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A longitudinal study of adolescent educational aspirations and their relationship to college choice using hierarchical linear modeling and group-based mixture modeling

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A LONGITUDINAL STUDY OF ADOLESCENT EDUCATIONAL ASPIRATIONS AND THEIR RELATIONSHIP TO COLLEGE CHOICE USING HIERARCHICAL LINEAR MODELING AND GROUP-BASED MIXTURE MODELING

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ABSTRACT

The purpose of this study was four-fold: (1) to investigate the patterns of change in educational aspirations from the eighth grade through the twelfth in a large national sample of students from the National Educational Longitudinal Survey of 1988 (NELS:88); (2) to understand how demographic, socioeconomic, parental, academic, and school experience factors impact both initial aspirations and change in aspirations; (3) to investigate how educational aspirations relate to students' attempts to actualize plans for postsecondary education; and (4) to analyze the data and compare the results obtained using two different growth modeling techniques – hierarchical linear modeling and group-based mixture modeling.

Major findings of the study showed that (1) average student aspirations remained fairly stable from the eighth grade through the twelfth, showing a slight but not significant increase; (2) most of the factors considered in the study affected initial student aspirations; (3) seven distinct clusters of aspiration trajectories can be identified; (4) many students who had high aspirations had failed to build a wide choice set of postsecondary institutions to apply to; (5) among the factors considered, educational aspirations had the strongest impact on the number of applications filed; (6) parental expectations and involvement had effects on early student aspirations but not on the number of applications filed; (7) students who had both high and stable aspirations from the eighth grade through the twelfth generally had a wider choice set of applications than students who demonstrated a steady increase in aspirations.

Hierarchical linear modeling provided an understanding of the average growth in aspirations, the variability around that growth and the effects of covariates on initial aspirations and the change in aspirations. Group-based mixture modeling helped investigate the different clusters of aspiration trajectories and permitted a linkage of these clusters with patterns of student application to postsecondary institutions. The link between aspirations and the number of college applications filed was studied using modeling for ordinal responses. The strengths of the different modeling techniques are addressed and implications of the results for educational policy, practice, and future research are also discussed.

CHAPTER 1

INTRODUCTION

Behavioral scientists and educational researchers have long been concerned with the availability of valid statistical techniques to study individual change. Early researchers tended to view change in terms of increment, that is, a comparison of an individual's status before and after a certain time period. This led to an abundance of pretest-posttest designs with data collected at two time points. According to Willett (1988), this is an unnatural way to view change because individual change is a process of continuous development over time rather than the "quantized acquisition of skills, attitudes, and beliefs" (p. 345). Willett (1998) contends that using data from two points in time does not allow the researcher to examine questions that require an understanding of the parameters of change, thus leading to the many concerns about the measurement of change discussed by Harris (1963). Rogosa, Brandt, and Zimowski (1982) argue that two waves of data provide such meager information on change that they are not much better than one.

Reliable statistical techniques to measure growth rather than change began to emerge in the late 1970s and early 1980s. These techniques enabled the researcher to study individual growth over multiple points in time, and provided explicit models to analyze the data. They also helped to alleviate the inadequacies in conceptualization, measurement, and design that plagued earlier studies (Bryk & Raudenbush, 1987).

The past ten years have seen tremendous advances in the field of measurement and analysis of change (Collins & Sayer, 2001). According to Collins and Sayers, even as recently as in the early nineties, investigators were primarily concerned with interindividual variability and used traditional analysis procedures. The focus has shifted considerably since then, and the emphasis today is on the study of intraindividual variability. Collins and Sayer also note that methods such as factor analysis, autoregressive models, growth curve models, and latent class models, that were previously considered separate, are now beginning to move toward integration. The fast growth of longitudinal modeling has also led to an explosion of new terminology, models, and software (Willett, 1988; Raudenbush, 2001).

Measuring growth and change is crucial to educational research. Students undergo educational and personal development as they move through the educational system. An understanding of the impact of institutional, curricular, social, cultural, and familial factors that affect students' growth is very useful to policymakers as well as practitioners. According to Willett (1998), a major focus of educational researchers should be the measurement of changes that are created by classroom activities and institutional resources, and the investigation of the nature of the relationships between these resources and activities and student development. Multiwave longitudinal studies help to understand change as a dynamic process, and also enable the researcher to better differentiate the causes and the consequences of change.

One method that has gained wide acceptance is hierarchical linear modeling (HLM). HLM provides two linked statistical models: a model for individual growth, and a model for interindividual differences in growth (Willett, 1998; Rogosa & Willett; 1985). This enables the measurement of change as well as the ability to investigate how any activities of an individual, or resources that he or she may have, relate to this change.

When multiwave data involves the collection of repeated observations nested within individuals who may be in turn nested within organizations, hierarchical linear (multilevel) modeling which takes into account this hierarchical nature of the data, is more suitable as an analytical tool than are traditional repeated measures methods such as MANOVA. In hierarchical linear modeling, each of the levels (intraindivuidual and interindividual) is formally represented by its own sub-model (Goldstein & Woodhouse, 2001). At level-1, each person's development is represented by an individual growth trajectory, giving rise to a unique set of parameters. These parameters are then used as the outcomes of the level-2 model which may include person-level covariates (Raudenbush & Bryk, 2002). According to Raudenbush and Bryk, treating repeated observations as nested within persons avoids difficulties even when the number and spacing of observations across individuals is variant.

A more recent development in the field of longitudinal data modeling is the emergence of mixture models for estimating developmental trajectories. While hierarchical linear modeling is concerned with modeling population distributions of growth curves based on continuous distribution functions, trajectory modeling is a group-based approach to growth modeling (Nagin, 1999). According to Nagin (1999), the group-based approach uses a multinomial modeling strategy and is designed to identify homogeneous clusters of developmental trajectories. More specificially, the goal of this type of model is to "draw attention to the differences in the causes and consequences of different developmental trajectories within the population."(Nagin, 1999; p. 140). Growth mixture modeling uses a two-level modeling framework, the first level being similar to the level-1 model of HLM. The second level, however, is reconceptualized such that the population is seen as falling into a fixed number of groups, where each group's developmental trajectory is characterized by a common set of parameters (Raudenbush, 2001). A multinomial regression model is then used to predict group membership.

Mixture models for estimating developmental trajectories have considerable potential. According to Raudenbush (2001), although one can reasonably assume in most studies, that all participants grow according to some common function and that only the growth parameters vary in magnitude, in some cases, this may not be entirely true. For example, if a trait such as depression or physical aggression is being studied, the participants may actually fall into distinct groups. Some people have chronic depression, while others are never high in depression. Yet another group may be becoming increasingly depressed, while some others may be recovering from depression. In such cases modeling the developmental trajectories of these distinct groups can be very informative.

The HLM approach offered distinct advantages over traditional repeated measures approaches such as MANOVA, as well as latent curve modeling, especially when it comes to the relaxation of the "time-structured" data requirements of the other methods. HLM has the power to accommodate a wide variety of data structures and level-1 models and permits the exploration of more complex substantive questions than is possible with traditional techniques (Raudenbush & Bryk, 2002). However, the HLM methodology assumes certain types of growth trajectories. This in fact may not be borne out in empirical data. Mixture models for estimating developmental trajectories allow for explicit investigation of the types of growth trajectories present in a data set. To the extent that variation exists, many intriguing substantive questions can ensue. The present study was designed to explore this issue for the substantive question of the development of educational aspirations. Specifically, the present study was designed to determine if Nagin (1999)'s model for estimating developmental trajectories offers advantages over HLM when the focus is on the development and realization of educational aspirations. The study uses data from a large national longitudinal data set and thus has policy implications.

The remaining sections of this chapter provide a brief introduction to the literature on educational aspirations and present the goals, objectives, and significance of this study.

Educational Aspirations and College Choice

Since the 1960s, social scientists have recognized that the educational and occupational aspirations of youth play a pivotal role in the status attainment process. According to Trusty and Pirtle (1998), 1992 female high-school seniors were almost four times more likely to have intentions of attending graduate or professional school than were female seniors in 1972. Students' educational expectations play an important role in college placement (Hearn, 1984). Thomas (1980) found expectations to be the single strongest predictor of four-year college attendance.

This research has led to many attempts to understand the process by which youth develop educational and occupational aspirations and translate these into actual achievements. Having high educational expectations at an early age seems to strongly impact future pursuit of postsecondary education. McDonough (1997) citing Alexander and Cook (1979), states that the likelihood of actual college attendance increases by 21 percent when students' intentions to go to college develop prior to the tenth grade, when compared to plans formulated during their senior years. According to Hossler, Schmit, and Vesper (1999), most students develop postsecondary aspirations by the time they complete the ninth grade, but the stability of these plans is an important factor in determining if the students actualize them. Students whose plans changed between ninth and twelfth grades were less likely to go to college than those who had more stable plans.

One of the more widely discussed recent attempts to understand this process with respect to educational attainments is the college choice model proposed by Hossler and Gallagher (1987). Hossler and Gallagher proposed a conceptual model of college choice that combines econometric and sociological variables, and views college choice as a process consisting of three steps: predisposition, search, and choice. They define the predisposition stage as "the developmental phase in which students determine whether or not they would like to continue their formal education beyond high school" (p. 211). Research on the factors that play important roles in the predisposition stage has examined students as early as middle school (Somers, Cofer, & VanderPutten, 1999). Predisposition and aspirations are related notions, and Hossler and Stage (1992) proposed a theoretical model of students' predisposition to college. This model looks at the relationships among demographic characteristics, socioeconomic variables, parental/peer expectations and encouragement, ability, and high school experiences on student predisposition, is based on status attainment research (Hossler, Braxton, & Coopersmith, 1989) and focuses on factors that influence aspirations for college attendance.

Status attainment literature evolved in the sixties, and has long been the dominant paradigm in the study of educational and occupational aspirations (Kao & Tienda, 1998; Carter, 2001). Early exploration of status attainment processes focused on the impact social class membership has on variation in aspirations and attainment (Kao & Tienda, 1998). Subsequent refinements incorporated several other factors such as parental influence, high school factors, and the influence of significant others such as peers and teachers (Hossler & Stage, 1992).

Hossler et al. (1999) found that some students, particularly students from low-income or first-generation backgrounds, in spite of having high aspirations fail to meet their goals to attend college. McDonough (1997) concluded that first-generation and low SES students begin to think about going to college much later than do students whose parents have gone to college. High SES students, she argues, get a head start on college preparations in elementary and middle schools by taking the right courses and maintaining good grades. They also, according to McDonough, have an advantage in the search stage of the college choice process, and make strategic decisions that optimize their chances of getting into a college they aspire to attend.

The high-aspirations low-attainment paradox is along the lines of the "attitude-achievement paradox" among black and low SES adolescents referred to by Mickelson (1990). According to Mickelson (1990), although blacks have displayed consistently positive attitudes toward education, black youth have failed to translate this into scholastic achievement. Mickelson goes on to hypothesize that this paradox manifests itself because of two distinct sets of attitudes toward schooling – abstract and concrete. Abstract attitudes reflect the general notions that schooling is a vehicle for success, while concrete attitudes are based on actual experiences of the community.

This abstract-concrete attitude notion has a rough equivalent in college choice, in that, although certain groups of students, such as low-income, minority and first-generation students, have high early aspirations, these aspirations may be toned down later, based on concrete personal and community experiences. It is also possible that even if the aspirations remain stable or grow, the students may not be translating them into action toward college attendance. Applying to four-year colleges involves a series of steps that have to be completed, such as taking SAT/ACT tests, maintaining high grades, narrowing down a choice set of colleges, and gathering information about and applying for financial aid. If any of these concrete steps are neglected or not done on time, it is often difficult for students to realize their aspirations of attending college. So, although certain students are predisposed to attend college, their search and choice processes may not be optimized.

According to Hossler et al.(1999) there is a dramatic shift in the factors that influence students' thinking and decisions on post-secondary education between the developmental years of schooling and their junior/senior years. They posit that in their developmental years, students are influenced primarily by internal sources of influence and information such as parents. By the time they are in their junior or senior years, peers, teachers, and other external sources become more influential. This implies the possibility of a growth or decline in aspirations and expectations that may affect future decisions.

Kao and Tienda (1998) also argue that early change in educational aspirations from the eighth to tenth grades is driven by changes that transform abstract ideas into likely possibilities, whereas the later changes in aspirations from the tenth to twelfth grades may result from changes in concrete plans. Thus, a longitudinal study of changes in student aspirations' from middle school to their senior year, and the relationship of these changes to other demographic, socioeconomic, achievement, and school-related factors could be of use in further understanding the college choice process. Also, how these changes relate to the college search stage would be worth looking into.

Aspirations themselves are not necessarily indicators of eventual achievement; however, they have considerable psychological and predictive value to identify future educational and occupational options (Holland & Gottfredson, 1975). A study on the stability of aspirations and the factors that influence this could contribute to policymaking decisions in the future.

Statement of the Problem

Students' early educational aspirations play an important role in guiding their later achievement. However, merely having high aspirations is not enough; the stability of these aspirations, as students transition from a vague awareness of future plans to a more focused exploration of options, is also an important factor in increasing students' likelihood to actually attend a postsecondary institution. Past research has shown that several factors influence the formation and maintenance of educational aspirations in complex ways, and that the sources of influence in early and late adolescence may be quite different. Also, having high aspirations does not always translate into concrete action toward actual postsecondary attendance.

There is a need to systematically investigate the growth and change in educational aspirations as students make progress through their schooling. There are few longitudinal studies that examine development in adolescents' educational aspirations, and still fewer that use powerful analytical tools to study this change. This study seeks to fill this gap by using individual growth modeling and group-based trajectory modeling to study changes in students' educational aspirations from the eighth grade to the twelfth, and the factors that impact these changes, using a large national data set.

Objectives of the Study

The primary purpose of this study is to use individual growth curve modeling within the HLM framework to investigate the patterns of growth of educational aspirations from the eighth grade to the twelfth in a large national sample of students. In addition, the study seeks to gain an understanding of the factors that may influence this growth, and how the patterns of change vary among students who are in the process of taking concrete steps toward realizing their aspirations. The study also explores the use of group-based mixture modeling of growth trajectories to study the different patterns of changes in aspirations that may occur.

The specific objectives of this study are as follows:

(1) To describe and analyze the development of educational aspirations of adolescents over a five-year period using individual growth modeling from a hierarchical linear model perspective.

(2) To explore, from an HLM perspective, demographic, socioeconomic, parental, ability, and school experience factors that may possibly impact growth in aspirations.

(3) To describe and analyze the patterns of development of educational aspirations of adolescents over a five-year period using Nagin (1999)'s multilevel group-based technique for analyzing development trajectories.

(4) To explore, using Nagin's model, demographic, socioeconomic, parental, ability, and school experience factors that may impact patterns of growth in aspirations.

(5) To compare and contrast the conclusions drawn about the growth and development of aspirations from the HLM and growth mixture modeling perspectives.

(6) To explore the associations between demographic, socioeconomic, parental, ability, and school experience factors and the postsecondary application patterns of students using multinomial modeling.

(7) To study variations in growth patterns over time among those students who have taken concrete steps toward postsecondary education in their senior year, and those who have not.

Significance of the Study

College choice research has shown that early high aspirations (as early as before the first year of high school) play an important role in predicting later college attendance (Hossler et al., 1999). It has also been shown that students who change their aspirations between the ninth grade and the twelfth are at risk of not going to college. Even among the students who maintain high aspirations, many do not actually realize their plans because of various reasons, some of which may have to do with parental involvement, socioeconomic status, academic performance, and demographic background.

This study is significant in that it attempts to examine educational aspirations as a dynamic process. The period between the eighth and the twelfth grades is one of transition, when goals are formed and steps are taken to realize them. Students may increase or lower their educational goals for a number of reasons as mentioned above. Although there is an abundance of literature on educational aspirations, very few studies in the past have looked at aspirations with a longitudinal perspective, and the factors that influence the growth, rather than the formation, of aspirations have not been systematically studied.

Another significance of this study is that it seeks to use a sophisticated analytical tool, namely, individual growth modeling to study the development of aspirations. In this way, the influence of a variety of demographic, socioeconomic, achievement, and parental variables, on both initial status (eighth grade aspirations), as well as change in aspirations can be simultaneously evaluated.

Past research has shown that although many students have high aspirations, not all succeed in achieving their goals. This study seeks to throw light on the aspirations-achievement paradox (Kao & Tienda, 1998), by looking at patterns of variation in aspirations growth among students who have and have not taken concrete steps toward college attendance during the pivotal senior year.

This study also seeks to explore the use of mixture modeling of growth trajectories, which is a relatively new technique in growth modeling. This will be used to identify any distinct clusters of individuals and to study the characteristics of individuals in those clusters. A comparison of the results obtained with mixture modeling with the traditional HLM approach will offer insights into the significance of this technique for the substantive questions considered in this project.

This study uses a large national data set with a representative sample. There are data from over 1000 schools and 15,000 students across the country, which adds to the generalizability of the results and offers policy implications. An understanding of the dynamics of educational aspiration development among adolescents would enable educators, parents, counselors, and policymakers to adopt measures tailored to meet the specific needs of students, thus helping enhance their career opportunities and options. This study thus seeks to use growth modeling techniques to examine the patterns of change in aspirations among students who have and have not taken concrete steps toward postsecondary attendance in their senior year, and the factors that may influence the change.

Definitions of Terms

The following are some of the terms that are frequently used in the discussion of this study:

- College: For simplicity, this term is used in this study to denote any type of postsecondary educational institution.
- College Choice: The process by which students choose a postsecondary institution they will attend.
- Educational Aspirations: Educational goals that students would like to achieve, measured by how far they would like to go in school.
- Group-based Mixture Modeling: A semiparametric, group-based approach for identifying distinctive clusters of individual trajectories within a population and for profiling the characteristics of individuals within the clusters.
- Hierarchical Linear Modeling (Multilevel Modeling): When a variable is a sub-category of another variable, the former is considered being "nested" with the latter and their relationship is termed as hierarchical. Hierarchical Linear Modeling (HLM) is the analysis of models with two or three levels of nesting

(i.e., multilevel analysis). Such nested models may be used to analyze growth and change within individuals.

- Individual Growth Model: An analysis model where individual change phenomena are represented by hierarchical models in which each person's development is represented by an individual growth trajectory at the lowest level. The parameters of this model then become the outcomes of the next level model.
- Longitudinal Study: A study executed over time that consists of repeated measurements on the same units over a number of occasions, with fixed or varying time spells between occasions.

Assumptions and Limitations of the Study

One limitation of this study is related to the definition and measurement of variables. Since the study uses an extant database, there is the inability to get the exact set of variables of interest and the definition and measurement of the variables used is limited by the questionnaire items available. This limitation is addressed in the conclusions section of this document and implications for the design of future efforts are discussed.

As with many longitudinal studies, there is the problem of missing data and attrition. Although the modeling techniques used in the analysis are fairly robust to missing data problems, there is probably some degree of bias in the usable sample. Also, between the eighth and the twelfth grade, many students dropped out of school, and these dropouts may have potentially been at the lower end of the aspiration scale, thus leading to a "better" group of students in the usable sample.

Finally, even though this study uses longitudinal data, it is an exploratory study, and the relationships inferred are correlational. Care should be taken not to interpret the results using logical causal relationships.

CHAPTER 2

REVIEW OF THE LITERATURE

This chapter presents a review of the literature related to educational aspirations, college choice, longitudinal studies, growth modeling, hierarchical linear modeling, and group-based mixture models. The first part of this chapter describes the procedures used to conduct the search of relevant literature. This is followed by a discussion of the literature on educational aspirations and the measurement of change.

Search of Relevant Literature

This literature review was conducted using the following electronic databases: ERIC, Dissertation Abstracts International, ProQuest Digital Dissertation Services, and Infotrac, and spanned the period 1960 to 2002. In addition to electronic databases, resources such as the World Wide Web, discussion groups, and personal communication with researchers were used, due to the relatively recent developments in some methods used in the current study.

Educational Aspirations and the Attitude-Achievement Paradox

In the past, there has been some debate about the exact definition and measurement of aspirations (Carter, 2001). There have been several terms including "expectations", "aspirations", "intentions", and "plans" often used interchangeably, without clear distinctions being drawn. However "aspirations" has often been used as a general term to refer to the concepts mentioned above, and this study will consequently use this term. This study is specifically interested in how far in school the student thinks he or she will go.

The theoretical foundations of educational aspirations studies are laid in the status attainment literature in sociology, which was elaborated in the late 1950s and the 1960s.

The status attainment process is concerned with the role played by various factors in the allocation of individual occupations of varying degrees of prestige (Sewell & Shah, 1978). The first status attainment model was developed by Blau and Duncan (1967). This model consisted only of five variables; specifically, father's educational attainment and occupational status are used to predict the respondent's educational attainment and first job status. These four variables are then used to predict the respondent's occupational attainment. Blau and Duncan's model could not, however, sufficiently explain the relationships among these variables (Carter, 2001).

Recognizing the limitations of the Blau and Duncan (1967) model, Sewell, Haller, and Portes (1969), expanded it to include social psychological variables such as expectations and aspirations, leading to the Wisconsin model of attainment. This social psychological model assumes that the socioeconomic status and ability of the student affect the encouragement and the support that the student receives from significant others around him or her, such as parents, peers and teachers, and this in turn affects the student's goals and aspirations (Kerckhoff, 1976). Aspirations in turn affect attainment, and educational attainment affects occupational attainment. Aspirations thus play a significant role in the status attainment process.

In the late 1960s, the Blau and Duncan (1967) model and the Wisconsin model offered two competing theories of status attainment (Carter, 2001). These models were more thoroughly examined in the 1970s, and the general conclusion was that the Wisconsin model explained more variance in attainment than did the Blau and Duncan model.

Kerckhoff (1976) offered an alternate perspective by arguing that expectations are based on the knowledge of the real world, and that in the real world, individuals may be constrained by the social structure that they find themselves in. According to Kerckhoff, for students from disadvantaged backgrounds, expectations may start out high, but may eventually be lowered as they observe the successes and failures of those around them, thus leading to social reproduction (Hanson, 1994). Bourdieu (1973) posited a theory of cultural reproduction in which he suggested that the selection process in the educational system ensures the status quo of the system, and is based on structures such as social class.

Bourdieu (1977/1977) also used the concept of habitus, which is a common set of perceptions held by all members of the same group or class. According to Bourdieu, habitus is deeply internalized, and shapes an individual's expectations, attitudes, and aspirations (McDonough, 1997). Children thus do not form aspirations by rational analyses, but by looking at those around them and at their own chances of mobility in a subjective manner.

Two additional perspectives on the shaping of aspirations for college were offered by Boyle (1966) and Alwin and Otto (1977). Boyle and Alwin and Otto focus on the role of the high school context. Boyle concluded that the kind of high school students attend has an influence on aspirations, but offers an explanation that this effect could be due to the differential success high schools have in developing the academic abilities of students. Alwin and Otto found that school context variables do not substantially affect college aspirations, but school process variables such as curriculum placement and peers' plans do. They also state that individual background variables such as gender, socioeconomic status, and academic ability may indirectly affect aspirations through school process variables.

The results cited above suggest that it is important for studies of aspirations to examine factors like socioeconomic status, gender, and race that may offer potential hurdles in the development of high aspirations. The sample in the Wisconsin study consisted entirely of white male seniors. Subsequent studies did include females and blacks, but only a handful have included other minorities such as Asians or Hispanics. According to Kao and Tienda (1998), this is unfortunate because Asian and Hispanic students represent the highest and lowest achieving of all students respectively.

Social psychological theory posits that educational aspirations strongly influence scholastic outcomes, and there have been many studies that cite educational aspirations as being one of the most important determinants of eventual educational attainment (Wilson & Wilson, 1992). However, several studies have showed that educational aspirations do not translate into comparable attainment among students from different racial, ethnic and gender lines (Gottfredson, 1981; Duran & Weffer, 1992; Kao, 1995; Ponec, 1997; Kao & Tienda, 1998; Trusty, 2000).

An interesting perspective toward understanding this gap was offered by Mickelson (1990). Mickelson suggests that among blacks and disadvantaged students, there is an "attitude-achievement paradox", that is, a positive attitude toward schooling in general, combined with low achievement. Mickelson offers an explanation for this paradox, by suggesting that it arises because students hold two sets of attitudes toward education – abstract and concrete attitudes. Abstract attitudes are those expressed by the dominant ideology and picked up by disadvantaged students (Mickelson, 1990). Concrete attitudes are those rooted in students' everyday realities and in what they see around them. Kao and Tienda (1998) and Trusty (2000) suggest that aspirations may also be a factor that is affected by this paradox. Thus students from lower socioeconomic classes may express high educational aspirations because that reflects the dominant ideology. They may not take suitable steps toward achieving these aspirations because the culture around them may not be able to provide them with concrete models and support.

There is some evidence that the relationship between socioeconomic status and aspirations is particularly complicated. Marjoribanks (1986) conducted a study on 512 Australian adolescents and found that in different social class groups, adolescent aspirations are influenced by the interplay between individual characteristics and parental encouragement and support in different ways. In general, adolescent educational aspirations were found to be strongly related to their perceptions of parental support, parents' aspirations and their own early attitudes toward school. However, aspirations of middle-class adolescents were primarily related to their attitude toward school, whereas aspirations of adolescents from lower socioeconomic class were mainly influenced by their parents' aspirations.

Wilson and Wilson (1992) and Smith (1991) also stress the importance of the home environment on adolescent educational aspirations. This includes parents' aspirations as well as their concrete support for their children, including regular discussions on school issues. Kao and Tienda (1998) found that parental education and resources at home have an influence on aspirations as do prior school experiences. Taylor (2002) also found that parental aspirations for their children and parental educational attainment influenced adolescents educational and occupational aspirations, whether the youth came from urban, suburban, or rural areas.

According to Carter (2001), there is some evidence that the longer a student holds an aspiration, the more likely he or she will meet that goal. Alexander and Cook (1979) found that students who planned before the 10^{th} grade on going to college, were about 47% more likely to attend college as students who decided in the 12^{th} grade to go to college. Carter (2001) stresses the importance of early, sustained, and stable aspirations for the future attainments of students.

The Stability of Aspirations

Although there exist many studies that examine aspirations at a certain point in time, there are far fewer studies that look at the maintenance of aspirations over time. According to Inoue (1999), the development and maintenance of aspirations exert a profound influence on the probability of an individual's success in the adult and occupational world. According to Paulsen (1990), the development of aspirations can take place over a long period from early childhood through high school and even beyond. Thus, longitudinal studies may offer important insights into the factors that influence educational aspiration formation. Kao and Tienda (1998) argue that understanding how aspirations are formed and how they change over time is crucial for clarifying why aspirations lead to diverse outcomes along demographic lines. Their study found that while minority youth exhibit high aspirations at any given point in time, they are less likely to maintain high aspirations through high school, and suggest that this could be due to differential family resources, which once again brings socioeconomic status into the picture. They also found that while minority students were much more likely to aspire to graduate school training early on, these effects disappear by the twelfth grade.

Howell and Frese (1980) studied the stability of educational and occupational aspirations from preadolescence to early adulthood and found that socioeconomic background has a continuous and at times increasing influence on the level of educational and occupational aspirations. They also found that students from low grade school to early high school change their level of aspirations and are thus susceptible to career awareness interventions, whereas aspirations get more stable after the sophomore year or later, and intervention programs may not be as effective.

Hanson (1994) and Trusty (2000) examined the stability of educational expectations across adolescence. Their studies revealed that among high achievers, whites were more likely to lower their expectations than were minority students. Also, the process leading to lowered expectations was different for male and female students. According to Hanson (1994), young men were significantly more likely than young women to have reduced educational expectations, especially in late adolescence. Trusty (2000) found that while SES, race, mother's expectations, self-efficacy, parent's attendance at high school extra curricular activities, and suspensions from school all had significant effects on the stability of aspirations for both men and women, availability of computers in the eighth grade, and talking to school counselors in the eighth grade were significant factors in maintaining the stability of aspirations only for male adolescents. McClelland (1990) found that marriage dampens the aspirations of female students, while Kao and Tienda (1998) found small gender effects in the level of aspirations, but significant gender variation in the maintenance of these aspirations. They argue that family structure has an influence on girls' but not boys' aspirations, but this effect is negligible once the females enter high school.

Hall (2002) studied the development and stability of educational and occupational aspirations, as well as subsequent educational pursuits, over five years from late adolescence to early adulthood, in a sample of students in Canada. She found four distinct educational pathways with varying degrees of socioeconomic promise, and found that the degree of stability of aspirations varied among these pathways. This study reveals the importance of the role that stable aspirations play in future educational and socioeconomic outcomes. Hall (2002) argues that early academic achievement is the only variable that consistently predicts educational aspirations and educational pathways in early adulthood, and suggests early intervention to align aspirations academic skills to develop appropriate career plans for students. Early intervention is also recommended by Yeung and Yeung (2001) who found that motivation interventions had a greater impact on educational aspirations when conducted at the seventh grade than when executed at the ninth or eleventh grades.

In summary, the aspirations literature has revealed that complicated mechanisms operate in the formation and maintenance of educational aspirations. However, most studies have so far mainly focused on studying factors that influence the educational and occupational aspirations of students at one point in time. More longitudinal studies that look at the stability of aspirations are needed to throw light on the attitude-achievement paradox. This study seeks to look at the factors that influence the formation of early aspirations and their maintenance over time, while also investigating the link between the stability of aspirations and the translations of aspirations into action.

Aspirations as Predisposition: The College Choice Literature

A longitudinal study of student aspirations may help understand the factors that influence the formation and stability of aspirations, but additional value can be obtained by also looking to see if aspirations actually translate into action, especially when students are in their senior year. The senior year is when many students make important decisions regarding their future, particularly if they intend to go to college. Hossler et al. (1999) state that the decision about going to college is an important marker in students' transition from the final stages of childhood to the first stages of adulthood. A college education now has substantial impact on future economic success and the quality of life. According to Snyder and Schafer (1996), the earnings gap between those who have a 4-year college degree and those who do not has widened considerably from the 1970s to the 1990s.

The college choice literature intersects with the aspirations literature in many ways (Carter, 2001). According to Carter, "the process by which students choose institutions is an important element of understanding the process of educational aspirations development" (p. 36) and this process appears to be different for students from different backgrounds. Given the importance of college attendance, there is a need to understand the process students go through in choosing a college to attend. Hossler et al. (1989) define college choice as "a complex, multistage process during which an individual develops aspirations to continue formal education beyond high school, followed later by a decision to attend a specific college, university, or institution of advanced vocational training" (p. 234). Educational researchers with backgrounds from sociology, economics, and psychology have conducted research on the college choice process, leading to varied theoretical perspectives (Paulsen, 1990). Hossler et al. (1999) broadly divide these varying approaches into three categories: (1) economic models, which are based on assumptions that students act rationally and base college choice decisions on careful cost-benefit analyses, (2) status-attainment models which are based on sociological theory and are concerned with describing how variables interact as students make decisions about attending college and about which college to go to, and (3) information-processing models that are concerned with how students search for colleges and how they gather and process information about colleges.

In recent years, there have emerged models that combine the economic and sociological perspectives. The major combined models are those proposed by Jackson (1982), Chapman (1984), Hanson and Litten (1982), and Hossler and Gallagher (1987). Each of these models views college choice as a process with several stages, ranging from Chapman's two-stage model to Hanson and Litten's model with five stages. The most popular among these is Hossler and Gallagher's three stage model which provides the theoretical framework for this study.

Hossler and Gallagher's (1987) college choice model is primarily sociological and sees college choice as a process that begins very early with the formation of educational aspirations. The student then develops a broad overview of the various educational opportunities available, and finally narrows these options into a single set of institutions (McDonough, 1997). The model specifies these stages as predisposition, search and choice.

According to Hossler and Gallagher (1987), predisposition is defined as "the developmental phase in which students determine whether or not they would like to continue their formal education beyond high school" (p. 211), and this stage is influenced by different student background characteristics. The predisposition literature has examined students as early as middle school (Somers et al., 2002). The search stage of the process is the period when students seek information about college opportunities and develop a limited set of potential colleges to attend. Gilmour, Spiro, & Dolich (1981) posit that the junior year of high school is when the predisposition stage ends and the search stage begins. In the choice stage, the students apply to some or all of the schools they have selected, compare these institutions, and make a final decision about which college to attend.

Hossler et al. (1999) conducted a longitudinal study of 4,923 students in Indiana between 1986 and 1994, starting when the students were in their freshman year in high school. They found that most students had developed postsecondary plans by the time they completed the ninth grade. The educational aspirations of most of these sophomores and juniors actually increased after ninth grade. More than half of the students who were undecided about their plans in the ninth grade said that they intended to continue their postsecondary education by the time they were in the junior year. However, Hossler et al. (1999) also found that students whose plans changed from the ninth grade to the twelfth were less likely to go to college, thus stressing the importance of inculcating high aspirations in students very early in their lives. Hossler et al. (1999) recommend that the best time to influence postsecondary plans is during or even before the first year of high school.

McDonough (1997) found that low SES first-generation college-bound students begin to think about going to college much later than do students whose parents have postsecondary education. The latter students appeared to have a head start on preparing for college by taking the appropriate courses and maintaining good grades from an early stage, whereas students from disadvantaged backgrounds often did not take the right courses, and experience a cultural conflict between "their new college-oriented world and the world of their friends, families, and communities" (p. 6). According to Hafner et al. (as cited in Sanders, Field, & Diego, 2001), approximately 75% of eighth graders surveyed in the National Educational Longitudinal Study of 1988 (NELS:88) expected to obtain a college degree, yet less than 30% planned to take college preparatory classes. Overall, high aspirations when formed early seem to help actual college attendance, but do not add much value when formed later.

Hossler et al. (1999) suggest that during the time frame of the eighth through tenth grade, parents are most influential in developing student aspirations. Students who discussed their plans with their parents and who reported that their parents supported their plans were more likely to plan to go to college. Paulsen (1990) claims that aspiration formation can take place over a period of time from early childhood, and parental encouragement is the most influential factor in the development of aspirations. Sewell and Shah (1978) had earlier found parental encouragement to be a "powerful intervening variable between socioeconomic class background and intelligence of the child and his educational aspirations…" (p. 571). Hossler and Stage (1992) developed a model for predisposition which will be used as the theoretical framework for this study.

Besides parental encouragement, several past studies have found parental education, SES, student achievement, and race to be related to predisposition to attend college (Somers et al., 2002). There are contradictory reports about the significance of gender. While Hossler and Stage (1997) and Stage and Hossler (1989) reported that females thought more about going to college but received less family support, Carpenter and Fleischman (1987) and Tuttle (1981) found that gender had no impact on postsecondary aspirations. There are also contradictory results about the effect of school-related variables such as high school quality and the role of counselors and teachers (Hossler & Stage, 1992). However, involvement in high school activities and peer influence have been found to have significant effects on predisposition (Hossler & Stage, 1992; Hearn, 1984; Hossler et al., 1999).

Although factors that influence predisposition to college attendance have been studied extensively, there are far fewer studies that look at the link between intentions and behaviors. Carter (2001) reported that initial aspirations have an effect on the type of postsecondary institution a student attends, and there seems to be a consensus in the literature as to the importance of educational aspirations in predicting actual college attendance. However, there is a need to study in depth the relation between aspirations and actual application behavior.

Actually attending college involves a series of steps including preparing an application, writing essays, and taking college entrance tests like the SAT or the ACT. Hossler et al. (1999) state that most students send out applications between October and January of their senior year. Thus, by the end of their senior year, it is expected that students who are interested in postsecondary education would have taken several steps toward actual attendance, and students who wish to increase their opportunities to attend college would have probably applied to more than one college (Hurtado et al. 1997). However, Hurtado et al. (1997), using the NELS:88 data found that this was not the case for many students. According to them, "..such expectations or plans for postsecondary education are not immediately evident in students' college search and choice behaviors. It appears as if students experience continuing barriers on route to college education" (p. 63). Hurtado et al. (1997) also discovered that there are distinct patterns across racial/ethnic groups and SES classes with respect to this behavior, with only a few Hispanic students even applying to college and many Asian students applying to many colleges.

To throw more light on these issues, this study proposes to look at the application behavior of students in their senior year, and relate it to the stability of their aspirations from the eighth through the twelfth grades. By exploring the factors that influence the maintenance of aspirations within groups that display different applications behaviors, this study will attempt to understand better the characteristics of students who translate their aspirations into concrete steps and those who do not.

Methodology Used in Aspirations and College Choice Studies

According to Paulsen (1990), the majority of studies that focus on relationships between the college choice behavior of students and various environmental, institutional, and student characteristics have been cross-sectional in nature. Multiple regression, logit, probit, and discriminant analysis models have been used to predict how individual students make decisions and choices in these studies.

The studies on college choice in the 1990s also use cross sectional models for the most part. However, according to Hossler et al. (1989), student college choice is not a single event, but the result of a process that begins at an early age with developing aspirations toward college education. Thus, in order to address a broad range of topics associated with college choice, they recommend that a systematic research line is essential, and longitudinal studies provide the cornerstone for such research. In fact, the study of Indiana students done by Hossler et al. (1999) was "unique" because of its longitudinal nature, according to them, showing that there is a lack of college choice studies using data collected over time.

As early as 1977, Alwin and Otto (1977) felt that much of the research on school contexts and aspirations was cross-sectional. They saw the need for "multi-wave data on children in schools at all levels" (p. 270). Later, Farris, Boyd, and Shoffner (1985) also pointed out the limited research available on the development of aspirations from a longitudinal perspective. Although there have been longitudinal studies with educational aspirations in the past, most of them have either focused on using aspirations as a predictor of a future outcome such as attainment, or on identifying early factors that influence the formation of later aspirations.

The few studies which have examined the stability of students' aspirations over time have used difference scores (Williams, 1972), two-state discrete-time Markov models (Kayser, 1973), chi-square tests of association (Armstrong & Crombie, 2000), loglinear symmetry models (Kao & Tienda, 1998), multiple or logistic regression (Hanson, 1994; Trusty, 2000), or discriminant analysis (Hossler et al., 1999). Most of these studies examine whether a change has occurred rather than actually describing the pattern of change.

Howell and Frese (1980) used confirmatory factor analyses to study stability of educational aspirations over time. Rojewski and Yang (1997) used latent variable structural equation modeling to analyze the influence of select variables on occupational aspirations development, but such a study is lacking in the area of educational aspirations.

Gottfredson (1996) did several studies on occupational aspirations, and concluded that the influence of occupational aspirations on career attainment most likely follows a developmental sequence. Rojewski and Yang (1997) argue that knowledge about the developmental nature of aspirations during adolescence is useful for several reasons. First, longitudinal inquiry provides a better theoretical understanding of the role played by aspirations in determining future attainment. Second, the long-term effects of psychological and sociological factors on the development of aspirations can be determined. Third, this knowledge may help in development of appropriate career-related interventions at the right times.

The current study seeks to examine aspirations from a developmental perspective and look into the factors that play a role in the development of adolescent educational aspirations. To do this, this study uses two alternate methods: individual growth modeling from a hierarchical linear modeling perspective, and a group-based developmental trajectory modeling.

The Measurement of Change

In the social, biological, and medical sciences, the formative period of longitudinal panel studies has generally been dated as the late nineteenth century, with the evolution of developmental psychology (Baltes & Nesselroade, 1979). According to Menard (1991), longitudinal research has two main purposes: to describe the patterns of change, and to establish the direction and magnitude of causal relationships. Menard (1991) goes on to say that change is usually measured with reference to either chronological time or age. Time is external to the subjects under study, whereas age is measured internally. In either case, in order to describe and explain change, it is important to be able to measure change in an appropriate manner.

The measurement of change has long been a familiar topic in the behavioral sciences, and papers related to this topic have appeared in the literature for over 70 years (Rogosa et al., 1982). Most empirical studies during this time have been based on two-wave data. Two popular measures of change used with two-wave data are difference scores (or raw gains) and residual gains (Menard, 1991).

The Difference Score

The difference score is merely the difference between the later score and the earlier score on a variable. As early as 1956, Lord (1956) questioned the reliability of difference scores. Cronbach and Furby (1970) argued against the use of difference scores, saying that they are systematically related to any random error of measurement, are less reliable than the scores on the variables from which they are derived, and this unreliability may lead to wrong conclusions and inferences. Another deficiency of the difference score is that it is negatively correlated with the initial status (Cohen & Cohen, 1975), leading to an unfair advantage for individuals who have certain pretest scores. Lord (1958) also questioned whether numerically equal difference scores are really equal in a meaningful manner.

Other researchers have offered dissenting opinions on using difference scores as a measure of change. Bereiter (1963) demonstrated that the negative correlation of change with initial status was, in part, a statistical artifact of measurement error. Liker, Augustyniak, and Duncan (1985) argued that first difference equations that use difference scores may be better than both cross-sectional equations and the use of lagged endogenous variables for certain linear models. Plewis (1985) cited in Menard (1991) suggested that difference scores may be appropriate for certain economic data, while Baltes and Nesselroade (1979) concluded that it may not be practical to avoid difference scores, especially when a study uses a pretest-posttest design.

Rogosa et al. (1982), while acknowledging the defects of the difference score, also felt that these deficiencies – low reliability and negative correlation with initial status – are "more illusory than real" (p. 735). They argued that the difference score is not always unreliable, and that low reliability does not necessarily imply lack of precision. Rogosa et al. (1982) citing Nesselroade, Stigler, and Baltes (1980), also stated that the effect due to regression toward the mean, which is connected with the correlation between change and initial status, had been given exaggerated importance in the behavioral sciences literature, and this phenomenon could be a consequence of the standardization of the variables used in many studies.

In summary, Rogosa et al. (1982) argued that the main deficiency lies not in the use of the difference score, but in the use of two-wave data to study change. According to these authors, two-wave data provide very minimal information about individual change, and to really understand change, multiwave data is necessary.

The Residual Gain Score

A second measure that has been used in the measurement of change is the residual gain. According to Menard (1991), in order to calculate a residual gain, the variable Y_2 is first regressed on Y_1 using linear regression. The predicted, or expected value of Y_2 is then obtained from this regression. The residual gain score is then computed as:

Residual gain (Y) = $Y_2 - E(Y_2) = Y_2 - a - bY_1$

where $E(Y_2)$ is the expected value of Y_2;

a is the intercept from the regression of Y_2 on Y_1; and

b is the slope from the same regression equation.

Cronbach and Furby (1970) argued against residual gain scores for the same reasons that they cited in their argument against difference scores – lack of reliability and correlation of change with initial status. They suggested that residual gain scores be used only to identify cases that changed more (or less) than expected based on the initial scores. Plewis, as cited in Menard (1991), agreed with this, and pointed out that the problems with residual gain scores are just as serious as those for difference scores. Rogosa et al. (1982) stated that "statistical problems with (the residual gain score) abound" (p. 739). According to these authors, there is considerable bias in the estimated residual gain, and the estimator lacks precision. Reviewing the existing literature on residual gain scores, they posit that residual change scores have two uses: (1) in assessment and comparison of individuals, and (2) in correlational work. Since the estimate of residual gain is the difference between the dependent variable and its expected value from its regression on the independent variable, the residual gain score does help to single out individuals who change more (or less) than expected, as Cronbach and Furby (1970) stated. Correlational work is concerned with the estimation of the correlation between individual change and some background variable (Rogosa et al., 1982) and the correlation between the residual gain score and the variable is used as an estimate of the population correlation.

Lord (1963) argued that residual change is only an estimate and should not be confused with a real measure of change. Rogosa et al. (1982) stated that the value of the residual change is uncertain because of the complexity of interpreting it. They concluded that residual change scores should not be used to replace difference scores, but rather be a supplement to them.

Menard (1991) concluded that the decision to use any measure of change is not a simple issue and depends on the theoretical justification for using the measure. Baltes and Nesselroade (1979) argued that the problems cited within the context of measuring change stem from the usage of only two waves of data, and that any study of developmental change should involve more than just differences between two scores. They argued that multiple occasions of measurement permit the specification of change functions rather than rely on the constant rate of change, and recommended multiwave data for the study of change. Rogosa et al. (1982) also argued strongly in favor of multiwave data simply because more waves of data would provide additional information on individuals, and allow for richer models such as growth curve models, thus yielding far better determinants of change than do two-wave data.

Growth Curve Modeling

Group and individual learning curves have been central to psychological literature for a long time. Various methods have been used to describe and analyze individual growth and learning by developmental and clinical psychologists since the 1930s (Bayley, 1949; Woodrow, 1940). However, according to Osgood (2001), it was Rogosa et al. (1982) who first presented the idea of individual growth curves as an improved version of change scores, a tool in the measurement of change. In their 1982 paper, Rogosa et al., after discussing the deficiencies of two-wave data, state that they intend to "direct the emphasis in the measurement of change to the statistical analysis of collections of individual time paths" (p. 744).

Rogosa et al. (1982) proposed explicit linear growth models for individuals, formulated as least squares regression models with the true score of an attribute regressed on time. The two parameters in the model are the value of the growth curve at the initial time point and the rate of change. The rate of change would be the key parameter in the measurement of individual change. Rogosa et al. (1982) stated that this model could be extended to higher degree polynomial models if sufficient data are available.

Very often, researchers interested in change are motivated by more than a desire to understand the rate and magnitude of change, they also frequently seek to examine other variables that may have an impact on change. This led Rogosa and Willett (1985) to extend the simple individual growth model described above, to a model that accommodated and attempted to understand correlates of change. They did this by representing systematic individual differences in growth using a two-part model: (1) a part for individual growth, and (2) a part for the dependence of parameters from the growth models on individual attributes. Rogosa and Willett (1985) used ordinary least squares to separately estimate the parameters of these two models, and used reliability-based adjustments to the level-2 model, based on the marginal maximum likelihood methods of Blomqvist (1977). Willett (1988) extended this approach and provided weighted least squares methods for obtaining estimates of the parameters of the level-2 model.

Bryk and Raudenbush (1987) applied their hierarchical linear modeling framework to these ideas by treating the coefficients of the first level models as randomly varying across individuals. In this framework, at stage 1, each individual's observed development is expressed as a function of an individual growth trajectory and random error (Bryk & Raudenbush, 1987). This trajectory can be summarized by a set of parameters for each individual. In stage 2, these individual parameters are allowed to vary as functions of the individual's characteristics. Thus the parameters in the first stage become outcomes in the second stage. Bryk and Raudenbush used empirical Bayes estimation to obtain estimates of the parameters at both levels simultaneously.

Other researchers used alternate frameworks such as covariance structure modeling to study growth curves (Meredith & Tisak, 1984, 1990; Muthen, 1991, 1992; Willett & Sayer, 1994; MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997). Meredith and Tisak (1990), provided an approach that allowed the estimates of individual growth parameters and estimates of the level 2 means, variances and covariances of these parameters across all members of the population, thus evaluating not only the general shape of the individual trajectories, but also the population average growth curve. Model parameters are estimated using covariance structure analysis.

According to Willett and Sayer (1994), McArdle (1986, 1989, 1991) and his colleagues, in the late 1980s, extended the covariance structure approach of Meredith and Tisak (1984), and demonstrated several applications of this framework to varied problems in the behavioral sciences. These include using covariance structure methods to (1) estimate average growth curves, (2) to study the presence of interindividual differences in change in a single domain and in many domains simultaneously, (3) to conduct convergence analysis in which segments of average growth curves are linked into a single continuous trajectory, and (4) to model the level 2 relationship between the slope and a single predictor when only a slope parameter is present in the linear growth model (a restricted model). This established covariance structure analysis along with hierarchical linear modeling as alternate frameworks to study individual growth modeling.

MacCallum et al. (1997) demonstrated the relationships between the hierarchical linear modeling approach and the covariance structure approach to growth modeling, and discussed the advantages and disadvantages of both approaches. Raudenbush (2001) discussed the conditions under which one or the other of these two approaches should be used. According to Raudenbush, the choice of either approach involves certain compromises. Whereas the structural equation modeling (SEM) approach allows more flexible modeling of covariance structures, there are limitations on the data structures it can handle. The HLM approach is more robust to missing and unbalanced data, but offers a more limited choice in modeling covariance. MacCallum et al. stated that the choice of approach would depend on the structure of the data available and the research questions asked.

To summarize, Rogosa and Willett (1985) listed four purposes for studying change in the behavioral sciences: (1) to assess individual change, (2) to detect the correlates or predictors of change, (3) to compare change among experimental groups, and (4) to compare change among nonequivalent groups. Growth curve modeling is a simple and straightforward technique that allows the researcher to deal with the above issues. Growth curve modeling also addresses the problems of unreliability and correlation between initial status and change that created debate among the users of difference scores and residual gain scores which were discussed in the previous section.

Asendorpf (1991) and Raudenbush and Bryk (2002) discuss the major advantages of using growth curve modeling as: (1) it can handle nonlinear growth functions and multiple assessments, (2) the reliability of change parameters can be tested without the need for parallel measures by comparing the observed scores and the estimates, and (3) the model of developmental change can be stated explicitly giving researchers more flexibility in analysis.

Hierarchical Linear Modeling

Hierarchical Linear Models (HLM) are referred to by many other names depending on the field in which they are applied. They are also known as multilevel linear models, mixed-effects models, random-effects models, random-coefficient regression models, and covariance component models (Raudenbush & Bryk, 2002). According to Raudenbush and Bryk, the term “hierarchical linear models” was introduced by Lindley and Smith in 1972 as part of their research on Bayesian estimation of linear models. In this contribution, Lindley and Smith developed a general framework for nested data and complex error structures. However, because of the lack of an efficient algorithm for estimation, their contribution could not be widely applied until Dempster, Laird, and Rubin (1977) developed the EM algorithm. This approach was shown to be applicable to hierarchical data structures and was used both in growth modeling and in cross-sectional analysis. Other estimation methods were also developed, including iteratively reweighted generalized least squares (Goldstein, 1986), and a Fisher scoring algorithm (Longford, 1987).

Hierarchical data structures occur commonly in the social sciences, with individuals being nested in various types of groups. Often, the researcher is interested in the effects of variables at different levels of the hierarchy. Hierarchical linear models are used to analyze such data and permit a separation of within-group and between-group phenomena, while allowing for simultaneous consideration of the effects of group characteristics on group means and on relationships within groups. These models have a variety of applications in fields such as drug prevention research, school effectiveness, clinical therapy, growth curve analysis, geographical information systems, meta-analysis, and twin and family studies (Kreft & de Leeuw, 1998).

Analyzing nested data while ignoring the multilevel nature of the data leads to either aggregation by averaging the lower level data within each higher level, or disaggregation where data are treated only at the lower level. Either of these approaches may lead to problems, especially if the researcher is interested in propositions at the level that is not considered in the model. According to Snijders and Bosker (1999), aggregation leads to shift of meaning, ecological fallacy, and the neglect of the original data structure, while disaggregation leads to ‘the miraculous multiplication of the number of units’ by exaggerating sample size. Hierarchical linear modeling avoids these problems, and provides improved estimation of individual effects, estimation of cross-level interactions, and allows the partitioning of variance into within and between group components (Raudenbush & Bryk, 2002).

The basic notion behind the hierarchical linear model is that separate models are fitted for each context and these models are linked together by a second-level model in which the regression coefficients of the first-level model are regressed on the second-level explanatory variables. According to Kreft and de Leuw (1998), the character of the second-level linking model determines the nature of the model for the complete data. When certain terms in the full hierarchical linear model (including level-1 and level-2 models) are set to zero, a set of simpler models are obtained. According to Raudenbush and Bryk (2002), these 'submodels' include the one-way ANOVA model with random effects, regression models with means as outcomes, a one-way ANCOVA model with random effects, a random-coefficients regression model, a model with intercepts and slopes as outcomes, and a model with nonrandomly varying slopes. Thus, connections can be drawn between hierarchical linear models and more common data analysis techniques.

In a two-level hierarchical analysis, there are three types of parameters that can be estimated: fixed effects, random level-1 coefficients, and variance-covariance components. Because the level-1 regression coefficients in a multilevel model are treated as random, some researchers like to think of hierarchical linear models as random effects models for nested data (Littell, Milliken, Stroup, & Wolfinger, 1996).

Several different estimation methods and computational algorithms are used in hierarchical linear modeling. The most commonly used estimation method for two-level models are maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian methods. Full ML is the general estimation method used with three-level models, while both two- and three-level hierarchical generalized linear models use full ML or penalized quasi-likelihood estimation (Raudenbush & Bryk, 2002). The choice of modeling software depends partly on the estimation method desired. There are a variety of packages available today, including HLM, MlwiN, VARCL, MIXFOO, MLA, BMDP5-V, and SAS PROC MIXED (de Leeuw & Kreft, 2001).

Bryk and Raudenbush (1987) first put forth the possibility of using the hierarchical linear modeling framework to study individual change. In their 1987 paper, they stated that the research on individual change had thus far been "plagued by inadequacies in conceptualization, measurement, and design"(p. 147), and stated that HLM offered an integrated approach that provided the researcher with tools to not only study the structure of individual change, but also to examine the reliability of instruments for measuring status and change, investigate the correlates of status and change, and test hypotheses about the effects of background variables and experimental interventions on individual change.

Bryk and Raudenbush (1987) proposed that individual change can be conceptualized using a two-level hierarchical model where, in level-1, each individual's development is represented by his or her own trajectory of growth that depends on a unique set of parameters. These individual growth parameters then become outcomes in the level-2 model, where they can be regressed on person level characteristics.

The HLM approach to growth modeling is flexible in many ways. Polynomials of any degree can be fit provided enough data are available, discrete outcomes can be modeled, and alternative time metrics can be accommodated by suitable transformations of the outcome or the time variable. It is also possible to use piecewise linear models when an exploratory examination of the data suggests nonlinearity (Raudenbush & Bryk, 2002), and indicates that the data have time-varying covariates in level-1, that is, other level-1 predictors besides age or time.

Another advantage of modeling change using the HLM framework is that it is possible to predict future status. Raudenbush and Bryk (2002) state that the empirical Bayes estimates of the level-1 covariates have smaller mean-squared error than do ordinary least square estimates that use only the separate time trend data from each subject. Thus, when there is more random noise, better predictions can be made using empirical Bayes estimates. However, the usual care that should be taken when using any predictive model also applies in this case, namely, predictions should be made only for time points that are close to the time points in the data.

Using the HLM to model individual change is an alternative to using traditional multivariate repeated measures and structural equation modeling (SEM). MacCallum et al. (1997), Raudenbush (2001), and Raudenbush and Bryk (2002) discuss the advantages and disadvantages of these approaches. The main advantage of using HLM in growth modeling is its relative robustness to data that are not 'time-structured', that is, it does not require that all subjects be measured at the same time points, nor does it require the same number of time points. Also, the various response variables may be measured at different time points or different number of time points.

According to Raudenbush (2001), if the observed data are completely balanced, SEM offers a wide array of possibilities to model covariance structures. However, this condition is not always satisfied in longitudinal studies. It is possible to ease the constraint on balance by viewing the 'complete' data, that is, the data that the researcher aimed to collect, as balanced, but data that is missing as random. Then it is possible to use a modified framework provided by Jennrich and Schluchter (1986). However, if the complete data are unbalanced, that is, when level-1 predictors have different distributions across people, then HLM is the best way to analyze the data.

According to McLeod (2001), the HLM approach to repeated measures analysis is often preferred because of its ability to handle missing data efficiently. Raudenbush and Bryk (2002) state that an important advantage of using HLM with maximum likelihood estimation to study growth is the flexibility of the approach in handling missing data. All subjects who have been observed at least once can be incorporated in this approach, and results can be interpreted as if there were no missing data, provided that the data are missing at random. Raudenbush and Bryk state that this is not such a severe assumption, and HLM is even robust to nonignorable missingness provided the fraction of missing data is small.

The HLM methodology capitalizes on the strength of the data. According to Bryk and Raudenbush (1987), if the individual growth trajectory estimates are reliable, then the model weights them heavily. If they are not reliable, then the model substitutes values from the mean growth trajectories, conditioned on the background information. Thus, it offers a robust and flexible approach to growth curve modeling.

Traditional Repeated Measures

Analysis of variance methods are among the most dependable and effective methods available for detecting and describing trends in cross-sectional and longitudinal data if the conditions and assumptions are met. Cross-sectional data are especially easy to analyze, because, if there is random sampling, then the residuals can be assumed to be independent. With longitudinal data, the residuals are correlated between time points and the correlation patterns can rarely be specified in advance (Bock, 1979). If the number of time points is not too large, MANOVA deals with this problem very effectively by using the within-group variation to estimate the covariance structure of the residuals.

The term ‘repeated measures’ is normally associated with traditional multivariate analysis of variance (MANOVA) models where the subjects have been measured over time on the same attributes. In this approach, main effects and interactions are specified, and they describe the trajectory for different subgroups of individuals. Also, the variation and covariation of the repeated measures over time are specified. Usually, there is only one random effect, namely subject. The repeated measures effect, namely time, is considered fixed. Because of this, the traditional repeated measures model does not require multilevel modeling.

One strength of multilevel modeling is that the repeated measures variable, time, can be treated as random, and nested within the higher-level units. Also, time can be regarded as continuous, and the response can be modeled over time as a continuous curve rather than as a series of changes as in the MANOVA approach. Another strength of the multilevel approach over the MANOVA approach is that the number of time points and the placement of time points may vary, whereas traditional repeated measures models require that the number and spacing of time points be invariant (Raudenbush & Bryk, 2002). According to Bock (1979), the MANOVA approach is “best suited to the analysis of trends in group (population) means when the times of observation are fixed in advance in equal intervals and the trends or differences in trend between groups is sufficiently regular to be described by simple polynomial models” (p. 199).

Also, the multilevel approach allows the introduction of a third level, context, into growth modeling. The researcher can study how the external environment can affect individual growth (Raudenbush & Bryk, 2002), whereas the MANOVA approach does not accommodate this.

The MANOVA approach is modest in its demands on effort to formulate the problem and on computing resources (Bock, 1979). However, it uses least-squares analysis techniques, and requires a simplification of the assumptions in order to take full advantage of its strengths. Other growth modeling approaches are better when more complex or nonlinear models are to be fit. Ultimately, the choice of analysis methods depends on the researcher's questions and hypotheses.

A Group-Based Approach to Analyzing Growth

In many growth studies, it can be assumed that all subjects grow according to some common function, with only the growth parameters varying among them (Raudenbush, 2001). However, there are cases where this assumption may not be met. For example, in studies on depression or physical violence, while some participants show a steady increase in the attribute, others may be recovering due to therapy, or may have constantly low or high values on the attribute. In such cases, a group-based approach to trajectory model developed by Nagin (1999) may offer a better understanding of the topic.

According to Nagin (1999), this modeling strategy was presaged by the work of Rindskopf (1990) who developed a fully nonparametric methodology to analyze repeated measurements of dichotomous response data. Rindskopf's method was designed to identify distinct groups of response sequences across individuals. Nagin's model expands Rindskopf's approach by increasing the variety of response variables, by providing a basis to link group membership to individual level characteristics, and by developing a formal method to select the optimal number of groups.

Nagin's (1999) model has two levels. The first level is similar to the level-1 model in the HLM framework. The second level is reconceptualized such that the population is seen as falling into a fixed number of groups, where each group's development has a common set of change parameters (Raudenbush, 2001). The results from this modeling yield a set of conditional probabilities for each person: the probabilities that the person belongs to group 1, group 2, and so on. Then, a multinomial regression model can be used to predict the probabilities of group membership. The characteristics of a person in one group may be very different from the characteristics of an individual who falls in another group, and this model helps to better understand these differences. It is possible to test for the appropriate number of groups by comparing models using the Bayesian Information Criterion (BIC). It is also possible to test many models for alternate explanations, and this tool is thus useful for exploratory analysis.

Nagin (1999) developed this method in reaction to the emphasis on the correlational coefficient as an analysis tool in the fields of developmental psychology, psychopathology and criminology. According to Nagin the correlation coefficient masks the behavior of "increasers", "decreasers", and "no-changers" who may belong to distinct groups.

The group-based model assumes that the population may be composed of a mixture of groups with distinct developmental trajectories, and that the profiles of the individuals in these groups may be quite varied (Nagin & Tremblay, 1999). Nagin (1999) makes it clear that the assumption does not mean that the population is composed of distinct groups. Rather, the purpose of the modeling is to draw attention to the differences in the "causes and consequences of different developmental trajectories within the population" (p.140). The estimation procedure, which is based on mixture modeling, identifies the shape of the trajectory of each group and the proportion of population that constitutes each group (Nagin, 1999). The dependent variable can have binomial, poisson, or censored normal distributions, which is usually applicable to psychometric scale data.

Nagin (1999) argues that this mixture methodology is very useful in exploratory analysis, and helps in the identification of categories of developmental trajectories and the profiles of members following these different developmental paths. It differs from growth curve modeling in that growth curve modeling treats the population distribution of development as continuous, whereas mixture modeling is designed to identify distinct developmental trajectories.

This methodology is relatively new, and there are still questions that have to be investigated. According to Nagin (1999), "opportunities for extension abound" (p. 154). It is especially useful when the groups identified have different functional forms of growth. In the present study, only three time points of data are available, thus allowing only the fit of linear models. However, since the study is exploratory in nature, this method may provide deeper insight into the research questions.

New Developments

The areas of multilevel modeling and longitudinal modeling are growing rapidly, with new developments emerging at a fast pace. Some growing areas are hierarchical generalized linear models, hierarchical models for latent variables including item response and measurement error models, cross-classified multilevel models, estimation methods such as Markov chain Monte Carlo methods, dealing with missing data in longitudinal analysis, multiple imputation, the development of more reliable measurement instruments, trait-state methods for longitudinal data and so on. Steps are also being taken to improve the efficiency and the scope of the software, which now sometimes limits what a researcher can do. All these methods will, in the future, provide social scientists with more powerful tools to do more extensive data modeling.

Chapter Summary

This goal of this chapter was to briefly review the issues and literature relevant to both the substantive and the methodological concerns of this study. The chapter included a review of the literature related to aspirations, college choice, the history of the measurement of change, growth curve modeling, hierarchical linear modeling, group-based trajectory modeling, the issues in modeling complex data, and new developments.

CHAPTER 3

METHODS AND PROCEDURES

This chapter provides information about the data collection methods and the statistical analysis involved in the present study. It begins with an overview of the data, the research design and the sampling procedures, followed by a discussion on the weights and design effects adjustments used. A description of the variables used in the study is then presented. Finally, the statistical models and the analysis strategies are discussed.

Overview of the Data and Research Design

The National Education Longitudinal Studies (NELS) program is a long-term project instituted by the United States Department of Education's National Center for Education Statistics (NCES), with the goal of collecting policy-relevant longitudinal data on nationally representative samples of elementary and secondary students (National Center for Educational Statistics [NCES], 1994). According to the NCES (1994), "the general aim of the NELS program is to study the educational, vocational, and personal development of students at various grade levels, and the personal, familial, social, institutional, and cultural factors that may affect that development" (pp. 1-2). The National Longitudinal Educational Study of 1988 (NELS:88) was one component of the NELS program, and represents the educational experience of students from the 1990s.

The NELS:88 data consists of five waves of data, referred to as the base year, first, second, third and fourth follow-ups. The base year data were collected in 1988 when the students were in the eighth grade. This data contains information about educational processes and outcomes pertaining to student learning, predictors of dropping out, and school effects on students' access to programs and opportunity to learn.

The first follow-up data (F1) were collected between February and May of 1990, when the students were in the tenth grade. This study captured the population of early dropouts and monitored the transition of the students from middle school to high school. A sub-sampling of the original sample occurred during this follow-up, due to the transition of the students to numerous high school settings. The sample in this follow-up was also freshened with additional tenth graders so that it would be representative of sophomores.

The second follow-up (F2) was conducted during the spring term of 1992, when the students were in the twelfth grade. This follow-up resurveyed all the students from the eighth-grade cohort, including students who were identified as dropouts in 1990 (NCES, 1994). Freshening of this sample was also implemented with additional students so that the sample was representative of the twelfth-grade class of 1992.

The third follow-up (F3) occurred in 1994, when most of the sample members were either in the labor force or in postsecondary institutions. A second major sub-sampling occurred during this follow-up. The goals of this follow-up were to provide data for trend comparisons with other NCES data sets such as the National Longitudinal Study of 1972 (NLS-72) and High School and Beyond (HS&B), and also to continue cross-wave comparisons with previous NELS:88 rounds (NCES, 1994).

The fourth follow-up (F4) occurred in the year 2000, when most of the sample members had completed some postsecondary education, and were in the labor force. The data for this follow-up were released in September 2002.

NELS:88 is designed to provide trend data about critical transitions experienced by youth as they attend school and embark on their careers. This study intends to use the base year through second follow-up data to examine the period that envelops the end of middle school through the end of high school, and to study the factors that influence the formation and stability of student aspirations during this time, and how they translate into concrete actions toward attaining higher education.

Sampling and Data Collection Methods

Base Year

In the NELS:88 base year, a two-stage stratified probability sampling design was used to select a nationally representative sample of eighth-grade school and students in the spring term. Schools were the primary sampling units (PSU), with 1,052 schools contributing usable student data. The probability of selection of each school was proportional to the eighth-grade size, and private schools were oversampled. For 1,035 of these schools, both student and school administrator data were collected. Schools were stratified along sector (private, Catholic, public), and also along composition (large or small percentage of black or Hispanic students).

For the base year data, students were the secondary sampling unit. This second stage sampling resulted in the participation of 24, 599 randomly selected students from the selected schools. On average, each of the schools was represented by 23 participating students (NCES, 1994). Hispanic and Asian/Pacific Islander students were oversampled to permit analysis of the performance of language minority students. Approximately 5% of the selected students were classified as base year ineligible by school principals who determined that these students' lack of English proficiency, or physical or mental disability, would make it unduly difficult for them to complete the questionnaires or cognitive tests.

The study design was comprised of four components: surveys and tests of students, surveys of parents, school administrators, and teachers. A student questionnaire gathered information about background, school work, educational and occupational aspirations, social relationships and various other topics. Students also completed curriculum-sensitive cognitive tests to measure educational and cognitive growth up to the twelfth grade. These tests were administered in four areas – reading, mathematics, science, and social studies. One parent of each student was asked to respond to a parent survey. Selected teachers in two of the above four areas completed a teacher questionnaire. Also, the school principals completed a school administrator questionnaire.

First Follow-up

The general sampling strategy for this round involved subsampling students from the base year data. This was done because students from around 1000 middle schools had been distributed into approximately 4000 high schools. So, base year students who were reported to be attending a school with at least 10 other base year students were sampled with certainty, while all others were sampled with probabilities greater than zero but less than one (NCES, 1994).

The first follow-up of NELS:88 had the same components as the base year data, except for the parent survey which was not administered. Three new components – the dropout survey, base year ineligible survey and the school effectiveness study were incorporated in this round.

The selection of students was done in two stages. In the first stage, 21,474 students who were in the eighth-grade cohort were selected. Because some students who were now sophomores had not been in the country during the first round of data collection, or were not in the eighth grade in the spring of 1988, a freshening of the sample was done. 1,229 new students (of whom 1,043 were retained) were added to the sample in order to make it representative of the sophomore population of 1989-90. Also, some base-year ineligible students were added to this sample.

After the initial selection of the longitudinal cohort, the combined longitudinal-freshened sample was further subsampled. As a result, the first follow-up sample size was 20,706.

Second Follow-up

When the second follow-up was completed, it was found that the first follow-up sample was more widely dispersed than anticipated (NCES, 1994). After careful consideration, it was decided that all first follow-up sample members would be included in the second follow-up sample. A total of 2,258 schools were identified, out of which all 1,030 schools with four or more first follow-up members enrolled were included with certainty, and others were subject to a sampling process (NCES, 1994).

The second follow-up repeated all the components of the first follow-up. In addition, the parent questionnaire was administered once again. There were two new components: the transcript and the course offering components, which provided additional data about the students.

Once again, the data was freshened in order to make it representative of the twelfth-grade population in the spring term of 1992. Students who had dropped out between the eighth and twelfth grades were also surveyed. Base-year ineligible students who participated in the first follow-up were also part of this follow-up. One teacher (instead of two as in the earlier study) was asked to complete the teacher questionnaire.

Thus, the sampling in the base year implemented the two-stage sample design, whereas the first and second follow-up samples were student driven, that is, the individual student was pursued outside of school. Further details about the sampling procedures used can be obtained from NCES (1994).

Nonresponse Issues

Unit nonresponse occurs when an individual respondent declines to participate, or when the cooperation of a school cannot be secured (NCES, 1994). For the NELS:88 data, there was practically no school-level nonresponse (NCES, 1994), and cooperation levels approached 99 percent in the two follow-up rounds. According to NCES (1994), the effect of student-level nonresponse within the selected schools was not assessed in the base year, although males, blacks, and Hispanics tended to be nonparticipants more often than females, whites or Asians, respectively. From the analysis perspective, however, the NELS:88 weights adjust for unit nonresponse. These weights were adjusted for nonresponse by forming weighting cells based upon the combination of certain levels of variables representing school type, region, ethnicity, and gender. The products of a preliminary school weight and the student's design weight was first formed. Then, these products were summed across all students. The ratio of the sums for all sampled students to participating students was used as the nonresponse adjustment factor for each student's design weight (NCES, 1994).

Item nonresponse occurs when a respondent fails to complete certain items on the survey instrument. In the NELS: 88 data collection, efforts were made to compensate for item nonresponse in three ways. First, machine editing was done through which certain nonresponse problems are rectified by forcing logical agreement between filter and dependent questions (NCES, 1994). Second, some key variables were constructed in part by using additional sources of information such as school records or other respondent sources, when questionnaire data were missing. The third was a language series filter question, where respondents who should have legitimately skipped the dependent items in the language series were identified (NCES, 1994).

According to NCES (1994), overall, the studies had a high rate of response. Cross-sectionally, around 93 percent of the students participated, while 96 percent of the in-school portion of the eighth-grade students were participants. The base year completion rate was 93 percent, and the first follow-up completion rate was 94 percent.

The average second follow-up item nonresponse rate is 3.3 percent for the 69 critical student items. For the base year it was 2.7 percent and for the first follow-up it was 2.6. Thus, according to NCES (1994), a reasonable rate of item nonresponse was achieved.

Theoretical Framework

This study uses the broad theoretical framework for predisposition to college developed by Hossler and Stage (1992). The present study seeks to examine the influence of select variables on the longitudinal development of adolescents' aspirations, and the variables to be used were selected based on this framework. According to this model, shown below, factors that influence predispostion can be grouped into socioeconomic, demographic, parental/peer expectations and encouragement, ability, and high school experiences. However, it should be kept in mind that Hossler and Stage's model was developed to explain predisposition at a single point in time, while this study seeks to examine the stability of aspirations over time. Hence a few modifications to the model were necessary, including not considering high school experiences which may not be relevant in the study of the stability of aspirations from middle to high school.

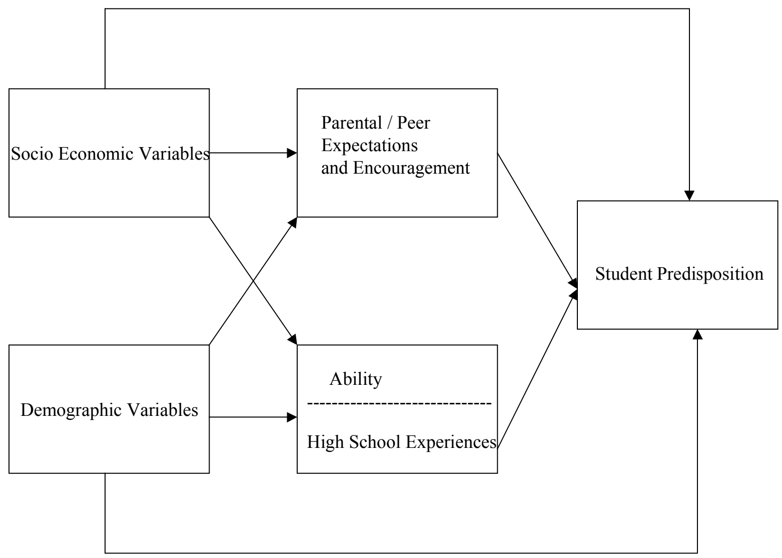


Figure 3.1: Hossler and Stage (1992)'s theoretical model of high school students' predisposition to college.

Variables

Dependent Variable

- Educational Aspirations: This variable measures how far in school the student thinks he will get, "as things stand now". In the base year data, this variable was measured on a 6-point scale, in the first follow-up on a 9-point scale, and in the second follow-up, on a 10-point scale. For the analysis in the current study, this variable will be measured on a 6-point scale ranging from "high school or less" to "graduate or professional degree."

Grouping Variable / Ordinal Response

- Applications filed: This variable measures the number of colleges that a student has applied to in the spring term of 1992. There are three categories: “none”, “one”, “two or more”. Hurtado et al. (1997) say that this variable “represents the fusion of the later phase of college search and the early phase of college choice in order to understand students’ strategies for college choice” (p. 47). According to Hurtado et al. (1997), this variable serves as a proxy for students’ plans to “increase their opportunities and their strategic selection of a college that might meet their preferences” (p, 47). Most college counselors suggest that students apply to more than one school in order to maximize their chances of obtaining a postsecondary education. Usually, at least one “dream school”, and one school to fall back on, are suggested as good choices to apply to. Hossler et al. (1999) state that most students apply to colleges between October and January of their senior year, and it can be assumed that the more serious students would have already finished the application process by the spring term of their senior year.

<u>Time-Varying Covariates</u>

- <u>Mathematics Ability:</u> The current study will use scores on a longitudinally-equated and curriculum-based mathematics test developed by the Educational Testing Service (ETS) specifically for NELS:88 researchers. The operational definition of this variable is the standardized score on the mathematics test. This test was administered in each of the three waves, and consisted of multiple choice items, and was timed and normed. The properties of this test are discussed below.

In addition to the NELS:88 student questionnaire, students completed a series of cognitive tests administered at school or off-campus survey sessions (NCES, 1994). The tests were in the areas of mathematics, reading comprehension, science and social studies. All the cognitive tests consisted of multiple choice items. In the base year, all the students received the same test form. For the first and second follow-ups, multiple forms were developed for the reading and mathematics tests. The mathematics test had 3 forms, and this significantly reduced the potentially serious problems of ceiling and regression effects (Owings et al., 1994).

The base year mathematics test contained 40 multiple-choice items. Students had 30 minutes to complete this test which contained a mix of word problems, diagrams and calculations covering a range of mathematical concepts (Rojewski & Yang, 1997). A Cronbach α reliability of 0.90 was obtained for the base year administration (Rock & Pollack, 1991).

For the subsequent test administrations, ETS devised three forms of the test – easy, moderately difficult, and difficult. Each of the versions maintained the same format used in the base year; a 30-minute time limit to complete 40 multiple choice questions. In the first and second follow-ups, the easiest and most difficult versions were distributed to students who had previously scored in the lowest and the highest quartiles, respectively (Rojewski & Yang, 1997). The middle half of the distribution from the base year, as well as freshened students, were given the moderately difficult test (NCES, 1994).

NELS:88 researchers used Item Response Theory (IRT) to link and vertically equate the various forms. This allowed the three sets of scores to be interpreted both within and across grade levels. Each IRT estimate is the "probability of a correct answer, given a person's demonstrated ability and the parameters of the item, summed over all test items" (NCES, 1994, p. H-40). IRT estimated mathematics achievement scores range from 15.81 to 66.81 at grade 8, 16.37 to 72.76 at grade 10, and 16.77 to 78.10 at grade 12, based on 81 items.

Several reports extensively document the psychometric properties of NELS:88 measures (Ingels, Scott, Rock, Pollack, & Rasinski, 1994; Kaufman, Rasinski, Lee, & West, 1991; Rock & Pollack, 1991). Kaufman et al., using several indicators to determine the validity and reliability of the tests, including the consistency among student responses to related items and the internal consistency reliability of scalable survey responses, found that the measures exhibited acceptable validity and reliability. Ingels, Scott, Lindmark, Franekel, and Myers (1992) reported Cronbach α coefficients of 0.79 to 0.90 for the mathematics test.

Academic achievement/ability has been consistently shown to be related to student aspirations (Hossler & Stage, 1992). According to Hossler and Stage, "as ability and academic achievement rise, students are more likely to aspire to attend a postsecondary institution and they are more likely to follow through with those plans" (p. 430). Mathematics achievement was specifically chosen as it has been found to be related to future attainment (Hurtado et al, 1997). Hinson (2002) also found a relation between scores on mathematics achievement tests and aspirations to go to a four-year college. Signer and Saldana (2001) found an interaction effect of ethnicity and mathematics achievement on educational aspirations. Also, according to Fan (2001), research in learning suggests that the more specific that the learning outcome is defined and measured, the more likely it is to detect the effect of a causal factor.

This variable is a time-varying covariate in that it has different values across time for the participants. Instead of being specified at level-2 of the HLM model as a fixed predictor, it will be specified as a level-1 effect that is allowed to vary with time. Thus the HLM framework is the preferred approach over structural equation modeling or traditional repeated measures to analyze the data (Raudenbush, 2001; Raudenbush & Bryk, 2002).

- <u>Mother's Expectations:</u> This variable measures a student's perception of how far in school his or her mother wants him or her to get. It is a continuous variable on a 6-point scale, measured in the base year as well as in the two follow-ups, and will thus be specified as a time-varying covariate. A student's perception of his or her parents' expectations over the years maybe a factor that affects the stability of aspirations. According to Davies and Kandel (1981), adolescent perception of parental expectations were more important than parents' reports of their own expectations.

Hossler et al. (1999) state that "parents play the most significant role in shaping the educational aspirations of their children" (p. 133). They feel that parents should communicate high educational expectations to their children when they are young, and that parents who say things like "a high school diploma is not enough" or "of course you will go to college" have children who aspire to go to college and never consider not doing so.

- <u>Parental Involvement:</u> This is a composite variable created for the current study by combining a number of variables in the NELS:88 data. This variable is the average of three variables measured in the base year and in the two follow-ups. The two variables measure how often the student has discussed with his parents about (1) selecting school programs and courses, (2) school activities, and (3) things studied in class. Each of these variables are measured on a 3-point scale in the NELS: 88 data set. Thus, the composite variable will also be on a 3-point scale.

As mentioned under the section on mother's expectations, parental support and encouragement are also crucial to students forming and maintaining high aspirations. One indicator of parental support is consistent parental involvement with the student's schooling over time. Hossler et al. (1999) found that parental education or income levels are not important determinants of high student aspirations, but their encouragement and support are.

Level-2 Independent Variables

- Gender: This variable is chosen from the second follow-up data. According to NCES, this is the most complete indicator of the respondent's gender, and is based on the first follow-up composite and augmented by second follow-up information, and if still missing, imputed using student's first names.

Although women have historically been underrepresented in postsecondary education, the Washington Office of the College Board (1986) reported, as far back as in 1986, that there are more women than men enrolled in college, and the trend continues to this day. Stage and Hossler (1989) showed that women thought more about going to college, but received less family support. Kao and Tienda (1998) and Mau and Bikos (2000) found that gender did have impact on aspirations when examined in conjunction with race.

- Race: This is a composite variable from the second follow-up, and indicates a student's "best-known" race (NCES, 1994). Although the original variable had five categories, the analysis in the current study uses only four of these categories: Asian/Pacific Islander, Hispanic, Black/Not Hispanic, and White/Not Hispanic. The fifth category, namely American Indian/Alaskan will not be included as it has a very small sample size.

Many studies have shown that race does have an impact on student aspirations and postsecondary attendance. Although the number of black students in postsecondary education tripled between 1966 and 1977, participation rates fell slowly through most of the 1980s (Hossler & Stage, 1992). Also, Asian students in general have very high aspirations, and black and Hispanic students start with high aspirations but are less likely to maintain them from eighth through twelfth grade (Kao & Tienda, 1998).

- <u>Socioeconomic Status:</u> This is a second follow-up composite variable that estimates the socioeconomic status of a respondent. It is derived from the base year parent questionnaire data, the base year student questionnaire data, and the supplemental data from the first and second follow-ups. According to NCES (1994), the overall logic behind this variable is that if sufficient information exists in the parent file, this variable is created from the base year parent's education, occupation, and total household income. If that information is inadequate, it is based on the student-reported parent's education and occupation, as well as the number of selected items that exist in the household as reported in the base year student file. If neither parent nor student base year files have the required information, data from new student supplement file in the second-follow up is used.

Socioeconomic status has been consistently found to be positively associated with a predisposition to attend college, according to Hossler and Stage (1992) who did a comprehensive literature survey. Marini and Greenberger (1978) found that the impact of SES on aspirations may differ for men and women. In a path analytic study (1981), Tuttle found that SES had an indirect effect on aspirations through student ability/achievement. Hossler and Stage state that SES does have an impact on aspirations, but some of the impact is indirect, as it has a positive effect on academic success of students and the educational expectations that they perceive that others have for them.

- Early Academic Experience: This variable measures if a student had ever been held back a grade before the ninth grade. The status attainment tradition in sociology emphasizes the impact that early experiences can have on subsequent outcomes. Kao and Tienda (1998) showed that having ever repeated a grade early greatly dampens college aspirations, especially among black and Hispanic students who, they claim, are disproportionately retained in school.

- Early Academic Achievement: This is an average of the self-report of grades over four subject areas (mathematics, english, science, and social studies) of the student from the sixth to the eighth grades. It is a continuous variable on a scale of 0.5 to 4.

As mentioned earlier, academic achievement/ability has been consistently shown to be related to student aspirations. Early high achievement has several implications and, together with parental involvement, it may have an impact on students' choice of high schools and academic program or curriculum in high school. Students enrolled in college preparatory curriculum in high school have been consistently shown to have higher aspirations (Conklin & Dailey, 1981; Jackson, 1986; McDonough, 1997). In summary, the variables that will be used in the current study are as given in Table 3.1, along with their actual definitions in the questionnaire, the level of measurement. The definition of parental involvement as created for this study is also given in this table.

Table 3.1: List of Variables in the Current Study

Variable Status	Variable Name	Variable Type	Description
Dependant	Educational Aspirations	Continuous	How far in school the student thinks he/she will get
Grouping/ Ordinal Response	Applications Filed	Categorical	The number of applications filed in the spring term of the senior year (0, 1, 2 or more)
Time-Varying Covariates	Time	Continuous	Coded as 0, 1, 2
	Mathematics Ability	Continuous	Standardized score on NELS:88 mathematics test
	Mother's Expectations	Continuous	How far in school the student thinks his mother wants him/her to go
	Parental Involvement	Continuous	Average of 3 variables that measure how often the student discusses with his/her parents the following: (1) selecting school programs and courses, (2) school activities, and (3) things studied in class
Time-Stable Covariates	Gender	Categorical	Male/Female
	Race	Categorical	Asian/Hispanic/Black/White
	SES	Continuous	Composite socioeconomic status created from parental education, occupation, and total household income (see description earlier)
	Early Academic Experience	Categorical	Ever held back in school up to eighth grade (yes/no)
	Early Academic Achievement	Continuous	Student self-reported grades from sixth to eighth grades (0.5 – 4.0)

Statistical Methods

Modeling of Complex Data

Sample surveys can conceptually be divided into two broad categories: descriptive surveys and analytical surveys (Lehtonen & Pahkinen,1995). In descriptive surveys, usually a few specific population characteristics such as means and frequencies need to be estimated accurately. Analytical surveys are less concerned with descriptive goals and are more ‘directed at the underlying causes that have made the frequencies of various classes of the population what they are’ (Deming, 1950). Thus, statistical testing and modeling play important roles in analytical surveys.

Both types of surveys can be *complex,* that is, involving a complex sampling design such as multi-stage stratified cluster sampling (Lehtonen & Pahkinen, 1995). Complex survey designs provide several practical advantages to the investigator. It is possible to study a large population, while being cost-effective and getting higher response rates. Very often the populations surveyed have inherently complex structures with systematic differences between sub-populations which may be based on several different factors such as geographical location or other community-related characteristics (Skinner, Holt, & Smith, 1989). Complex surveys use this natural population structure and try to incorporate them into the survey using *stratification* and/or *clustering*, leading to substantial gains in efficiency (Skinner et al., 1989).

These advantages of complex surveys are offset by the challenges presented for data analyses (Fan, 2001). Standard statistical procedures, that are based on the assumptions of simple random sampling or the sample being independently and identically distributed (IID), are usually inappropriate for complex survey data (Skinner et al., 1989). In order to obtain precise estimates and to conduct hypothesis testing, it is necessary to take into account the complexities of the sampling design. Many of the large national surveys conducted by the National Center for Educational Statistics (NCES), including the one used in this study (the National Education Longitudinal Survey of 1988 (NELS:88)) are complex surveys that have stratified and clustered data, and any inferences made should take the sampling scheme into account.

Stratification is when the population is subdivided into non-overlapping subpopulations (strata), such as regional or demographic groups, and the sampling is done independently within these subpopulations (Lehtonen & Pahkinen, 1995). According to Lehtonen and Pahkinen, stratification is cost efficient, and the variation within strata is usually small. It is usually done for administrative purposes, to increase the precision of estimates within strata, and to guarantee the representation of small subpopulations. However, according to Skinner et al. (1989), conventional point estimators of parameters can be severely biased under disproportionate stratification.

Sometimes, the population is divided into naturally occurring groups of population elements such as households, census blocks, school districts, or schools. Then, *cluster sampling* can be done, wherein a sample of clusters is drawn from this population of clusters, and a subsample of elements is obtained from each cluster. The clusters are then called primary sampling units (PSU). Cluster sampling can be done in one or more stages if necessary. According to Lehtonen and Pahkinen (1995), an important advantage of cluster sampling is that a sampling frame is not necessary at the level of the element, only at the cluster level. Cluster sampling offers economic advantages to the investigator since the cost of data collection per sample element is usually low. However, it leads to decreased statistical efficiency (Lehtonen & Pahkinen, 1995). In a cluster sample, the probability of being chosen in the sample is conditional on the membership in a specific cluster (Skinner et al., 1989). Thus, the sample does not satisfy IID assumptions. Conventional standard errors can thus be misleading with clustered data (Skinner et al., 1989).

In complex surveys, sometimes, certain groups are intentionally oversampled so that more stable estimates could be obtained for these small populations (Fan, 2001). *Oversampling* can lead to biased estimates for population parameters if it is ignored in the analysis. Sampling weights have to be used to adjust for oversampling.

The statistics from a complex design are thus more variable than they would have been had they been derived from a simple random sample of the same size (NCES, 1994). Variances that are wrongly based on IID assumptions and estimates from highly stratified samples are in general biased (Skinner et al., 1989).

The impact of departures from a simple random sample on the precision of estimates is measured by the *design effect* (Kish, 1965). For any statistical estimator, the design effect is the ratio of the estimate of the variance of a statistic derived considering the complex design, to the variance obtained using the formula for simple random samples. The design effect does not affect a statistic itself; it only affects the standard errors of statistics. If analyses were carried out ignoring the design effect, the Type I error in significance testing is inflated (Fan, 2001).

Also, in a complex survey, because of multi-stage sampling schemes, selection probabilities are usually unequal. Appropriate weighting is necessary in order to get unbiased and consistent estimators (Lehtonen & Pahkinen, 1995). In a simple random sample design, each case is selected with equal probability, that is, each case in the sample represents the same number of cases in the population. In a complex design, each case in the sample may be selected with a different probability and represents a different number of cases in the population. The sampling weight is the inverse of the selection probability, that is, it is the number of cases in the population that each case in the sample represents. Ignoring sampling weights leads to statistics that give some cases in the sample more than their representation of the population, leading to biased parameter estimates.

Sampling weights can also be used to adjust for total (or unit) *nonresponse* in a survey, that is, where the data are not available for some sampling units. In such cases, the adjustment for the missing data can be done by reweighting the response data set with an inflation factor to produce a data set which better agrees with the intended sample size (Lehtonen & Pahkinen, 1995). Not adjusting for nonresponse may lead to seriously biased estimation (Skinner et al. 1989; Lehtonen & Pahkinen, 1995). Reweighting is commonly used in the large surveys conducted by national statistical agencies.

There are two broad approaches to analyzing survey data: model-based and design-based. In the model-based approach, the variables that determine sample selection (such as the stratification variables) are included in the substantive model (Kam & Wagstaff, 2001). The design-based approach on the other hand, takes into account the structure of the sampling scheme. Any of the complexities in the sampling are properly accounted for in the estimation. Thus weights may be used in order to compensate for unequal selection probabilities due to oversampling, and also for nonresponse adjustments. Design effect adjustments may be made in cluster sampling schemes. Since the model-based approach ignores sampling complexities, it assigns an equal weight to each observation. The standard errors associated with this approach will be smaller than those derived from a design-based approach (Korn & Graubard, 1995). Pfefferman et al. (1998) as well as Tipa (as cited in Kam & Wagstaff, 1998), who studied the use of weights with nonignorable missing data, suggest that weights can reduce bias even when design variables are included in the substantive model.

NCES (1994) recommends the use of a design-based approach to analyze many of their complex data sets because of the use of multistage stratified and cluster sampling, oversampling and nonresponse adjustments in these data. They also provide the design effects associated with many variables in their data sets, and weights for cross-sectional and longitudinal analyses.

The data used in this study are from a large national survey, the National Education Longitudinal Survey of 1988 (NELS:88). The sample design for this survey involved stratification, disproportionate sampling of certain strata, and multi-stage clustering (NCES, 1994). Also, some minority groups were intentionally oversampled. This study will use longitudinal panel weights provided by the NCES to compensate for unequal probability sampling and to adjust for nonresponse. It will use a conservative approach suggested by Fan (2001) to resolve the complexities of the design effect issues encountered when using longitudinal analysis on a complex survey. This use of a design-based approach is done in the hope that the estimates obtained and the inferences made will be as reliable and as accurate as possible.

Multilevel Models (Hierarchical Linear Models)

Data that have a hierarchical structure, with lower-level observations nested in higher-level units, such as students in schools, are very common in the social and behavioral sciences. Traditional general linear models are not suitable for the analysis of such data because of the violation of the assumption of independence when data are clustered. Multilevel modeling is specifically designed for the analysis of such non-independent or clustered data, and can incorporate predictors at the individual and group levels, as well as individual by group interactions. Multilevel models take into account the variability associated with each level of nesting, thus avoiding many methodological errors that may lead to false conclusions when this hierarchy is ignored (Kreft, 1996; Snijders & Bosker, 1999).

Multilevel linear models are often also referred to as hierarchical linear models, mixed-effects models, random-effects models, random-coefficient models, and covariance component models (Raudenbush & Bryk, 2002). Raudenbush and Bryk say that there are three general purposes of this type of modeling: (1) improved estimation of effects within individual units, (2) the formulation and testing of hypothesis on cross-level effects, and (3) the partitioning of variance and covariance components among levels.

In multilevel models, separate (first level) linear models are fitted for each context. These models are then linked together by a second-level model in which the regression coefficients of the first level model are used as outcomes and the explanatory variables are at the second level (Kreft & de Leeuw, 1998). Longitudinal data can be considered to have a hierarchical structure, where the occasions of measurement are nested within individuals (MacCallum et al., 1997). The basic longitudinal multilevel growth model is explained below using the Hierarchical Linear Model (HLM) framework of Raudenbush and Bryk (2002).

The general hierarchical growth model: Suppose that Y_{ti} is the observed status of individual *i* at time *t*. Let T_i be the number of measurements. Suppose the growth over time can be represented as a polynomial of degree P. Then, the level-1 model is described as

$$Y_{ti} = \pi_{0i} + \pi_{1i} a_{ti} + \pi_{2i} a_{ti}^2 + ...+ \pi_{Pi} a_{ti}^P + e_{ti}$$

where a_{ti} is the age at time t for person i;

e_{ti} represents random error in the level-1 equation; and

π_{pi} is the growth trajectory parameter p for individual i associated with the polynomial of degree P.

It is commonly assumed that e_{ti} is independently and normally distributed with mean 0 and homogeneous variance σ^2.

For the level-2 model, the level-1 regression coefficients are allowed to vary across level-2 units, namely, the individuals. The π_{pi} are used as outcomes, and individual characteristics can be used as predictors, leading to the level-2 equations:

$$\pi_i = \beta_{p0} + \sum_{q=1}^{Q_p} \beta_{pq} X_{qi} + r_{pi}$$

where X_{qi} is an individual characteristic or experimental treatment;

β_{pq} represent the effect of X_q on the pth growth parameter; and

r_{pi} is a random effect with mean 0. The P+1 random effects for person i are assumed to be multivariate normally distributed with covariance matrix **T**, with dimensions (P+1) X (P+1).

According to Raudenbush and Bryk (2002), the individual growth model can be applied to several ends including (1) estimating a mean growth curve and individual variation around it, (2) assessing the reliability of measures to study change and status,

(3) estimating the correlation between the intercept (initial status) and the slope (rate of change), and (4) modeling relations of individual predictors to the intercept and slope.

Not only can familiar models such as slopes-as-outcomes and random coefficient models be used in this framework, but also more complex models such as higher-degree polynomial models, piecewise linear growth models, and models with discrete outcomes can be fit. Individual growth modeling also accommodates time-varying covariates, that is, level-1 coefficients other than time itself that may have different distributions across participants (Raudenbush, 2001). Also, more complex error structures for the level-1 error term e_{ti} are possible (Raudenbush & Bryk, 2002).

One strength of multilevel growth modeling is that it allows time to be treated as random and nested within the upper-level units. Another strength is that time can be regarded as continuous and the outcome that has been repeatedly measured can be modeled over time as a continuous curve. Other benefits are that time points need not be evenly spaced, they may be variably spaced for different individuals, and the number of time points may vary for different individuals (Rauenbush, 2001). In other words, this method is flexible in handling missing data that are missing at random (MAR).

Thus the HLM approach to model longitudinal data has several advantages over traditional repeated measures approaches such as MANOVA, as well as latent curve modeling, especially when it comes to the relaxation of the "time-structured" data requirements of the other methods. HLM has the power to accommodate a wide variety of data structures and level-1 models, and allows level-1 predictors to have different distributions across individuals (Raudenbush & Bryk, 2002).

This data structure issue becomes very important when a large national database is used for analysis, such as in this study. Data collection in large longitudinal studies often have missing data, and it may not always be feasible to discard these observations that may provide valuable insight into the question at hand. HLM offers a robust methodology that allows the inclusion of all participants who have been observed at least once.

Group-Based Mixture Models

This type of modeling is a semiparametric, group-based approach for modeling developmental trajectories, developed by Nagin (1999). This is also a multilevel approach that uses a two-level model to study growth trajectories.

The level-1 model in this approach is similar to that in the HLM framework, but in the level-2 model, the population is viewed as falling into distinct groups, with each group's development characterized by a set of change parameters. The output of the model is a set of conditional probabilities for each person, the probabilities that the person belongs to each group. The response variable can be a binary variable, a scale, or a count variable. For scale data (as in the current study), the underlying model is based on the censored normal distribution. The model can be represented as in Figure 3.2.

As in hierarchical and latent curve modeling, a polynomial relationship is used to model the link between time (or age) and behavior. Specifically, a censored normal model could be expressed as:

$$y_{it}^{*j} = \beta_0^j + \beta_1^j \left(AGE_{it}\right) + \beta_2^j \left(AGE_{it}^2\right) + \varepsilon_{it},$$

where y^{*j}_{it} is a latent variable that can be thought of as measuring the potential for engaging in the behavior of interest for individual *i* at time *t* in group *j*,

ε is the residual assumed to be normally distributed with zero mean and constant variance σ^2.

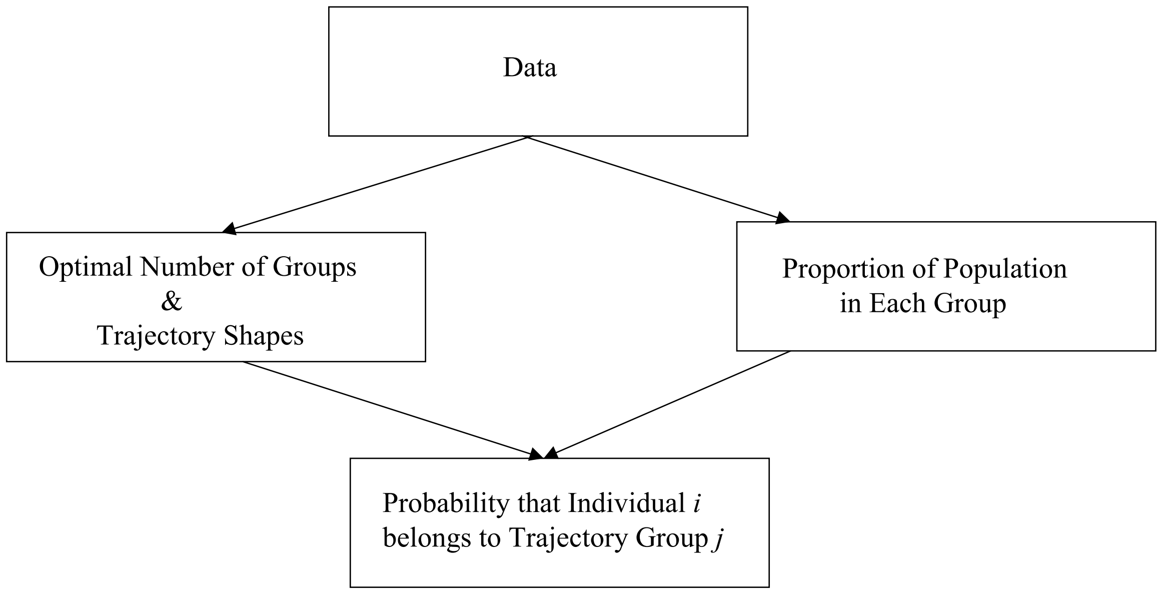


Figure 3.2: An Overview of Nagin (1999)'s Model

The latent variable y^{*j}_{it} is linked to its observed but censored counterpart y_{it} as follows (Nagin, 1999). Let S_{min} and S_{max} be the minimum and maximum possible score on the measurement scale. The model assumes

$y_{it} = S_{min}$ if $y^{*j}_{it} < S_{min}$,

$y_{it} = y^{*j}_{it}$ if $S_{min} <= y^{*j}_{it} <= S_{max}$, and

$y_{it} = S_{max}$ if $y^{*j}_{it} > S_{max}$.

The three parameters defining the trajectory are allowed to vary across groups. According to Nagin (1999), this allows for easy identification of population heterogeneity not only in the level of behavior at any given age, but also in the development of behavior over time. Thus different groups can have different functional forms of the trajectory.

The trajectories are products of maximum likelihood estimation. Since group membership is not observed and available beforehand, the proportion of the population composing group *j*, namely, π_j is a parameter of interest. The likelihood function is constructed as follows:

$$P(Y_i) = \sum_j \pi_j P^j(Y_i),$$

where $P(Yi)$ is the aggregation of the J conditional likelihoods $P^j(Y_i)$ of the probabilities of Y_i given membership in group *j*, and π_j is the probability of membership in group *j*. Details of the derivation of the likelihood are given in Nagin (1999).

One issue of importance is the determination of the optimal number of groups required to compose the mixture. Nagin (1999) suggests the use of the Bayesian Information Criterion (BIC) to choose the optimal model, saying that if the BIC is used as the basis of choice, expansion of the model by adding a trajectory group is desirable only if the resulting improvement in the log likelihood exceeds the penalty for more parameters. Nagin cites Keribin's 1997 demonstration of the use of the BIC in identifying the optimal number of groups in finite mixture models. However, Nagin warns that determination of the number of groups is not always clear-cut, and there is a need for further development of methodology towards this end.

While it is not possible to make a definitive identification of the group an individual belongs to, it is possible to calculate the posterior probabilities of group membership. Individuals can then be "assigned" to the group to which their posterior probability is largest. Nagin (1999) states that one important use of posterior probabilities is that they allow the creation of profiles of the average individual in each group. Thus the differences among these groups can be studied. Another area in which the posterior probabilities can be used is in the selection of subsamples for any follow-up study.

Thus the mixture model of developmental trajectories has two essential parts: (1) an expected trajectory given membership in a group, and (2) a probability of group membership. This latter probability can also be seen as the proportion of population in each group. Nagin (1999) states that by allowing this probability π_j to vary with individual characteristics, it is possible to test by how much a given factor affects probability of group membership, controlling for any other factors.

Modeling for Multicategory Ordinal Responses

A number of logistic regression models for analyzing ordinal responses have been developed. When response categories are ordered, logits can incorporate the ordering (Agresti, 1996). These models are called cumulative logit models and according to Agresti (1996), these models have simple interpretations and greater power than ordinary multicategory logit models.

In these models, cumulative logits which are based on cumulative probabilities are created. The cumulative probabilities are the probabilities that the response Y falls in category j or below, for each possible j. The jth cumulative probability is

$$P(Y <= j) = \pi_1 + \ldots\ldots + \pi j, \qquad j = 1, 2, \ldots\ldots J.$$

The logits of the first $J - 1$ cumulative probabilities are

$$\text{Logit}\ [\,P(Y <= J)] = \log\ [\,(\,P(Y <= j)) / (1 - P\,(Y <= j)]$$

These are called cumulative logits.

Each cumulative logit uses all J response categories. A model for the jth cumulative logit looks like an ordinary logit model for a binary response in which categories 1 to j combine to form a single category, and categories $j + 1$ to J form a second category (Agresti, 1996). Ordinal models simultaneously provide a structure for all $J – 1$ cumulative logits.

One type of cumulative logit model is the proportional odds model. In this model, it is assumed that the log cumulative odds are proportional to the distance between the explanatory variable values and that the influence of the explanatory variables is independent of the cutpoint for the cumulative logit (Stokes, Davis, & Koch, 2000).

If the proportional odds assumption is violated in the data, the use of a proportional odds model can lead to invalid results (Bender & Grouven, 1998). In such a case, other strategies such as separate binary logistic regression or the partial proportional odds model can be used. The separate binary regression model approach consists of dichotomizing the ordinal response variable by means of several cutoff points and using separate binary logistic regression modes for each dichotomized response. The partial proportional odds model is an ordinal model that constrains some predictors to have common parameters and leaves other predictors free to have separate parameters. According to Bender and Grouven (1998), the partial proportional odds model is equivalent to separate binary logistic regressions but represents a joint model of the response categories and contains less model parameters. Thus it is usually more efficient than separate binary logistic regressions. Until recently, no comfortable standard software was available to fit partial proportional odds models (Bender & Grouven, 1998). However, SAS PROC GENMOD using a generalized estimating equations (GEE) approach to fit a partial proportional odds model is now available.

Study Issues

Sample and Population

The current study seeks to explore the patterns of growth and stability of students' educational aspirations and how it relates to college search activities. The population to which the study results are generalized includes all the eighth graders who also participated in the first and second follow-ups of NELS:88, who took the mathematics tests, and who were high school graduates in 1992.

Weights

In order to compensate for unequal probabilities of selection and to adjust for the effects of nonresponse, appropriate weights will be used in the analysis. For this current study, the weight F2PNLWT will be used. This is the panel weight that allows the generalization of the results to the specified population.

Design Effects

Because the NELS:88 sample design involved stratification, disproportionate sampling of certain strata, and oversampling, and clustered probability sampling, the resulting statistics will be more variable than they would have been had they been obtained from data collected from a simple random sample of the same size. Some statistical packages (such as SUDAAN and STRATTAB) take account of complex sample designs. However, they do not address the needs of the statistical analysis to be used in the current study. So, a method suggested by Fan (2001) will be used to adjust the standard errors of statistics in the current study.

The effect of the cluster sampling is usually measured by the design effect, which is the ratio of the correct standard error of a statistic under the cluster sampling design to the standard error obtained from using a simple random sample while ignoring the complexities of the design. The design effect does not cause biased estimates but rather causes higher Type I error rates in inferential testing (Fan, 2001).

Due to the complexity of the analyses used in this study, it would be very difficult to analytically resolve the design effect issues. So, to take into account the design effect, the average design effect from simple analyses will be used as the correction factor for standard error in the complex analyses in this study. It has been noted that more complex estimators show somewhat smaller design effects than simple estimators (NCES, 1994; Kish and Frankel as cited in Fan, 2001) Thus, regression coefficients tend to have smaller design effects than subgroup comparisons, which in turn have smaller design effects than means. Therefore, it will be conservative to use the mean root design effects provided by the NCES (1994) in calculating approximate standard errors for complex statistics (NCES, 1994). Thus, a standard error is calculated using the formula from a simple random sample; then, this calculated standard error is multiplied by the appropriate mean root design effect.

According to NCES (1994), the mean root design effect for the standard error for the 1988-1992 student panel data was 1.858 (p. 56, Table 3.3.1-13). In the analysis for the current study, this value will be used as the correction factor for the effect of the cluster sampling.

The major effect of ignoring the cluster sampling design in statistical inferences is the inflation of Type I error. This conservative approach will ensure that this risk is avoided, and that any significant effects present are not artifacts of the nonadjustment for the sampling design.

Data Analysis Procedures

Preliminary Exploration

Initially, exploratory data analysis will be conducted to inspect the data. This will include generating frequency tables and graphs for each variable in the study. Sample means and variances will also be calculated for the continuous variables. Also, the missing data will be examined, and the characteristics of the missing and usable data will be compared in order to check for any abnormal patterns in the missing data. Imputation using hot deck methods will be done for explanatory variables with missing data. A visual analysis will be also done to examine the growth trajectories of individuals selected at random, using simple linear regression. Wave-by-wave univariate statistics on the dependent variable will also be used to check if they are normal.

Data Analysis

This study will adopt a three-phase analysis in order to address the research objectives. The first phase, corresponding to objectives (1) and (2) of the study, will involve using hierarchical linear modeling to describe and analyze the development of educational aspirations of adolescents over a four year period. The second phase, corresponding to objectives (3) and (4) will use Nagin's (1999) group-based developmental trajectory modeling to study the same development over time, and try to identify the optimal number of groups that the sample falls into. The results from phase 1 and phase 2 will then be compared, thus clarifying objective (5). The third phase, corresponding to objectives (6) and (7) will involve building an ordinal response model that will relate the number of postsecondary applications filed to average educational aspirations as well as the other factors considered in the study, and will also study the development of aspirations within three groups created on the basis of steps taken toward translating aspirations into concrete actions.

Phase 1: Hierarchical Linear Modeling

This phase of the analysis addresses research objectives (1) and (2), and aims to describe and analyze the development of educational aspirations of adolescents over a five-year period, and to explore, from an HLM perspective, demographic, socioeconomic, parental, ability, and school experience factors that may possibly impact any change in aspirations.

Toward this end, the first step will involve the fitting of a simple, linear, unconditional two-level model, that is, with no level-2 effects, and only TIME as a level-1 effect. TIME, which reflects grade level, will be coded as 0, 1, and 2, so that the intercept estimates the value of aspirations at the initial status (occasion 0), and the slope estimates the rate of change in aspirations across occasions. According to Singer (1998), this scale for TIME makes the parameters of the within-person growth model become interesting in their own right. In the notation used by Singer, this model is:

$$Y_{ij} = \pi_{0j} + \pi_{1j}(TIME)_{ij} + r_{ij}, \quad \text{where} \quad r_{ij} \sim N(0, \sigma^2)$$

and

$$\pi_{0j} = \beta_{00} + u_{0j}, \quad \text{where} \quad \begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} & \tau_{01} \\ \tau_{10} & \tau_{11} \end{pmatrix}\right]$$

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

This model will provide estimates of the mean aspirations at the eighth grade level, as well as the mean growth in aspirations. The standard deviation of the individual observations around the mean growth trajectory may also be obtained from this model.

This model has two parts: a fixed part with two fixed effects (intercept and TIME), and a random part with three random effects (intercept, TIME, and the within-person residual). There are no other level-1 covariates or any level-2 covariates. This analysis will help shed light on objective (1), namely, to describe the development of educational aspirations in adolescents over a five-year period.

Intermediate multilevel models will then be built – one containing only time-stable covariates and another with time-varying covariates alone. The final step will consider a full model which includes the time-varying covariates at level-1, as well as the person-level covariates at level-2. Time-varying covariates are other level-1 predictors, besides TIME, that explain variation in the response. In this study, mathematics achievement, mother's expectations, and parental involvement are all time-varying covariates as they vary with time across students. Thus the level-1 model of student educational aspirations at time *t* of student *i* in school *j* would be:

$$Y_{ti} = \pi_{0i} + \pi_{1i}(TIME) + \pi_{2i}(MATH) + \pi_{3i}(PARENT\ \ EXPEC) + \pi_{4i}(PARENT\ \ INV) + \pi_{5i}(SELF) + e_{ti}$$

Because these variables are intended to be covariates, they will be specified at level-2 as fixed. However, according to Raudenbush and Bryk (2002), they can also be specified as nonrandomly varying effects or even as random effects.

The level-2 covariates in this model are the other demographic, socioeconomic, and school experience factors such as gender, race, SES, held back, and early achievement. SES and early achievement will be centered around the grand mean in order to make it more interpretable (Singer, 1998). Thus, variation in the random effects, that is, the intercept and growth parameters from the level-1 model will be modeled as a function of level-2 covariates. For example, the combined model with only TIME and main effects of the level-2 covariates would be

$$Y_{ij} = \beta_{00} + \beta_{10}(TIME)_{ij} + \beta_{01}(GENDER) + \beta_{02}(RACE) + \beta_{03}(SES) + \beta_{04}(HELDBACK) + \beta_{05}(EARLYACHVT) + r_{ij}$$

The model described above helps capture the relationship between the covariates and the initial status, as well as, the covariates and growth rates. The variance estimates of the intercept and slope can be compared to the unconditional or to other nested models to see if the fitting of the covariates improved the fits. Interactions between time, mathematics achievement and various level-2 factors, as well as interactions among certain level-2 factors can be studied. Hypothesis testing of the fixed effects will be done after adjusting for design effects as explained in an earlier section. This analysis helps shed light on objective (2) of the study, namely, to explore the factors that may possibly have an impact on aspirations growth.

Phase 2: Group-Based Mixture Modeling

This phase of the analysis addresses objectives (3) and (4), and aims to describe and analyze the patterns of development of educational aspirations of adolescents over a five-year period using Nagin's (1999) multilevel group-based technique for analyzing development trajectories, and to explore, using Nagin's model, demographic, socioeconomic, parental, ability, and school experience factors that may impact patterns of growth in aspirations. The analysis will seek to identify groups following different trajectories and to study the characteristics of group members.

The theoretical details of this modeling have been described in an earlier section. As the first step, the optimal number of groups that explain the data have to be selected. For this, models which specify increasing number of groups (1, 2, 3, 4, etc.) will be specified, and the optimal model will be selected by using the Bayesian Information Criterion (BIC), as suggested by Nagin (1999), Jones, Nagin, and Roeder (2001) and Nagin and Tremblay (2001). The groups resulting from this optimal model will then be described, and the percentage of individuals falling into each group will be calculated. This analysis helps clarify objective (3), namely, to describe the patterns of development of educational aspirations of adolescents over a five-year period.

In the second step, a model that includes the time-stable covariates, namely, race, gender, and whether the student was ever held back, as well as the time-varying covariates, namely, mathematics achievement, mother's expectations and parental involvement will be built. The optimal number of groups obtained from the first step will be used in the specification of this model. The parameter estimates for the covariates, standard errors, and tests for hypothesis that the parameter equals zero, as well as the p-values for the tests will be obtained. The tests of hypothesis will be interpreted after adjusting for the design effects as discussed in an earlier section. This step will help to elucidate objective (4), namely, to explore the demographic, socioeconomic, parental, ability, and school experience factors that may impact patterns of growth in aspirations.

The software used in phase 2 of the analysis will be SAS PROC TRAJ that was developed using SAS/TOOLKIT by Jones et al. (2001). Since this procedure is relatively recent, its limitations and strengths are as yet undocumented.

The results from phase 1 and phase 2, namely, the hierarchical linear modeling and group-based mixture modeling approaches will then be compared in order to clarify objective (5). The effects of the model covariates from the HLM approach and the effects of the model covariates for each different group from the group-based approach can be compared. The strengths and limitations of the two approaches will be discussed.

Phase 3: Analysis Using Application Groups

Objective (6) of the current study is to explore the associations between demographic, socioeconomic, parental, ability, and school experience factors and the postsecondary application patterns of students using multinomial modeling. In order to do this, the data will be first partitioned into three sets: those students who have not applied to any colleges by the final term of their senior year, those students who have applied to only one college, and those who have applied to more than one college. Each of these populations will be described using frequency tables and graphs.

A multicategory logit model will be built to study the associations between the independent variables and the number of applications filed. The averages for each of aspirations, mother's expectations, parental involvement and math scores will be taken across the three time points, and these averages will be used as predictors in the model. Since the response (number of applications) is ordinal, a cumulative logit model for an ordinal response will be built using number of applications as response and gender, race, SES, early grades, ever held back, mother's expectations, parental involvement and math scores as predictors.

Objective (7) of the current study is to examine variations in growth patterns over time among those students who have taken concrete steps toward postsecondary education in their senior year, and those who have not. Hierarchical linear models as described in phase 1 will be fit separately for each group. In particular, an unconditional means model and an unconditional growth model will be built for each group and the results compared across groups. This will help elucidate the differences among high-aspiring adolescents who have and have not taken action toward achieving their dreams.

Chapter Summary

In this chapter, an overview of the data, including research design, sampling procedures, and nonresponse issues is provided. The broad theoretical framework for the study, the variables selected for analysis, as well as the data analysis that will be performed for each study objective, is presented. Also described are the details of the hierarchical linear modeling and the group-based mixture trajectory modeling approaches to longitudinal data analysis. The issues that have to be addressed when analyzing complex data sets are also presented.

CHAPTER 4

SUMMARY OF RESULTS

This chapter describes the findings from this study, and includes the following sections: (1) characteristics of the sample and descriptive statistics; (2) results from the exploratory data analysis; (3) hierarchical modeling results; (4) group-based mixture modeling estimates and results, (5) multinomial modeling estimates and results.

Characteristics of the Sample

The sample from this study was drawn from the National Educational Longitudinal Study of 1988 (NELS: 88). The sample contained students who participated in the first three waves of data, collected when students were in the eighth, tenth, and twelfth grades. Only students who participated in all three waves, who took the mathematics test administered at all these time points, and who graduated in 1992 were considered for the study. Also, Native Americans were not included in the study sample as their sample size was very small.

In the base year of NELS:88 (eighth grade), schools were the primary sampling units, and students were the secondary sampling units. This sampling resulted in the participation of 24, 599 randomly selected students from the selected schools. The sample was freshened in the tenth and twelfth grades in order to make it more representative of students at that particular grade in the year the survey was administered. A total of 16, 489 students participated in all three waves, which is about 67% of the eighth grade group.

Out of the 24,599 students in the eighth grade, 23,701 students (96.3%) took the mathematics test. The corresponding percentages in the tenth and twelfth grades were

85.4% and 67.1%, respectively. 13,859 students graduated in or before 1992 which is about 84% of the students who participated in all three waves of the study.

The sample included N = 9837 observations. Data were imputed for the independent variables (other than demographic variables) which had any missing data. The independent variable with the least missing data was eighth grade math scores, with 0.07% of the data missing, while the independent variable with the most missing data was mother's expectations in the 12^{th} grade, with 13.44% of the values missing. Appendix A gives a breakdown of the percentage of missing cases on each variable. Imputation was done using a hot deck algorithm provided by McNally (1997). The "characteristic" variables used for the hot deck imputation were gender and race. Data were not imputed for the dependent variable. Appendices B and C compare the sample characteristics and descriptive statistics for the data with and without imputation.

The main idea behind the hot deck method is to use the existent data (donor data) to provide imputed values for the records with missing values. The case most similar to the case with a missing value is identified and the most similar case's value is substituted for the missing case's value. This matching is carried out using "characteristic" variables, that is, the records match if they have the same values on these filter variables. There are no set rules to select filter variables, and this is usually driven by the researcher's understanding of the data and the size of the complete data set (McNally, 1997). This method is often used to impute values in large national data sets (McNally, 1997).

Hot deck imputation is commonly used for item non response as it has several advantages over other imputation methods such as mean imputation, ratio imputation or regression imputation. Because a hot deck approach selects imputed values at random from the donor data, it introduces variation into the analysis set consistent with the range of possible values seen in the complete data (McNally, 1997). As a result, there is less tendency towards the mean of the sample. Also, it preserves the distribution of item values so that valid estimators that depend on the entire distribution of item values can be obtained based on the imputed data set (Chen & Shao, 1999). It also allows the use of the same sample weight for all items, and the results obtained from different analyses are consistent with one another (Schoier, 1999).

The following tables summarize the characteristics of the sample based on the variables included in the study. In order to better describe the sample, SES was divided into tertiles, and early grades into quartiles as shown in Table 4.1.

Table 4.1: Sample Characteristics by Gender, Race, SES, Early Grades and Held Back.

Variable	N	Percent	Range of the Variable (Low)	Range of the Variable (High)
Gender				
Male	4837	49.17		
Female	5000	50.83		
Race				
Asian /Pacific Islander	617	6.27		
Hispanic	1003	10.2		
Black	814	8.27		
White	7403	75.26		
Ever Held Back				
No	8823	89.69		
Yes	1014	10.31		
SES Tertile				
Low	3276	33.3	-2.429	-0.217
Medium	3300	33.55	-0.216	0.498
High	3261	33.15	0.499	1.98
Early Grades Quartile				
Lowest (first)	2518	25.6	0.5	2.5
Middle Lower (second)	2422	24.62	2.6	3.0
Middle Upper (third)	2475	25.16	3.1	3.5
Upper (fourth)	2422	24.62	3.7	4.0
Total	9837	100.00		

Sample descriptive statistics for the independent variables are shown in Table 4.2. Approximate normality was tenable for these variables.

Table 4.2: Descriptive Statistics for the Sample

Variable	Mean	Standard Deviation
SES		
Low	-0.74	0.40
Medium	0.13	0.20
High	0.997	0.35
Early Grades		
Lowest	2.17	0.40
Middle Lower	2.9	0.10
Middle Upper	3.40	0.10
Upper	3.92	0.10
Mother's Expectations		
Eighth	5.01	0.96
Tenth	4.88	0.96
Twelfth	5.03	1.06
Parental Involvement		
Eighth	2.45	0.47
Tenth	2.08	0.49
Twelfth	1.99	0.52
Math Scores		
Eighth	53.35	10.16
Tenth	53.21	9.58
Twelfth	52.99	9.55

In Table 4.2, SES is a composite variable with values ranging from -3.243 to 2.753. Early grades is a measure of self-reported grades over four subject areas when the students were in the eighth grade, and ranges from 0.5 to 4.0. Mother's expectations is a variable ranging from 1 (less than high school) to 6 (higher school after college), parental involvement is a composite variable ranging from 1 to 3 formed as an average of scores on three items (1) student discusses programs at school with parents, (2) student discusses activities with parents, (3) student discusses things studied in class with parents, while math scores is the standardized score on a math test administered at each of the grades in the study.

Table 4.3 gives the descriptive statistics for the dependent variable, educational aspirations, at each grade level.

Table 4.3: Educational Aspirations for the Sample at Each Grade Level.

Grade	Mean	Std Deviation	Minimum	Maximum
Eighth	4.83	1.12	1 (Less than High School)	6 (Graduate Degree)
Tenth	4.82	1.16	1 (Less than High School)	6 (Graduate Degree)
Twelfth	4.93	1.12	1 (Less than High School)	6 (Graduate Degree)

These results show that overall student aspirations seem to be somewhat steady from the eighth grade to the tenth, but increase from the tenth grade to the twelfth.

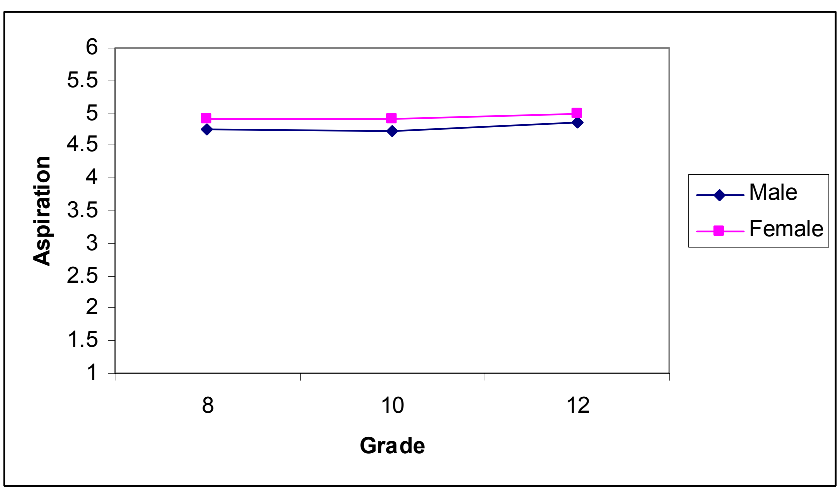


Figure 4.1: Aspiration Mean Plots by Gender

Figure 4.1 shows the mean curves of educational aspirations by time for males and females. It can be seen that females had higher aspirations than males at all time points.

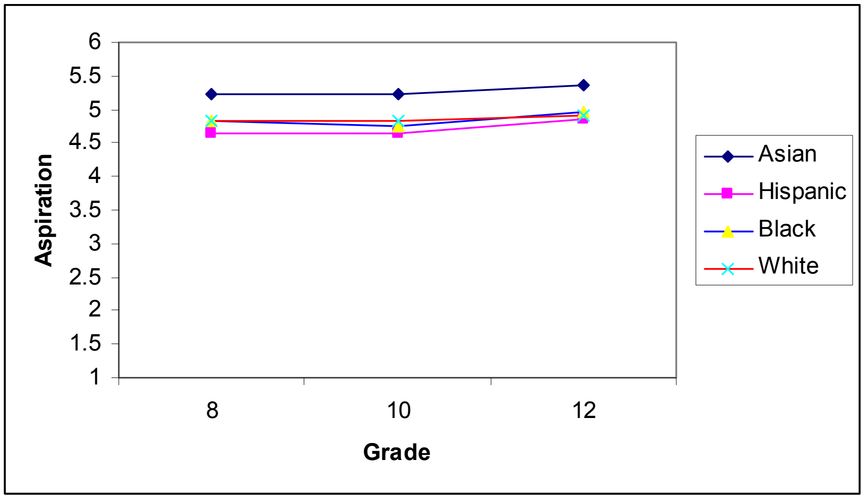


Figure 4.2: Aspiration Mean Plots by Race

Figure 4.2 depicts the means of educational aspirations by ethnicity group. Asians had overall high aspirations at all time points, while Hispanics had the lowest among the four groups at all times. The curves for Blacks and Whites fell in between the others.

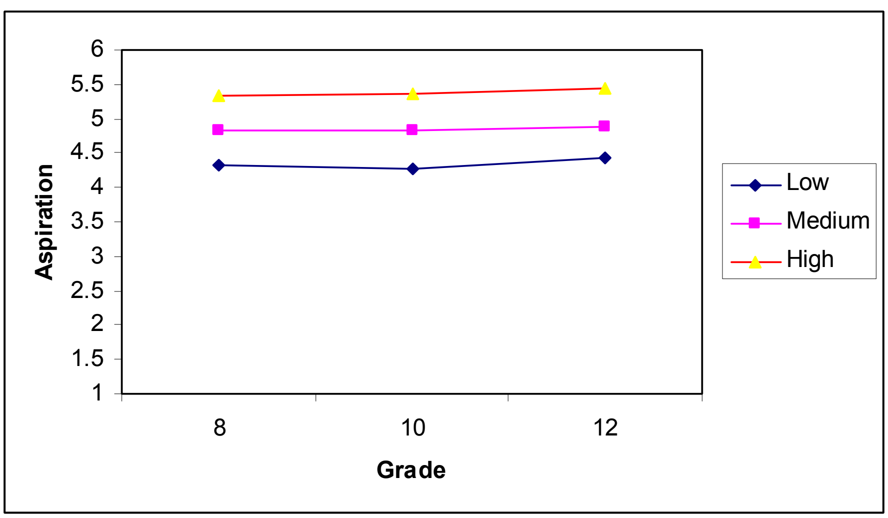


Figure 4.3: Aspiration Mean Plots by SES

Figure 4.3 shows the aspiration mean plots by the three tertiles of socioeconomic status. As can be seen, the low SES group had the lowest aspirations at all time points, while the high SES group had the highest aspirations at all time points.

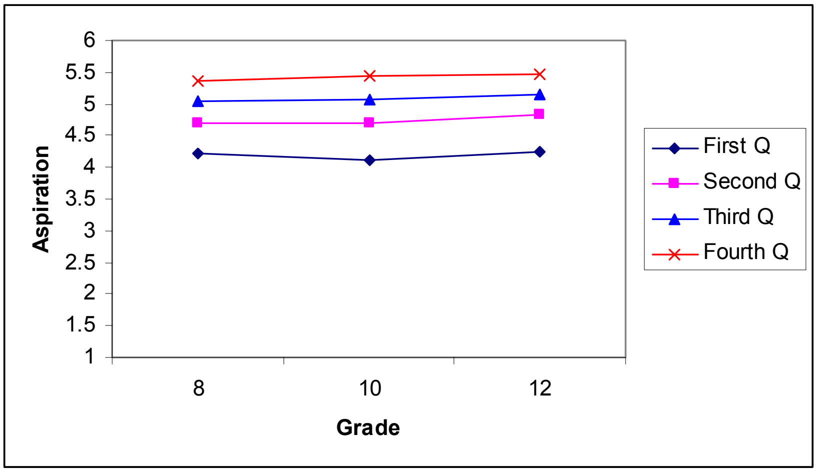


Figure 4.4: Aspiration Mean Plots by Early Grades

Figure 4.4 depicts the aspiration mean plots by self-reported grades in the eighth grade. The aspiration means fall according to quartile at all time points, with the students in the lowest grade quartile having the least aspirations, while the students in the highest quartile had the highest aspirations.

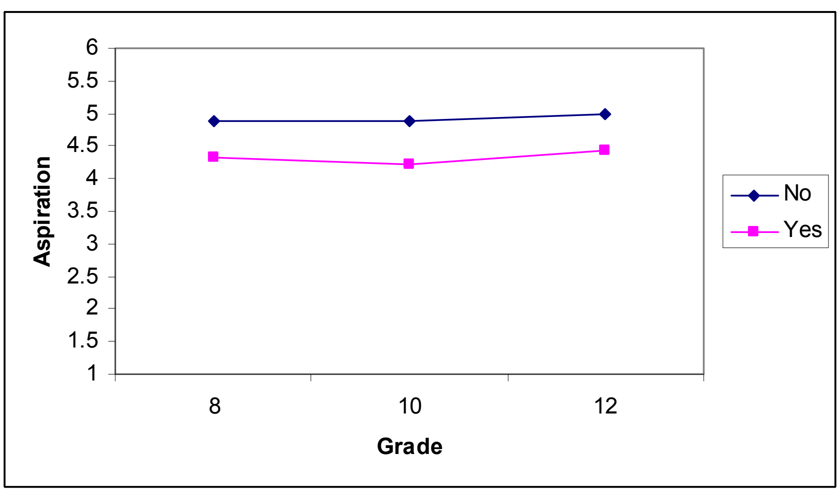


Figure 4.5: Aspiration Mean Plots by Held Back

From Figure 4.5, it can be seen that students who had been held back early in their school careers had lower educational aspirations at all time points when compared to students who had never been held back.

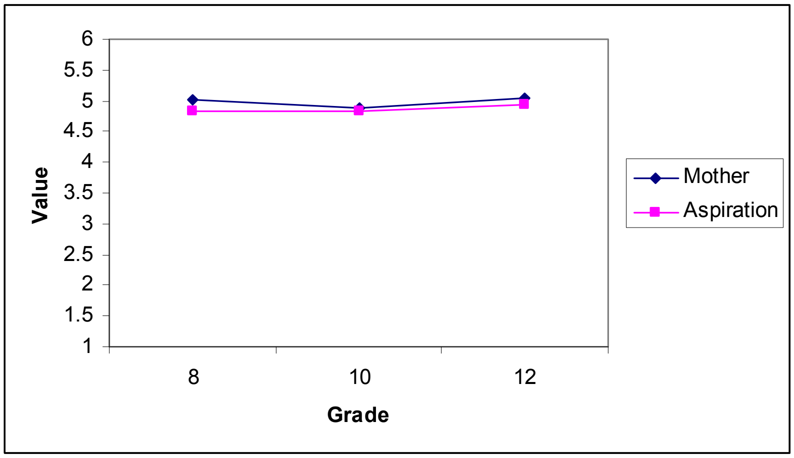


Figure 4.6: Mean Plots of Educational Aspirations and Mother's Expectations

Figure 4.6 shows the mean plots of aspirations and mother's expectations over time. Aspirations remained fairly stable from the eighth grade through the tenth and increased slightly from the tenth grade through the twelfth. Mother's expectations on the other hand, were lower in the tenth grade than in the eighth or the twelfth.

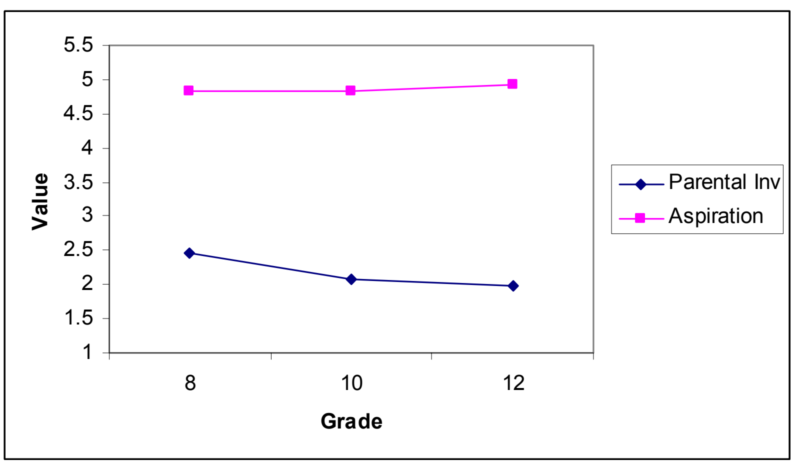


Figure 4.7: Mean Plots of Educational Aspirations and Parental Involvement

From Figure 4.7, it can be seen that whereas aspirations remained fairly stable over time, parental involvement showed a steady decline from the eighth grade through the twelfth.

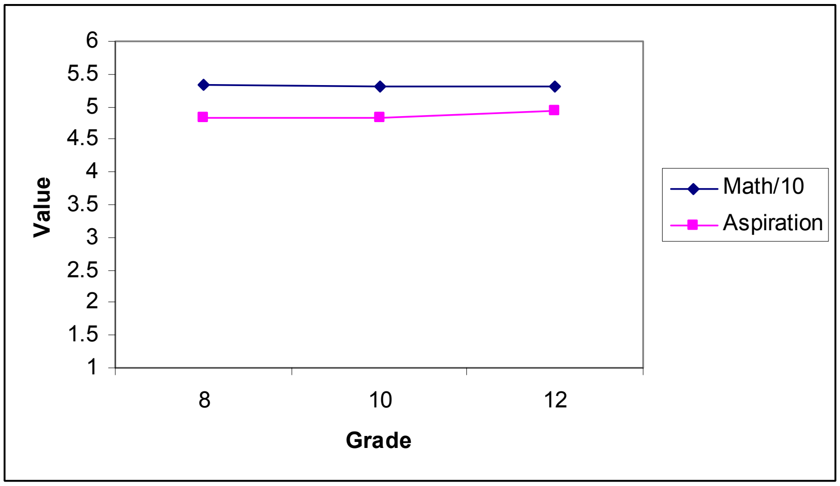


Figure 4.8: Mean Plots of Educational Aspirations and Math Scores/10

Figure 4.8 depicts the mean plots for aspirations and math scores over time. Math scores were divided by 10 for scaling convenience. Both math scores and aspirations remained fairly stable from the eighth grade to the tenth. Aspirations showed a slight increase from the tenth grade to the twelfth, while math scores showed a slight decrease from the tenth grade to the twelfth.

Results from the descriptive analyses suggest that while overall aspirations remained fairly stable across time, there maybe differences in aspirations among certain sub-populations (based on gender, race, SES etc.).

Exploratory Data Analysis

A series of exploratory analyses was conducted in order to better understand the patterns of changes in aspirations over time. The normality assumptions for the dependent variable were also checked by examining univariate statistics by wave.

Due to the large size of the data set, a stratified random sample of 24 individuals were selected (stratified based on Gender, Race, and SES) for in-depth exploratory analyses as suggested by Singer and Willett (2003). These individuals' growth record was then summarized by fitting a separate model to each person's data using ordinary least squares regression (OLS) methods. Fitting OLS models is "intuitive, easy to implement and are very useful for exploratory purposes" (Singer & Willett, 2003). Figure 4.9 presents the growth plots for the 24 adolescents chosen.

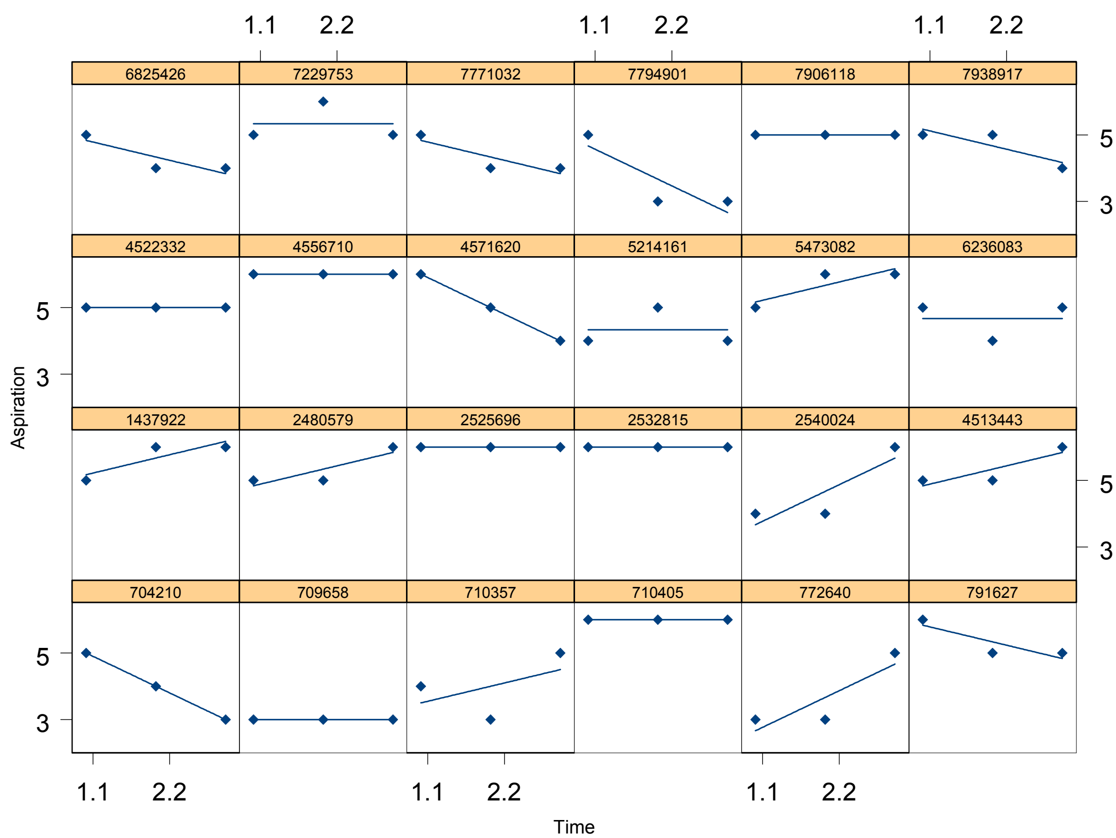


Figure 4.9: OLS summaries of change over time

It can be seen from Figure 4.9 that there is evidence of heterogeneity in observed change across individuals, with some showing increasing aspirations and others displaying fairly stable or decreasing aspirations. In order to better summarize change, summary statistics from all the within-person regression models were collected and examined. These included each individual model's intercept, slope, R-square value, and residual variance statistics, and are given in Figure 4.10.

Obs	ID	Initial Status	Initial StatusSE	Rate Of Change	RateOf ChangeSE	Residual Variance	Rsquared
1	704210	5.00000	0.00000	-1.0	0.00000	0.00000	1.00
2	709658	3.00000	0.00000	0.0	0.00000	0.00000	.
3	710357	3.50000	1.11803	0.5	0.86603	1.50000	0.25
4	710405	6.00000	0.00000	0.0	0.00000	0.00000	.
5	772640	2.66667	0.74536	1.0	0.57735	0.66667	0.75
6	791627	5.83333	0.37268	-0.5	0.28868	0.16667	0.75
7	1437922	5.16667	0.37268	0.5	0.28868	0.16667	0.75
8	2480579	4.83333	0.37268	0.5	0.28868	0.16667	0.75
9	2525696	6.00000	0.00000	0.0	0.00000	0.00000	.
10	2532815	6.00000	0.00000	0.0	0.00000	0.00000	.
11	2540024	3.66667	0.74536	1.0	0.57735	0.66667	0.75
12	4513443	4.83333	0.37268	0.5	0.28868	0.16667	0.75
13	4522332	5.00000	0.00000	0.0	0.00000	0.00000	.
14	4556710	6.00000	0.00000	0.0	0.00000	0.00000	.
15	4571620	6.00000	0.00000	-1.0	0.00000	0.00000	1.00
16	5214161	4.33333	0.74536	0.0	0.57735	0.66667	0.00
17	5473082	5.16667	0.37268	0.5	0.28868	0.16667	0.75
18	6236083	4.66667	0.74536	-0.0	0.57735	0.66667	0.00
19	6825426	4.83333	0.37268	-0.5	0.28868	0.16667	0.75
20	7229753	5.33333	0.74536	0.0	0.57735	0.66667	0.00
21	7771032	4.83333	0.37268	-0.5	0.28868	0.16667	0.75
22	7794901	4.66667	0.74536	-1.0	0.57735	0.66667	0.75
23	7906118	5.00000	0.00000	0.0	0.00000	0.00000	.
24	7938917	5.16667	0.37268	-0.5	0.28868	0.16667	0.75

Figure 4.10: Summary Statistics from Separate OLS Regression Models

Figure 4.11 presents a stem-and-leaf display for the intercepts from the OLS models. It can be seen that the majority of the individuals in this sample display high initial aspirations, while a few have low initial aspirations.

```
                     Variable:  InitialStatus

         Stem Leaf                  #             Boxplot
            6 0000                  4                |
            5 778                   3             +-----+
            5 002222                6             *-----*
            4 777                   3             |  +  |
            4 3                     1             |     |
            3 78                    2             +-----+
            3 22                    2                |
            2 58                    2                |
            2                                        |
            1 5                     1                |
              ----+----+----+----+
```

Figure 4.11: Stem-and-Leaf plot for OLS intercepts

Figure 4.12 presents a stem-and-leaf display for the slopes from the OLS models. It can be seen that most individuals are clustered around the middle and register little change over time.

```
                     Variable:  RateOfChange

Stem Leaf                    #             Boxplot
   1 555                     3                0
   1 00                      2                |
   0 5555555                 7             +-----+
   0 00000000                8             *--+--*
  -0                                          |
  -0 5                       1                |
  -1 000                     3                0
     ----+----+----+----+
```

Figure 4.12: Stem-and-Leaf plot for OLS slopes

Both Figures 4.11 and 4.12 further illustrate the heterogeneity that was seen in the OLS plots. However, the general trend seems to be that students start out with high initial aspirations that remain fairly stable across time.

Next, the OLS plots were examined by the stratification variables used, namely, Gender, Race, and SES in order to better uncover any systematic patterns in the individual change trajectories corresponding to interindividual variation in personal characteristics. Asking whether the observed trajectories differ by gender allows an exploration into whether boys (or girls) have initial higher aspirations and whether they tend to have different rates of change.

Figure 4.13 presents the OLS trajectories separately by gender. The bold lines represent the average trajectories of the groups. It can be seen that females showed higher initial aspirations than did males, and also showed lower growth rates. For males, the average trajectory is given by 4.431 + 0.375 * time while for females it is 4.81 + 0.17* time.

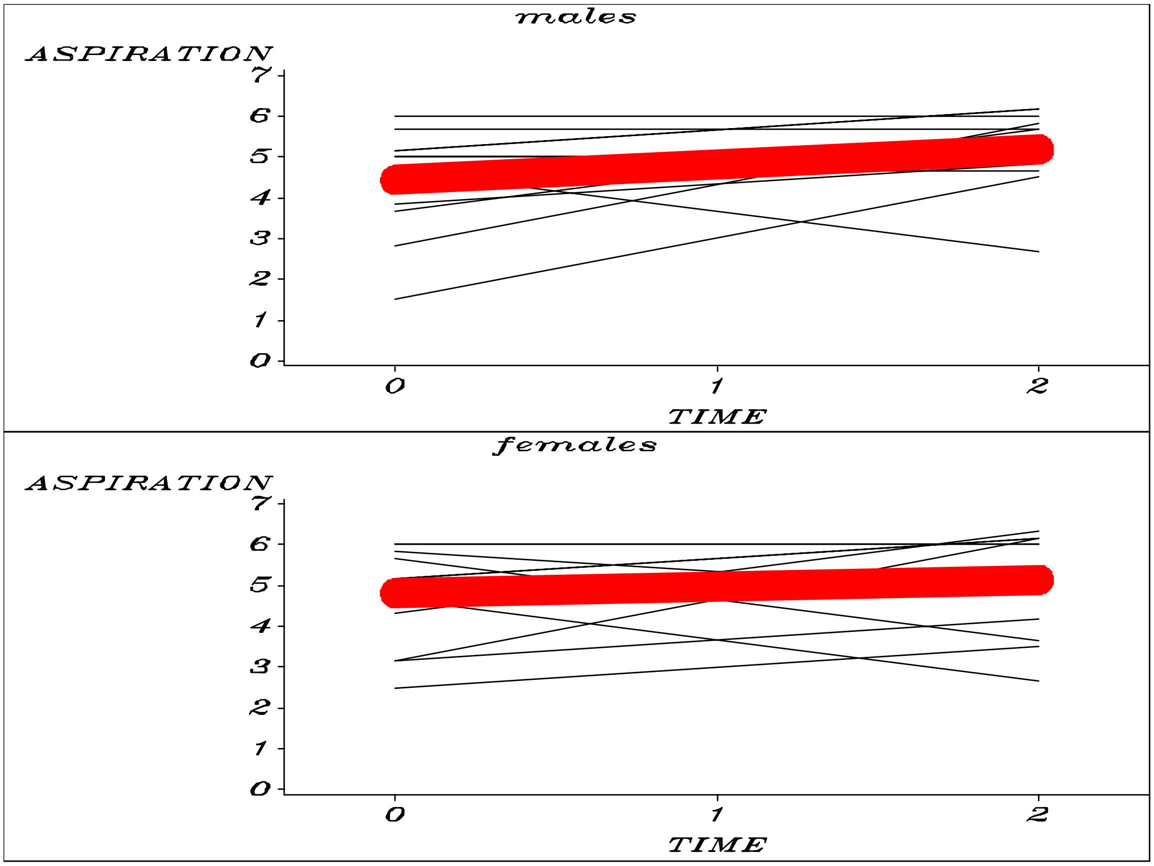


Figure 4.13: OLS Trajectories Summarizing Linear Growth in Aspirations over Time by Gender.

Figure 4.14 presents the OLS trajectories separately by race. The plots show some variation in aspiration trajectories for the different ethnic groups. Based on the average trajectory, Asians exhibited high initial aspirations that were stable across time, while whites had the lowest initial aspirations but the highest growth rates among the four groups. The average trajectories for the four groups are as follows:

Asian: 5.67 + 0 * time

Hispanic: 4.14 + 0.42 * time

Black: 4.97 - 0.08 * time

White: 3.69 + 0.75 * time

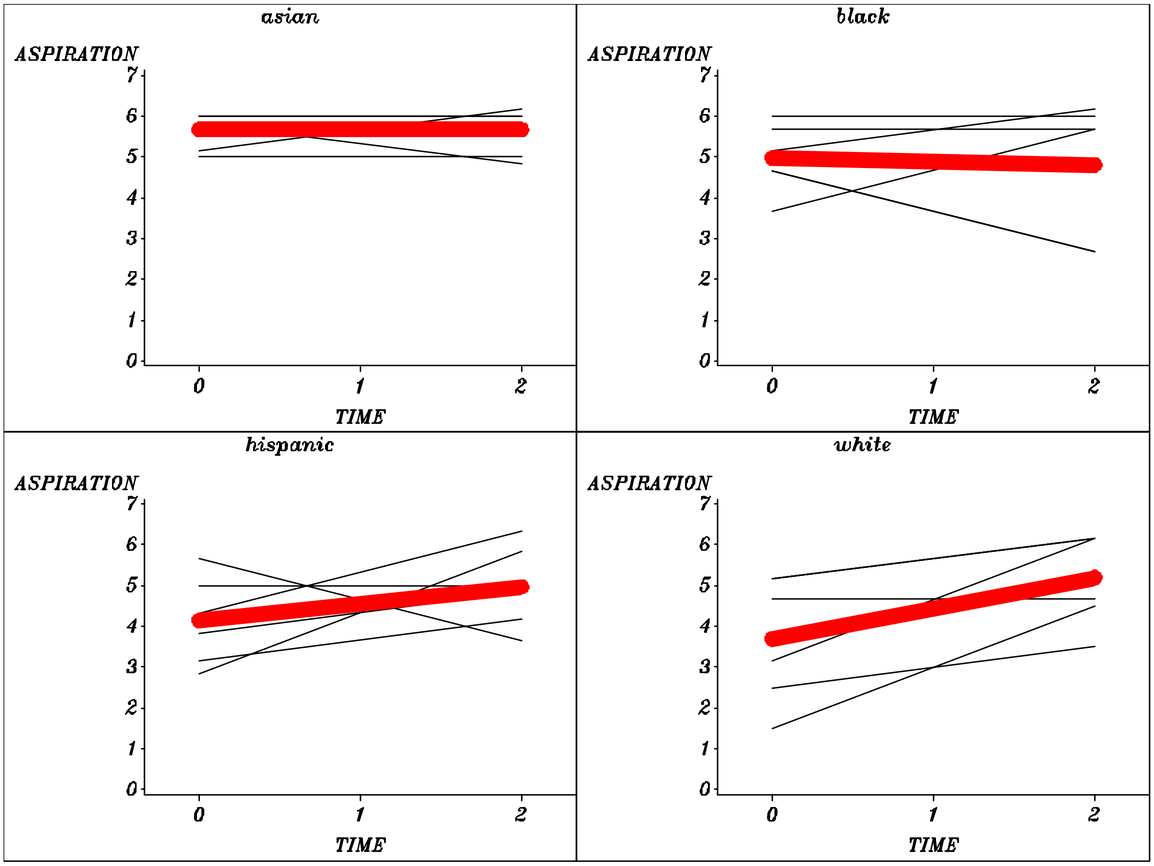


Figure 4.14: OLS Trajectories Summarizing Linear Growth in Aspirations over Time by Race.

Figure 4.15 presents the OLS trajectories separately by SES. Variations among the OLS lines showed variation based on socioeconomic status. Individuals from a high SES background had the highest average initial status but close to zero growth. Subjects from the lowest SES tertile had higher initial status values than those from the middle tertile, but their growth rate was lower than those with medium SES background. The average trajectories for the three groups were:

Low SES: 4.4 + 0.06 * time

Medium SES: 4.21 + 0.75 * time

High SES: 5.25 + 0*time

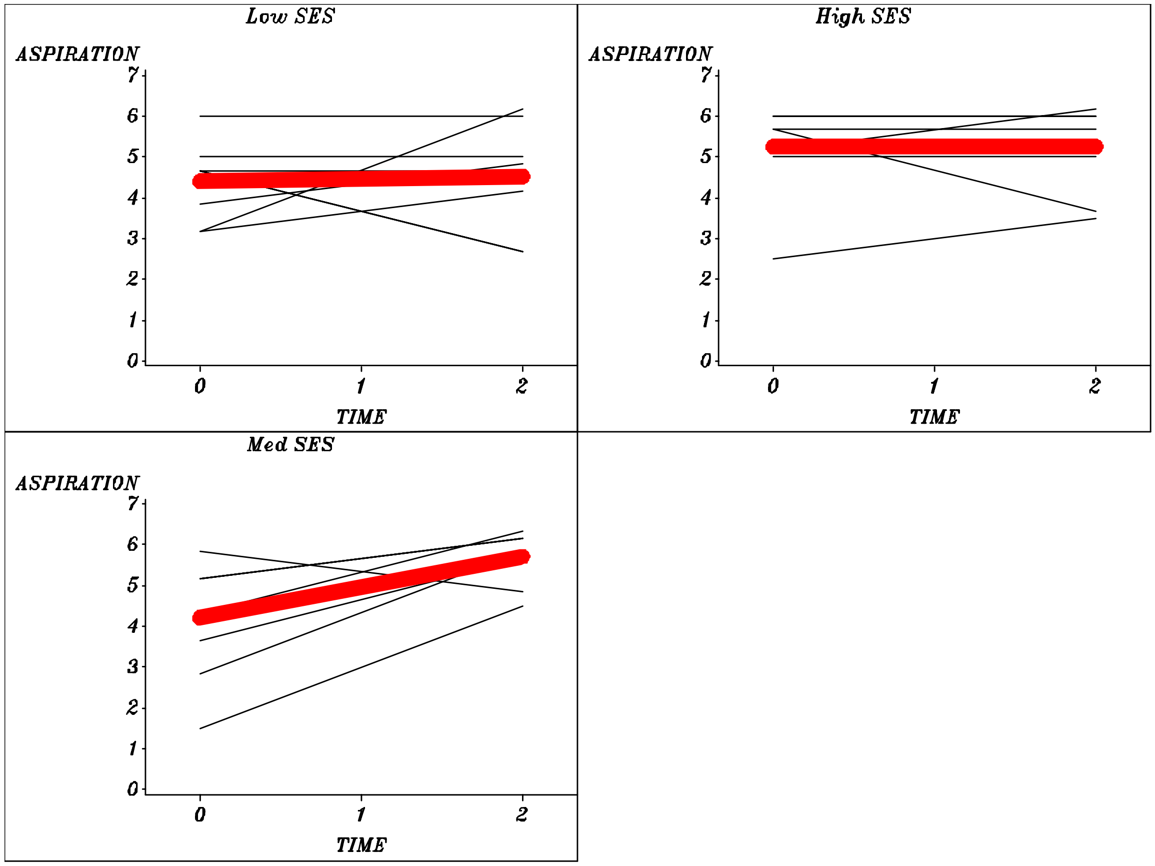


Figure 4.15: OLS Trajectories Summarizing Linear Growth in Aspirations over Time by Socioeconomic Status.

Next, univariate statistics of the distributions of the dependent variable were examined by wave. Table 4.4 gives the means, standard deviations, skewness and kurtosis values of these variables. Skewness is a measure of symmetry about the mean, while kurtosis is a measure of peakedness of the distribution. It can be seen that while the kurtosis values were minimal (with reference to zero), the distributions were negatively skewed, implying that there were many cases which fell above the mean value. This was true especially for the eighth grade aspirations. However, the assumptions of approximate normality can still be made as the values are not sufficiently high compared to zero.

Table 4.4: Univariate Statistics for Aspirations by Grade

Wave	Mean	Standard Dev.	Skewness	Kurtosis
Eighth	4.83	1.12	-1.18	0.93
Tenth	4.82	1.16	-0.91	0.05
Twelfth	4.93	1.12	-0.99	0.19

Weights and Design Effect Corrections

In order to compensate for unequal probabilities of selection and to adjust for the effects of nonresponse and oversampling, appropriate weights were used in all analyses in the current study based on the NELS:88 user guidelines. More specifically, because only sample members with data in all three waves were usable for this study, the panel weight variable for the longitudinal panel of 1988 to 1992, F2PNLWT, is the appropriate weight to be used. This weight was normed by dividing it by the sample mean to both adjust the data for nonresponse bias and to redistribute the sample so that it corrects for exaggerated sample sizes that would affect significance tests due to weighting of the data.

A more difficult issue in using NELS:88 data is related to cluster sampling. Since schools formed the sample clusters, and students were sampled within schools in the NELS:88 data collection, standardized statistical procedures which ignore this clustering and assume simple random sampling create problems for data analyses by underestimating standard errors. The effect of the cluster sampling design is usually measured by the quantity known as the design effect and it is the ratio of the correct standard error of a statistic under the cluster sampling design to the standard error under the assumption of simple random sampling. If the design effect is ignored, inflated Type I error would result, invalidating any significance test results.

Since it was difficult or even impossible to analytically resolve the design effect issues in this study, the average design effect from simple analyses was used as the correction factor for standard errors in the complex analyses in this study as suggested by Fan (2001). According to NCES (1994), the average design effect for the standard error for the 1992 panel data was estimated to be 1.86 (p. 56, Table 3.3.1-13). In the following analyses, this value was used to correct the standard errors. The research literature supports the validity of this approach (Kish & Frankel, 1974; NCES, 1994; Fan, 2001) as complex estimators show smaller design effects than do simple estimators. This is thus a conservative approach that avoids the risk of inflated Type I errors in the analyses.

Results from the Hierarchical Linear Modeling Analyses

Two objectives of this study were to describe and analyze the development of educational aspirations of adolescents over a five-year period using individual growth modeling from a hierarchical linear modeling perspective, and to explore from an HLM perspective, demographic, socioeconomic, parental, ability, and school experience factors that may possibly impact growth in aspirations.

To meet these objectives, a series of hierarchical linear models were built using the SAS PROC MIXED routine. The estimation method used for all the models was Full Maximum Likelihood (FML). This was done because: (1) the sample size was relatively large and thus biased estimates were less of a problem , (2) goodness-of fit statistics are easier to interpret and they can be used to test hypotheses about any effect, either fixed or random, whereas fit statistics from Restricted Maximum Likelihood Estimation (RML) can be used to test only hypotheses about variance components, and not fixed effects, and

(3) literature that compares these two methods has shown that there is no clear winner (Kreft & de Leeuw, 1998; Singer & Willett, 2003).

As mentioned earlier, missing values on any covariates were imputed using hot deck methods. The missing values of the dependent variable aspiration were not deleted or imputed. This is because multilevel modeling does make use of any values that it can to estimate parameters. Observations with aspiration level at two time points may still provide information in building models.

The sequence of models included two unconditional models: the unconditional means model and the unconditional growth model. Then, models with demographic predictors, all time-invariant predictors, time-varying covariates, and all possible predictors were built. At each stage, parameter estimates for fixed effects and variance components and their associated tests were examined. Tables 4.5 and 4.6 summarize intermediate models that served as important building blocks.

<u>The Unconditional Means Model</u>

As a first step, an unconditional means model (model A) was fit. This model does not describe change in the outcome over time, it simply describes and partitions the outcome variation. There are no predictors at any level in this model.

This model stipulates that at level-1, the true individual trajectory for any subject is perfectly flat, sitting at elevation π_{0i}. The primary reason for fitting this model is to estimate two variance components - σ^2_ε, the within-person variance, that is the pooled scatter of each person's data around his or her own mean, and σ^2_0, the between-person variance, the pooled scatter of the person-specific means around the grand mean. These variance components assess the amount of variation that exists at each level. Associated hypothesis tests for these help determine whether there is sufficient variation at that level to conduct further analysis.

Table 4.5: Summary of Results from Hierarchical Linear Modeling with Corrections for Design Effects: Models A, B, and C

		Parameter	**Model A**	**Model B**	**Model C**
Fixed Effects					
Initial Status	Intercept	γ_{00}	4.8126*** (0.0184)	4.7810*** (0.0214)	4.6323*** (0.0644)
	Gender	γ_{01}			-0.1235*** (0.0374)
	Race (A-W)	γ_{02}			0.2092* (0.0869)
	Race (H-W)	γ_{03}			0.2257*** (0.0662)
	Race (B-W)	γ_{04}			0.3359*** (0.0670)
	SES	γ_{05}			0.4705*** (0.0268)
	Early Grades	γ_{06}			0.5363*** (0.0286)
	Held Back	γ_{07}			0.1850** (0.0625)
Rate of Change	Intercept	γ_{10}		0.0370*** (0.0119)	0.0142 (0.0413)
	Gender	γ_{11}			0.0084 (0.0240)
	Race (A-W)	γ_{12}			0.0481 (0.0582)
	Race (H-W)	γ_{13}			0.0434 (0.0435)
	Race (B-W)	γ_{14}			0.0315 (0.0426)
	SES	γ_{15}			0.0068 (0.0173)
	Early Grades	γ_{16}			0.0107 (0.0184)
	Held Back	γ_{17}			0.0091 (0.0402)
Variance Components					
Level 1	Within-Person	σ^2_ε	0.5772*** (0.0108)	0.4402*** (0.0102)	0.4314*** (0.0099)
Level 2	In Initial Status	σ^2_0	0.7059*** (0.0253)	0.8395*** (0.0335)	0.5207*** (0.0242)
	In Rate of Change			0.1281*** (0.0095)	0.1309*** (0.0095)
	Covariance			-0.1080*** (0.0140)	-0.1172*** (0.0123)
Fit					
R-sq y,y				0.0012	
R-sq ε				0.2374	0.02
R-sq 0					0.3797
R-sq 1					-0.0219
Deviance			86557.2	85212.4	80711
AIC			86563.2	85224.4	80751
BIC			86584.8	85267.6	80894.9

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Model A of Table 4.5 shows the results of fitting this model. The one fixed effect γ_{00} estimates the outcome's grand mean across all individuals and occasions. The null hypothesis associated with this parameter is rejected ($p < 0.001$). This indicates that the average outcome of the average subject is non-zero.

The estimated within-person variance in this model is 0.5772, and the estimated between-person variance is 0.7059. The null hypotheses associated with both are rejected at the 0.001 level using Z-scores. This model also allows us to evaluate the relative magnitude of the within and between person variance components through the intraclass correlation coefficient ρ. This describes the proportion of variation that lies between people. Here

$$\rho\text{-hat} = 0.7059 / (0.7059 + 0.5772) = 0.55$$

This indicates that about 55% of the total variation in aspiration is attributable to differences among the subjects.

<u>The Unconditional Growth Model</u>

Next, the unconditional growth model (model B) was fit. This model included time as a predictor. This model, instead of postulating that an individual *i*'s score on occasion *j*, Y_{ij}, deviates from his person-specific mean, states that it deviates from his true change trajectory. By altering the level-1 specification, the meaning of the variance components is also altered. The residual variance σ^2_ε now summarizes the scatter of each person's data around his or her own linear change trajectory. The level-2 residual variances σ^2_0 and σ^2_1 now summarize between-person variability in initial status and rates of change.

The fixed effects for intercept and rate of change estimate the starting point and slope of the population average change trajectory. The null hypothesis is rejected for both ($p < 0.001$) implying that the average true change trajectory for aspiration has a non-zero intercept of 4.781 and a non-zero slope of 0.0370. This implies that aspirations rise steadily between grades 8 and 12, from 4.781 to 4.855.

To determine if there is statistically significant variation in individual initial status or rate of change that level-2 predictors can explain, the variance components are examined. If the true change trajectory is linear with time, the unconditional growth model will do a better job of predicting he observed outcome data than Model A, resulting in smaller level-1 residuals and a smaller level-1 residual variance. Comparing σ^2_ε between the two models, there is a decline of 0.137 (0.5772 to 0.4402). This means that about 13.7 percent of within-person variation in aspiration is systematically associated with linear time.

The level-2 variance components quantify the amount of unpredicted variation in the individual growth parameters. σ^2_0 assesses the unpredicted variability in true initial status, and σ^2_1 the unpredicted variability in true rates of change. Both associated null hypotheses are rejected. These two parameters cannot be compared with those from Model A as their meanings have changed with the introduction of time as a factor in the analyses.

SAS PROC MIXED uses Z-scores and corresponding *p*-values to test hypotheses related to random effects. This is a single parameter test and the Z-score is assumed to be approximately normally distributed under the large-sample theory of maximum likelihood estimates. However, according to Raudenbush and Bryk (2002), in many cases, this normality approximation will be extremely poor, especially when the parameter estimate itself is near zero. Singer and Willett (2003) suggest that they be used only with extreme caution as they may lead to imprecise assessment. Longford (1999) describes their sensitivity to sample size and imbalance and argues that they are extremely misleading and should not be used at all. Littell et al. (1996) also state that these tests are unreliable in small samples.

The covariance between these two level-2 residuals is -0.1080, and is statistically significant. If this is expressed as a correlation coefficient it becomes

$$-0.1080 / (\sqrt{(0.8395)(0.1281)} = -0.3293$$

This implies that the relationship between the true initial status and the true rate of change is negative and strong. That is, subjects who have higher aspiration in the eighth grade show a slower growth in aspirations over time.

Two pseudo R-square statistics are computed for this model in order to summarize how the model helps to explain variability in the outcome. The first pseudo R-square statistic is constructed by first computing a predicted outcome value for each person on each occasion of measurement and then squaring the sample correlation between the observed and predicted values. This statistic for this model has a value of 0.0012. This means that 0.12% of the total variability in aspiration is associated with linear time. When more substantive predictors are added, this statistic may increase.

The second pseudo R-square statistic is computed from the variance components. This examines the proportional reduction in residual variance. This is computed as

$$\text{Pseudo R-square } \varepsilon = [\sigma^2_\varepsilon \text{ (Model A)} - \sigma^2_\varepsilon \text{ (Model B)}] / \sigma^2_\varepsilon \text{ (Model A)}$$

This reduces to [0.5772 – 0.4402] / 0.5772 = 0.2374. This implies that about 23.74% of the within-person variation in aspiration is explained by linear time. The only way to reduce this variance component is by adding time-varying predictors at level-1.

Model with All Time-Invariant Predictors

One intermediate model which is an important building block in the taxonomy is the model that includes all time-invariant predictors (gender, race, SES, early grades, and ever held back) as predictors of both initial status and rate of change. This is labeled as model C and the estimates for this model are given in Table 4.5. SES was centered around its mean in order to facilitate interpretation of the intercept.

An examination of the fixed effects of this model shows that while gender, race, SES, early grades, and being held back all have a significant impact on initial aspiration, none of these factors are significant predictors of the rate of change in aspiration.

Males exhibited lower initial aspirations than females. Black, Asian, and Hispanic students all had higher initial aspirations than did White students. As SES increased, so did initial aspirations. This was true of early grades too. Also, students who had never been held back had higher initial aspirations than students who had been held back early in their school careers.

An examination of the variance components shows that these predictors accounted for a 37.97% reduction in level-2 variation for initial status in this model when compared to the unconditional growth model. All the level-1 and level-2 variance components are still highly statistically significant ($p < 0.001$).

The fit statistics, namely, the deviance, AIC and BIC are all lower for this model when compared to model B, implying that this model is a better overall fit to the data.

Table 4.6: Summary of Results from Hierarchical Linear Modeling with Corrections for Design Effects: Models D and E

		Parameter	Model D	Model E
Fixed Effects				
Initial Status	Intercept	γ_{00}	-1.1415***(0.1096)	0.0203 (0.1419)
	Gender	γ_{01}		-0.0867* (0.0348)
	Race (A-W)	γ_{02}		0.0396 (0.0791)
	Race (H-W)	γ_{03}		0.1326* (0.0606)
	Race (B-W)	γ_{04}		0.2799*** (0.0627)
	SES	γ_{05}		0.1894*** (0.0259)
	Early Grades	γ_{06}		0.2167*** (0.0288)
	Held Back	γ_{07}		0.0541 (0.0580)
	Avg MExpec	γ_{08}	0.7261*** (0.0179)	0.6356*** (0.0182)
	Avg ParInv	γ_{09}	0.3949*** (0.0335)	0.2788*** (0.0339)
	Avg Math	γ_{10}		0.0182*** (0.0017)
Rate of Change	Intercept	γ_{10}	0.0531*** (0.0121)	0.0581 (0.0422)
	Gender	γ_{11}		0.0108 (0.0246)
	Race (A-W)	γ_{12}		0.0579 (0.0578)
	Race (H-W)	γ_{13}		0.0136 (0.0435)
	Race (B-W)	γ_{14}		-0.0268 (0.0437)
	SES	γ_{15}		-0.0118 (0.0175)
	Early Grades	γ_{16}		-0.0034 (0.0192)
	Held Back	γ_{17}		-0.0147 (0.0411)
M. Expectation	Intercept	γ_{20}	0.3070*** (0.0166)	0.3286*** (0.0526)
	Gender	γ_{21}		-0.0339 (0.0335)
	Race (A-W)	γ_{22}		-0.1676* (0.0809)
	Race (H-W)	γ_{23}		-0.0376 (0.0551)
	Race (B-W)	γ_{24}		-0.1027~ (0.0547)
	SES	γ_{25}		-0.0018 (0.0244)
	Early Grades	γ_{26}		0.0232 (0.0246)
	Held Back	γ_{27}		0.0243 (0.0495)
Parent Involvmt	Intercept	γ_{30}	0.0903*** (0.0272)	0.1004 (0.0926)
	Gender	γ_{31}		0.0309 (0.0551)
	Race (A-W)	γ_{32}		0.11 (0.1263)
	Race (H-W)	γ_{33}		-0.0577 (0.0952)
	Race (B-W	γ_{34}		-0.0435 (0.0967)
	SES	γ_{35}		-0.0621 (0.0392)
	Early Grades	γ_{36}		-0.0191 (0.0422)
	Held Back	γ_{37}		-0.0283 (0.0897)
Math Scores	Intercept	γ_{40}	0.0054 ~(0.0032)	0.0154 (0.0115)
	Gender	γ_{41}		0.0022 (0.0063)
	Race (A-W)	γ_{42}		-0.0003 (0.0141)
	Race (H-W)	γ_{43}		-0.0002 (0.0113)
	Race (B-W	γ_{44}		-0.002 (0.0121)
	SES	γ_{45}		0.0002 (0.0045)
	Early Grades	γ_{46}		-0.0036 (0.0048)
	Held Back	γ_{47}		-0.0122* (0.0112)
Variance Comp				
Level 1	Within-Person	σ^2_ε	0.2181*** (0.0087)	0.2166*** (0.0086)
Level 2	In Initial Status	σ^2_0	0.4439*** (0.0223)	0.4110*** (0.0214)
	In Rate of Change	σ^2_1	0.1008*** (0.0102)	0.1001*** (0.0100)
	Mexpec	σ^2_2	0.1985*** (0.0158)	0.1958*** (0.0158)
	ParInv	σ^2_3	0.4317*** (0.0469)	0.4307*** (0.0467)
	Math Scores	σ^2_4	0.0034*** (0.0006)	0.0034*** (0.0006)
Fit				
R-sq ε			0.5045	0.508
Deviance			72622.6	71786.7
AIC			72670.6	71904.7
BIC			72843.3	72329.1

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Model with All Time-Varying Covariates

The variables for this study included 3 time-varying covariates (TVCs) – mother's expectations, parental involvement, and standardized math scores. First, these time-varying covariates were centered within-person, that is, a person's mean on each time-varying covariate was computed, and the deviance of each score on the variable from this mean was calculated. Also, the mean of the time-varying covariates (within-person) was incorporated in the level-2 model for the intercept. According to Raudenbush and Bryk (2002), this would serve to eliminate any bias in the effect of a level-1 predictor. This means that under within-person centering, two parameters are included for each TVC – a time-invariant average value, and deviations from that average. This approach also provides greater insight into the effects of the predictor. For example, math scores may actually comprise two components. Perhaps the scores in any given year is less important to aspirations than the average score or how much the scores change across the three waves of data. Shanahan, Elder, Burchinal, and Conger (1996) provide an example of how this type of analysis does provide greater insight into the data. In these models, the time-varying covariates were allowed to have both fixed and random effects.

One of the intermediate models examined in this study was one which included all the three time-varying covariates and no level-2 predictors. This was done to understand the impact time-varying covariates had as well as to examine the reduction in within-person variance when compared to the unconditional growth model.

The parameter estimates and significances for this model (Model D) are given in Table 4.6. The initial status for an average student with known values of mother's expectations, parental involvement, and math scores can be computed as -1.1415 +

0.7261 (Mothers Expectations) + 0.3949 (Parental Involvement) + 0.0276 (Math Score). Average mother's expectations (0.7261), parental involvement (0.3949), and math scores (0.0276) all show significant positive effect on aspirations, with mother's expectations having the strongest effect, followed by parental involvement and then math scores. The parameter estimates for mother's expectations and parental involvement reveal that the relative magnitude of each of them at each point in time is strongly and positively associated with student aspirations for an average student, while this effect is marginally significant for math scores.

The level-1 residual variance component was further reduced by adding the time-varying covariates to the model. The reduction in the level-1 variance component was around 50.45% when compared to the unconditional growth model. Thus, over half of the within-person variation in aspirations can be explained by the addition of the three time-varying covariates.

The addition of the time-varying covariate makes it very difficult to ascribe any meaning to the observed changes in the level-2 variance components, and it is not interesting to compare these across successive models. However, it is to be noted that these are still highly statistically significant.

The deviance, AIC, and BIC of this model were smaller than those of the unconditional growth model, thus making this model a better fit to the data.

<u>Final Model: Model with Both Time-Invariant and Time-Varying Predictors</u>

A final model (Model E) was built which included all the time-invariant predictors as well as the three time-varying covariates. As before, the time-varying covariates were within-person centered and their means were included as level-2 predictors in the model for initial status.

The parameter estimates of this model are given in Table 4.6. A comparison of the fixed effects of this model with those of model C (with all time-invariant predictors only) shows that, after controlling for the three time-varying covariates, being held back is no longer a significant predictor of initial aspirations, while the other effects are smaller in magnitude.

Females still exhibited higher initial aspirations than males, though the effect was less pronounced after the introduction of the time-varying covariates. Race continued to have an impact on initial aspirations. The only difference observed was that the difference in initial status between Asians and Whites is no longer statistically significant after the introduction of the time-varying covariates into the model. Also, the differences between Blacks and Whites and Hispanics and Whites were less pronounced. SES continued to have a strong effect on initial aspirations though this was also less pronounced. As socioeconomic status increased, so did initial aspirations. Early grades continued to impact initial aspiration status, again less strongly than in model C. As mentioned earlier, once the time-varying covariates are controlled, being held back or not does not impact initial aspirations very strongly. Mean mother's expectations, mean parental involvement and mean math scores all had positive impacts on initial aspirations, with mother's expectations having the strongest effect.

The parameter estimates relating to rate of change once again demonstrate that although there is a some growth in students' aspirations, most of the level-2 predictors included in this study do not have an impact on this growth.

An examination of the estimates relating to mother's expectations shows that for an average student, as mother's expectations increased by one unit, aspirations increased by 0.33 units at any time point. There are also interaction effects between mother's expectations and race, indicating that the effect of mother's expectations on aspirations was different for Blacks and Whites.

The parameter estimates for parental involvement and math scores reveal that the relative magnitude of each of them at each point in time is not significantly associated with student aspirations for an average student at that time point.

The level-1 variance component for this model is 0.2166. When compared to the unconditional growth model, this model explained 50.8% of the within-person variation. The addition of the time-varying covariate makes it very difficult to ascribe any meaning to the observed changes in the level-2 variance components, and it is not interesting to compare these across successive models. However, it is to be noted that these are still highly statistically significant.

The fit statistics for this model are lower than those for the previous model, showing that this model is a better fit to the data. Since the focus of the current study is to illustrate the use of multilevel modeling in studying the effects of time-invariant and time-varying covariates on growth, this model is used as the final model. A sparser model would not serve this purpose.

Brief Summary of the Results from Hierarchical Linear Modeling

The results from the hierarchical linear modeling suggest that student aspirations, in general, start out high initially. The level-2 (time-invariant) predictors used in this study were all, with the exception of 'being held back', powerful predictors of initial aspirations, but were poor predictors of rate of change. Females had higher initial aspirations than males. Initial aspirations were also increased with the increase in socioeconomic status and early grades. After controlling for other factors in the model, race continued to have an impact on initial aspirations, with Blacks and Hispanics having higher initial aspirations than Whites. Among the time-varying covariates, mother's expectations was the only one which was significantly and positively associated with aspirations at each point in time, although average mother's expectations, parental involvement and math scores all had significant impact on initial aspirations.

Results from Group-Based Mixture Modeling

Two additional objectives of this study were to describe and analyze the patterns of development of educational aspirations of adolescents over a five-year period using Nagin's (1999) multilevel group-based technique for analyzing development trajectories, and to explore, using Nagin's model, demographic, socioeconomic, parental, ability, and school experience factors that may impact patterns of growth in aspirations. Toward this end, a sequence of models were built using mixture modeling using PROC TRAJ, a SAS procedure for estimating developmental trajectories, developed by Jones et al. (2001).

PROC TRAJ is based on a semiparametric, group-based modeling strategy, the model being a mixture of probability distributions that are suitably specified to describe the data to be analyzed. The group-based approach employs a multinomial modeling strategy, and is useful for modeling unobserved heterogeneity in a population (Jones et al., 2001).

PROC TRAJ does handle missing data, so the complete data set with 9837 observations was used in this analysis. The norm of the design weight was used in the weight statement. All the terms used in model fitting were linear as only three time points are available in the data for this study. Linear models have two parameters, the intercept and the slope. As a general rule, in order to avoid having too many degrees of freedom and overfitting, there should be more data points than parameters. As a consequence, with three data points a linear model works best. Using three data points to fit two parameters gives more data points than parameters, and a good chance to find a model that fits the data without the risk of overfitting.

Selecting the Optimal Number of Groups

In order to select the optimal number of groups, a series of models were run starting with a one-group model. These models were compared using the change in the Bayesian Information Criterion (BIC) to evaluate change in model fit (Jones et al., 2001). The BIC is the log likelihood evaluated at the maximum likelihood estimate less one-half the number of parameters in the model times the log of the sample size, and it favors more parsimonious models than likelihood ratio tests.

The BIC log Bayes factor approximation is

$$2 \log_e (B_{10}) \approx 2 (\Delta BIC)$$

where ΔBIC is the BIC of the alternative (more complex) model less the BIC of the null (simpler model). The log form of the Bayes factor is interpreted as the degree of evidence favoring the alternative model (Jones et al., 2001). According to Jones et al. (2001), the interpretation of $2 \log_e (B_{10})$ is as given in Table 4.7. Also, for the current study, a seven-group model was chosen as optimal based on the BIC for model fits given in Table 4.8.

Table 4.7: Interpretation of 2 $\log_e (B_{10})$

$2 \log_e (B_{10})$	B_{10}	Evidence against H_0
0 to 2	1 to 3	Not worth mentioning
2 to 6	3 to 20	Positive
6 to 10	20 to 150	Strong
> 10	> 150	Very Strong

Table 4.8: Bayesian Information Criteria (BIC) and 2 $\log_e (B_{10})$ for Alternate Models.

Number of Groups	BIC	Null Model	$2 \log_e (B_{10})$
1	-45260.73		
2	-42504.29	1	5512.88
3	-41103.51	2	2801.56
4	-40985.06	3	236.9
5	-40817.12	4	335.88
6	-40642.88	5	348.48
7	-40458.21	6	184.67
8	-40514.28	7	-112.14

The seven-group solution offered the most parsimonious fit to the data, with the change in BIC being 184.67, compared to a change of -112.14 for an eight-group solution. Negative changes in BIC suggest decrements in fit.

Support for the seven-group model was evaluated using the average probability of group-membership and the percentage of cases that might be considered “hard” to classify. Since posterior probabilities of group membership can be obtained readily, the average probability of group membership was computed (Chassin, Pitts, & Prost, 2002).

This average probability was found to be 0.82, which supported the choice of a seven-group model.

Also, the number of cases that might be considered "difficult" to classify was computed based on guidelines given by Nagin (D. S. Nagin, personal communication, September 9, 2003). According to Nagin, if the posterior probability of an observation for the classified group is less than 0.7, it could be reasonably called hard to classify. For this study, only about 11.99% of the observations were found "hard to classify".

The "sigma" value for the seven-group model was found to be 0.841. This value measures the average standard deviation of the dependant variable at each of the time points within groups.

Although PROC TRAJ is equipped to incorporate missing data, an assessment of the missing data by group was carried out. The seven groups were compared with respect to the missing data at each time point. The percentage of missing data at each time point for each group is given in Table 4.9.

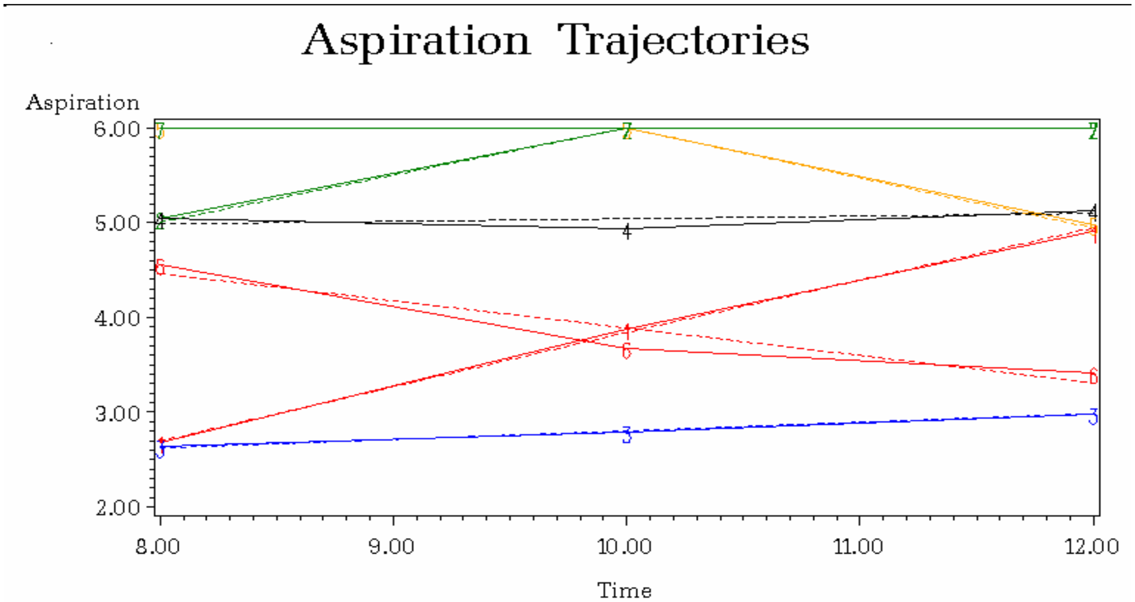
Table 4.9: Percentage of Cases with Missing values within Each Group in the Seven-Group Model.

Group	8th	10th	12th
1	1.03	1.03	13.7
2	0	1.12	7.31
3	0.48	0.73	11.14
4	0.02	0.75	5.09
5	0	0	0
6	0.29	1.17	9.82
7	0.55	0.9	4.92

Most of the missing data is from the twelfth grade, the last point in the trajectory, which is particularly important to defining the trajectory. However, the groups did not significantly differ in this count (except group 5 which had no missing data). This taken together with the fact that less than 8% of the observations in the entire data set had any missing data at all implies that attrition should not substantially influence the findings.

<u>A Description of the Seven Groups</u>

The seven-group model was then examined to be able to better describe the groups. Figure 4.16 presents the trajectories of the seven groups.



<u>Figure 4.16</u>: Growth Curve Trajectories of Aspirations. Expected (Dashed Lines) Versus Observed (Solid Lines) Trajectories.

The groups can be roughly described as in Table 4.10. The frequency and percentage of individuals in each group for this sample is also given in Table 4.10.

Table 4.10: Descriptive Statistics for the Seven Groups

Group	Description	Frequency	Percentage
1	Steady Increasing	387	3.93
2	Early Increasing	889	9.04
3	Low Stable	826	8.40
4	Moderate Stable	4909	49.90
5	Late Decreasing	353	3.59
6	Steady Decreasing	1029	10.46
7	High Stable	1444	14.68

The steady increasing group was characterized by a steady increase in aspirations from the eighth grade through the twelfth. This group will be used as a baseline for any further analyses. The early increasing group started with initial aspirations that were fairly high. Their aspirations increased to the tenth grade and remained stable after that. Group 3, the low stable group exhibited the lowest aspirations at all time points. The moderate stable group (group 4) encompassed the majority of the students who had stable aspirations from the eighth grade through the twelfth. Group 5 contained students who had very high initial aspirations, but whose aspirations showed a decline from the tenth grade through the twelfth. Group 6 had steadily decreasing aspirations across time, while group 7 had consistent and very high aspirations.

From Table 4.10, it is clear that about half of the students had moderately stable aspirations. The next largest group was the high stable group, showing that almost two-thirds of the students had stable aspirations from the eighth grade through the twelfth. About 10% of the students showed steady decreasing aspirations from the eighth grade through the twelfth.

The seven groups can be roughly divided into three “strata”. Three of the groups namely “low stable”, “steady increasing”, and “steady decreasing” are at the lower end of the spectrum of trajectory groups, and can be thought of as the “lower” groups. Three other groups, namely, “early increasing”, “late decreasing”, and “high stable” are at the higher end, and can be labeled as “upper”. The “moderate stable” group falls in the middle.

Descriptive statistics for the seven groups were then calculated which helped better understand the characteristics of the groups. Table 4.11 breaks down the seven groups on the basis of gender.

Table 4.11: Descriptive Statistics for the Seven Groups by Gender

Group	1	2	3	4	5	6	7
	Steady Increasing	Early Increasing	Low Stable	Moderate Stable	Late Decreasing	Steady Decreasing	High Stable
	Percent	Percent	Percent	Percent	Percent	Percent	Percent
Male	4.67	8.08	9.72	49.07	3.02	11.78	13.25
Fem	3.22	9.96	7.12	50.32	4.14	9.18	16.06

Females outnumber males in the early increasing, moderate stable, late decreasing and high stable groups. Notably, these are the four groups at the upper end of the trajectory spectrum. The three groups in which males outnumber females all have trajectories at the lower end, clearly below the other four groups.

Table 4.12 breaks down the seven groups on the basis of race. Although most members of all the ethnic groups fell into the moderate stable category, it can be noted that the three “upper” groups, namely, high stable, early increasing and late decreasing had high percentages of Asians. The high number of Asians in the high stable group supports research in the past, as well as other results from this study.

Table 4.12: Descriptive Statistics for the Seven Groups by Race

Group	1	2	3	4	5	6	7
	Steady Increasing	Early Increasing	Low Stable	Moderate Stable	Late Decreasing	Steady Decreasing	High Stable
	Percent	Percent	Percent	Percent	Percent	Percent	Percent
Asian	2.43	9.56	2.59	44.89	4.21	5.35	30.96
Hispanic	6.18	8.77	9.57	47.46	3.69	11.67	12.66
Black	4.67	9.46	6.88	50.37	3.69	12.04	12.90
White	3.67	8.98	8.89	50.60	3.51	10.55	13.79

Table 4.13: Descriptive Statistics for the Seven Groups by Ever Held Back

Group	1	2	3	4	5	6	7
	Steady Increasing	Early Increasing	Low Stable	Moderate Stable	Late Decreasing	Steady Decreasing	High Stable
	Percent	Percent	Percent	Percent	Percent	Percent	Percent
No	3.65	9.38	7.16	50.83	3.79	9.66	15.53
Yes	6.41	6.02	19.13	41.81	1.87	17.46	7.30

Table 4.13 presents the percentages of students in each of the seven groups who had been ever held back early in their school careers. It can be noted that many students who had been held back belonged to the low stable group when compared to those who had never been held back. The steady increasing and steady decreasing groups also had higher percentages of students who had been held back early. These three are the groups with trajectories at the lower end of the spectrum, indicating that students who have been

held back early have aspirations that are generally lower than students who have not been held back early. Some of them continue to have low stable aspirations while others increase them slightly over time. Some others show a decrease in aspirations over time. Also, more than twice as many students who had never been held back belonged to the high stable group, when compared to those who had been held back.

Table 4.14: Descriptive Statistics for the Seven Groups by SES

Group	1	2	3	4	5	6	7
	Steady Increasing	Early Increasing	Low stable	Moderate stable	Late decreasing	Steady Decreasing	High stable
Mean	-0.3486	0.335	-0.555	0.1461	0.3601	-0.2902	0.6956
S.D.	0.658	0.7422	0.5975	0.7116	0.729	0.6335	0.7416

Table 4.14 presents the average SES levels of the seven groups in the model. It can be seen that the high stable group had the highest SES, while the low stable group had the lowest SES. The three upper groups, namely, the high stable, early increasing, and late decreasing had the highest average SES, while the three "lower" groups, namely, the steady increasing, steady decreasing, and the low stable, had the lowest average SES.

Table 4.15: Descriptive Statistics for the Seven Groups by Early Grades

Group	1	2	3	4	5	6	7
	Steady Increasing	Early Increasing	Low stable	Moderate stable	Late decreasing	Steady Decreasing	High stable
Mean	2.6512	3.3175	2.4529	3.1286	3.3963	2.691	3.5593
S.D.	0.6754	0.5897	0.6845	0.6134	0.5242	0.6353	0.4955

Table 4.15 presents the means and standard deviations of the early grades for students in the seven groups. The same trend as was seen with SES continues with early grades. The 3 "upper" groups (groups 2, 5, and 7) had higher early grades, with the "high stable" group having the highest average grade. The three "lower" groups (namely groups 1, 3, and 6) had the lowest average early grades, with the low stable group having the lowest average. The "moderate stable" group fell in the middle.

Table 4.16: Descriptive Statistics for the Seven Groups by Mother's Expectations

	Group	1	2	3	4	5	6	7
Grade		Steady Increasing	Early Increasing	Low stable	Moderate stable	Late decreasing	Steady Decreasing	High stable
8th	Mean	4.2119	5.09	3.931	5.0405	5.6601	4.7619	5.6787
	S.D.	1.3259	0.6029	1.3747	0.7557	0.6511	0.9787	0.595
10th	Mean	4.4134	5.2553	3.7179	4.8857	5.3711	4.3382	5.6655
	S.D.	1.1126	0.6983	1.3836	0.7061	0.8017	1.0439	0.5618
12th	Mean	4.8889	5.6108	3.868	5.1059	5.119	4.0991	5.7722
	S.D.	1.0704	0.7851	1.3351	0.7858	0.8478	1.2615	0.5719

Table 4.16 presents descriptive statistics for mother's expectations at each grade level for the seven groups. The same trend that was seen for the previous variables continues for mother's expectations with the "upper" groups generally having higher mother's expectations than the "lower" groups at all time points, with the moderate stable group in the middle. Again, the extremes were for the high stable and the low stable groups.

Table 4.17 presents descriptive statistics for parental involvement at each grade level for the seven groups. The trend that was seen for the earlier variables continues for parental involvement with the "upper" groups generally having more involved parents than the “lower” groups at all time points, with the moderate stable group in the middle. Again, the extremes were for the high stable and the low stable groups.

Table 4.17: Descriptive Statistics for the Seven Groups by Parental Involvement

	Group	1	2	3	4	5	6	7
Grade		Steady increasing	Early increasing	Low stable	Moderate stable	Late decreasing	Steady decreasing	High stable
8th	Mean	2.23	2.5418	2.1707	2.4639	2.5902	2.3145	2.6551
	S.D.	0.5165	0.4353	0.4965	0.4529	0.4266	0.479	0.4080
10th	Mean	1.9061	2.1946	1.8471	2.0944	2.17	1.9252	2.2498
	S.D.	0.4859	0.4809	0.4862	0.4678	0.5331	0.486	0.4948
12th	Mean	1.8811	2.0799	1.7498	2.005	2.1001	1.8254	2.1731
	S.D.	0.5176	0.5126	0.4817	0.4965	0.5378	0.5215	0.5348

Table 4.18: Descriptive Statistics for the Seven Groups by Math Scores

	Grp	1	2	3	4	5	6	7
Grade		Steady Increasing	Early Increasing	Low stable	Moderate stable	Late decreasing	Steady Decreasing	High stable
8th	Mean	47.2077	56.7188	45.2216	53.3877	56.5598	47.4382	60.856
	S.D.	8.3112	9.6836	6.9507	9.4775	9.9429	7.5613	9.503
10th	Mean	47.3095	56.9159	44.4477	53.5087	56.3699	46.9085	60.194
	S.D.	9.1106	8.5167	7.6936	8.7403	8.4805	7.9154	7.835
12th	Mean	47.2538	56.7915	43.8015	53.3914	56.0292	46.2466	60.127
	S.D.	9.2315	8.4996	7.5556	8.6094	8.2323	7.7724	7.61

Table 4.18 presents descriptive statistics for mathematics scores at each grade level for the seven groups. The same trend that was seen for the previous four variables continues for math scores with the “upper” groups generally having higher math scores

than the “lower” groups at all time points, with the moderate stable group in the middle. Again, the extremes were for the high stable and the low stable groups.

Model with Time-Stable Predictors

Next, a model was built which introduced the time-stable predictors of student aspirations. According to Nagin (in press), the introduction of predictors of group membership typically has no impact on the form of the trajectories themselves if these predictors are time invariant because they do not include information that will affect the actual shape of a trajectory. When such predictors are added to the model, Nagin recommends an efficient three-stage procedure.

The first stage involves the identification of the preferred number of groups as well as the order of the trajectories for a model without predictors of trajectory group membership. This was done in the earlier section, and a seven-group model was found to be optimum. All the trajectories were specified to be linear.

The second stage is focused on the identification of significant predictors of group membership probability. In this stage, multinomial logit models are estimated, relating group assignment to hypothesized predictors of group membership. The group membership identifications required for these analyses are based on maximum posterior probability assignments from the first stage model without predictors. A multicategory logit model for this study showed that all the time-stable predictors are significant as shown in Figure 4.17.

In the third stage, the final model is estimated. It jointly estimates the parameters defining the trajectories and the probabilities of group membership. The number and order of the trajectories are from the stage one search, whereas the predictors of the probabilities of group membership are the products of the second stage search. Nagin (in press) however, goes on to say that the search for the best predictors of trajectory group membership could also be conducted using the joint-estimation procedure utilized in stage 3. Added computation time is the only difference.

The CATMOD Procedure

Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Intercept	6	1925.12	<.0001
F2SEX	6	70.28	<.0001
F2RACE1	18	237.84	<.0001
cSES	6	1180.24	<.0001
cGRADS	6	1154.30	<.0001
BYS74	6	57.62	<.0001
Likelihood Ratio	5E4	24832.48	1.0000

Figure 4.17: SAS Proc Catmod Output of Multicategory Logit Model

Unlike a multinomial logit model, using PROC TRAJ to study the time-stable covariates accounts for the uncertainty in group membership, thus preventing bias (Jones et al., 2001). For this study, risk factors were introduced directly into the model, thus accounting for assignment uncertainty automatically. A model was built using SAS PROC TRAJ and the 5 time-stable covariates – gender, race, SES, early grades and ever held back. Since PROC TRAJ does not accommodate a class statement, the race variable which has four levels was recoded into three dummy variables, one each for Asian, Hispanic and Black.

Figure 4.18 presents the risk factor parameter estimates, standard errors, tests for the hypothesis that the parameter equals zero, and p values for the tests. Group 1 (steady increasing) was used as a baseline group. As of today, it is not straightforward to change this baseline group. Also, when this model was run, the group definitions were slightly altered. In the explanation below, the following are the codes for the groups.

Table 4.19: Description for the Seven Groups in the Model with Time-Stable Covariates

Group	Description
1	Steady Increasing
2	Early Increasing
3	Moderate Stable
4	Steady Decreasing
5	Late Decreasing
6	Low Stable
7	High Stable

Table 4.20 presents the results from the seven group model with time stable covariates. The following is an example of interpreting the output from this model. This example will compare the two extreme groups, namely, the low stable group (group 6) and the high stable group (group 7) to the steady increasing group (group 1), in turn.

When group 6 (low stable) is compared to group 1, it can be seen that while gender and being held back do not have any impact on group membership, the other factors do. SES has the strongest impact, and as SES increases, the likelihood of belonging to the low stable group decreases when compared to belonging to the steady increasing group. Also, the likelihood of belonging to the low stable group when compared to the steady increasing group is higher for those who had lower early grades than for those who had not, although this effect is only marginally significant ($p < 0.1$). The likelihoods of belonging to the low stable group for Hispanics, and Blacks are lower than those for Whites when compared to belonging to the steady increasing group.

Table 4.20: Results from the Seven Group Model with Time-Stable Predictors after Correcting for Design Effects.

Group	Parameter	Estimate	Std Error	T	Prob > |T|
2	Constant	0.5762	0.4112	1.4013	0.1612
	Gender	0.6108	0.4574	1.3354	0.1818
	Race (A-W)	-0.7651	1.1590	-0.6601	0.5092
	Race (H-W)	0.3677	0.7040	0.5223	0.6015
	Race (B-W)	0.7941	0.6586	1.2057	0.2280
	SES	1.4884	0.3655	4.0722***	0.0001
	Early Grades	1.7286	0.4881	3.5415***	0.0004
	Held Back	-0.0059	0.6484	-0.0091	0.9927
3	Constant	2.3858	0.3752	6.3587***	0.0001
	Gender	0.2774	0.4157	0.6673	0.5046
	Race (A-W)	-0.9756	1.0587	-0.9215	0.3568
	Race (H-W)	-0.2166	0.6285	-0.3446	0.7304
	Race (B-W)	0.4135	0.5747	0.7195	0.4719
	SES	0.8955	0.3300	2.7136**	0.0067
	Early Grades	0.7279	0.4114	1.7693~	0.0769
	Held Back	-0.0428	0.5522	-0.0775	0.9382
4	Constant	0.9941	0.4187	2.3743*	0.0176
	Gender	0.0821	0.4600	0.1785	0.8583
	Race (A-W)	-1.4522	1.1138	-1.3038	0.1923
	Race (H-W)	-0.6577	0.6616	-0.9941	0.3202
	Race (B-W)	-0.2255	0.7857	-0.2870	0.7741
	SES	-0.0568	0.3011	-0.1886	0.8504
	Early Grades	-0.0724	0.3947	-0.1834	0.8545
	Held Back	0.4791	0.6168	0.7768	0.4373
5	Constant	0.6813	0.7137	0.9546	0.3398
	Gender	0.8989	0.5150	1.7454~	0.0809
	Race (A-W)	-1.6230	1.4378	-1.1288	0.2590
	Race (H-W)	0.2469	0.802	0.3079	0.7582
	Race (B-W)	0.5384	0.9400	0.5728	0.5668
	SES	2.1664	0.3915	5.5336***	0.0001
	Early Grades	2.7714	0.6030	4.5960***	0.0001
	Held Back	-0.3128	0.8699	-0.3596	0.7192
6	Constant	-0.0387	0.4856	-0.0797	0.9365
	Gender	-0.0351	0.4922	-0.0713	0.9432
	Race (A-W)	-2.1735	1.4156	-1.5354	0.1247
	Race (H-W)	-1.7016	0.7025	-2.4222*	0.0154
	Race (B-W)	-1.3883	0.8100	-1.7140~	0.0866
	SES	-0.9179	0.3367	-2.7262**	0.0064
	Early Grades	-0.7074	0.4226	-1.6739~	0.0942
	Held Back	0.8362	0.5840	1.4318	0.1522
7	Constant	-0.6820	0.5364	-1.2714	0.2036
	Gender	0.6574	0.4708	1.3963	0.1627
	Race (A-W)	-0.4311	1.2903	-0.3341	0.7383
	Race (H-W)	0.7347	0.7524	0.9765	0.3288
	Race (B-W)	1.2211	0.7338	1.6641	0.0961
	SES	2.9586	0.4302	6.8773***	0.0001
	Early Grades	3.5252	0.5803	6.0748***	0.0001
	Held Back	-0.4334	0.8203	-0.5283	0.5973

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

When group 7 (high stable) is compared to group 1 (steady increasing), it can be seen that most of the effects are reversed when compared to the corresponding effects in the case of group 6. As SES and early grades increase, the likelihood of belonging to the high stable group increases when compared to belonging to the steady increasing group. Gender, race and being held back do not have significant impact on group membership.

Similar comparisons and interpretations can be made for other groups. Overall, it can be seen that SES and early grades affect group membership significantly. As SES decreases, the likelihood of a student belonging to a "lower" group, namely, the low stable group is higher than the likelihood of belonging to group 1. This trend also holds as early grades are lower. Similarly, having high SES and/or high early grades increases the likelihood of belonging to the "higher" groups, namely the early increasing, late decreasing, and high stable groups when compared to the baseline group. Interestingly, none of the factors have a significant impact when the steady decreasing group is compared to the steady increasing group, although the direction of the effects are similar to that of the other "lower" group, namely, the low stable group.

Model with Time-Stable and Time-Varying Predictors

In addition to the time stable predictors described above, one of the objectives of this study was to test whether, for some trajectory groups, mother's expectations, parental involvement or math scores are associated with an increase in aspiration. The structure of the model allows for the possibility that the impact may vary by trajectory group (Jones et al., 2001).

The addition of time-varying covariates presents several challenges beyond the scope of this project, one of which includes model selection. Because time-varying predictors vary with the response, it can no longer be readily assumed that the shapes of the trajectories will remain the same. This means that it cannot be assumed that the seven group model will still be the best model, and model selection may have to be initiated again. Also, an attempt at fitting this model led to estimation and convergence problems. In general, in growth mixture modeling, increasing model complexity adds to execution time, convergence problems, and the likelihood of improper solutions (Li, Duncan, Duncan, & Acock, 2001).

Since this study contained three continuous time-varying covariates, introducing them adds several complexities beyond the scope of this project. The introduction and interpretation of time-varying covariates are topics for future studies.

A Comparison of the Results from Hierarchical Linear Modeling and Group-Based Mixture Modeling

Conventional hierarchical linear modeling (as also latent curve analysis) models population variability in growth with multivariate continuous distribution functions. HLM attempts to model unconditional and conditional population distributions of growth curves. Unconditional models estimate the mean and covariance of the population distribution of growth curve parameters, while conditional models attempt to explain this variability by relating growth parameters to explanatory variable (Nagin, 1999).

Mixture modeling, on the other hand, is a semi-parametric approach intended to identify distinct clusters of individual trajectories within the population and to understand the characteristics of individuals within these clusters. It is a multinomial modeling strategy which is of primary use when a population contains clusters which have very distinct developmental courses.

Both methods were used in this study, and although it is difficult to draw strict parallels between them, a comparison of the results from the two methods helps understand the strengths and the weaknesses of each.

Model C of Table 4.5 is the model that includes all the time stable predictors in the study – gender, race, SES, early grades, and ever held back. Table 4.20 presents the results of mixture modeling when the same time stable covariates are included. Results from model C reveal that gender, race, SES, early grades, and being ever held back all have an impact on initial aspirations of students, while none of these factors have any impact on the growth in aspirations over time. Since HLM is based on the assumption of continuous distribution functions, it is assumed that all students exhibit linear growth trajectories, and the impact of the explanatory variables on the growth parameters from these linear trajectories, namely, the initial aspirations, and rate of change is examined.

The mixture modeling results, on the other hand, identify seven distinct clusters of students based on their growth trajectories. This modeling thus allows room for modeling a variety of trajectories of different orders (linear, quadratic, cubic etc.) at the same time, although this was not feasible for this study due to the limited number of time points. The trajectory of each of the seven groups identified is then treated like a response in a multinomial model, and the impact of the explanatory variables on this response is studied. Thus the results reveal how any explanatory variable changes the likelihood of belonging to one group when compared to any other cluster.

Both methods have advantages and disadvantages. Hierarchical linear modeling provides an explanation of how explanatory variables affect growth in the general population and has more “absolute” value in the sense that the conclusions hold for all members in the population and is thus more straightforward to interpret. However, when a population consists of clusters that have very different developmental trajectories, the assumption of continuous distribution functions may not be valid. Raudenbush (2001, p. 513) remarks: “It makes no sense to assume that everyone is increasing (or decreasing) in depression….many persons will never be high in depression, others will always be high, while others will become increasingly depressed.”

Mixture modeling is very useful when a population has unusual mixtures of trajectories. Then, it provides a basis for not only identifying an optimal number of groups and describing the different clusters, but also linking group membership probability to individual-level characteristics. However, there are limitations to this approach in that there is a risk of overfitting or underfitting data and creating trajectory groups that reflect random variation (Nagin, Pagani, Tremblay, & Vitaro, in press). Other pitfalls mentioned by Nagin et al. are that the existence of the various developmental trajectories cannot be tested and are assumed a priori, and that the rules provide no basis for calibrating the precision of individual classifications to the groups.

For this study, mixture modeling serves as a complement to HLM methods. HLM helped to understand better the stability of aspirations and the factors that influence the initial aspirations as well as the stability. Mixture modeling helped to better understand the effect that these factors had on the underlying clusters of student trajectories.

Another advantage of mixture modeling in this study can be seen in the analyses that follow. Mixture modeling allows the linkage of the characteristics of the trajectories of the different groups to the application behavior of the students while they were in the twelfth grade. Thus it can be seen, for example, that students with low stable trajectories behaved differently from students with high stable trajectories or unstable trajectories. An understanding of this kind would be useful to plan any interventions for different groups of students.

Results from Ordinal Modeling

One of the research questions in this study is to investigate the role that aspirations play in the college choice process, particularly the effect that aspirations have on widening the college choice set. Toward this end, the data were first partitioned into three sets: those students who have not applied to any colleges by the final term of their senior year, those students who have applied to only one college, and those who have applied to more than one college. Then, a multinomial model was built using application group as a response and aspirations as well as the other independent variables as predictors.

Preliminary Analyses

The three application groups are labeled as None, One and Many for convenience. Table 4.21 presents the average aspirations for these three groups at each grade level. Figure 4.18 gives the mean plots for the three groups with the means from the above table.

From Table 4.21 and Figure 4.18, it can be seen that the aspiration levels of the three groups are different, in that the NONE groups seems to have the lowest level of aspirations and the MANY group the highest. Interestingly, although the students in the NONE group have not filed a single application, their average aspirations are still quite high. The NONE group is the only group that shows a dip in average aspiration in the tenth grade. The NONE and ONE groups have about 28% each of the sample, while the

MANY group has about 45% of the sample, indicating that about 45% of the sampled students have not only high aspirations, but are taking some steps toward college attendance.

Table 4.21: Average Aspirations for the Three Application Groups by Grade

Group/Grade	N	Mean	Standard Deviation
NONE			
Eighth	2843	4.35	1.23
Tenth	2817	4.20	1.25
Twelfth	2522	4.27	1.21
ONE			
Eighth	2506	4.85	1.07
Tenth	2590	4.87	1.08
Twelfth	2411	4.98	0.98
MANY			
Eighth	4187	5.25	0.80
Tenth	4176	5.31	0.81
Twelfth	4045	5.42	0.70

In order to better understand the characteristics of the three groups, they were further broken down by the independent variables as presented in Tables 4.22 and 4.23. Table 4.22 uses the categorical variables while Table 4.23 uses the continuous variables.

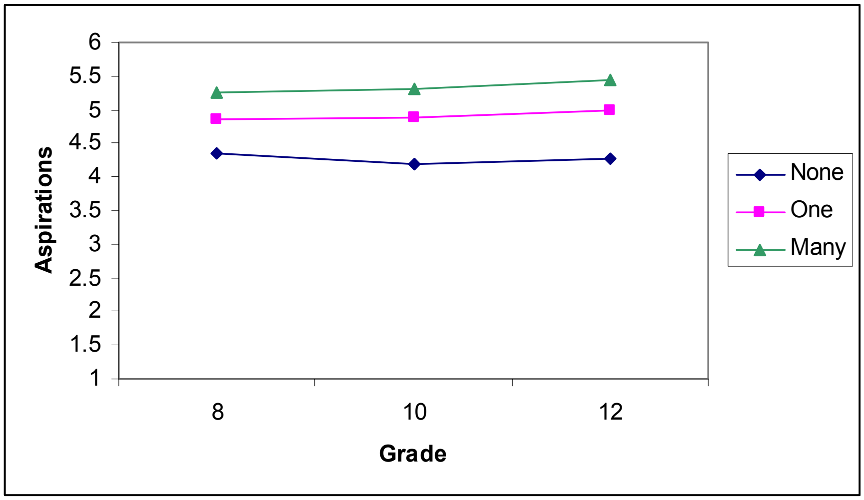


Figure 4.18: Mean Plots of the Aspirations of the Three Groups Across Time

Table 4.22: Descriptive Statistics for the Three Application Groups – Gender, Race, and Ever Held Back.

	NONE		ONE		MANY	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
Gender						
Female	1301	45.59	1396	55.62	2226	53.01
Male	1553	54.42	1114	44.38	1973	46.99
Race						
Asian	114	3.99	111	4.42	386	9.19
Hispanic	415	14.54	236	9.4	308	7.34
Black	288	10.09	163	6.49	339	8.07
White	2037	71.37	2000	79.68	3166	75.4
Held Back						
No	2407	84.34	2281	90.88	3922	93.4
Yes	447	15.66	229	9.12	277	6.6

Table 4.23: Descriptive Statistics for the Three Application Groups – SES, Early Grades, Mother's Expectations, Parental Involvement, and Math Scores.

	NONE			ONE			MANY		
	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.
SES	2854	-0.23	0.68	2510	0.10	0.74	4199	0.43	0.75
Early Grades	2854	2.79	0.67	2510	3.14	0.66	4199	3.32	0.58
Mother's Expectations									
Eighth	2854	4.74	1.12	2510	5.00	0.90	4199	5.23	0.76
Tenth	2854	4.54	1.07	2510	4.87	0.91	4199	5.17	0.74
Twelfth	2854	4.67	1.21	2510	5.01	0.98	4199	5.36	0.78
Parental Involvement									
Eighth	2854	2.34	0.50	2510	2.47	0.47	4199	2.54	0.43
Tenth	2854	2.00	0.49	2510	2.08	0.50	4199	2.16	0.47
Twelfth	2854	1.87	0.52	2510	2.02	0.51	4199	2.09	0.51
Math Scores									
Eighth	2854	48.24	8.23	2510	53.50	9.79	4199	57.18	9.94
Tenth	2854	48.06	8.39	2510	53.43	9.15	4199	57.10	8.66
Twelfth	2854	47.67	8.39	2510	53.25	9.04	4199	57.02	8.48

Figures 4.19, 4.20, and 4.21 present the mean plots for mother's expectations, parental involvement, and math scores for the three application groups using the means from Table 4.23.

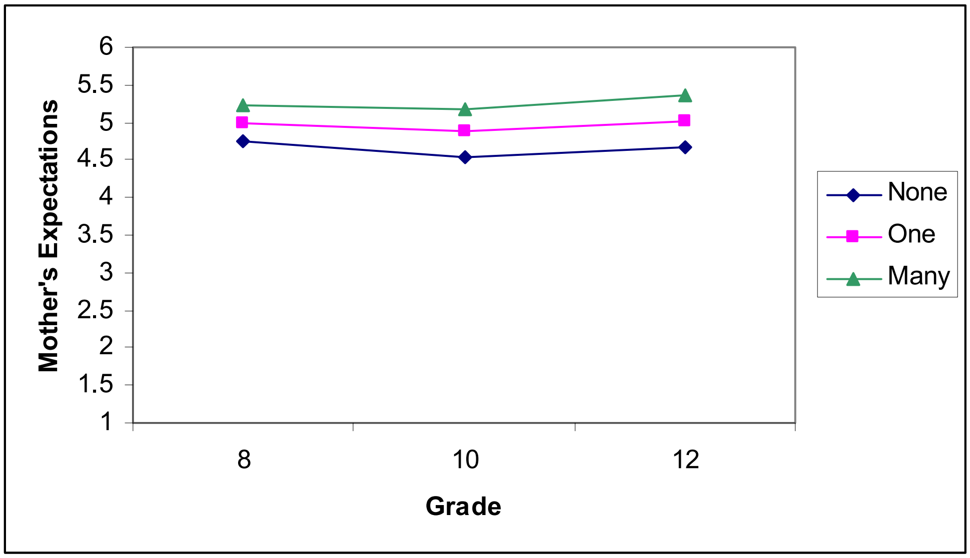


Figure 4.19: Mean Plot for Mother's Expectations by the Three Application Groups.

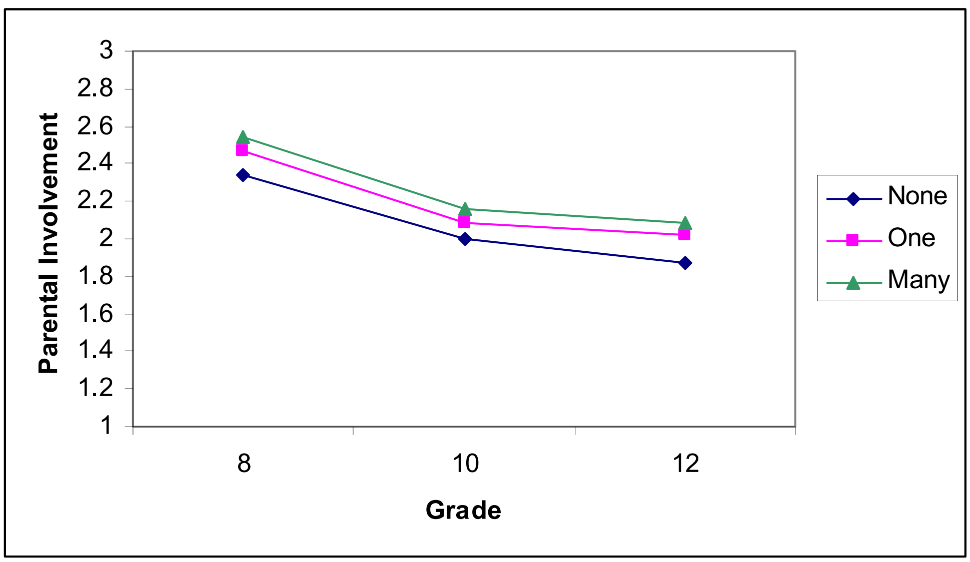


Figure 4.20: Mean Plot for Parental Involvement by the Three Application Groups.

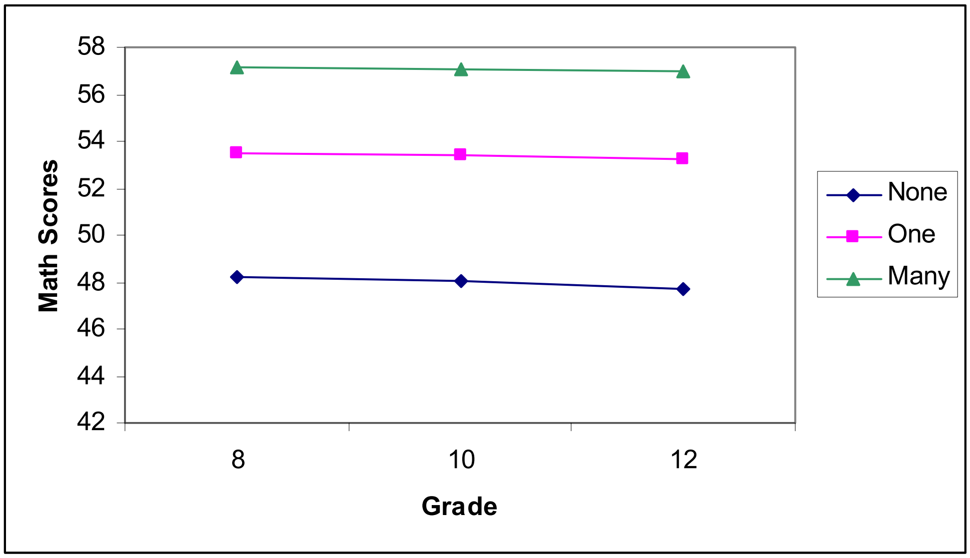


Figure 4.21: Mean Plot for Math Scores by the Three Application Groups.

On inspection of Tables 4.22 and 4.23, and Figures 4.19, 4.20, and 4.21, some interesting points emerge. The NONE group is the only one that has a majority of males. The other two groups have more females. In terms of race, it is interesting to note that the number of Hispanics is largest in the NONE group and smallest in the MANY group, while the reverse is true for Asians. The percentage of students who answered YES to ever being held back shows a steady decline from the NONE group to the MANY group.

Both early grades and SES show steady increases from the NONE group to the MANY group. Mother's expectations also show a steady increase from the NONE group to the MANY group. While parental involvement shows a decrease from the eighth grade to the twelfth for all groups, the average parental involvement shows an increase from the NONE to the MANY groups. Perhaps math scores exhibit the most dramatic differences among the groups. While the average math scores are about the same within each group across grades, there are distinct differences among groups, with a steady increase from the NONE group to the MANY group.

A Proportional Odds Model

In order to better understand the factors that impact the application process, a multinomial model was built. The outcome for these models was the application group – NONE, ONE or MANY, while the predictors included aspirations as well as the other independent variables. Since the response is at one point in time, the time-varying covariates – mother's expectations, parental involvement, and math scores – were averaged across time. The weight variable used was again the normalized design weight.

First, SAS PROC LOGISTIC was used to fit a multinomial logit model for ordinal responses. According to Bender and Grouven (1998), the most popular method for ordinal data is the proportional odds model. Cumulative probabilities are the probabilities that the response Y falls in category j or below, for each possible j. The logits of the first $J – 1$ cumulative probabilities are called cumulative logits (Agresti, 1996). The proportional odds model is a cumulative logit model that assumes that the odds of response below a given response level are constant regardless of which level is picked. This model has an intercept for each cumulative logit, but constrains each predictor to have a single parameter for all logits. This means that the fitted surfaces for the logits are all parallel and they are only allowed to differ by a constant shift that necessitates the separate intercepts that are obtained when an ordinal model is fitted. When the logit link is used, this parallelism assumption also implies that the effect of a given predictor is the same regardless of where the ordinal response divided to dichotomize it. The proportional odds test simply tests whether the parameters are the same across logits, simultaneously for all predictors (SAS Institute, 2003).

For this study, the score test showed that the proportional odds assumption was violated ($\chi^2 = 209.37$, $p < 0.0001$). This implies that some or all of the risk factors had different (not parallel) effects for each application group.

According to Bender and Grouven (1998), ignoring the violation of the proportional odds assumption may lead to misleading results. This calls for alternative procedures to be used in such a case. A powerful alternative method based on maximum likelihood procedures is the partial proportional odds model (Bender & Grouven, 1998).

A Partial Proportional Odds Model

This is a more flexible model that can be used when the proportional odds assumption is violated. It represents a joint model of the response categories and is usually more efficient than separate binary logistic regressions (Bender & Grouven, 1998). Basically, this model allows the relaxation of the proportional odds assumptions for some or all of the predictors.

Until recently, no standard software was available for computations (Bender & Grouven, 1998). However, SAS PROC GENMOD can now be used to fit this model using a generalized estimating equations (GEE) approach. In this approach, first, multiple response outcomes are formed from the univariate outcome by forming logits corresponding to the different cutpoints of the ordinal values (Stokes et al., 2000). For this study, since there are three response levels, two logits are formed, one comparing level 1 versus 2 and 3 (logit type 1), and the second comparing levels 1 and 2 versus 3 (logit type 2). Then, these logits are considered to be multiple response functions for the same subject and a GEE analysis is performed with a model that includes interactions between the explanatory variables and different types of logit (Stokes et al., 2000). If any interactions are significant, then there is a relationship between those explanatory variables and types of logit, and proportional odds does not hold for those explanatory variables. Nonsignificant interactions imply that the proportional odds assumption holds for those variables, and the interaction terms can then be removed. To fit this model, the data need to be rearranged so that an input data set is created that expands each original observation into a set of observations, one for each logit, with each containing a logit identifier variable and a binary response for the indicated logit.

The following is the SAS code used to create this data. LOGTYPE is the logit identifier variable, while PRESP is the new binary dependent variable.

```
data newall3; set newall;
    do;  if apply=2 then presp =1;
    else presp=0; logtype=2; output; end;
    do; if apply=2 or apply=1 then presp=1;
    else presp=0; logtype=1 ; output; end;
run;
```

In the new data, when a person has filed multiple applications (APPLY=2), PRESP takes on the value 1 both when LOGTYPE=1 and LOGTYPE=2. When a person has filed a single applications (APPLY=1), PRESP takes on the value 0 when LOGTYPE=2 and the value 1 when LOGTYPE=1. When a person has filed no applications, that is, APPLY=0, then PRESP = 0 both when LOGTYPE is 1 and 2. The levels of response are thus regrouped so that the model to be analyzed will be a binary response model for each of the two cumulative logits (groups ONE and MANY as opposed to group NONE, and group MANY as opposed to groups ONE and NONE).

A partial proportional odds model was built containing all the predictors (including early grades, held back, aspirations, parental involvement, mother's expectations, and math scores). At the first step for this model, the interaction of LOGTYPE with each of the predictors was included in the model, that is, all of the predictors were unconstrained. It was found that these interactions were significant only for gender, race, and math score. This implied that only these predictors violated the proportional odds constraint. In the second step, the interactions of LOGTYPE with the other predictors were removed, while they were still retained for these three predictors. The UNSTRUCTURED working correlation matrix is used in the GEE model. According to Stokes et al. (2000), this provides a more powerful assessment of logit type interactions, and produces smaller standard errors for within subject effects.

Figure 4.22 presents the output showing the score statistics for the effects of the model. It can be seen that the proportional odds assumptions are violated for gender, race, and math scores.

Score Statistics For Type 3 GEE Analysis

Source	DF	Chi-Square	Pr > ChiSq
F2SEX	1	7.62	0.0058
F2RACE1	3	15.64	0.0013
F2SES1	1	41.78	<.0001
BYS74	1	0.01	0.9279
BYGRADS	1	9.72	0.0018
aspi	1	97.95	<.0001
mothere	1	0.11	0.7409
parenti	1	0.16	0.6886
mathsco	1	57.87	<.0001
logtype	1	6.11	0.0134
logtype*F2SEX	1	25.73	<.0001
logtype*F2RACE1	3	13.99	0.0029
mathsco*logtype	1	11.09	0.0009

Figure 4.22: Score Statistics for the Effects in the Partial Proportional Odds Model.

Table 4.24 contains the final parameter estimates and significance tests from the partial proportional odds model. The main effects pertain to effects of corresponding factors for logit type 1, and interactions are the increments to the main effects to obtain the effects of the corresponding factors for logit type 2.

Table 4.24: Results from the Partial Proportional Odds Model with Corrections for Design Effects.

Effect	Estimate	Std. Error	Z	Pr > Z
Intercept	-6.0180	0.7559	-7.9614***	<0.0001
Gender	-0.0085	0.1295	-0.0656	0.9477
Race (A-W)	0.5935	0.3235	1.8346~	0.0666
Race (H-W)	0.0551	0.2565	0.2148	0.8299
Race (B-W)	0.5010	0.2314	2.1651*	0.0304
SES	0.3792	0.0991	3.8264***	0.0003
Held Back	-0.0106	0.2176	-0.0487	0.9612
Early Grades	0.1925	0.1136	1.6945~	0.0902
Aspirations	0.7278	0.1148	6.3397***	<0.0001
Mother's Expectations	-0.0247	0.1363	-0.1812	0.8562
Parental Involvement	0.0380	0.1761	0.2158	0.8291
Math Scores	0.0273	0.0089	3.0674**	0.0022
Logit Type	0.9198	0.4099	2.2440*	0.0248
Logit Type*Gender	-0.3318	0.1202	-2.7604**	0.0058
Logit Type*Race (A-W)	-0.3006	0.2850	-1.0547	0.2916
Logit Type*Race (H-W)	-0.2216	0.2094	-1.0583	0.2899
Logit Type*Race (B-W)	-0.3467	0.2079	-1.6676	0.0954
Logit Type*Math Score	0.0139	0.0076	1.8289	0.0674

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

An examination of the parameter estimates shows that the estimate for aspirations (averaged over time) is the strongest predictor of application group membership. Its parameter estimate is 0.7278 and exp (0.7278) = 2.07. Thus, as average student aspirations from eighth to twelfth grades increases by one unit, the odds of applying to more schools are 2.07 times higher than the odds of applying to fewer schools, both for multiple schools versus none or one school, and for one or more schools versus no schools at all.

Over and above aspirations, academic factors such as math scores and early grades had significant and marginal effects, respectively, on the number of applications filed. As early grades increase by one unit, the odds of applying to more schools increase by 1.21 for both logits.

Math scores does not satisfy the proportional odds assumption and needs different interpretations for the two logits. For logit 1 (MANY and ONE versus NONE), the log odds ratio is 0.0273 and exp (0.0273) = 1.0277. Thus, as math score increases by one unit, the odds of applying to at least one school increases by 1.03. For logit 2 (MANY versus ONE and NONE), the log odds ratio is 0.0273 + 0.0139 = 0.0412, and exp (0.0412) = 1.042. Thus, the odds of applying to many schools as opposed to one or none increases by 1.04 as math score increases by one unit.

Even after controlling for aspirations and academic factors, some background factors such as race and SES continue to have significant impact on the number of applications filed. The parameter estimate for SES is 0.3792. Also, SES does satisfy the proportional odds assumption. So, as SES increases by one unit, the odds of applying to more schools increases by exp (0.3792) = 1.46, for both logits. Thus, as SES increases by one unit, the odds of applying to more schools are about 1.46 times higher than the odds of applying to fewer schools, both for multiple schools versus none or one school, and for one or more schools versus no schools at all.

Race does not satisfy the proportional odds assumption. For logit 1, the log odds ratio for Asians versus Whites is 0.5935. Thus, the odds of Asians applying to at least one school are about 1.81 times the odds for Whites. Similarly, the odds of Blacks applying to at least one school are about 1.65 times the odds of Whites.

For logit 2, the log odds ratio for Asians versus Whites is 0.5935-0.3006 = 0.2929 and exp (0.2929) = 1.34. Thus the odds of Asians applying to many schools as opposed to restricting their choices or not applying at all are about 1.34 times the odds for Whites. Similarly, the odds of Blacks applying to many schools as opposed to one or none is Exp (0.5010-0.3467) = 1.41 times the odds for Whites.

In summary, aspirations have the strongest impact on the number of applications filed. As aspirations increase, so do the chances of filing applications to more schools and improving the choice set. Also having an impact are academic factors and certain background factors such as race and SES. As SES increases, the choice set for college widens. Blacks have greater odds of filing applications to more schools than do Whites, after academic and aspiration factors are controlled, while Asians have marginally higher odds than Whites. Hispanics do not seem significantly different from Whites in the number of applications filed, controlling for the other effects in the model. Parental expectations and involvement do not have an impact on the number of applications filed, neither does being held back early in school. Thus, having high aspirations alone may not be enough to increase a student's choice set, but the way the student performs academically as well as the student's background has an effect.

Linking Group Membership and Applications Filed

Next, in order to better understand the relationship between aspirations over time and the application process, the application filing pattern was examined for the seven groups identified from the mixture modeling results. Table 4.25 gives the frequencies of the applications filed by students in the seven groups.

Table 4.25: Applications Filed by Group Membership. Percentages are indicated in parentheses.

Group	No Applications	One Application	Many Applications	Total
Steady Increasing	182 (48.92)	116 (31.18)	74 (19.89)	372 (100)
Early Increasing	146 (16.53)	219 (24.80)	518 (58.66)	883 (100)
Low Stable	480 (70.18)	154 (22.51)	50 (7.31)	684 (100)
Moderate Stable	1271 (26.04)	1359 (27.84)	2251 (46.12)	4881 (100)
Late Decreasing	64 (18.39)	90 (25.86)	194 (55.75)	348 (100)
Steady Decreasing	614 (64.56)	235 (24.71)	102 (10.73)	951 (100)
High Stable	97 (6.72)	337 (23.34)	1010 (69.94)	1444 (100)
Total	2854	2510	4199	9563

An examination of Table 4.25 reveals that the groups at the "higher" end of the aspiration range, namely, early increasing, high stable, and late decreasing, all had the majority of students filing more than one application, thus maximizing their chances for acceptance into a postsecondary institution. The high stable group, the members of which had very high and very stable aspirations, had about 70% of the students filing multiple applications, while the numbers were slightly lower for the early increasing and the late decreasing groups, both of whose members showed high but slightly less stable aspirations.

Interestingly, for these three groups, a full 30% to 45% of students had filed one or no applications at all. Although these students had high aspirations, many of them even indicating an interest in graduate or professional degrees, they failed to file or filed only one application, thus failing to build a good choice set and maximizing the chances for postsecondary education. These students display high aspirations but fail to follow through with concrete steps toward college. This group needs to be followed up in greater detail in future studies to ascertain the reasons for the failure to take concrete steps, especially with those students for whom only demographic factors are a concern.

At the other end of the spectrum, about 70% of the members of the low stable group filed no applications at all. Also, about 65% of the students in the steady decreasing group failed to file a single application. In the moderate stable group, about half the students had filed multiple applications and a fourth had either filed one or no application at all.

Members of the steady increasing group displayed a steady increase in aspirations over time, going from not considering any postsecondary education in the eighth grade to wanting to obtain a college degree in the twelfth grade. However, about half of these students had not filed any applications at all, and only about a fifth had filed multiple applications. This group is of particular interest because, although the students from this group had high aspirations in the twelfth grade, many had failed to build a good choice set. This is evidence to show that the stability of aspirations over time seems to matter when it comes to taking concrete steps toward college.

The Stability of Aspirations within Application Groups

One of the objectives for this study is to better model the stability of aspirations within each application group (NONE, ONE or MANY) by building multilevel models for each group. In order to do this, unconditional means and unconditional growth models were built for each application group. The results are in Tables 4.26 and 4.27.

Table 4.26: Unconditional Means Models for the Three Application Groups with Corrections for Design Effects

		Para	No Applications	One Application	Many Applications
Fixed Effects					
Initial Status	Intercept	γ_{00}	4.2674*** (0.0346)	4.8672*** (0.0327)	5.2929*** (0.019)
	Gender	γ_{01}			
	Race (A-W)	γ_{02}			
	Race (H-W)	γ_{03}			
	Race (B-W)	γ_{04}			
	SES	γ_{05}			
	Early Grades	γ_{06}			
	Held Back	γ_{07}			
Rate of Change	Intercept	γ_{10}			
	Gender	γ_{11}			
	Race (A-W)	γ_{12}			
	Race (H-W)	γ_{13}			
	Race (B-W)	γ_{14}			
	SES	γ_{15}			
	Early Grades	γ_{16}			
	Held Back	γ_{17}			
Variance Components					
Level 1	Within-Person	σ^2_ε	0.9070*** (0.0320)	0.5485*** (0.0201)	0.3250*** (0.0091)
Level 2	In Initial Status	σ^2_0	0.6293*** (0.0482)	0.5333*** (0.0392)	0.2712*** (0.0166)
	In Rate of Change				
	Covariance				
Fit					
Deviance			26182.1	21226.5	30562.6
AIC			26188.1	21232.5	30568.6
BIC			26205.9	21250	30587.6

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 4.27: Unconditional Growth Models for the Three Application Groups with Corrections for Design Effects

		Para	No Applications	One Application	Many Applications
Fixed Effects					
Initial Status	Intercept	γ_{00}	4.3085*** (0.0424)	4.8162*** (0.0418)	5.1995*** (0.0244)
	Gender	γ_{01}			
	Race (A-W)	γ_{02}			
	Race (H-W)	γ_{03}			
	Race (B-W)	γ_{04}			
	SES	γ_{05}			
	Early Grades	γ_{06}			
	Held Back	γ_{07}			
Rate of Change	Intercept	γ_{10}	-0.0432~ (0.0264)	0.0548* (0.0227)	0.0994*** (0.0140)
	Gender	γ_{11}			
	Race (A-W)	γ_{12}			
	Race (H-W)	γ_{13}			
	Race (B-W)	γ_{14}			
	SES	γ_{15}			
	Early Grades	γ_{16}			
	Held Back	γ_{17}			
Variance Components					
Level 1	Within-Person	σ^2_ε	0.7212*** (0.0316)	0.4191*** (0.0195)	0.2412*** (0.0082)
Level 2	In Initial Status	σ^2_0	0.8234*** (0.0716)	0.7384*** (0.0591)	0.4236*** (0.0270)
	In Rate of Change		0.1582*** (0.0249)	0.1242*** (0.0182)	0.0737*** (0.0082)
	Covariance				
Fit					
R-sq y,y			0.0006	0.0026	0.0103
R-sq ε			0.2049	0.2359	0.2578
R-sq 0					
R-sq 1					
Deviance			25878	20920.9	29574.5
AIC			25890	20932.9	29586.5
BIC			25925.7	20967.9	29624.5

~ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

The one fixed effect in the unconditional means model is the estimate for the intercept, the grand mean aspiration across all individuals and occasions. When this is compared across the three models, it is clear that the mean aspiration is highest for the students who had applied to more than one school, followed by those for the students who had applied for one school and those who had not filed any applications at all. All the means were fairly high, indicating that even those who had not taken any steps toward college have fairly high aspirations.

The unconditional growth model results from Table 4. 26 indicate that while there was an increase in aspirations over time for the many applications and one application group, there was a marginally significant decrease in aspirations over time for those who had not filed college applications at all. The aspirations of this group decreased steadily from grades 8 through 12 from 4.31 to about 4.22. The many applications group had the highest initial aspirations as well as biggest growth rate in aspirations with their aspirations growing from 5.2 to about 5.4 from the eighth grade to the twelfth.

Thus, results from these analyses indicate that the initial aspirations of the three application groups show a linear trend, with the many applications group having the highest initial aspirations. Also, while the many applications and the one application groups show an increase in aspirations over time, the "no application" group shows a decrease in aspirations from the eighth grade through the twelfth. The many applications group has a higher rate of increase than the one application group even though their initial aspirations are higher.

Brief Summary of Major Results

The various data analyses and model fitting procedures used to study student educational aspirations and college application patterns reveal the following:

- Multilevel modeling revealed that students in general had high initial aspirations and fairly stable aspirations from the eighth grade through the twelfth.

- While background, parental and academic factors all had significant impact on initial aspirations, none of the factors considered in this study had significant effects on the rate of change in aspirations, as revealed by multilevel modeling.
- Group-based mixture modeling analyses identified seven different aspiration growth trajectories, namely, low stable, steady increasing, steady decreasing, moderate stable, early increasing, late decreasing, and high stable. The first three of these groups were at the lower end of the aspirations scale, while the last three were at the upper end.
- Trends showed that the "upper" (high aspiration) groups had more females, Asians, students from high SES backgrounds, high early grades, and students who had never been held back. Also, mother's expectations, parental involvement and math scores were higher for these students than for those from the "lower" groups.
- Mixture modeling results indicated that having low SES and low early grades both increase the likelihood of belonging to the "lower" groups when compared to the baseline.
- Ordinal modeling using a partial proportional odds model revealed that aspirations have the strongest impact on the number of applications filed. As aspirations increase, so do the chances of filing applications to more schools and improving the choice set. Also having an impact are academic factors and certain background factors such as race and SES. As SES increases, the choice set for college widens. Asians and Blacks have greater odds of filing applications to more schools than do Whites, after academic and aspiration factors are controlled.

- Parental expectations and involvement do not have an impact on the number of applications filed. Neither does being held back early in school.
- Linking the groups that were identified from the mixture modeling and the application groups revealed that there is evidence to show that the stability of aspirations over time seems to matter when it comes to taking concrete steps toward college. Students who had high stable aspirations had filed more applications than students who had high but more unstable aspirations. Students whose aspirations had increased with time from low to high had also filed fewer applications than those who had maintained high stable aspirations.
- Multilevel modeling to study stability within application groups revealed that while students in the one and many application groups had increasing aspirations over time, students in the no applications groups had decreasing aspirations over time.

CHAPTER 5

CONCLUSIONS AND DISCUSSION

This chapter details the conclusions that emerged from this study. The chapter is divided into the following broad sections: (1) an overview of the purpose and importance of the study; (2) a discussion of the main findings and conclusions; and (3) implications for policy, practice, and research.

Overview of the Study

It has been widely accepted that the social and economic returns to postsecondary education are high. Students' decisions to enroll in higher education have important implications on both individuals and society at large. According to the U.S. Department of Education (2003), "Today, more than ever before, education is the fault line between those who will prosper in the new economy and those who will not" (About Us section, para. 2). Yet, many students never receive a college education, either because they lack the preparation for college or because of financial constraints and other factors. Prior research on college choice has shown that early high educational aspirations and the maintenance of these aspirations through high school have an impact on the postsecondary attendance of students (Hossler et al., 1999). Findings have also shown that the stability of aspirations varies among students from different ethnic and socioeconomic backgrounds. Studies have shown that even among the students who maintain high aspirations, many do not actually realize their plans because of various reasons, some of which may have to do with background, parental, and academic factors. This study sought to better understand the factors that affect the stability of aspirations from the eighth grade to the twelfth, and examine the effects of variables such as parental involvement, achievement, and academic experiences in conjunction with demographic factors on student aspirations over time. This study also attempted to understand how the stability of aspirations relates to actual action taken by these students toward college attendance.

The study used data from the National Education Longitudinal Study: 1988-94 (NELS:88) to address the above mentioned research objectives. NELS:88 is a longitudinal data set containing five waves of data, collected from the time a nationally representative sample of students were in the eighth grade (base year data) until eight years after they were expected to complete high school. This study used data from the first three waves, namely, when students were in the eighth, tenth, and twelfth grades. A further subset was created which used only data from students who participated in all three of the above mentioned waves, who expected to graduate high school in 1992, and who took the mathematics cognitive test which was administered at each of these waves. The resulting sample contained 9837 of the initial 24,599 observations in the base year NELS survey.

The study was divided into three phases. The first phase examined the formation and stability of student aspirations and the factors that impact them, using hierarchical linear modeling methods. The second phase examined these issues in further detail using group-based mixture modeling techniques. The third phase used a partial proportional odds model to relate average aspirations over the period of time specified to the postsecondary application patterns of students.

This study used a large national data set and sophisticated analytical tools such as individual growth modeling and mixture modeling to investigate the development of aspirations. In this way, the influence of a variety of demographic, socioeconomic, achievement, and parental variables, on both initial status (eighth grade aspirations), as well as change in aspirations could be simultaneously evaluated. An understanding of the dynamics of educational aspiration development among adolescents would enable educators, parents, counselors, and policymakers to adopt measures tailored to meet the specific needs of students, thus helping enhance their career opportunities.

The next section discusses the main research objectives and findings of the study and the conclusions that can be drawn from them.

Main Findings and Conclusions

Research Objective Number One

The first goal of this study was to describe and analyze the development of educational aspirations of adolescents over a five year period using individual growth modeling from a hierarchical linear modeling perspective.

Results from the descriptive and exploratory analyses indicated that students, in general, had fairly high initial aspirations that were fairly stable with a slight growth from the eighth grade through the twelfth. When this was further investigated using hierarchical linear modeling, results confirmed that students did start with fairly high initial aspirations and exhibited a steady growth in aspirations from grades eight through twelve. However, this growth, though statistically significant, was not very large in magnitude.

Hossler et al. (1999) conducted a study that looked at overall student aspirations over their adolescent years. They found that most students develop postsecondary plans by the time they completed the ninth grade. In their study, the educational aspirations of most of the sophomores and juniors actually increased after ninth grade. More than half of the students who were undecided about their plans in the ninth grade said that they intended to continue their postsecondary education by the time they were in the junior year. The descriptive analyses from the current study show that students' aspirations may be well-formed even earlier, when students are still in middle school, suggesting that any interventions to help students have high aspirations need to start early. This confirms the findings related to students' early formation of aspirations in earlier studies (Ekstrom, 1985; New Hampshire Partnership for the Advancement of Postsecondary Education Research [NH PAPER], 2003). The study also confirmed Hossler et al.'s 1999 findings to some extent – overall student aspirations were found to be somewhat steady from the eighth grade through the tenth, but increased from the tenth grade through the twelfth.

Most studies on students' educational aspirations look at differences among student aspirations based on different factors such as gender, ethnicity, and SES. The next major objective of this study was to see if similar differences exist among students with regard to initial aspirations and the stability of aspirations from the eighth grade through the twelfth.

<u>Research Objective Number Two</u>

The second major research objective of this study was to explore, from an HLM perspective, demographic, socioeconomic, parental, ability, and school experience factors that may possibly impact growth in aspirations.

Results from the descriptive and exploratory analyses showed that females had higher aspirations than males at all time points. Asians had higher overall aspirations than students from other ethnic backgrounds, while Hispanics had the lowest aspirations at all time points. Educational aspirations among Asians were also the most stable across time. Students from the lowest SES tertile had the lowest aspirations at all time points and exhibited less growth in aspirations when compared to those from the middle tertile. Students from the upper tertile had the highest aspirations at all time points but exhibited very little growth across time. Similarly, when students from different quartile groups based on early grades were compared, those from the lowest grade group had the lowest aspirations, while those from the highest grade group had the highest. Those students who had been held back early in school had lower educational aspirations at all time points when compared to those who had never been held back.

Results from the hierarchical linear modeling showed that while all these factors with the exception of being held back did have an impact on initial aspirations, none of them had a significant effect on the stability of aspirations over time. When time-varying covariates such as mother's expectations, parental involvement and math scores were considered, it was again found that while all three had significant and positive impact on initial aspirations, only mother's expectations was significantly and positively associated with aspirations at each point in time.

Past research has shown that student aspirations and their stability vary with gender, race, SES, and other factors. While there have been extensive studies on aspirations at any given point in time, there have been far fewer studies on the stability of aspirations. In particular, while all the factors considered in this study have been found to have some effect on aspirations at any given point in time, most available studies have focused on one or two specific factors, particularly demographic factors, that may affect stability. Studies have shown that while minority youth exhibit high aspirations at any given point in time, they are less likely to maintain high aspirations through high school, and while they were much more likely to aspire to graduate school training early on, these effects disappear by the twelfth grade (Kao & Tienda, 1998). Others have shown that among high achievers, whites were more likely to lower their expectations than were minority students (Hanson, 1994; Trusty, 2000). Socioeconomic background has been found to have a continuous and at times increasing influence on the level of educational and occupational aspirations (Howell & Frese, 1980). Also, young men have been found to be significantly more likely than young women to have reduced educational aspirations, especially in late adolescence (Hanson, 1994). Kao and Tienda also report that there are small gender effects in the level of aspirations, but significant gender variation in the maintenance of these aspirations. The current study, while confirming the results of prior research on the effects of demographic, socioeconomic, academic, and family factors on eighth grade aspirations, has shown that none of these factors have an impact on the stability of aspirations from the eighth grade through the twelfth, after controlling for the other factors in the study. The study has thus revealed the importance of controlling the effects of confounding factors before the effect of a single variable can be commented upon.

Some past studies on college choice have shown that the educational plans of students are not fully formed until the tenth grade (Parish, 1979). The results from this study indicate that students formalize their educational plans at the eighth grade or even earlier, and that these plans do not change very much. The results confirm those from a prior study by Hossler et al. (1999) which found that many high school students develop stable postsecondary plans by the time they complete ninth grade. In fact, this study reveals that for most students, postsecondary plans are well-formed even by the eighth grade and remain fairly stable through high school. Demographic and socioeconomic factors do not have an impact on the growth of these plans after controlling for academic and family variables.

The results from the study indicate that mother's expectations, parental involvement in school activities, students' early achievement, mathematics ability and whether they had been held back or not, all have an influence on eighth grade aspirations above and beyond gender, race and socioeconomic status. This, combined with the results that student aspirations remain fairly stable from the eighth grade through the twelfth, implies that the best time to influence student postsecondary plans is before the end of middle school. Policymakers, parents as well as other school personnel can play active roles in influencing student aspirations and designing interventions as early as elementary and middle school, by having high expectations, being involved in students' academic activities, as well as encouraging early high academic achievement.

Research Objective Number Three

The third major research objective of the current study was to describe and analyze the patterns of development of educational aspirations of adolescents over a five-year period using Nagin's (1999) multilevel group-based technique for analyzing development trajectories.

Results from the mixture modeling revealed that the sample can be optimally divided into seven distinct groups, each with its own aspiration trajectory. For the purpose of this study, they were classified as steady increasing, early increasing, low stable, moderate stable, high stable, late decreasing, and steady decreasing. Three of these groups, namely, steady increasing, low stable, and steady decreasing, were at the "lower" end. That is, students belonging to these groups exhibited trajectories whose highest points did not indicate a desire to finish college. The moderate stable group consisted of the largest number of students. The trajectory for this group was stable from the eighth grade through the twelfth and indicated that students expected to finish a college degree. The three other groups, namely, the early increasing, late decreasing, and the high stable were at the "upper" end. Students in these groups expected to earn either a bachelor's or a higher graduate or professional degree. The three groups differed only in the stability of student aspirations. The early increasing group showed an increase in aspirations from the eighth grade to the tenth but stabilization later on. The late decreasing group had stable aspirations early on, but showed a decrease between the tenth grade and the twelfth.

Descriptive statistics relating to these seven groups reveal qualitative differences between the "upper" and "lower" groups with the moderate stable group falling in the middle. The "upper" groups had more females, more Asians, students from higher SES backgrounds, students who had higher early grades and those who had not been held back early for the most part. Also, mother's expectations, parental involvement and mathematics scores were higher for students from these groups.

These results are complementary to the results obtained from the hierarchical linear modeling analysis. Whereas the HLM analysis indicated that student aspirations are on the average fairly stable across time, this analysis enables us to explore the differences among those who had increasing, decreasing, or stable trajectories even though the number of students in the increasing or decreasing groups are smaller than those in the stable group.

The results from the descriptive analysis suggest that there are qualitative differences between the characteristics of students in the “lower” and “upper” groups, with the students in the “upper” groups faring better academically and having higher parental and family involvement and expectations. There were also differences between these two categories based on gender, race and SES. The fact that there are many differences between the “lower” and “higher” groups indicates that the absolute value of aspirations, over and above the stability of aspirations, is an important consideration in any interventions planned. Students who aim to finish college or even attain graduate or professional degrees differ in many ways from students who aim lower, and a further investigation of these factors is essential for policymakers and counselors to implement any interventions.

The next step is to examine the various trajectories within each of these groups (“upper” and “lower”) and see how the stability of aspiration trajectories varies within each of the two groups and what factors influence this stability. Research question number four attempted to address some of these issues.

Research Objective Number Four

The fourth major research question of this study was to explore, using Nagin (1999)’s model, demographic, socioeconomic, parental, ability, and school experience factors that may impact patterns of growth in aspirations.

Once the seven groups with different aspiration trajectories were identified by the analyses conducted for the previous research question, these groups were further studied to better understand the differences among them. Models were built to better understand the effects of gender, race, SES, early grades, and being held back on membership in the seven groups. Results indicated that early grades and SES impacted group membership significantly even after controlling for the other factors mentioned above. As SES decreases the likelihood of belonging to the “lower” groups described in the previous section were high when compared to the baseline steady increasing group. A similar effect was found for early grades too. Conversely, as SES or early grades increased, the likelihood of belonging to the “upper” groups increased. Race, gender, and being held back early were not significant factors after controlling for all the effects in the model.

Further exploration of the results indicate that while the effects of the factors considered were similar for the three “upper” groups when compared to the baseline group, there was variation in the effects among the “lower” groups. Race, SES, and early grades all had significant effects when the low stable group was compared to the baseline, while none of the factors had an impact when the steady decreasing group was compared to the baseline. Having lower SES and lower early grades increased the likelihood of belonging to the low stable group when compared to the other “lower” groups, namely, steady increasing or steady decreasing. Thus, while the differences between the “upper” and the “lower” groups were the most significant, the variation within the “lower” groups was higher than the variation within the “upper” groups.

It may be recalled that students in the “upper” groups aimed to finish college or obtain graduate education. These results indicate that students who had very stable and high aspirations did not differ much from students who displayed a slight decrease in the later years or started off wanting to finish college and increased their goals to attaining graduate education.

However, students in the “lower” groups had different characteristics based on the stability of their trajectories. The low stable group was more likely to have students with very low SES and low early grades. This is useful information for policymakers, high school counselors, and teachers to take into account when designing any interventions.

Past research has shown that there are differences between students whose aspirations remain stable and high across time, and those whose aspirations change over time. Hossler et al. (1999) found that students whose aspirations remain high and stable over time were more likely to actually attend college than those whose aspirations changed, especially when they were in high school.

A better understanding of the characteristics of students from the “lower” groups would help policymakers identify problems and design interventions that help these students develop and maintain high aspirations and translate intentions into actions toward college attendance or entrance into the job market. Further, any interventions would benefit from taking into account the stability of aspirations for members from the lower groups.

The findings suggest that it is important to take into account early academic achievement in any interventions planned. Encouraging high academic achievement in elementary and early middle school would probably help students develop high aspirations by the time they reach the eighth grade and also to maintain these aspirations through high school. Also, students from lower socioeconomic classes would benefit from intervention programs intended to influence educational aspirations.

Research Objective Number Five

The fifth major research objective of this study was to compare and contrast the conclusions drawn about the growth and development of aspirations from the HLM and mixture modeling perspectives.

Results from the HLM analysis revealed that student aspirations start high and remain fairly stable from the eighth grade through the twelfth. While demographic, socioeconomic, parental, and academic factors all have an effect on the initial aspirations, they do not have an effect on the growth in aspirations because of the high stability displayed.

Mixture modeling results helped to identify the optimal number of developmental trajectories and helped understand the differences among them. Seven groups were identified and their characteristics evaluated. It was found that there were three "high" groups which contained students who all aspired to a college education or more. There were three "low" groups with students who had low aspirations and did not aim to go to, or to finish, college. Within each of these two sets were students whose aspirations increased over time, decreased over time, or were stable. The largest group was a "moderate stable" group where students aspired to finish college and had stable aspirations across time.

HLM provided an insight into the average aspirations of students and the variation around this "mean" behavior. HLM attempts to model unconditional and conditional populations distributions of growth curves. Mixture modeling, on the other hand, is a semi-parametric approach intended to identify distinct clusters of individual trajectories within the population and to understand the characteristics of individuals within these clusters.

For this study, both methods complemented each other. Whereas HLM helped to understand the overall aspirations of students and how the different factors impacted these aspirations, mixture modeling helped to understand the how these factors influenced student membership in groups with different aspiration trajectories, even when the number of students in a certain group was small. Mixture modeling also helped to understand the relationships between students' aspiration trajectories and their college application filing patterns, which are addressed in the next section. An understanding of this kind would be useful to plan any interventions for different groups of students.

Both methods have advantages and disadvantages. The conclusions drawn from HLM analyses have a more "absolute" value in the sense that the conclusions hold good for all members in the population and are thus more straightforward to interpret. However, when a population consists of clusters that have very different developmental trajectories, the assumption of continuous distribution functions may not be valid, and mixture modeling may then prove more useful. Since this the current study was mainly exploratory in nature, both methods were useful in drawing conclusions about aspiration trajectories and the factors that influence them.

Research Objective Number Six

The sixth main research objective of this study was to understand the relationship between variations in aspiration growth patterns over time among students and their college application pattern behavior.

This question was addressed using three different analytical tools. First, a multinomial model was built with number of applications (zero, one or many) as response, and the different factors mentioned earlier as predictors. Time-varying predictors were averaged across time for the purpose of this analysis. Next, the application patterns among the seven groups identified by the mixture modeling were examined in detail. Finally, HLM methods were used to analyze the growth trajectories within each of the three application groups.

Preliminary analyses indicated that there were several differences among students who had filed one, many or no applications. Students who had filed no applications came from lower SES backgrounds and had lower early grades and math scores. Also, mother's expectations and parental involvement were lower for these students. These students had lower aspirations at all points of time when compared to the other two groups.

Results from the ordinal modeling indicate that average aspirations are the best predictors of the number of applications filed when all other study factors are controlled. Average math scores and SES had significant impact too, while race and early grades had minimal effect. Parental factors did not have significant effect. Prior studies have indicated that expectations or plans for postsecondary education are not immediately evident in students' college search and choice behaviors (Hurtado et al., 1997). The results from this study, which controls for more factors than similar prior studies, indicate that student aspirations do have an impact, but so do other factors such as academic performance. It is not enough for students to have high and stable expectations from an early age; these expectations should go together with high academic performance also from an early age. The results from this study also support other studies which have shown that race and SES have impact on college search and choice (McDonough, 1997). However, these effects are not as strong as student aspirations and academic performance, indicating that high and consistent aspirations and good academic performance from early on may help students overcome any disadvantages due to socioeconomic status.

This study also confirms results from Hurtado et al.'s 1997 study which showed that students of color tend to submit more college applications than white students. Results from this study indicate that after controlling for aspirations, academic and parental factors, Asians and blacks have higher odds of applying to more schools than do white students. This suggests that Asian and black students who have similar aspirations, parental support and expectations and academic performance have a more strategic approach than white students in the college application process.

The results reveal that parental factors such as mother's expectations and parental involvement do not have a direct effect on the number of applications filed. Only student academics and aspirations seem to have direct effects. However, earlier results from this study showed that parental expectations and involvement do have an impact on early aspirations and are positively associated with aspirations at each time point in the study. This result directly supports Hossler et al.'s (1999) conclusion that parental support seems to be the most important factor in the development of educational aspirations, but that some of the more traditional status-attainment variables such as SES and student academic performance emerge to play important roles in students' ability to actualize their plans.

Hossler et al. (1999) also found that, during the junior and senior years, students move from relying on internal sources of information and influence such as parents, to external sources such as peers and teachers. This shift beyond the family could be one reason why parental expectations and involvement do not have strong impacts on the number of applications filed.

However, while parental expectations and involvement were not significant in their ability to predict the number of college applications filed, socioeconomic status which takes into account parental education and income was. This implies that while parental encouragement is significant early on in the college choice process, ultimately lower levels of income and parental education do have a constraining effect on the realization of student aspirations.

This study also attempted to link student application filing patterns with results from the mixture modeling which identified seven groups based on the stability of aspirations. Results indicated that students who had high aspirations tended to file more applications to postsecondary institutions. Among students who had high aspirations, those who had high and stable aspirations filed more applications than did those who had high but more unstable aspirations. Also, about half the students who had steady increasing aspirations from the eighth grade to the twelfth had not filed any applications at all. Although students from this group had high aspirations in the twelfth grade, many had failed to build a wide choice set of colleges to apply to. This indicates the importance of the stability of aspirations over time when it comes to taking concrete steps toward college attendance. This also supports work by Hossler et al. (1999) which showed that students whose plans changed between ninth and twelfth grades were less likely to go to college than those who had more stable plans.

Among the "upper" groups (high stable, early increasing, late decreasing) 80% or more had filed at least one application to a postsecondary institution. In the moderate group, about 74% of the students had filed at least one application, while in the "lower" groups (steady increasing, steady decreasing, and low stable), less than 50% had filed at least one application. This supports Hossler et al.'s 1999 study which found that the higher the ninth grade plans of students, the more likely they were to actualize them. These students' aspirations stabilize around the twelfth grade and the plans reflect the original plans in the ninth grade. On the other hand, students whose plans shifted between the ninth and twelfth grades "were less likely to go on to school and were also the most variable" (p. 112).

Results also indicate that a greater proportion the "early increasing" group (the group of students who had high and increasing aspirations from the eighth grade to the tenth and stabilized after the tenth grade) filed many applications when compared to the "late decreasing" group (the group of students who had stable high aspirations from the eighth grade through the tenth but showed a slight decrease later). Also, a greater proportion of the latter group filed no applications at all when compared to the former. This could be because the "late decreasing" group experienced a change in concrete plans after the tenth grade. Kao and Tienda (1998) argue that early change in educational aspirations from the eighth to tenth grades is driven by changes that transform abstract ideas into likely possibilities, whereas the later changes in aspirations from the tenth to twelfth grades may result from changes in concrete plans. The "late decreasing" group needs to be studied in depth in future studies to better understand the factors that impact these changes.

Results from this study indicate that high and stable student aspirations and academic performance are the main factors in influencing the development of a wider choice set of colleges, with parental expectations and involvement not having a significant impact. This suggests that any interventions to help students take a more strategic approach to applying to postsecondary education should take place early on in their careers and focus on emphasizing both high academic expectations and performance.

This study also found that there are a significant number of students who have high aspirations, but who file no applications or only one application to postsecondary institutions, thus reducing their chances of entering higher education. This group of students needs to be studied in greater detail to understand better the factors that prevent these students from taking a more strategic approach to planning postsecondary education.

Research Objective Number Seven

The seventh main research objective of this study was to study variations in growth patterns over time among those students who have taken concrete steps toward postsecondary education in their senior year, and those who have not.

Toward this goal, multilevel unconditional means and unconditional growth models were built for each application group. Results indicate that the initial aspirations were the highest for the many applications group and were the least for the no application group. The many applications and the one application group showed an increase in aspirations over time, while the no application group showed a decrease in aspirations from the eighth grade through the twelfth. Also, the many applications group had a higher rate of increase than the one application group even as the initial aspirations of the many application group was higher.

These findings confirm the results relating to the previous objective that show that there is a relationship between aspirations and the number of applications filed. Students who have a more strategic college search process and have filed more applications had higher aspirations in the eighth grade and continued to maintain or increase their expectations over time. Students who had not filed any applications had lower aspirations and displayed a decrease in expectations from the eighth grade through the twelfth.

These results are consistent with other research, as well as other results from this study which show that having early high expectations and maintaining them is related to a better development of a student's choice set and indicated more strategic planning about the college selection process.

Summary of Major Findings

The following were the major findings from the study:

- Results from multilevel modeling reveal that average student aspirations remained fairly stable from the eighth grade through the twelfth, exhibiting a slight but not significant increase during this time.
- While gender, race, SES, parental expectations and involvement, and academic factors all had significant impact on eighth grade aspirations, none of had significant effects on the rate of change in aspirations, as revealed by multilevel modeling.

- After controlling for the other factors in the model, neither gender nor race had a significant impact on the stability of educational aspirations.
- Group-based mixture modeling analyses identified seven different aspiration growth trajectories, namely, low stable, steady increasing, steady decreasing, moderate stable, early increasing, late decreasing, and high stable.
- Many students who had high aspirations had filed no applications to postsecondary institutions in their senior year. Many others had filed only one application, restricting the size of their choice set of institutions.
- Among all the factors considered in the study, students' educational aspirations have the strongest impact on the number of applications filed. As aspirations increase, so do the chances of filing applications to more schools and widening the choice set. Also having an impact are academic factors and certain background factors such as race and SES. As SES increases, the choice set for college widens. Asians and Blacks have greater odds of filing applications to more schools than do Whites, after academic and aspiration factors are controlled.
- Parental involvement and expectations have a positive impact on students' early educational aspirations and have positive associations with aspirations at each time point in the study, but average parental involvement and expectations do not significantly impact the number of applications filed. However, socioeconomic status which takes into account parental income and education does have an impact on the number of applications filed.

- Students who had both high and stable aspirations from the eighth grade through the twelfth generally had a wider choice set of applications than students who demonstrated a steady increase in aspirations.

Implications for Educational Policy

A major finding of this study is the relative importance of early educational aspirations, aspirations that are formed as early as in middle school. These educational aspirations remain fairly stable from the eighth grade through the twelfth. The results of this study also reveal that high educational aspirations have a significant impact on a strategic college application process. These two aspects of the study when viewed together suggest that the timing of any efforts to help students develop high aspirations as well as take steps toward postsecondary education is crucial. Any interventions or programs planned to help students develop high aspirations need to be executed early, even while students are in middle school.

The Carnegie Council on Adolescent Development (1996) in its concluding report stated:

> The years from ten through fourteen are a crucial turning point in life's trajectory. This period, therefore, represents an optimal time for interventions to foster effective education, prevent destructive behavior, and promote enduring health practices. (Introduction section, para. 4).

Students in middle school face many serious decisions about the courses they will take as well as regarding their study habits and non-academic behavior. This is a time when the community in general, families, schools, state governments, religious organizations and businesses can make a difference and help to increase aspirations and awareness and emphasize the importance of academic performance and attaining postsecondary education.

Parental expectations and involvement were both found to have a strong impact on educational aspirations. Parents of young children should be the target of early awareness programs. Parents shape the expectations of children, and programs to encourage parents from lower socioeconomic backgrounds to convey high expectations to their children and to be involved in a child's schooling would benefit the children in many ways.

This study also found that parental factors, while having a strong impact on student aspirations in the eighth grade, and being positively associated with aspirations at each time point in the study, did not significantly impact the number of applications filed in the twelfth grade. This result is along the lines of Hossler et al.'s (1999) study which showed that parental support seems to be the most important factor in the development of educational aspirations until the twelfth grade, when traditional status attainment variables such as SES and academic performance play more important roles in students' ability to take concrete action toward college attendance. Since SES takes into account parental education and income, these variables do appear to constrain students' realization of their aspirations. To overcome this, programs that help parents understand early on, while students are still in middle school, what will be required of them to help their children toward gaining a postsecondary education will be beneficial. Parents, especially those from lower SES backgrounds, need to be educated on helping their children select appropriate courses to take, developing an awareness of the financial aid available to their children, and keeping their children motivated to attain postsecondary education will also enable them to be more involved in their children's college search process.

Academic factors such as early academic achievement, not being held back, and mathematics scores also have an impact both on student aspirations and on students taking a more strategic approach to college choice. Any efforts that help students succeed academically would thus help them have higher aspirations as well as to take steps to realize these plans. Again, the timing of these efforts is crucial and such programs should begin as early as in elementary school.

One result from the study showed that many students who had high aspirations failed to file any college applications by the end of their senior year, while others filed only one application thus limiting their chances to attend a postsecondary institution. This may be due to a lack of information or knowledge as to how to go about the college search and choice process, which seems to get more complicated with time. Early awareness programs that help inform students about the college search process, as well as other factors such as college costs and financial aid would benefit students, especially those from lower socioeconomic backgrounds or whose parents do not have a college education. Again, these programs can start as early as elementary or middle school where the emphasis can be on the importance of academic performance on future plans.

Another way in which policymakers can help students, especially those from lower SES backgrounds, is to organize more mentoring programs. Mentors can help students recognize the importance of a college education and help them understand the steps needed to go about doing this. They can also help students maintain interest in school and have stable and high aspirations, while serving as role models themselves. There are many mentoring programs available at this time. Programs such as the Berkeley Pledge, The "I Have a Dream" foundation, SummerMath, and the Middle

School Math and Science Project are all doing good work, but awareness of these programs needs to increase. Businesses and religious organizations can work with governments and parents, and get involved in mentoring programs as well as other efforts to reach out to students and offer them information and help them have high expectations from an early age.

Perhaps the most important factor in any regional or state programs to help students maintain high expectations and take steps toward college is providing information and creating awareness. Policymakers need to focus on getting students adequate information about postsecondary educational opportunities, the services available to them to help with the college search process, financial aid, as well as helping students understand how to meet career goals through by performing well academically and making appropriate curricular choices.

Implications for Educational Practice

The results of this study suggest that parents, teachers and counselors need to be aware of the importance of students' having high and stable educational aspirations and performing well academically from as early as elementary and middle school. Parents play a significant role in shaping student aspirations, no matter what their income level or background. School personnel can work with parents and help them understand the importance of having high expectations for their children, stressing the importance of academic performance, and being involved with their children's schooling from a very early age. Results from this study reveal that parental factors do not have a direct effect on the number of applications filed in the senior year, implying that parents have early impact on their children's actions. Educating parents from lower SES backgrounds and who have had no college education, about the college search and choice process and financial aid early on may help them to not only have higher expectations for their children, but also help them play a more active role later on when their children are in the college search stage.

Teachers and school counselors also play important roles in shaping student aspirations as well as in helping them with the college choice process. Elementary and middle school teachers can talk to students about college and emphasize the importance of consistently high academic performance from an early age. Teachers can also help students, particularly those from lower SES backgrounds to sustain high aspirations by motivating them on the advantages of a college education and providing information on how to go about the college search process. Counselors can help organize individual and group counseling sessions to talk to students about developing a strategic and wide college choice set and about the various steps involved in the college search process along with a timeline for these steps. With training, counselors can also help students with the particulars of the application process and help them develop a choice set of colleges appropriate for them. Since SES plays an important role both in the maintenance of aspirations and in the college application process, students from low SES backgrounds need to be given extra attention by counselors and teachers. Counselors and teachers can also work with parents and educate them about the college search process and about how best they can help their children.

Although many important decisions regarding course-taking etc. are made in middle school, it is common for guidance counselors at this level to be responsible for more than 500 students (Carnegie Council on Adolescent Development, 1989). To be able to help students, teachers and guidance counselors need the support and encouragement of principals, superintendents, and school board officials. Counseling interventions can be developed to address school and family issues for students with low aspirations. Counselors can help students understand their options, identify their goals and then get into suitable educational programs (academic, vocational etc) to enable them to actualize their goals. They can also use programs such as Upward Bound to help minority and low-income students maximize their full potential.

College admissions and marketing personnel as well as educators can also play a role in helping motivate students to go to college as well as providing information about how to do this. Campus tours and activities can be organized with not only high school students but also middle school students. Students and parents from lower socioeconomic backgrounds can be provided with information about various financial packages available in an effort to increase motivation.

Implications for Research Practice

Analysis of NELS:88 Data

This study used a national database to study student aspirations over time and its relation to college choice. There are several significant advantages to using such a database. The sample is nationally representative and sampling has been done with care to account for factors such as nonresponse. Methods have also been devised to account for issues such as oversampling, related to the complex sampling process. Data has been gathered at many levels including schools, students and teachers. It is sometimes difficult for individual researchers to conduct a large longitudinal study, and the availability of existing longitudinal data enables the researcher to examine various substantive and methodological issues. Much of the research in the area of educational aspirations is based on small sample local studies, limiting the generalizability of the results. This study, in using the NELS:88 database, overcomes many limitations associated with small sample studies and studies done at one point in time. The representativeness of the sample, the thoroughness of data collection, the ability to address a number of issues and use a variety of analytical techniques has enabled this study to address a variety of issues and come up with important implications for research practice.

This study also sought to overcome the deficiencies found in many past studies using large national databases such as NELS. Many prior studies did not take into account the complex sampling methods used in the collection of these national data sets. This study accounted for the complexity of the sampling design, and other issues like nonresponse, oversampling etc. by using the appropriate design weights and also accounting for the design effects. According to NCES (1994), if weights are not used, "the estimates that we produce will not be representative of the population about which we are attempting to estimate" (Appendix A). If appropriate design effects are not used, the resulting statistics are more variable than they would have been had they been based on data collected from a simple random sample of the same size. The researcher's attendance at a database training seminar for the NELS:88 data, organized by the National Center for Education Statistics (NCES), helped with the choice of appropriate weights and design effects to analyze the data used in this study. Accounting for a complex sampling scheme, which involved stratification, disproportionate sampling of certain strata, and clustering, makes this study have stronger implications for research practice.

The correction used for the design effects in this study is a conservative approach suggested by Fan (2001). It has been noted that more complex estimators show somewhat smaller design effects than simple estimators (NCES, 1994; Kish and Frankel as cited in Fan, 2001) Thus, regression coefficients tend to have smaller design effects than subgroup comparisons, which in turn have smaller design effects than means. Therefore, the mean root design effects provided by the NCES (1994) for simple statistics were used in adjusting the standard errors for complex statistics (NCES, 1994).

With multilevel modeling, the adjustments are made for standard errors from the level-1 model as well as those from the level-2 model. There is a concern that while the conservative adjustment for the level-2 model is appropriate, the design effect adjustment may be too conservative for standard errors from the level-1 model. This would lead to truly significant effects being considered non-significant. The effect of design effect adjustments for statistics from level-1 models needs to be studied in greater detail. This may lead to a better approach to adjusting for design effects in multilevel models.

Hierarchical Linear Modeling

This study used a variety of data analysis tools such as hierarchical linear modeling, group-based mixture modeling and ordinal modeling. Growth modeling techniques such as hierarchical linear modeling and mixture modeling allowed the study of student educational aspirations over time. Hierarchical linear modeling has several advantages over other repeated measures techniques such as multivariate ANOVA. Ware (1985) concludes that the multivariate approach is of limited use when there are missing data, unbalanced designs, time-varying covariates, or continuous predictors of the rate of change. According to Raudenbush and Chan (1993), such characteristics are common in large-scale longitudinal studies. Hierarchical linear modeling is a more flexible approach to model such data. Hierarchical linear modeling also allows the assessment of correlates of growth, enabling in-depth study of student aspirations as a dynamic process. In this study, results from hierarchical linear modeling revealed that background, academic, and parental factors, all had impact on students' eighth grade aspirations. Also, students' average aspirations remained stable from the eighth grade through the twelfth. This study only investigated the effects of student-level factors on aspirations. In future, HLM methods can be used to also investigate school-level factors, using three-level modeling.

One of the limitations of HLM is that it treats the population distribution of growth as continuous. The assumption is that the functional form of the growth is the same for all the observations, and that only the parameters of growth vary. Because of this assumption, HLM only allows the investigation of "average" growth tendencies and the study of variability about that average. It also attempts to explain this variability about the average using covariates of interest. However, in situations where it is not reasonable to assume that all participants are growing in the same functional form or that the development does not vary regularly among the population, the use of hierarchical linear modeling is limiting. This study is exploratory in nature as students' educational aspiration growth trajectories have not been investigated in depth in earlier studies. The use of a multinomial approach such as group-based mixture modeling, in conjunction with hierarchical linear modeling, provided more in depth information about growth in this case.

This study also attempted to link students' educational aspiration growth trajectories to the number of postsecondary applications filed. In this case, a separation of students with low and high trajectories is useful as these students may have different application filing behavior. Here, a modeling strategy such as HLM, designed to identify averages and explain variability around these averages is less useful than a group-based technique that identifies distinctive clusters of trajectories, as application behaviors across these clusters can be studied.

<u>Group-Based Mixture Modeling</u>

Group-based mixture modeling is another technique with a lot of potential in educational research. This method, unlike HLM, does not assume that the data come from a single population, and that the covariates of change within the population have the same influence on the growth factors of all individuals in the population. It provides a flexible approach to identify distinctive clusters of individual trajectories within the population and for defining the characteristics of individuals within clusters. This method uses a multinomial modeling strategy while making no assumption that the population distribution is continuous. It thus has implications in studies where "developmental trajectories vary greatly across population subgroups both in terms of the level of behavior at the outset of the measurement period and in the rate of growth and decline over time" (Nagin, 1999, p. 153).

Whereas HLM examined the average aspirations across time for all students and the variability in these aspirations, mixture modeling allows the separation of clusters of aspiration trajectories and to look into what factors impacted membership in one group versus another. In this case, where only linear models could be built, using group-based mixture modeling methods added to the findings obtained using hierarchical linear modeling. While HLM methods showed that students' average educational aspirations are stable, group-based mixture modeling divided the sample into clusters that included high, moderate and low stable groups. This allowed the investigation of the college application behavior of members of each group separately.

However, group-based mixture modeling is limited in that while it does allow the investigation of covariates of interest, it does not help explain variability in the population in terms of the covariates as does HLM. It only allows the study of how covariates affect membership in the groups, thus making any conclusions somewhat relative. For example, while it is possible to conclude that coming from a high SES background makes it more likely for a participant to belong to a high aspiration group rather than a low aspiration group, it is not possible to evaluate how much of an impact SES has on aspiration growth over time for the whole population.

Mixture modeling is applicable to data with many time points, and makes allowances for missing data as well. This study had data only from three time points, thus limiting the application of mixture modeling, since only linear models could be fit. However, this type of modeling can help provide insight into data from future large-scale longitudinal studies where data are collected over longer periods of time.

Other limitations of mixture modeling used in this study come from a software perspective. One of the deficiencies of the current version of SAS PROC TRAJ is that the baseline group in the multinomial model is fixed by the software, and currently there is no easy way for the researcher to specify a baseline. In this study, while it would have been of interest to use the low stable group as the baseline for comparison, the steady increasing group was chosen by the software.

Also, while PROC TRAJ allowed models with time-stable covariates to be fit, this study also included three time-varying covariates. PROC TRAJ does allow time-varying covariates to be included in the model, but having three time-varying covariates resulted in nonconvergence and was very computationally intensive. In general, increasing model complexity adds to execution time, to convergence problems, and to the likelihood of improper solutions (Li et al., 2001). Further research is needed in the estimation of complex growth mixture models.

Group-based mixture modeling is a semiparametric approach that does not make any assumptions about the distribution of growth parameters. It also accommodates missing data and allows varied spacing between time points. These are some advantages it has over similar growth mixture modeling methods such as the one proposed by Muthen (2001).

In this study, HLM and mixture modeling methods complemented each other. While HLM enabled the investigation of the average aspirations of students and of how different factors impacted these aspirations, mixture modeling helped to understand how these factors influenced student membership in groups with different aspiration trajectories, even when the number of students in a certain group was small. Mixture modeling also helped to understand the relationships between students' aspiration trajectories and their college application filing patterns. An understanding of this kind would be helpful in planning interventions for different groups of students.

Limitations and Next Steps

One of the methodological limitations of this study was that only three data points were used in the analyses. This limited the exploration of the variety of options available in fitting mixture models, such as being able to fit higher order models. A next step would be to use a fourth data point for educational aspirations from the 1994 wave of NELS:88 data. This was not used in this study as it would have involved addressing very different substantive questions. Also, this study used hot deck methods to perform imputations on the predictor variables. Future work can use multiple imputations methods which are now available for complex multivariate settings (Schafer, 1997).

This study used two available methods for longitudinal modeling – hierarchical linear modeling and group-based mixture modeling. There are other techniques such as growth mixture modeling from a latent class modeling perspective which can also offer insights into this data. Growth mixture modeling is a relatively new procedure for the analysis of longitudinal data that relaxes many assumptions associated with conventional growth curve modeling. In particular, growth mixture modeling tests for the existence of unique growth trajectory classes through a combination of latent class analysis and standard growth curve modeling (Kaplan, 2001).

Another limitation of this study was the use of existing data, which did not allow the researcher control over the definition of variables, the questions used, or the response categories. However, the national data set used had many indicators of the variables the researcher wished to use, allowing the researcher to formulate more specific variables. A qualitative component to the study would also help to overcome the limitations imposed by rigid variable and question design. Qualitative methods such as ethnography and case study analysis would help shed more light on the search stage of the college choice process where students narrow the choice set of postsecondary institutions they wish to apply to.

Finally, even though this study uses longitudinal data, it is an exploratory study, and the relationships inferred are correlational. Care should be taken not to interpret the results using logical causal relationships. To further substantiate the results from this study, more evidence-based experimental or quasi-experimental studies can be conducted in the future.

Ordinal Modeling

Another method used in this study is the partial proportional odds model for ordinal categorical data. This modeling approach has implications for data that are ordinal in nature but do not satisfy the proportional odds assumption used in most common ordinal modeling methods. This strategy allows for the relaxation of the proportional odds assumption for some of the explanatory variables but not others. The application of the proportional odds model is invalid and will yield misleading results when the main assumption is not fulfilled. With increasing use of ordinal modeling in social science research, the possible misuse of the proportional odds model also increases. The partial proportional odds model is a powerful tool and is better than separate binary regressions as it uses less model parameters and represents a joint probability model of the response categories (Bender & Grouven, 1998). This study illustrates one use of this type of modeling and thus has implications for future studies where such modeling may be called for.

Implications for Future Research on Aspirations

Status Attainment Perspective

The development and realization of educational aspirations has long been of interest to sociologists and usually comes under the umbrella of status attainment research (Blau & Duncan, 1967; Sewell et al., 1969). According to Carter (2001), "the competing assumptions of status attainment models have focused on conceptions of individual students' aspirations and attainment being the function of social constraints or that students are individual actors able to fulfill their goals unconstrained by society" (p. 130). The study described in this dissertation provides considerable support for the latter point of view and also some support for the former. Although background factors such as race, gender, and SES have significant impact on eighth grade aspirations, this study reveals that mother's expectations, parental involvement and academic performance, particularly in the early grades, have even stronger impact, supporting some earlier work (Conklin & Dailey, 1981; Wilson & Wilson, 1992; Mau & Bikos, 2000). This study also showed that, of all the factors considered, only SES and early grades have an impact on the likelihood of membership in high versus low aspiration groups.

Theoretical conceptualizations of students' aspirations have often been constrained to examining aspirations at one time point. However, the development of aspirations can be seen as a dynamic process which begins in early childhood and continues until the end of high school. The utilization of methodologies such as hierarchical linear modeling and mixture modeling have enabled us to examine the effects of social constraints and other controllable factors not only on aspirations at one point in time, but on the growth trajectories measuring the change in aspirations over time. Being able to study the effect of these factors on growth trajectories instead of a measure at one point in time may have implications for status attainment theory in that it allows an examination into the process of aspiration development, not merely the end result.

Future work from this perspective can include more specific studies that focus on why status attainment variables such as socioeconomic status become more important in the later years of high school when parental influences decline. One way to do this would be to conduct more precise studies with subpopulations from the population considered in this study, for example, students with low socioeconomic status.

College Choice Perspective

In addition to status attainment research, college choice research also looks at how traditional-age students go about realizing their educational aspirations. This study used the Hossler and Stage (1992) model of predisposition to attend college as part of the theoretical framework. Research on predisposition has looked both at the correlates of predisposition and the process characteristics (timing etc.) involved in the development of predisposition toward postsecondary education. This study sought to examine both aspects. It looked at the correlates in examining which characteristics impacted student expectations. This study also examined process issues such as how stable these aspirations were and when they stabilized.

According to Hossler et al. (1989), a predisposition toward postsecondary education is an “evolving process that proceeds at differential rates for different students” (p. 262). Findings from prior research regarding the certainty of when the student plans to attend college are contradictory. Some researchers have found that student educational plans are well-formed by the ninth grade (Hossler & Stage, 1987; Yeung & Yeung, 2001; NH PAPER, 2003), while others conclude that these plans are not fully formed until the tenth grade or later (Parish, 1979; Stewart et al., as cited in Hossler et al., 1999).

Results from this study support the former view and may have implications for the predisposition stage of the Hossler and Gallagher (1987) theoretical model. Results indicate that students' educational aspirations may be well-formed even earlier than has been hypothesized in many earlier studies. Most students seem to have formed educational aspirations by the eighth grade, perhaps even sooner, and these remain fairly stable until the twelfth grade. This suggests that the predisposition stage may be well underway even before students enter high school, and that aspirations remain stable through high school. These results are consistent with those from a more recent study by the New Hampshire Partnership for the Advancement of Postsecondary Education Research (2003) which reported that 55 to 80 percent of students said that they made their decision to pursue a postsecondary education in the sixth grade or earlier.

The Effects of Parental Support

One of the findings of this study, consistent with other past studies (Wilson & Wilson, 1992; Hossler et al., 1999) was that parental expectations and involvement have significant impact on students' eighth grade aspirations. Mother's expectations were also found to be positively associated with aspirations at each time point. Khattab (2002) defines social capital to refer to "family resources that consist of the social relations and interactions which facilitate a certain channeling of information, support, expectations and knowledge" (p. 78). Recent studies in educational aspirations have brought out the role of social capital, as a family resource, in shaping students' aspirations (Khattab, 2002). In families where social relationship ties are strong, students are more likely to adopt their parents' values, norms and expectations, and if parents from these families emphasize the importance of education, then their children are likely to have higher aspirations regardless of other background factors such as race (Schneider & Stevenson, 1999; Khattab, 2002).

However, this study revealed that average parental expectations and involvement do not have significant effects on the number of postsecondary applications filed, while socioeconomic status, which takes into account parental education and income, does have an effect. Thus, while parental encouragement is significant early on in the college choice process, lower levels of income and parental education ultimately do have a constraining effect on the realization of student aspirations. This result directly supports Hossler et al.'s (1999) conclusion that parental support seems to be the most important factor in the development of educational aspirations, but that some of the more traditional status-attainment variables such as SES and student academic performance emerge to play important roles in students' ability to actualize their plans.

Hossler et al. (1999) found that during the junior and senior years, students move from relying on internal sources of information and influence, such as parents, to external sources, such as peers and teachers. This shift beyond the family could be one reason why parental expectations and involvement do not have a strong impact on the number of applications filed.

Adolescence is a time for young people to define their place in the family, in peer groups, and in the larger community. At this stage of their lives, youth often struggle with the transition from childhood to adulthood. During childhood, they depended mainly on their parents for economic and emotional support and direction, while as adults they are expected to achieve independence and make choices about school, work, and personal relationships that will affect every aspect of their future. Adolescents find themselves moving from a family-centered world to the larger community within which they will begin to define their own identity. Part of this search for identity in the larger world may involve a recreation of the self that will allow them to survive without the day-to-day guidance of their parents. This may result in young people naturally beginning to pull away from the family and spend more time at school, with friends, or at a job. This in turn may result in resistance to parental influence in many spheres of their lives, and parental influences declining in the later years of high school when they are involved in college search and application. However, adolescents still mostly depend on their parents for material and financial support, and often require continued support if they enroll in postsecondary institutions.

Future studies could look more into the culture of adolescence to understand better the dynamics that operate during the later years of high school. In particular, qualitative studies using methods such as ethnography and case study analysis could offer insight into how adolescents go about making decisions regarding where to go to college and how to go about the process. This would also help understand more about any changes in student plans and what caused these changes.

Goal Theory and Aspirations

Psychological theories of motivation focus on the relationships of beliefs, values and goals with action (Eccles & Wigfield, 2002). Of these, goal theories focus on children's achievement goals and their relation to achievement behavior. Several different approaches to goal theory have emerged. One approach involves defining two major kinds of goal patterns: task-involved goals and ego-involved goals (Nicholls, 1984). Individuals with task-involved goals focus on mastering tasks and increasing their competence, while individuals with ego-involved goals focus on outperforming others and perform tasks they know they can do (Eccles & Wigfield, 2002). Individuals in the former group have a stronger work ethic, seek success based on self-improvement, and are generally more persistent. They are also better motivated because the factors they focus on are internal and more controllable (Woolard, 2004). Individuals in the latter group tend to give up more readily and select easier tasks. Ames (1992) has suggested that motivational climates that focus on self-improvement and skill learning promote task orientation while motivational climates that focus on comparison with peers promote ego orientation.

Task orientation would be more conducive to maintaining stable educational aspirations than would ego orientation, since it involves maintaining a desire for self-improvement and being more concerned with one's own progress rather than comparing oneself to peers and having high aspirations because ones' friends do so. The motivation for task-oriented individuals would stem from a desire to realize their full potential and the realization that higher education maybe an important step in this direction. Performing well academically and taking the necessary steps, such as filing college applications, to realize their goals would also be easier for such individuals. Future research can focus on how task versus ego orientation affects the formation and maintenance of educational aspirations, and what factors students consider are important in their continuous evaluation of the importance of education. Also, creating climates that foster task orientation rather than ego orientation can help improve the motivational level of students and result in higher educational aspirations. Future work can focus on how to go about achieving this.

Theories of Motivation and Volition

"Volition" refers to both the strength of will needed to complete a task, and the diligence of pursuit (Corno 1993). Eccles and Wigfield (2002) give an overview of psychological theories that seek to link motivation and volition. One such theory is proposed by Kuhl (1987). Kuhl opined that many motivational theorists falsely assume that motivation leads directly to outcomes, and argued that motivational processes only lead to the decision to act. Once the individual engages in action, volitional processes take over and determine whether or not the intention is fulfilled (Eccles & Wigfield, 2002). Many distracters and other opportunities can get in the way of even strong intentions to complete a task. Some of the volitional challenges students may face include trying to coordinate multiple tasks or dealing with vaguely specified goals (Corno, 1993).

In the current study, many students with high aspirations failed to actualize their desires and did not apply to postsecondary institutions at all. Applying and getting accepted to postsecondary institutions involves a series of steps (such as taking the SATs, getting letters of recommendation, writing an essay, getting good grades, etc.) none of which can be skirted around and all of which require hard work. It is conceivable that there would be many volitional challenges and distractions (getting a job etc.) that may deter students from focusing on completing all the necessary steps.

Kuhl (1987) proposed several specific volitional strategies to enable persistence in the face of distractions and other opportunities. These include (1) cognitive control strategies that help individuals stay focused on relevant information; (2) emotional control strategies that help keep negative emotional states such as anxiety and depression in check; (3) motivational control strategies that involve strengthening weak intentions against competing distractions, and (4) environmental control strategies that involve enhancing the environment to facilitate the motivational behavior.

Future research in this regard can focus on identifying the volitional challenges and distractions that students face when deciding to actualize their educational aspirations, and how to help students keep their focus on the importance of education. Once these challenges have been identified, Kuhl's (1987) strategies can be used to help students overcome these challenges and stay focused on the achievement of their dreams.

Directions for Future Research

The results of this study indicate several implications for future research in the area of educational aspirations and college choice, several of which have been listed throughout this chapter and are broadly summarized here. First, this study looked at the effects of individual student-level factors on educational aspirations. Future studies would benefit from considering the effects of school-level or neighborhood variables on student expectations. McDonough (1997) has put forth a theory of organizational habitus which suggests that organizational variables such as the counseling facilities available in a school have an effect on student college search. These may also impact student aspirations, especially for students from lower SES classes.

Second, a follow-up of the students in this study, to see what decisions they have taken on graduation, will further help understand the impact of aspirations on college choice. Attending a four-year college, a two-year college and joining the labor force are all different pathways students can take. The impact of aspirations, the other factors in this study, and the number of applications filed on the choice of one of these pathways can be a topic for future research.

Third, this study uses the number of applications as proxy to see how strategic students are in the college search process. This process is difficult to understand using only quantitative methods. Qualitative techniques such as ethnography would throw greater light into the thoughts and actions of students as they go about the college search process, and also help understand the effects of parental support and influence at this stage.

Fourth, research from goal theory or volition theory perspectives can be carried out to understand why some students succeed in maintaining high stable aspirations and actualizing their plans while others do not, and to identify the factors which students consider in their continuous evaluation of the importance of education. Future work can also focus on helping individuals identify their needs, persist with their plans, and take concrete steps toward realizing their dreams.

Summary

This dissertation describes a study of student educational aspirations over time and their relationship to the number of applications filed to postsecondary institutions. The study was guided by seven objectives that sought to describe the stability of student aspirations from the eighth grade through the twelfth, to investigate background, parental and academic factors which impact initial expectations and the stability of expectations, to identify and describe distinct clusters of aspiration trajectories, and to relate educational aspirations and the other factors to the number of college applications filed in the senior year.

Major findings of the study showed that (1) average student aspirations remained fairly stable from the eighth grade through the twelfth; (2) all the factors considered in the study with the exception of being held back affected initial student aspirations; (3) after controlling for the other factors in the study, neither gender nor race had a significant effect on the stability of students' educational aspirations; (4) seven distinct clusters of aspiration trajectories can be identified; (5) many students who had high aspirations had failed to build a wide choice set of postsecondary institutions to apply to; (6) among the factors considered, educational aspirations had the strongest impact on the number of applications filed; (7) parental expectations and involvement had effects on early student aspirations but not on the number of applications filed; (8) students who had both high and stable aspirations from the eighth grade through the twelfth generally had a wider choice set of applications than students who demonstrated a steady increase in aspirations.

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APPENDIX A

PERCENTAGE OF MISSING CASES ON EACH INDEPENDENT VARIABLE (IMPUTED USING HOT DECK METHODS)

Variable	Percentage of Missing Cases
Ever Held Back	4.54
Early Grades	0.62
Mother's Expectations (8th Grade)	10.44
Mother's Expectations (10th Grade)	8.92
Mother's Expectations (12th Grade)	13.44
Math Scores (8th Grade)	0.07
Math Scores (10th Grade)	0.18
Math Scores (12th Grade)	0.20
Parental Involvement (8th Grade)	
Discusses Programs at School	1.08
Discusses School Activities	0.90
Discusses Things Studied in Class	0.97
Parental Involvement (10th Grade)	
Discusses Programs at School	7.18
Discusses School Activities	7.30
Discusses Things Studied in Class	7.34
Parental Involvement (12th Grade)	
Discusses Programs at School	11.23
Discusses School Activities	11.41
Discusses Things Studied in Class	11.50

APPENDIX B

COMPARISON OF SAMPLE CHARACTERISTICS FOR THE STUDY SAMPLE WITH AND WITHOUT IMPUTATION

Variable	N (With Imputation)	Percent (With Imputation)	N (Without Imputation)	Percent (Without Imputation)
Gender				
Male	4837	49.17	4837	49.17
Female	5000	50.83	5000	50.83
Race				
Asian	617	6.27	617	6.27
Hispanic	1003	10.2	1003	10.2
Black	814	8.27	814	8.27
White	7403	75.26	7403	75.26
Ever Held Back				
No	8823	89.69	8431	85.71
Yes	1014	10.31	959	9.75

APPENDIX C

COMPARISON OF DESCRIPTIVE STATISTICS FOR THE STUDY SAMPLE WITH AND WITHOUT IMPUTATION

Variable	Mean (With Imputation)	S.D. (With Imputation)	Mean (Without Imputation)	S.D. (Without Imputation)
SES	0.13	0.78	0.13	0.78
Early Grades	3.10	0.68	3.10	0.68
Mother's Expectations				
Eighth	5.01	0.96	5.00	0.96
Tenth	4.88	0.96	4.88	0.96
Twelfth	5.03	1.06	5.04	1.05
Math Scores				
Eighth	53.35	10.16	53.35	10.16
Tenth	53.21	9.58	53.21	9.58
Twelfth	52.99	9.55	52.99	9.55
Parental Involvement				
Discussed School Courses				
Eighth	2.32	0.66	2.32	0.66
Tenth	2.08	0.59	2.08	0.59
Twelfth	1.92	0.63	1.92	0.62
Discussed School Activities				
Eighth	2.57	0.61	2.57	0.61
Tenth	2.12	0.65	2.12	0.65
Twelfth	2.05	0.68	2.06	0.68
Discussed Things Studied in Class				
Eighth	2.47	0.66	2.47	0.66
Tenth	2.05	0.62	2.05	0.62
Twelfth	2.01	0.63	2.02	0.63

APPENDIX D

RELEVANT SAS CODE FOR HIERARCHICAL LINEAR MODELING USING PROC MIXED

```
LIBNAME N2P 'C:\ECBW\N2P';

DATA X1;INFILE 'E:\NELS92\STMEG.PUB' LRECL=1024 PAD;INPUT ID 1-7
  BYS36A 133-133 BYS36B 134-134 BYS36C 135-135 BYS45 174-175
  BYS48A 178-179 BYS48B 180-181 BYS74 310-310 BYTXFLG 389-389
  BYGRADS 464-465 .1  BY2XMSTD 487-490 .2  F1S48A 897-898
  F1S48B 899-900 F1S49 901-902 /  F1S105A 184-184
  F1S105B 185-185 F1S105C 186-186 F1TXFLG 239-239
  F12XMSTD 320-323 .2  F2S42A 765-766 F2S42B 767-768
  F2S43 769-770 F2S60A 877-877 /  F2S99A 28-28 F2S99B 29-29
  F2S99C 30-30 F2PNLWT 207-216 .4  F2TXFLG 268-268
  F2PNLFLG 271-271 F2SEX 294-294 F2RACE1 295-295
  F2SES1 302-306 .3  F22XMSTD 355-358 .2  F2RTROUT 572-573
  / / / / / / ;

data x2; set x1;
if F2PNLFLG ne 1 then delete;
if F2RTROUT GE 4 then delete;
if F2RACE1 in (5,8) then delete;
if BYTXFLG ne 1 then delete;
if F1TXFLG ne 1 then delete;
if F2TXFLG ne 1 then delete;
*if BY2XMSTD = '.' then delete;
*if F12XMSTD = '.' then delete;
*if BYS48B = 98 then BYS48B = '.';

data reco; set all;
normwt =9837*F2PNLWT/1566113.3;
meanSES = 0.1275;
meanGRAD = 3.0972;
cSES= F2SES1 - meanSES;
cGRADS = BYGRADS - meanGRAD;
if F2SEX = 1 then F2SEX = 0;
if F2SEX=2 then F2SEX = 1;
if BYS74 = 1 then BYS74 = 0;
if BYS74=2 then BYS74=1;
if F2RACE1 = 1 then F2RACE1 = 0;
if F2RACE1 = 2 then F2RACE1 = 1;
if F2RACE1 = 3 then F2RACE1 = 2;
if F2RACE1 = 4 then F2RACE1 = 3;
```

```
data reco2; set reco;
mnmath = (BY2XMSTD+F12XMSTD+F22XMSTD)/3;
mnmexpec = (mexpec8+mexpec10+mexpec12)/3;
mnparinv = (parinv8+parinv10+parinv12)/3;
cmath8 = BY2XMSTD-mnmath;
cmath10 = F12XMSTD - mnmath;
cmath12 = F22XMSTD-mnmath;
cmexpec8 = mexpec8-mnmexpec;
cmexpec10=mexpec10-mnmexpec;
cmexpec12=mexpec12-mnmexpec;
cparinv8 = parinv8-mnparinv;
cparinv10=parinv10-mnparinv;
cparinv12=parinv12-mnparinv;

data X3; set newanal;
  time=1; t=time; asp=eighth; mexpec=mexpec8;
            parinv=parinv8; math=BY2XMSTD; output;
  time=2; t=time; asp=tenth; mexpec=mexpec10;
            parinv=parinv10; math=F12XMSTD; output;
  time=3; t=time; asp=twelfth; mexpec=mexpec12;
            parinv=parinv8; math=F22XMSTD; output;
run;

proc mixed data=X3 method =ml noclprint covtest;
class ID;
model asp=  /s ddfm=bw solution;
random intercept /type=un sub=ID g;
weight normwt;
title2 "Unconditional Means Model- Model A";
run;

proc mixed data=X3 method =ml noclprint covtest;
class ID;
model asp=time /s ddfm=bw solution;
random intercept time /type=un sub=ID g;
weight normwt;
title2 "Unconditional Growth Model - Model B";
run;

proc mixed data=X3 method =ml noclprint covtest;
class ID F2SEX F2RACE1 BYS74;
model asp=time F2SEX F2RACE1 cSES cGRADS BYS74 F2SEX*time F2RACE1*
time cSES*time cGRADS*time BYS74*time/s ddfm=bw solution;
random intercept time /type=un sub=ID g;
weight normwt;
title2 "Model with all Time-Invariant Predictors - Model C";
```

```
run;

proc mixed data=X3 method =ml noclprint covtest;
class ID F2SEX F2RACE1 BYS74;
model asp=time mnmexpec cmexpec mnparinv cparinv mnmath cmath /s ddfm=bw
solution;
random intercept time cmexpec cparinv cmath/type=un sub=ID g;
weight normwt;
title2 " Model With Time-Varying Effects only - Model D";
run;

proc mixed data=X3 method =ml noclprint covtest;
class ID F2SEX F2RACE1 BYS74;
model asp=time mnmexpec mnparinv mnmath cmexpec cparinv cmath F2SEX
F2RACE1 cSES cGRADS BYS74 F2SEX*time F2RACE1* time cSES*time
         cGRADS*time BYS74*time F2SEX*cmexpec F2RACE1* cmexpec
         cSES*cmexpec cGRADS*cmexpec BYS74*cmexpec F2SEX*cparinv
         F2RACE1* cparinv  cSES*cparinv cGRADS*cparinv BYS74*cparinv
         F2SEX*cmath F2RACE1* cmath cSES*cmath cGRADS*cmath BYS74*cmath /s
        ddfm=bw solution;
random intercept time cmexpec cparinv cmath/type=un sub=ID g;
weight normwt;
title2 " Model With All Time-Stable and Time-Varying Covariates: Model E";
run;
```

APPENDIX E

RELEVANT SAS CODE FOR MIXTURE MODELING USING SAS PROC TRAJ

```
DATA X1;INFILE 'D:\NELS92\STMEG.PUB' LRECL=1024 PAD;INPUT ID 1-7
  BYS36A 133-133 BYS36B 134-134 BYS36C 135-135 BYS45 174-175
  BYS48A 178-179 BYS48B 180-181 BYS74 310-310 BYTXFLG 389-389
  BYGRADS 464-465 .1  BY2XMSTD 487-490 .2  F1S48A 897-898
  F1S48B 899-900 F1S49 901-902 /  F1S105A 184-184
  F1S105B 185-185 F1S105C 186-186 F1TXFLG 239-239
  F12XMSTD 320-323 .2  F2S42A 765-766 F2S42B 767-768
  F2S43 769-770 F2S60A 877-877 /  F2S99A 28-28 F2S99B 29-29
  F2S99C 30-30 F2PNLWT 207-216 .4  F2TXFLG 268-268
  F2PNLFLG 271-271 F2SEX 294-294 F2RACE1 295-295
  F2SES1 302-306 .3  F22XMSTD 355-358 .2  F2RTROUT 572-573
  / / / / / / ;

data reco; set all;
normwt =9837*F2PNLWT/1566113.3;
meanSES = 0.1275;
meanGRAD = 3.0972;
cSES= F2SES1 - meanSES;
cGRADS = BYGRADS - meanGRAD;
if F2SEX = 1 then F2SEX = 0;
if F2SEX=2 then F2SEX = 1;
if BYS74 = 1 then BYS74 = 0;
if BYS74=2 then BYS74=1;
if F2RACE1 = 1 then F2RACE1 = 0;
if F2RACE1 = 2 then F2RACE1 = 1;
if F2RACE1 = 3 then F2RACE1 = 2;
if F2RACE1 = 4 then F2RACE1 = 3;
parinv8= (BYS36B + BYS36A + BYS36C)/3;
parinv10= (F1S105A + F1S105B + F1S105C)/3;
parinv12 = (F2S99A + F2S99B + F2S99C)/3;

data reco2; set reco;
mnmath = (BY2XMSTD+F12XMSTD+F22XMSTD)/3;
mnmexpec = (mexpec8+mexpec10+mexpec12)/3;
mnparinv = (parinv8+parinv10+parinv12)/3;
cmath8 = BY2XMSTD-mnmath;
cmath10 = F12XMSTD - mnmath;
cmath12 = F22XMSTD-mnmath;
cmexpec8 = mexpec8-mnmexpec;
cmexpec10=mexpec10-mnmexpec;
cmexpec12=mexpec12-mnmexpec;
cparinv8 = parinv8-mnparinv;
```

```
cparinv10=parinv10-mnparinv;
cparinv12=parinv12-mnparinv;
t1=8;
t2=10;
t3=12;

proc traj data=reco2;
var eighth tenth twelfth;
indep t1 t2 t3;
model cnorm;
ngroups 7;
max 6;
order 1 1 1 1 1 1 1 ;
risk F2SEX Asian Hispanic Black cSES cGRADS BYS74 mnmexpec mnparinv mnmath
;
weight normwt;
run;

 %trajplot (OP,OS,"Aspiration Trajectories",,"Aspiration", "Time");
```

APPENDIX F

RELEVANT SAS CODE FOR A PARTIAL PROPORTIONAL ODDS MODEL USING PROC GENMOD

```
LIBNAME N2P 'C:\ECBW\N2P';
libname perma 'C:\Documents and Settings\blotto\My Documents\My SAS Files\V8';

DATA X1;INFILE 'D:\NELS92\STMEG.PUB' LRECL=1024 PAD;INPUT ID 1-7
  BYS36A 133-133 BYS36B 134-134 BYS36C 135-135 BYS45 174-175
  BYS48A 178-179 BYS48B 180-181 BYS74 310-310 BYTXFLG 389-389
  BYGRADS 464-465 .1  BY2XMSTD 487-490 .2  F1S48A 897-898
  F1S48B 899-900 F1S49 901-902 /  F1S105A 184-184
  F1S105B 185-185 F1S105C 186-186 F1TXFLG 239-239
  F12XMSTD 320-323 .2  F2S42A 765-766 F2S42B 767-768
  F2S43 769-770 F2S60A 877-877 /  F2S99A 28-28 F2S99B 29-29
  F2S99C 30-30 F2PNLWT 207-216 .4  F2TXFLG 268-268
  F2PNLFLG 271-271 F2SEX 294-294 F2RACE1 295-295
  F2SES1 302-306 .3  F22XMSTD 355-358 .2  F2RTROUT 572-573
  / / / / / / ;

data x2; set x1;
if F2PNLFLG ne 1 then delete;
if F2RTROUT GE 4 then delete;
if F2RTROUT = '.' then delete;
if BYTXFLG ne 1 then delete ;
if F1TXFLG ne 1 then delete;
if F2TXFLG ne 1 then delete;
if F2RACE1 in (5,8) then delete;

data reco; set all;
normwt =9837*F2PNLWT/1566113.3;
meanSES = 0.1275;
meanGRAD = 3.0972;
cSES= F2SES1 - meanSES;
cGRADS = BYGRADS - meanGRAD;
if F2SEX = 1 then F2SEX = 0;
if F2SEX=2 then F2SEX = 1;
if BYS74 = 1 then BYS74 = 0;
if BYS74=2 then BYS74=1;
if F2RACE1 = 1 then F2RACE1 = 0;
if F2RACE1 = 2 then F2RACE1 = 1;
if F2RACE1 = 3 then F2RACE1 = 2;
if F2RACE1 = 4 then F2RACE1 = 3;
```

```
if F2S60A in (6,7,8,9) then delete;
if F2S60A=0 then apply=0;
if F2S60A=1 then apply=1;
if F2S60A=2 then apply=2;
if F2S60A=3 then apply=2;

data none; set groups; if apply = 0;
data ones; set groups; if apply = 1;
data more; set groups; if apply = 2;
data groups3; set groups;
if apply = 0 then apply1 = 2;
if apply = 1 then apply1 = 1;
if apply = 2 then apply1 = 0;

data newall; set groups3;
aspir=eighth+tenth+twelfth;
mother = mexpec8+mexpec10+mexpec12;
parent = parinv8+parinv10+parinv12;
mathsc = BY2XMSTD + F12XMSTD + F22XMSTD;
aspi = aspir/3;
mothere=mother/3;
parenti=parent/3;
mathsco=mathsc/3;

data newall3; set newall;
    do;  if apply=2 then presp =1;
    else presp=0; logtype=2; output; end;
    do; if apply=2 or apply=1 then presp=1;
    else presp=0; logtype=1 ; output; end;
run;

proc genmod data=newall3 descending;
    class id logtype F2SEX F2RACE1 BYS74;
            output out=out2 stdreschi=stresid reschi=resc resdev=resd predicted=pre;
model presp = F2SEX F2RACE1 F2SES1 BYS74 BYGRADS aspi mothere parenti
                mathsco logtype logtype*F2SEX logtype*F2RACE1 logtype*mathsco/
                link=logit dist=bin type3;
                repeated subject=id/type=unstr;
                weight normwt;
title "Partial Proportional Odds Model-All Main Effects";
run;
```

VITA

Aruna Lakshmanan obtained Bachelor of Science and Master of Science degrees in mathematics from the University of Madras in India. She then attended Louisiana State University at Baton Rouge, where she received a Master of Arts degree in mathematics education in 1996, followed by a Master of Applied Statistics degree in 1999. She will be awarded a Doctor of Philosophy degree in educational leadership and research at the spring commencement in 2004.

While at Louisiana State University, Aruna was appointed as a graduate assistant. Her work involved teaching freshman mathematics as well as assisting several faculty members with a variety of research projects, particularly with statistical analyses. She also served as editorial assistant for the Journal of Personnel Evaluation in Education. Aruna also worked as an intern at the Louisiana Department of Environmental Quality, where she conducted SAS training for the employees and worked on a large national project on air pollution. From 1999 to 2001, Aruna worked as a research statistician at Kraft Foods in Glenview, Illinois. During this time, she was an internal consultant and supported several divisions at Kraft, including Research and Development, Marketing, and Operations. She also developed and delivered several statistics training modules for a wide variety of employees at Kraft.

While working on her dissertation, Aruna was awarded a dissertation grant by the American Educational Research Association. Her dissertation proposal was also awarded the Charles I. Brown fellowship for the outstanding dissertation proposal of the year by the Association for Institutional Research. She was also selected and funded to attend a database training seminal for the NELS:88 data by the National Center for Educational Statistics.

Aruna has published several articles in refereed journals and presented papers at various annual meetings of regional and national professional organizations. She is a member of the American Statistical Association, the American Educational Research Association, and the Association for Institutional Research. She plans to continue to remain active in educational research. As a first step, she will work on several research questions that emerged from her dissertation. Aruna will also be working on analytical projects at the Office of Institutional Research at the University of North Carolina at Wilmington.