td>
<td>(0.177,0.337)</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-0.76871</td>
<td>0.463611</td>
<td>(0.040,5.322)</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>-0.474747</td>
<td>0.622043</td>
<td>(0.022,17.634)</td>
</tr>
<tr>
<td><strong>For FIRST_YE slope, B1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G10</td>
<td>0.037044</td>
<td>1.037739</td>
<td>(1.033,1.042)</td>
</tr>
<tr>
<td>FT_STUDE, G11</td>
<td>-0.060893</td>
<td>0.940924</td>
<td>(0.909,0.974)</td>
</tr>
</tbody>
</table>

### Odds Ratios and Confidence Intervals

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>Odds Ratio</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>For INTRCPT1,B0</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G00</td>
<td>-0.060893</td>
<td>0.940924</td>
<td>(0.909,0.974)</td>
</tr>
<tr>
<td>FT_STUDE, G01</td>
<td>-0.046575</td>
<td>0.952471</td>
<td>(0.919,0.987)</td>
</tr>
<tr>
<td>PELL_PRC, G02</td>
<td>0.164858</td>
<td>1.178117</td>
<td>(1.026,1.352)</td>
</tr>
<tr>
<td><strong>For FT slope,B2</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
<td>0.058727</td>
<td>1.059788</td>
<td>(1.040,1.080)</td>
</tr>
<tr>
<td>FT_STUDE, G21</td>
<td>-0.785997</td>
<td>0.455687</td>
<td>(0.418,0.495)</td>
</tr>
<tr>
<td>PELL_PRC, G22</td>
<td>0.194045</td>
<td>1.208973</td>
<td>(1.148,1.274)</td>
</tr>
<tr>
<td><strong>For GPA slope, B3</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td>0.046043</td>
<td>1.046078</td>
<td>(1.028,1.066)</td>
</tr>
<tr>
<td>FT_STUDE, G31</td>
<td>-0.36199</td>
<td>0.698873</td>
<td>(0.652,0.749)</td>
</tr>
<tr>
<td>PELL_PRC, G32</td>
<td>-0.194045</td>
<td>0.817126</td>
<td>(0.759,0.880)</td>
</tr>
<tr>
<td><strong>For AGE slope, B4</strong></td>
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</tr>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.07488</td>
<td>0.929791</td>
<td>(0.903,0.958)</td>
</tr>
<tr>
<td>FT_STUDE, G41</td>
<td>0.068991</td>
<td>1.071257</td>
<td>(1.049,1.095)</td>
</tr>
<tr>
<td>PELL_PRC, G42</td>
<td>-0.043041</td>
<td>0.957875</td>
<td>(0.919,0.998)</td>
</tr>
<tr>
<td><strong>For GENDER slope, B5</strong></td>
<td></td>
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</tr>
<tr>
<td>INTRCPT2, G50</td>
<td>-0.311855</td>
<td>0.729695</td>
<td>(0.694,0.767)</td>
</tr>
<tr>
<td>FT_STUDE, G51</td>
<td>-0.169928</td>
<td>0.844693</td>
<td>(0.821,0.869)</td>
</tr>
<tr>
<td>PELL_PRC, G52</td>
<td>0.565816</td>
<td>1.785772</td>
<td>(1.702,1.872)</td>
</tr>
<tr>
<td><strong>For INTENT slope, B6</strong></td>
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</tr>
<tr>
<td>INTRCPT2, G60</td>
<td>0.833653</td>
<td>2.288266</td>
<td>(2.165,2.416)</td>
</tr>
<tr>
<td>FT_STUDE, G61</td>
<td>0.52331</td>
<td>1.695815</td>
<td>(1.621,1.775)</td>
</tr>
<tr>
<td>PELL_PRC, G62</td>
<td>0.192433</td>
<td>1.206371</td>
<td>(1.160,1.255)</td>
</tr>
<tr>
<td><strong>For BLACK slope, B7</strong></td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G70</td>
<td>-0.306164</td>
<td>0.736775</td>
<td>(0.707,0.767)</td>
</tr>
<tr>
<td>FT_STUDE, G71</td>
<td>-0.725546</td>
<td>0.478584</td>
<td>(0.449,0.509)</td>
</tr>
<tr>
<td>PELL_PRC, G72</td>
<td>-2.780597</td>
<td>0.007311</td>
<td>(0.003,0.017)</td>
</tr>
<tr>
<td>Variable, Group</td>
<td>Coefficient 1</td>
<td>Coefficient 2</td>
<td>95% CI</td>
</tr>
<tr>
<td>-----------------</td>
<td>---------------</td>
<td>---------------</td>
<td>--------</td>
</tr>
<tr>
<td>For FT slope, B2</td>
<td>-0.046575</td>
<td>0.954493</td>
<td>(0.903,1.009)</td>
</tr>
<tr>
<td>INTRCPT2, G20</td>
<td>0.058727</td>
<td>1.060485</td>
<td>(0.943,1.193)</td>
</tr>
<tr>
<td>FT_STUDE, G21</td>
<td>-0.785997</td>
<td>0.455665</td>
<td>(0.181,1.148)</td>
</tr>
<tr>
<td>PELL_PRC, G22</td>
<td>0.164858</td>
<td>1.179225</td>
<td>(0.365,3.815)</td>
</tr>
<tr>
<td>For GPA slope, B3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G30</td>
<td>0.046043</td>
<td>1.04712</td>
<td>(1.017,1.078)</td>
</tr>
<tr>
<td>FT_STUDE, G31</td>
<td>-0.36199</td>
<td>0.69629</td>
<td>(0.560,0.866)</td>
</tr>
<tr>
<td>PELL_PRC, G32</td>
<td>-0.194045</td>
<td>0.823621</td>
<td>(0.604,1.122)</td>
</tr>
<tr>
<td>For AGE slope, B4</td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G40</td>
<td>-0.07488</td>
<td>0.927855</td>
<td>(0.920,0.936)</td>
</tr>
<tr>
<td>FT_STUDE, G41</td>
<td>0.068991</td>
<td>1.071426</td>
<td>(1.005,1.143)</td>
</tr>
<tr>
<td>PELL_PRC, G42</td>
<td>-0.043041</td>
<td>0.957872</td>
<td>(0.871,1.053)</td>
</tr>
<tr>
<td>For GENDER slope, B5</td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G50</td>
<td>-0.311855</td>
<td>0.732088</td>
<td>(0.678,0.791)</td>
</tr>
<tr>
<td>FT_STUDE, G51</td>
<td>-0.169928</td>
<td>0.843726</td>
<td>(0.462,1.541)</td>
</tr>
<tr>
<td>PELL_PRC, G52</td>
<td>0.565816</td>
<td>1.760884</td>
<td>(0.796,3.893)</td>
</tr>
<tr>
<td>For INTENT slope, B6</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>INTRCPT2, G60</td>
<td>0.833653</td>
<td>2.301712</td>
<td>(2.110,2.511)</td>
</tr>
<tr>
<td>FT_STUDE, G61</td>
<td>0.52331</td>
<td>1.687604</td>
<td>(0.851,3.345)</td>
</tr>
<tr>
<td>PELL_PRC, G62</td>
<td>0.192433</td>
<td>1.212195</td>
<td>(0.506,2.903)</td>
</tr>
<tr>
<td>For BLACK slope, B7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTRCPT2, G70</td>
<td>-0.306164</td>
<td>0.736266</td>
<td>(0.623,0.870)</td>
</tr>
<tr>
<td>FT_STUDE, G71</td>
<td>-0.725546</td>
<td>0.48406</td>
<td>(0.126,1.867)</td>
</tr>
<tr>
<td>PELL_PRC, G72</td>
<td>-2.780597</td>
<td>0.062001</td>
<td>(0.009,0.446)</td>
</tr>
</tbody>
</table>