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Comparison of Event History Analysis and Latent Growth Modeling for College Student Perseverance

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COMPARISON OF EVENT HISTORY ANALYSIS AND LATENT GROWTH MODELING FOR COLLEGE STUDENT PERSEVERANCE

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

by
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Abstract

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Event history analysis is the most prevalent modeling technique used to model event occurrence with longitudinal data (Cox & Oakes, 1984; Menard, 1991; Singer & Willett, 1993, 2003). An alternative is to model longitudinal data within the SEM framework, known as latent variable growth modeling (McArdle, 1988; Meredith & Tisak, 1990), which can provide a more robust framework. Whether or not a student remains in college presents an appropriate context within which to examine the modeling of event occurrence with longitudinal data. The purpose of the study was to compare event history and latent growth modeling as for predicting change in college student perseverance, with college student persistence literature serving as the framework. Students are defined as having persevered if they have earned hours and the end of the semester rather than if they are enrolled at the beginning of the semester, which is the traditional definition of persistence.

The population for the study was the 2001 and 2002 cohorts of first-time, full-time freshmen at a large mid-Atlantic urban research university. Stopouts and transfer students were excluded. Data was analyzed for the first five semesters for each cohort. The results showed that parameter estimates were quite consistent across model type and time frame and were mostly consistent with previous research. No one method outperformed the others in terms of predicting correct classification. Using event history analysis with the structural equation modeling framework, however, appeared to be a very promising alternative to event history analysis with logistic regression since one can model error term and examine the differential effects of predictors at each time period. Finally, while latent growth modeling did not outperform the other methods in predictive classification, the study demonstrated it can be used for event occurrence analysis to test more complex theories.

Chapter 1

Introduction

One of the goals of research is to be able to make claims about causation. While research can never be definitive, certain methodologies and techniques can provide stronger evidence and greater confidence that causal claims may be warranted (Asher, 1983; Finkel, 1995). The analysis of longitudinal data is one method to strengthen claims about causation. Another method to strengthen claims about causality is to model longitudinal data within a structural equation modeling (SEM) framework (Chan, 2001a; Duncan *et al.*, 1999; McArdle, 1988; Meredith & Tisak, 1990; Willett & Sayer, 1994). Whether or not a student remains in college presents an appropriate context within which to examine the modeling of event occurrence with longitudinal data.

Rationale for the Study

Cross-sectional data analysis is the predominant methodology in studies on whether or not a student remains in college (Cabrera *et al.*, 1993; Chen, 2005; Murtaugh *et al.*, 1999; Pascarella & Chapman, 1983; Pritchard & Wilson, 2003), though longitudinal designs are being conducted (DesJardins *et al.*, 1999, 2002b; Ishitani & DesJardins, 2002-2003). With cross-sectional data, researchers can describe why students do not remain in college at that given point in time, but they are left to generalize that the same description applies to a student's change in status over time. In order to model change, researchers need longitudinal data (Singer & Willett, 2003). Event history analysis is the predominant statistical technique used to model event occurrence with longitudinal data (Allison, 1984; Cox & Oakes, 1984; Menard, 1991; Singer & Willett, 1993, 2003; Wright, 2000). An alternative technique is to model longitudinal data within the SEM framework, known as latent variable growth modeling (McArdle, 1988; Meredith & Tisak, 1990), which provides a robust framework for testing hypotheses and supporting claims of causality.

Most studies on whether or not a student remains in college have used enrollment at the beginning of a given semester as the dependent variable, which is the traditional definition of student persistence. This dependent variable for this study is earned hours, which indicates whether the student successfully completed course work, i.e., persevered through the semester. Using earned hours more appropriately matches event occurrence with the semester the student did not remain in college. The purpose of the study was to compare event history analysis and latent growth modeling as statistical techniques for predicting change in college student perseverance, with college student persistence literature serving as the framework.

Review of the Literature

Student persistence presents an ideal circumstance within which to examine the longitudinal modeling of change. Lancaster (1990) points out the when studying whether or not a student remains in college, we are making inferences about individuals' choices, but observing the "movement of persons between states" (p. 5), or the change in states. Singer and Willett (2003) point out that researchers make leaps from cross-sectional data that describe differences among individuals at a given point in time to making generalizations about change in individuals over time. The interesting question is not, what are the predictors of whether or not the student is enrolled at a given point in time, but rather what are the predictors of whether or not students are enrolled over time? Event history analysis and latent growth modeling are ideal techniques to address research questions in student perseverance. The following review will discuss the conditions for causality, provide an overview of event history analysis and latent growth modeling, and conclude with a brief discussion the current state of research in college student persistence.

Causality

For a causal effect to exist from variable X to variable Y, the following well-known conditions must be met (Menard, 1991): (a) X and Y must covary; (b) X must precede Y in time; and (c) the relationship must not be produced by X and Y's join association with a third variable. Longitudinal data offer multiple ways of strengthening the causal inference process, including estimating models that contain a variety of lag specifications, reciprocal effects, and imperfectly measured variables (Finkel, 1995). Finkel (1995) also indicates that the process of causal inference should be undertaken by attempting to reject other plausible models, including those with no causal effects and those that test direct causal hypotheses. Asher (1983) states that poor theory is more likely to confound analysis than technical mistakes in building the model.

Event History Analysis

Singer and Willett (2003) state that there are three methodological characteristics of event history analysis: 1) a target event in which an individual transition from one "state" to another "state"; 2) in the first time period no one under study has yet experienced the target event; and 3) a metric for measuring the time in which event occurrence is recorded. The timing of the events can occur in either discrete- or continuous-time. In discrete-time, the periods under study are longer in duration and there are many subjects who experience the event in the same period, such as looking at student persistence by semester.

The unit of measure used to assess the risk of an event occurring within a discrete time period is known as hazard. Denoted by $h(t_{ij})$, discrete-time hazard is the conditional probability that individual *i* will experience the event in time period *j*, given that the individual did not experience it in an earlier time period. It is conditional in the sense that once the event is experienced, it cannot be experienced again. To build a statistical model that represents the relationship between the hazard function and predictors, a logit transformation is employed (Cox & Oakes, 1984; Singer & Willett, 2003).

Event history analysis represents an appropriate statistical technique for modeling change in a dichotomous outcome over time. The technique can analyze longitudinal data, accommodate time-invariant and time-varying predictors, and be estimated using maximum likelihood logistic regression routines (Singer & Willett, 1993). In addition, residual variance (error) can be modeled with certain event history analysis procedures (L. K. Muthen & Muthen, 2006).

Latent Growth Modeling

Latent growth modeling (LGM) analyzes intra- and inter-individual change over time within the structural equation modeling (SEM) framework (McArdle, 1988; Meredith & Tisak, 1990). SEM can be thought of in simplest terms as a combination of regression and factor analysis and most models use maximum likelihood to determine the estimates. In latent growth models, the slope and intercept are latent variables used to estimate the outcome measure (event) in each time period under study.

Two of the strengths of the SEM framework are its ability to model error and test other plausible models. SEM can explicitly model the error terms, which allows a variety of *a priori* error covariance structures to be modeled, such as heteroscedasticity and different forms of correlated error (Chan, 2001a). A persuasive case that a model has been correctly specified can be made when there is a differentially better fit of a given model compared to the fit of numerous other plausible models (Thompson, 2000).

LGM represents an appropriate statistical technique for modeling change in an outcome (either continuous or dichotomous) over time. Chan (2001a) lists two of the strengths of LGM as the ability to enhance the explanatory power of nonexperimental data by testing and ruling out alternative models and assess a variety of structural relationships. The structural portion of the SEM model can be changed to test rival hypotheses in ways that event history analysis cannot.

Student Persistence

A variety of statistical models have been used in student persistence research, including path analysis (Braxton *et al.*, 1988b; Pascarella & Chapman, 1983), structural equation modeling (Cabrera et al., 1993), logistic regression (Chen, 2005), and event history analysis (DesJardins et al., 1999; Zhang & RiCharde, 1998). Most of the studies have either tested or expanded on Tinto's (1975, 1993) model of student integration, which looks at family background, individual attributes, goal commitment and integration within the institution as determinants of a student's decision to dropout or persist. Recent studies (Cabrera et al., 1993; Hagedorn, 2006; Herzog, 2005; Murtaugh et al., 1999; Tinto, 2006) have incorporated family and friend influences and institutional characteristics into modeling a student's intent to persist. With the exception of event history analyses, the previously mentioned studies have used cross-sectional data.

Research Questions

The study was guided by the following questions.

1. Does the best statistical technique vary depending on the time frame of perseverance under study, e.g., into the 3rd, 4th, or 5th semester?
2. Which statistical technique provides the best predictions of the change from student perseverance to non-perseverance?

3. Are the predictors and parameter estimates of student perseverance different between techniques?
4. What are the distinct advantages and disadvantages of each technique with regard to data requirements, assumptions, ease of use, and interpretation?

The hypothesis was that latent growth modeling will provide more accurate prediction and better model fit of the change from student perseverance to non-perseverance.

Methodology

The purpose of this study was to compare and contrast two statistical techniques for modeling change with a dichotomous outcome using longitudinal data – event history analysis and latent growth modeling.

Population

The population for the study was the 2001 and 2002 cohorts of first-time, full-time freshmen at a large mid-Atlantic urban research university. Data were available for the first five semesters for each cohort and the total sample size before exclusion for stopouts (students who left the university and later returned or attended another university) is 5,689. A random sample of 25 percent students was selected as a hold out group for out of sample model evaluation. Data was provided by the university's Institutional Research department. The specific cases and variables in the data set provided to the researcher were collected as part of an internal study on the effects of financial aid on student perseverance.

Variables

The independent variables included gender, ethnicity, high school GPA, SAT verbal and math scores, whether or not the student took a remedial math course, semester GPA, financial aid, on campus housing, undeclared versus declared major. The dependent variable in the study was student perseverance. Perseverance in each semester was determined by whether or not the student had earned semester hours, i.e., successfully completed at least one class that semester.

Data Analysis

Event history analysis was conducted using a discrete-time hazard model estimated by logistic regression as suggested by Singer and Willett (2003) and also maximum likelihood with modeling of residual variance (L. K. Muthen & Muthen, 2006). Latent growth modeling was conducted using Mplus (L. K. Muthen & Muthen, 2006). For each technique, a “best” model was selected based upon measures of model fit, predictive classification, and theoretical reasonableness of parameter estimates. The parameters for the independent variables were then used to estimate the dependent values for the hold out sample. The two techniques were compared based on measures of model fit, predictive classification, and theoretical reasonableness of parameter estimates.

Summary

The purpose of the study was to compare event history analysis and latent growth modeling for predicting college student perseverance. In essence, this study examines the use of LGM, which is more commonly used with continuous dependent variables, within the discrete-time hazard context. Future research implications include examining parameter differences in gender, ethnicity, or academic major and investigating if the methodology is applicable to similar issues such as teacher retention or high school drop out rates.

Chapter 2

Review of Literature

Whether or not a student remains in college presents an ideal framework to model event occurrence with longitudinal data. Investigation into the factors that affect whether or not a student remains in college is not a new area of research (Astin, 1975; Bean, 1980; Braxton *et al.*, 1988a; Cabrera et al., 1993; DesJardins et al., 1999; Hagedorn, 2006; Herzog, 2005; Seidman, 2005; Spady, 1971; Tinto, 1975). With the exception of a few studies using event history analyses (DesJardins et al., 1999), most studies have used cross-sectional data (Braxton et al., 1988b; Cabrera et al., 1993; Chen, 2005; Pascarella & Chapman, 1983; Wohlgemuth *et al.*, 2006). With cross-sectional data, researchers can describe why students are no longer in college at one point in time, but that same description is not necessarily applicable to a student's *change* in status over time.

In order to model change, researchers need longitudinal data. Singer and Willett (2003) point out that too many empirical researchers go from drawing conclusions from cross-sectional data that describe differences among individuals at a given point in time to making generalizations about change in individuals over time. They go on to state that although change is a compelling explanation of this situation – and that it might even be the true explanation – cross-sectional data cannot confirm this possibility because there are equally valid and competing explanations. Statistical methodologies for longitudinal modeling of discrete outcomes have become widely available and accessible to the research community.

Event history analysis, and more specifically hazard modeling, is the predominant statistical technique used to model event occurrence with longitudinal data (Allison, 1984; Cox & Oakes, 1984; Menard, 1991; Singer & Willett, 1993, 2003; Wright, 2000). Two of the drawbacks of event history analysis are that it is uncommon to find procedures that can model residual variance, and those that do are limited, and the predictor variables cannot be temporally ordered, i.e., all variables are in the model simultaneously. Modeling longitudinal data within the SEM framework, known as latent variable growth modeling (McArdle, 1988; Meredith & Tisak, 1990), provides a framework for modeling residual variance, testing hypotheses for structural relationship between latent variables, and supporting claims of causality.

The following review will first address causality, and then briefly path analysis and logistic regression as static statistical techniques for modeling discrete outcomes. The next section will then provide an in-depth look at two dynamic statistical techniques: event history analysis and latent growth modeling. The final section will briefly examine modeling results in the student persistence framework.

Causality

For a causal effect to exist from variable X to variable Y, the following well-known conditions must be met (Menard, 1991): (a) X and Y must covary (nonzero bivariate correlation); (b) X must temporally precede Y; and (c) the relationship must not be "spurious," or produced by X and Y's join association with a third variable. Cross-sectional data can provide evidence regarding covariation, but the same can not be said for providing evidence regarding temporality or nonspuriousness. In addition, the capability to specify models that correct for measurement error is limited (Finkel, 1995). In cross-sectional analyses, the measurement of variables at a given point in time makes it difficult to establish temporal order, and therefore to rule out the possibility that Y might not be causing X, or that there is a reciprocal causal relationship. Nonrecursive causal models, which permit reciprocal relationships among variables, allow the researcher to determine which reciprocal link is stronger. In instances where reciprocal causality is suspected, longitudinal analysis can estimate nonrecursive models with feedback effects between variables with fewer restrictive assumptions than in the cross-sectional case (Finkel, 1995). Whereas spurious association in cross-sectional analysis only can be tested by including outside variables in the model, in longitudinal studies certain patterns of spuriousness caused by unmeasured factors may also be tested against the data, in addition to allowing for estimation of measurement error (Finkel, 1995).

Asher (1983) points out that researchers should not build models solely on the basis of statistical results and devoid of theoretical underpinnings. The researcher makes inferences that a causal relationship exists on the basis of patterns observed in the data *and* with theoretical assumptions made about the relationships among one's variables. The process of causal inference should not, then, be a simple matter of specifying and testing the effects that one wants to prove; rather it should move forward by attempting to reject other plausible models, including those with no causal effects and those that test direct causal hypotheses (Finkel, 1995).

Longitudinal data offer multiple ways of strengthening the causal inference process, including estimating models that contain a variety of lag specifications, reciprocal effects, and imperfectly measured variables (Finkel, 1995). Finkel (1995) states that the most important feature of longitudinal studies is that, in contrast to static cross-sectional analyses, change is explicitly incorporated into the design so the individual changes are directly measured. At the same time, however, it should be emphasized that statistical models using longitudinal data are not the "silver bullet" for the issues of causal inference. Singer and Willett (2003) remind us that

> statistical models are mathematical representation of population behavior; they describe salient features of the hypothesized process of interest among individuals in the target population. When you use a particular statistical model to analyze a particular set of data, you implicitly declare that this population model gave rise to these sample data. Statistical models are not statements about sample behavior; they are statements about the population process that generated the data. (p. 46)

Asher (1983) argues that if casual analysis goes astray, it will more likely be due to poor execution of the earlier steps in the research rather than to any misuse of the statistical techniques, which he considers relatively straightforward and easily learned. Asher goes on to say that poor theory and unsatisfactory operational definitions are more likely to confound analysis than technical mistakes in building the model.

Static Statistical Techniques

The following sections briefly discuss path analysis and logistic regression techniques. A discussion is included as both these techniques have been widely used in the literature. Examining the limitations of these techniques for modeling change helps set the stage for the subsequent discussion of dynamic models.

Path Analysis

Path analysis allows researchers to test a theory of causal order among a set of variables, and is an extension and specific application of multiple regression (Klem, 1995; Mertler & Vannatta, 2005). Path analyses are recursive (unidirectional) and can be represented by path diagrams (see Figure 1). Path

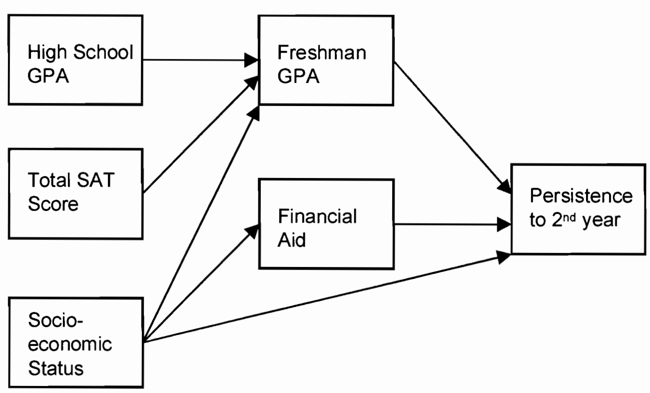

Figure 1: Hypothetical Path Analysis

analysis tests that the proposed model is consistent with the observed data. If the model is not consistent with the observed data, the model can be rejected as being unlikely. Conversely, if the model and data are consistent, the model can be considered. Since different models can be consistent with the same observed data, one cannot prove whether a path analysis model is the correct one (Klem, 1995).

One of the main advantages to path analysis is that it enables the measurement of both the direct and indirect effect that one variable has on another (Asher, 1983). Direct effects of one variable on another are estimated by regression coefficients, while indirect effects are estimated by all the indirect routes (compound paths) by which influence can flow from one variable to another. These path coefficients are comparable to standardized coefficients from multiple regression (Agresti & Finlay, 1997) and their interpretation is similar (Asher, 1983). Model fit can be evaluated by comparing the average of the absolute values of all of the differences between the implied correlation (calculated by summing the direct, indirect, spurious, and unanalyzed effects) with corresponding observed correlation (Klem, 1995).

While path analysis can account for temporal order in specifying the causal path, it is limited in two ways: 1) recursive nature; and 2) cross-sectional data structure. Path analysis can also be considered a special case of structural equation modeling, which can help address the first of the aforementioned limitations. Three issues, however, still exist: 1) latent variables with a single indicator are still considered to be measured without error, which is typically an unrealistic assumption (Pedhazur & Schmelkin, 1991); 2) most commercially available software packages require that the outcome latent variable be continuous; and 3) cross-sectional data structure does not allow the study of change. The first issue can be resolved with multiple indicators for the latent variable, if they are available and make theoretical sense, within a structural equation model framework where error can be modeled. The second issue is being addressed by some commercially available packages (L. K. Muthen & Muthen, 2006) that incorporate latent modeling of dichotomous outcomes. The third issue can only be addressed with longitudinal data in order to be able to model change.

Logistic Regression

In logistic regression, the dependent variable is dichotomous, or binary, and attempts to predict the probability that an observation belongs to each of two mutually exclusive groups. As an example, Chen (2005) used logistic regression to study how demographics, admission test scores, undergraduate GPA, medical school GPA, course grades, and financial aid support predicted whether or not students passed the U. S. Medical Licensure Examination. Unlike multiple regression, logistic regression has no assumptions about the distributions of the predictor variables. In other words, the predictors do not have to be normally distributed, linearly related, or have equal variances within each group (Mertler & Vannatta, 2005). These unrestrictive assumptions, along with a better understanding of how to interpret the results, have made the technique popular and available to a broader range of researchers (Agresti, 1996; Hosmer & Lemeshow, 2000; Menard, 2002). Osborne (2006), however, does caution, however, that many researchers still do not appropriately interpret the output of logistic regression by confusing probability and odds.

In logistic regression, the relationship between the predictor (or predictors) and the predicted values is assumed to be nonlinear. The regression equation creates the *logit* or log of the odds – that is, the natural log of the probability of being in one group divided by the probability of being in the other group. The procedure for estimating coefficients is maximum likelihood, and the goal is to find the best linear combination of predictors to maximize the likelihood of obtaining the observed outcome frequencies (Tabachnick & Fidell, 2006). Conceptually, maximum likelihood estimate are the “guesses” (a computationally iterative process) for the values of the unknown population parameters that maximize the probability of observing a particular sample of data (Singer & Willett, 2003). The Wald statistic is commonly used to test the significance of the individual predictors and their logistic regression coefficients (Hosmer & Lemeshow, 2000). The -2 Log Likelihood provides an index of model fit. A perfect model would have a value of 0; consequently the lower the value, the better the model fits the data (Mertler & Vannatta, 2005).

Logistic regression offers researchers an accessible technique for modeling a dichotomous dependent variable. The drawbacks include the inability to model 1) independent variables temporally, 2) residual variance (error), and 3) longitudinal data in the structure in which the models are typically developed. In the next section, however, a framework, event history analysis, will be examined that can address those issues within a defined data structure.

Dynamic Statistical Techniques

Event history analysis and latent growth modeling are two statistical techniques that can provide analysis of longitudinal data, and particularly the analysis of change. Singer and Willett (2003) state that there are three requisite methodological features of any study of change: the availability of 1) multiple waves of data; 2) a substantively meaningful metric for time; and 3) an outcome that changes systematically. They distinguish between two types of questions that are addressed: 1) within-individual change – How does each person change over time? and 2) inter-individual differences in change – What predicts difference among people in their change? The first question is descriptive and characterizes each individual's pattern of change over time. The second question is relational and examines the association between predictors and the patterns of change over time.

Event History Analysis

In order for a research question to lend itself to event history (or hazard) analysis, the study must have certain methodological features. Singer and Willett (2003) state that there are three methodological features necessary for event history analysis: 1) target event whose occurrence is being studied; 2) beginning of time as an individual starting point when no one under study has yet experienced the target event; and 3) metric for measuring time which is a meaningful scale in which event occurrence is recorded. Event occurrence is defined as an individual's transition from one "state" to another "state". Event history analysis has been used in the literature in a variety of research settings, including education (Denson & Schumacker, 1996; DesJardins et al., 1999; DesJardins & Moye, 2000; Ishitani & DesJardins, 2002-2003), social issues (Kalmijn *et al.*, 2004; Lewin, 2005; Panchanadeswaran & McCloskey, 2007), health risks (Clatts, 2005; Erlangsen *et al.*, 2005; Hser, 1995), business (Arthaud-Day *et al.*, 2006; Schoonhoven, 1990), and criminal justice (Lee, 2005).

Censoring

Censoring occurs whenever a researcher does not know an individual's event time, i.e., the individual is a subject in the study, but did not experience the event during the time periods when data were collected. There are two major reasons for censoring: 1) some individuals will never experience the target event; and 2) others will experience the event, but not during the study's data collection. If censoring is under a researcher's control, i.e., determined in advance by design, then it is considered to be noninformative. Informative censoring occurs if someone is likely to have experienced the event and the information to support event occurrence is not available to the researcher. The validity of an event history analysis rests on the assumption that censoring is noninformative, either because it occurs at random or at a time determined by the research design (Singer & Willett, 2003).

Singer and Willett (2003) caution against imputing event time. Imputing event times for censored cases simply changes all the “nonevents” into “events” and further assumes that all these new “events” occur at the earliest possible time – that is, at the moment of censoring. They state that “surely these decisions are most likely wrong. It is this insight – that, in telling us about event nonoccurrence, the censored cases do provide some information about event occurrence – that leads to a comprehensive strategy for incorporating censored cases into analyses.” (p. 323).

Discrete- versus continuous-time

Distinguishing between discrete- and continuous-time data is a critical methodological detail. Although the earliest descriptive methods for event occurrence (e.g., life tables) were developed for discrete-time data, some methods of analysis, such as Cox regression (Cox, 1972), assume that time is recorded on a continuous scale. Unfortunately, continuous-time methods break down when event times are relatively long in duration due to a problem know as “ties” (Cox & Oakes, 1984). With continuous-time data, the probability that two or more individuals share an identical event time (are “tied”) is small. Because actual ties are few, those that do occur can be treated as little more than noise (Singer & Willett, 2003). In discrete-time data, such as in the study of student persistence, ties are pervasive. Singer and Willett (2003) pose two pointed questions: "Why analyze your data using an adaptation of a method that assumes that ties do not exist when you know, *a priori*, that they will be commonplace? Even more to the point, why use a method that you know is likely to break down with the data you actually have in your hand?" (p. 315). The discussion of the hazard that follows deals solely with discrete-time data.

Hazard function

The basic quantity used to assess the risk of an event occurring within a discrete-time period is known as hazard. Denoted by $h(t_{ij})$, discrete-time hazard is the conditional probability that individual *i* will experience the event in time period *j*, given that the individual did not experience it in an earlier time period. Let T represent a discrete random variable whose values T_i indicate the time period *j* when individual *i* experiences the event. T is characterized by its conditional probability density function: the distribution of the probability that individual *i* will experience the event in time period *j*, given that he or she did not experience the event at any time prior to *j*. The set of discrete-time hazard probabilities expressed as a function of time is known as the discrete-time hazard function:

$$h(t_{ij})=\mathrm{PR}[T_i = j \mid T_i \geq j].$$

Note that each individual in the sample has a unique discrete-time hazard function that describes the individual's true risk of event occurrence over time. Ultimately the model will distinguish each member of the population on the basis of the hazard function and predictors.

Conditionality ensures that hazard represents the probability of event occurrence among individuals eligible to experience the event in that period – those in the risk set. A crucial feature of the risk set's definition is that it is irreversible: once an individual experiences the event (or is censored) in one time period, the individual drops out of the risk set in all future periods. Irreversibility is essential, for it ensures that everyone remains in the risk set only up to, and including, the last moment an individual could experience the event. This allows us to analyze event occurrence among the members of each year's risk set yet generalize results back to the entire population (Singer & Willett, 2003).

To build a statistical model that represents the relationship between the population discrete-time hazard function and predictors, two complications must be resolved. The first is that any hypothesized model must describe the shape of the entire discrete-time hazard function over time, not just its value in any one period. The second complication is that, as a conditional probability, the value of discrete-time hazard must lie between 0 and 1. For conditional probabilities like the values of discrete-time hazard, (Cox, 1972) recommends two potential transformations: the odds and the log odds transformation. Taking the natural logarithm of odds – log_e(odds), commonly referred to as a logit transformation is the preferred method (Singer & Willett, 2003).

The discrete-time hazard model includes two types of parameters: the α's, which represent the baseline logit hazard function, and β's, which assess the effects of predictors. If the α's are approximately equal, the risk of event occurrence is unrelated to time and the hazard function is flat. Precise interpretation of the α's requires identification of the baseline group, i.e., where every predictor in the model takes the value of zero. For predictor variables, a Wald chi-square statistic compares a maximum likelihood parameter estimate to its asymptotic standard error in much the same way as a *t*-statistic in regression analysis compares a least-squares parameter estimate to its standard error (Singer & Willett, 2003).

Data Structure

The data structure for event history analysis is referred to as a person-period data set. Most people are familiar with a person-level data set where each subject has one record. The person-period set has one record for each person *at each time period*, so time is actually a variable (see Figure 2). The notion that

ID	Time Period	Female	Lagged GPA	Persistence
5	1	0	3.25	0
5	2	0	3.47	0
5	3	0	3.15	1
12	1	1	3.11	0
12	2	1	2.75	1
45	1	1	3.07	0
45	2	1	2.92	0
45	3	1	3.41	0
87	1	0	2.51	1

Figure 2: Example of person-period data set

each individual contributes only one record to an analysis is a holdover from cross-sectional analysis. A person-period data set allows each person to contribute data whenever the individual is in the risk set. Values of time-varying predictors can be missing for periods subsequent to event occurrence in person-period data format. For instance, student with ID 12 was present in the first semester, but did not persist in the second semester – so no third semester information is present. Student ID 5 did not persist (was not present) in the third semester, while Student ID 45 persisted through all three time periods. Singer and Willett (2003) point out the apparent paradox of the discrete-time hazard model: time, the conceptual outcome, is actually the fundamental predictor. They state that "this seeming anomaly reflects our reformulation of the research question from 'What us the relationship between event times and predictors?' to 'What is the relationship between the risk of event occurrence in each time period and predictors?'" (p. 371).

Standard logistic regression routines available in all major statistical packages, when applied appropriately in the person-period data set, provide estimates of the parameters of the discrete-time hazard model (Singer & Willett, 2003). Singer and Willett (2003) address the issue of how an analysis of the multiple records in a person-period data set yield appropriate parameter estimates, standard errors, and goodness-of-fit statistics when: 1) the sample size appears to have been inflated, and 2) the J_i records for each person in the person-period data set do not appear to be obtained independently of each other. As for the nonindependence of the multiple records within a person, that can be resolved by remembering that the hazard function describes the conditional probability of event occurrence, where the conditioning depends on the individual surviving up to the period of event occurrence and also on the individual's substantive predictors. We therefore assume that all records in the person-period data set are conditionally independent and appropriate for inclusion in the data (i.e., the data set size is not inflated).

Predictors

Observed heterogeneity is the hypothesis that individuals will have different hazard functions if they have different values for the predictor variables. Conceptually, then, the model attributes any vertical displacement in logit hazard to predictors in much the same way as it attributes differences in mean levels of a continuous dependent variable to predictors in a linear regression model (Singer & Willett, 2003). Singer and Willett (2003) state that there are three assumptions inherent in discrete-time hazard models: 1) for each value of the predictor, there is an assumed logit hazard function; 2) each individual logit hazard functions has an identical shape, although there is great flexibility in the specification of that shape, and the shape of each function is constrained to be the same for all predictor values; and 3) the distance between the individual logit hazard functions is identical in every time period. Regardless of the common shape of the assumed logit hazard functions, the differences in level for the different values of the predictors remain the same.

Assumptions

Singer and Willett (2003) indicate that there are three important assumptions embedded in the discrete-time hazard model: 1) linear additivity (all predictors operate only as main effects); 2) proportionality (the effects of each predictor are constant over time), and 3) no unobserved heterogeneity (population hazard depends only on predicted values). Linear additivity assumes that a one unit difference in the value of a predictor (whether time-invariant or time-varying) corresponds to a fixed difference in the logit hazard as it is presumed that a predictor's effect does not depend upon 1) the values of other predictors in the model (i.e., the effect is additive) or 2) the position of the unit difference along its scale (i.e., the effect is linear). Proportionality assumes that each predictor has an identical effect in every time period. This constraint specifies that a predictor's effect does not depend on the individual's duration in the initial state. No unobserved heterogeneity assumes that any pair of individuals who share identical values of the predictors will have identical hazard functions.

The net result of unobserved heterogeneity is that the overall hazard function will decline over time, owing to nothing more than the changing composition of the risk set. Singer and Willett (2003) suggest that most empirical researchers proceed ahead, if not ignoring the problem, at least not addressing it. They go on to state that if you find sample hazard functions that increase over time, you are probably safe. On the other hand, if you find sample hazard functions that decrease over time – a pattern common in events in which individuals face a high initial risk – interpretation can be ambiguous.

One method for attempting to account for unobserved heterogeneity is to model the residual variance. DesJardins et al. (1999, 2002b) demonstrated how model fit improved when residual variance was accounted for as a parameter in modeling student persistence. However, the analysis they used, which involved a series of regression equations to allow parameter estimates to vary across time periods, utilized a customized FORTRAN program run on a mainframe computer. Mplus (L. K. Muthen & Muthen, 2006) statistical analysis software allows for modeling residual variance in a discrete-time hazard model (B. O. Muthen & Masyn, 2005) and is commercially available.

Summary

Event history analysis offers compelling evidence for its use as a statistical technique for modeling change in a dichotomous outcome. The model can analyze longitudinal data, accommodate time-invariant and time-varying predictors, and be estimated using maximum likelihood logistic regression routines (Singer & Willett, 1993). Thorough methods for checking assumptions and model fit are available (Singer & Willett, 2003). The primary drawback is that the predictor variables cannot be temporally ordered and measurement error is typically not modeled, with noted exceptions (DesJardins et al., 1999, 2002b; DesJardins & Moye, 2000; L. K. Muthen & Muthen, 2006).

Latent Growth Modeling (LGM)

Latent growth modeling analyzes intra- and inter-individual change over time within the structural equation modeling (SEM) framework (McArdle, 1988; Meredith & Tisak, 1990). Growth models also can be constructed within a multilevel framework (Singer & Willett, 2003), however, that is outside the scope of the study. Some of the strengths of LGM approach include the capacity to test the adequacy of the growth trajectories, incorporate time-varying covariates, and develop a common trajectory, thereby ruling out cohort effects (Duncan *et al.*, 1999). LGM has been used in the literature in a variety of research settings, including education (Kaplan, 1998; Raykov, 1999; Wisnicki, 1999), health care (Cacioppo *et al.*, 2006; Huang *et al.*, 2001; McArdle, 1990), and business (Chan, 2001b; Vandenberg & Self, 1993). While most LGM studies have been conducted using continuous dependent variables (Chan, 2001a; Singer & Willett, 2003), estimation techniques also allow the use of dichotomous dependent variables (B. O. Muthen, 1996). The following discussion starts with an overview of the SEM framework and then shows how growth modeling fits within the framework.

Structural Equation Modeling (SEM)

SEM can be thought of in simplest terms as a combination of regression and factor analysis. SEM typically uses maximum likelihood to determine the estimates that will most nearly reproduce the matrix of observed relationships. In traditional SEM, there is a measurement model and a structural model. It has generally been agreed that it is useful to explore the measurement models embedded within structural models prior to evaluating the structural model (Thompson, 2000).

Figure 3 presents an example of a structural equation model. The solid lines represent the measurement model and the dashed lines represent the structural model. The circles represent latent constructs, i.e., something that is unobserved and not directly measurable. The small boxes represent measurements, or more accurately, indicators. In the example, each latent construct has three indicators. The single headed arrows from the latent construct to the indicator reflects the belief that the construct causes its indicators to take on specific values (Singer & Willett, 2003), which are the equivalent of factor loadings. The arrow pointing to the indicators from the side opposite of the construct represent an error term. In SEM, error terms include effects of variables omitted from the model as well as effects of measurement error (Klem, 2000).

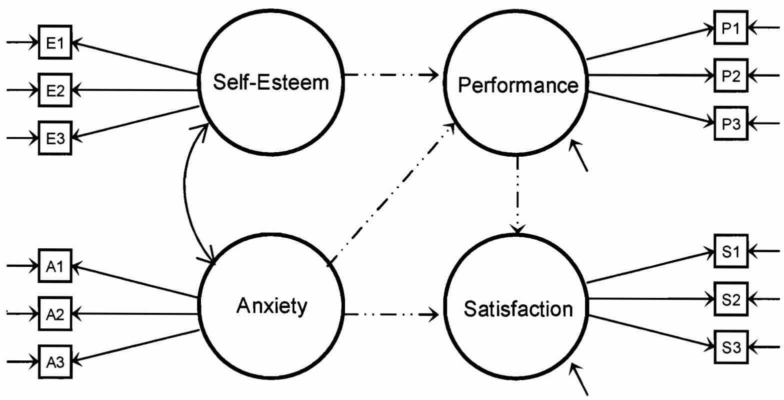

Figure 3: Example of structural equation model

The double-headed arrow between self-esteem and anxiety allows them to be associated (correlated), meaning that we have no theory about whether one causes the other. This is similar to what happens in regular regression, where you hypothesize that predictors “cause” the outcome, but the predictors themselves can be interrelated (Singer & Willett, 2003). The dashed lines represent the proposed relationship among the constructs. As an example, the model posits that anxiety affects satisfaction directly and also through performance. Although these parameters describe relationships among constructs, they are similar in interpretation to regression coefficients, in that they represent the difference in the "outcome" construct per unit difference in the "predictor" construct (Singer & Willett, 2003).

Latent Growth Modeling (LGM) within SEM Framework

LGM not only describes individual development trajectories, but also captures individual differences in trajectories over time. Another critical attribute is the ability to study predictors of individual differences to answer questions about variables that affect the outcome. At the same time, the growth model can also capture group statistics the researcher can use to study change at the group level (Duncan et al., 1999). The works of McArdle (1988) and Meredith and Tisak (1990) have demonstrated how to use the current standards in estimation and testing procedures found in SEM for growth curve analysis.

Figure 4 represents an example of a basic LGM with four waves of data. Notice that the intercept and slope are represented as latent constructs, hence the term "latent" growth modeling. The intercept corresponds to the initial status or value of the outcome variable, i.e., the value of the variable at Time 1, and is fixed for all time periods. The slope corresponds to the rate of change in the outcome variable, i.e., the rate of change over the period under study of the outcome variable. According to Chan (2001a), "the task in LGM analysis is to identify an appropriate growth curve form that accurately and parsimoniously describes intra-individual change over time (at the aggregate level of analysis) and also the examination of inter-individual differences in the parameters (intercept and slope) that describe the pattern of intra-individual change over time (at the individual level of analysis)." (pp. 304-305). The intercept and slope are allowed to covary, which allows for the modeling of any intercept-slope covariance that may occur due to statistical artifacts, such as ceiling and floor effects (Chan, 2001a).

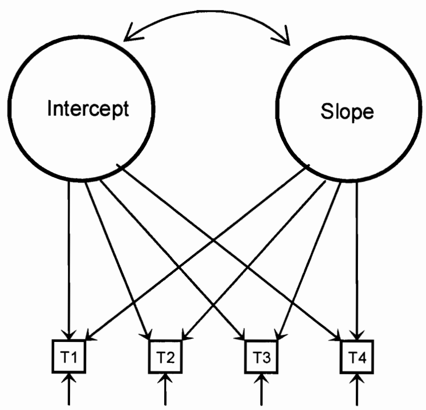

Figure 4: Example of basic latent growth model

Data Structure

To determine how well a model fits, SEM compares the sample and predicted covariance matrices. In order to compare matrices the data set must be in the person-level format, rather than the person-period format used for event history analysis. The person-level format has a variable for each time period and is the structure used in cross-sectional analysis.

Predictors

LGM can incorporate both time-invariant and time-varying predictors. Figure 5 shows an LGM with two time-invariant predictors. The satisfaction predictor is a latent construct, but note that gender is not. Gender is shown as a box because there is one measure, and it is assumed to be measured without error. If satisfaction was measured at all four time periods, the arrows would go from the construct to each of the four time periods, instead of to the intercept and slope. LGM can also determine whether a change in an outcome is associated with a *change* in a time-varying predictor by simultaneously modeling individual change in both variables to investigate the relationship between the two sets of individual growth parameters (Singer & Willett, 2003).

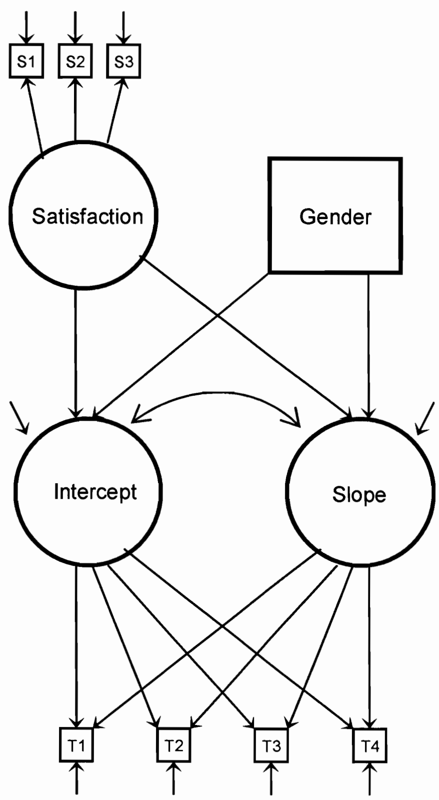

Figure 5: Example of latent growth model with time invariant predictors

Interpretation

Huberty and Morris (1988) observed that "as in all of statistical inference, subjective judgment cannot be avoided. Neither can reasonableness!" (p. 573). Interpretation within the SEM framework is more subjective than most statistical techniques and involves assessment of model fit, testing of alternative models, and examining parameter estimates for reasonableness. The two most commonly used indices to determine if the model fit the data well are the Comparative Fit Index (CFI) (Bentler, 1990) and the root mean square error of approximation (RMSEA) (Thompson, 2000). Values of .90 or .95 and higher for the CFI and .08 or less for the RMSEA are considered as indicators of good fit (Browne & Cudek, 1993).

A persuasive case that a model has been correctly specified can be made when a researcher finds a differentially better fit of a given model compared to the fit of numerous other defensible, thoughtfully formulated, rival plausible models (Thompson, 2000). Researchers are interested in models that spend fewer degrees of freedom and are therefore more parsimonious. Such models are preferred because there are more ways in which these models are potentially falsifiable, and so these models can more rigorously test our conceptions of latent constructs (Thompson, 2000). After the parameters of a model have been estimated, they should be thoroughly assessed from a theoretical perspective, i.e., results should be theoretically sensible (Klem, 2000). Klem (2000) points out that a misspecified model can result in improper results, such as negative variances and correlations greater than one, so there must be a reasonableness check of the parameters.

Assumptions

The assumptions within the SEM framework are somewhat different than more regularly used statistical techniques. SEM has three assumptions: 1) the constructs and errors scores have multivariate normal distributions, 2) the model must be identified, and 3) the constructs have measurement invariance. The multivariate normal distribution assumption is often violated in practice (particularly when there are dichotomous variables), however, ML estimation has been found to be fairly robust to violation of multivariate normality (Chou & Bentler, 1995). SEM also can explicitly model the error terms, which allows a variety of *a priori* error covariance structures to be modeled, such as heteroscedasticity and different forms of correlated error (Chan, 2001a).

A model is identified if, given the model and the data, only one single set of model parameters can be computed (Thompson, 2000). In SEM, the degrees of freedom is a function of the number of nonredundant pieces of information present in the matrix associations being analyzed (not the number of subjects). Each estimated parameter (e.g., weight, path coefficient, variance or covariance among latent variables) uses one degree of freedom. A model cannot be identified if the number of estimated parameters exceeds the total degrees of freedom. Measurement invariance refers to the assumption that the same construct is being measured and that it is being measured with the same precision across time in the period under investigation (Chan, 2001a).

Summary

LGM provides a framework for modeling inte-rindividual differences in the attributes of intra-individual change trajectories. Chan (2001a) lists the strengths of LGM to include the ability to account explicitly for the biasing effects of measurement error, test a variety of complex theoretical interrelationships among variables, enhance the explanatory power of nonexperimental data by testing and ruling out alternative models, and assess a variety of structural relationships across multiple groups. LGM can also be easily extended to incorporate mediational effects linking predictors to change variables using intervening variables.

Statistical Models of Student Persistence

Whether or not a student remains in college provides an ideal situation in which to evaluate the utility of event history analysis and latent growth modeling because of the longitudinal nature of the data and the factors that affect student decisions over time. Lancaster (1990) points out the when studying a student's change in status, we are making inferences about individuals' choices, but observing the "movement of persons between states" (p. 5). Student persistence models assume that "a person will tend to withdraw from college when he perceives that an alternative form of investment of time, energies, and resources will yield greater benefits, relative to costs, over time than staying in college" (pp.

97-98). By studying students' transitions from attending college to leaving college, i.e., perseverance to non-perseverance, we are indirectly examining students' cost/benefit calculations with regard to college attendance. That students make college continuation decisions on internal optimally, and changing, conditions is an often overlooked, but important theoretical point (DesJardins & Moye, 2000).

A variety of statistical models have been used in student persistence research, including path analysis (Braxton *et al.*, 1988b; Pascarella & Chapman, 1983), structural equation modeling (Cabrera et al., 1993), logistic regression (Chen, 2005), and event history analysis (DesJardins et al., 1999). The vast majority of literature has focused on confirming or expanding Tinto's (1975, 1993) model of student integration, which looks at family background, individual attributes, goal commitment and integration within the institution as determinants of a student's decision to dropout or persist. Recent studies (Cabrera et al., 1993; Hagedorn, 2006; Herzog, 2005; Murtaugh et al., 1999; Tinto, 2006) have elaborated and built on Tinto's model to account for a broader array of factors that can influence an increasingly diverse student population. Cabrera et al. (1993), in particular have proposed a model that integrated Tinto and Bean (1980) and demonstrated through the use of structural equation modeling that the integration and attrition models are complementary and not competing. Integration of the models incorporates student characteristics, family and friend influences, and organizational attributes and experiences in determining a student's intent to persist.

Predictors of student persistence have included attributes such as gender, ethnicity, major, pre-college academic performance such as high school GPA and SAT scores, measures of institutional integration and goal commitment through student surveys (i.e., extracurricular activities, relations with peers and faculty, residency), financial aid, and current academic performance (Aitken, 1982; Bean, 1980; Berger & Braxton, 1998; Cabrera et al., 1993; DesJardins et al., 1999, 2002a; Murphy, 2006; Murtaugh et al., 1999; Pascarella & Chapman, 1983; Patrick, 2001; Tinto, 1993; Wohlgemuth et al., 2006). In most studies, while gender was included as predictor, it was not significant with all the other predictors present. The exception is Berger & Braxton (1998), who found that females were more likely to persist in college. Several studies have found ethnicity to be a significant indicator of persistence. Murtaugh et al. (1999) found Blacks significantly more likely to persist in college than non-Blacks and Desjardins et al. (1999) found Asians significantly more likely to persist in college than non-Asians. Other research found significant race differences, but the articles did not provide sufficient information on how the data was coded (Braxton et al., 1988b; Stage, 1988). High school GPA and college GPA has been found consistently to be a significant predictor of persistence (Berger & Braxton, 1998; Cabrera et al., 1993; DesJardins et al., 1999, 2002b; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999; Pascarella & Chapman, 1983). When the time period under study is the first year, SAT and ACT are generally not significant, however, when the study spans multiple years, total SAT scores have been shown to be a significant predictors of persistence (DesJardins et al., 1999; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999). In addition, on campus residency and receiving financial aid have been shown to be positive predictors of persistence (DesJardins et al., 1999; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999; Stage, 1988).

In the aforementioned studies, the dependent variable is student persistence, which is defined as enrollment at the beginning of the semester or time period under study. This dependent variable for this study is student perseverance. Perseverance is operationally defined as a student who has earned hours for a given semester, which indicates whether the student successfully completed course work, i.e., persevered through the semester. Using earned hours more appropriately matches of event occurrence with the semester the student did not remain in college. A more detailed discussion of the difference between persistence and perseverance is included in the methodology section.

Summary

As discussed previously, the issue is of a temporal nature, or predicting in a static state versus a dynamic state. Cross-sectional data looks at one point in time, e.g., are students still attending the university at the beginning of their second year. This “snapshot” looks at the predictors of whether or not the student is in college at that point in time. What is more interesting than predictors of whether or not the student is enrolled at a given point in time, is the predictors of whether or not students are in college over time. The use of longitudinal data can provide insight into what affects the change in status over time rather than whether or not someone attended college at a certain point in time (DesJardins et al., 1999, 2002b; DesJardins & Moye, 2000). Event history analysis and latent growth modeling are the most appropriate statistical techniques to address research questions in student perseverance. The study was guided by the following questions.

1. Does the best statistical technique vary depending on the time frame of perseverance under study, e.g., into the 3^{rd}, 4^{th}, or 5^{th} semester?
2. Which statistical technique provides the best predictions of the change from student perseverance to non-perseverance?
3. Are the predictors and parameter estimates of student perseverance different between techniques?
4. What are the distinct advantages and disadvantages of each technique with regard to data requirements, assumptions, ease of use, and interpretation?

Chapter 3

Method

The purpose of this study was to compare and contrast two statistical techniques for modeling change with a dichotomous outcome using longitudinal data – event history analysis and latent growth modeling. The use of event history analysis has provided evidence of more robust modeling by including time-varying predictors and a residual variance parameter (DesJardins et al., 1999, 2002b; DesJardins & Moye, 2000; Singer & Willett, 2003). In essence, this study examines the use of latent growth modeling within the traditional event history analysis (or hazard) context. The hypothesis was that latent growth modeling would provide more accurate prediction and better model fit of the change from student perseverance to non-perseverance.

Population and Sampling

The population for the study was the 2001 and 2002 cohorts of first-time, full-time freshmen at a large mid-Atlantic urban research university. Data was available for the first five semesters for each cohort. The 2001 cohort contained 2,674 students of which 58 percent were female, 61 percent were White, 22 percent were African American, 10 percent were Asian, and the average math and verbal SAT score was 1037 (SD = 153). The 2002 cohort contained 3,015 students of which 60 percent were female, 91 percent were in-state residents, 61 percent were White, 21 percent were African American, 10 percent were Asian, and the average math and verbal SAT score was 1050 (SD = 152). For analysis purposes the two cohorts were combined for a total of 5,689 students. 446 students who re-enrolled in a semester after their first dropout (called stopouts) and 578 students who dropped out but were enrolled in another institution of higher education within the state (these data are available from the governing education agency) were excluded, which left 4,665 students for the analysis. Allison (1984) states that the "failure to distinguish among event types may produce misleading results" (p.50). The aforementioned cases will be excluded in an attempt to have a cleaner delineation between students who persevere in higher education and those who do not. A random sample of approximately 25 percent of the students (1,163) was selected as a hold out group for out of sample model evaluation. The sample was selected using the random sample selection feature in SPSS.

Data was provided in an Excel file by the university's institutional research function. The information in the data set was housed in the university's central records systems (e.g., admissions, housing, financial aid) and was collected in the normal course of business. The specific cases and variables in the data set that were provided to the researcher were collected as part of an internal study on the effects of financial aid on student persistence. All variables that could uniquely identify the students were removed from the data set by the university's institutional research staff prior to receipt by the researcher to ensure confidentiality. There are two unique characteristics about the university which may bias the results. The first is that all entering freshmen are guaranteed on campus housing. The descriptive statistics presented later in Table 2 show a dramatic drop off in percent of students in on campus housing starting in the third semester. The second is that the university's persistence rate is higher compared to its peer institutions for the first year and lower for the second year. This is a result of student programs the university has in place to assist first year students and several majors, e.g., arts, business and engineering, where students find out if they qualify for the program in the second year, so that students who do not qualify are more likely to leave and not switch to another major.

Definition of Variables

Variables included in the study were limited to those that are already available in the data set. Table 1 presents the independent variables in the study, which were selected based on previous research (Aitken, 1982; Bean, 1980; Berger & Braxton, 1998; Cabrera et al., 1993; DesJardins et al., 1999, 2002a; Murphy, 2006; Murtaugh et al., 1999; Pascarella & Chapman, 1983; Patrick, 2001; Tinto, 1993; Wohlgemuth et al., 2006). While declaring a major was not a specific variable from the literature review, whether or not a student had declared a major could be seen as a measure of commitment. In addition, while taking a remedial math course was not a specific variable from the literature review, it could be seen as a measure of academic preparedness.

Table 1

Independent Variables

Variable	Time Type	Measurement
Gender	Invariant	Dichotomous
SAT Math	Invariant	Continuous
SAT Verbal	Invariant	Continuous
Ethnicity/Black	Invariant	Dichotomous
Ethnicity/Hispanic	Invariant	Dichotomous
Ethnicity/Asian	Invariant	Dichotomous
Ethnicity/Other	Invariant	Dichotomous
Remedial Math Course	Invariant	Dichotomous
High School GPA	Varying	Continuous
Lagged GPA	Varying	Continuous
Financial Aid	Varying	Dichotomous
On Campus Housing	Varying	Dichotomous
Undeclared	Varying	Dichotomous

Chi-square and t-tests showed that students who were excluded from the analysis (stopouts and those attending another in-state university) were significantly different compared to those who were included on several characteristics: male (44.4% versus 39.9%, χ^2 (1, N = 5,689) = 7.0, p<.01), living off campus the first semester (39.4% versus 32.3%, χ^2 (1, N = 5,667) = 18.9,

p<.001), not receiving financial aid the first year (34.6% versus 28.1%, χ^2 (1, N = 5,667) = 16.9, p<.001), enrolled in the remedial math course (23.4% versus 20.2%%, χ^2 (1, N = 5,689) = 5.3, p<.05), and high school GPA (M = 3.15 versus 2.93, t(5,570) = 13.59, p<.001, d = .46). Ethnicity, enrollment in the remedial math class, SAT Math, and SAT Verbal were not significantly different.

For the 4,665 students in the analysis, 60 percent were female, 60 percent were White, 23 percent were African American, 10 percent were Asian, 20 percent were enrolled in the remedial math course, the average math SAT score was 516.6 (SD = 86.4), the average verbal SAT score was 529.3 (SD = 87.1), and the average High School GPA was 3.15 (SD = .53). Multicollinearity was checked using variance inflation factors (VIF) and tolerance values as suggested by Field (2005). There were no variables identified through collinearity diagnostics based on the criteria of tolerance values less than .1 (Menard, 1995) and a VIF value greater than 10 (Myers, 1990). Descriptive statistics for the time varying independent variable are shown in Table 2. Chi-square and t-tests revealed no significant differences between the 1,163 students in the hold out sample and the 3,502 students used to build the models.

Table 2

Descriptive Statistics for Time Varying Variables

	Semester				
Measure	1	2	3	4	5
Percent Receiving	72	72	57	57	48
Financial Aid (N)	(4,469)	(4,469)	(4,033)	(4,033)	(3,389)
Percent On Campus	68	64	18	17	12
Housing (N)	(4,649)	(4,413)	(4,021)	(3,718)	(3,355)
Percent	23	20	14	9	4
Undeclared (N)	(4,649)	(4,413)	(4,021)	(3,718)	(3,355)
Average	2.63	2.48	2.60	2.71	2.76
GPA (SD)	.95	1.02	.98	.93	.95

The dependent variable in the study was student perseverance. Perseverance in each semester was determined by whether or not the student had earned semester hours, i.e., successfully completed at least one class that semester. In determining perseverance in semesters two through five, there was no minimum criterion for earned hours – so students who switched to a part-time status but remained enrolled were included in the study. Using earned hours defines perseverance as being enrolled at the end of the semester. Earned hours was chosen rather than attempted hours (i.e., enrolled at the end of the semester rather than at the beginning of the semester) to account for student who left during the semester. If attempted hours were used, the students who left the university during a semester would have been counted as persevering in the semester they actually left and then be counted as not persevering in the semester after they had already left.

Table 3

Perseverance by Semester

Semester	Student with Earned Hours	Change	Percent
1	4,530	-135	-2.9
2	4,250	-280	-6.2
3	3,888	-362	-8.5
4	3,625	-263	-6.8
5	3,234	-391	-10.8

Table 3 shows perseverance by semester for the 4,665 students included in the analysis.

To illustrate the mismatch when using the traditional definition of persistence, one can simply look at the 135 student who had zero earned hours, and did not persevere at the end of the first semester. Under the definition of persistence as enrollment, these 135 students would have been categorized as persisting in the first semester and would have experienced the event, i.e., classified as having left the university, in the second semester. This misclassification would result in inaccurate parameter estimates for predictors of persistence. Using perseverance corrects for the misclassification. It should be noted that students who successfully complete a semester and choose not to come back to the university the following semester would be correctly classified in both the persistence and perseverance definition.

Methods

Event history analysis was conducted using logistic regression as suggested by Singer and Willett (2003) and also using maximum likelihood with modeling of residual variance using Mplus (L. K. Muthen & Muthen, 2006). Latent growth modeling was conducted using Mplus (L. K. Muthen & Muthen, 2006). The logistic regression procedure in SPSS was used to estimate parameters for the event history analysis. As Singer and Willett (2003) point out, when the person-period data set is constructed with each time period coded as a dummy variable (i.e., the variable for time period 3 has a value of 1 in period 3 and zero in all other period), the model provides estimates of the parameters of the discrete-time hazard model. A person-level data structure was required for Mplus discrete-time hazard and residual variance was modeled by freeing the parameter to be estimated.

The latent growth model with all the predictors that was tested is presented in Figure 6. In Figure 6, T1 represents student persistence in the second semester, T2 in the third semester, and so on. The predictors that are represented as boxes are not latent constructs and include only one measurement (note that several do not have error terms and are assumed to be measured without error). The time-varying predictors are shown at the bottom of the Figure 6. The arrows are drawn differently for ease of interpretation, however, each predictor was measured at each time period. GPA was lagged by one semester with high school GPA serving as the predictor for first semester perseverance.

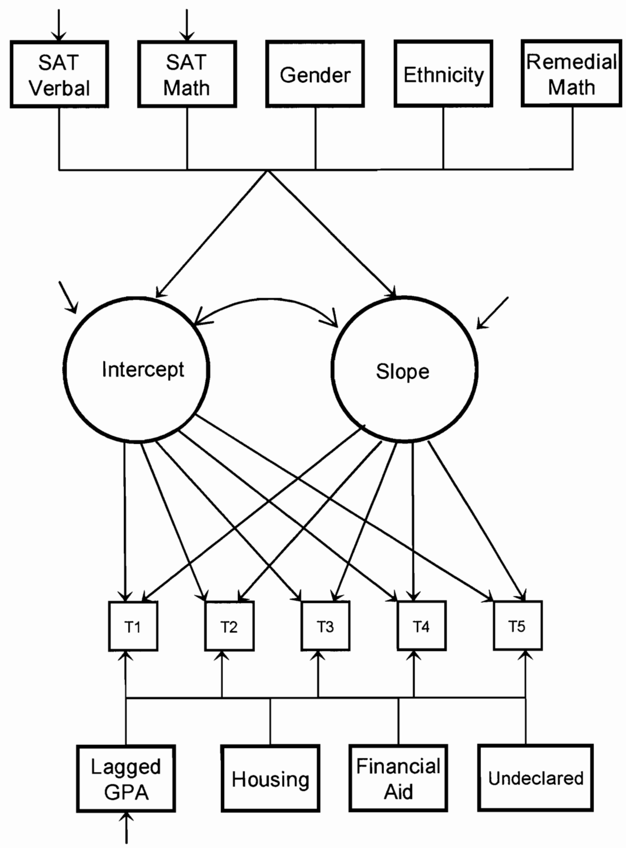

Figure 6: Latent growth model with all predictors and all periods

Data Analysis

For both event history analysis and latent growth modeling, a three step process was followed using the same dataset. In the first step, the baseline hazard or growth function was modeled, i.e., no predictors were included. The second step added time-invariant predictors and the third step included the addition of time-varying predictors. For event history analysis, models with and without a residual variance parameter were estimated. For each technique, the model was evaluated (compared to the previous model) at each subsequent stage to determine if the model had improved. The criteria used to evaluate the models were a chi-square difference test for the change in the log likelihood function (a measure of model fit), predictive classification, and theoretical reasonableness of parameter estimates based on the literature (Hubert & Morris, 1988; Klem, 2000). Predictive classification was defined as the overall percent of correct classifications for both perseverance and non-perseverance. For each of the three techniques, these steps also were estimated for three different time horizons – semesters 1 through 3, semesters 1 through 4, and semesters 1 through 5.

For each technique and time horizon a "best" model was selected based on the criteria mentioned above. The parameters for the independent variables were then used to estimate dependent variable values for the hold out sample. The three techniques were compared based on predictive classification.

Chapter 4

Results

For discussion purposes, event history analysis conducted using logistic regression as suggested by Singer and Willett (2003) is referred to as the logistic model, event history analysis using maximum likelihood with modeling of residual variance using Mplus (L. K. Muthen & Muthen, 2006) is referred to as the survival model (to be consistent with the nomenclature in the software), and latent growth modeling conducted using Mplus (L. K. Muthen & Muthen, 2006) is referred to as the latent growth model. For each of the techniques, odds ratios, log likelihood estimates, and predictive classifications are presented in Tables 4 through 6 for perseverance through the 3rd semester, Tables 7 through 9 for perseverance through the 4th semester, and Tables 10 through 12 for perseverance through the 5th semester.

Odds ratios, rather than parameter estimates are presented for ease of interpretation and discussion. Odds ratios are interpreted as whether someone in the group (with a characteristic or score value) is 'X' times more, or less, likely to experience the event (on-perseverance) than someone who is not in the group. Parameter estimates and standard errors can be found in Appendices A, B, and C for the logistic, survival, and latent growth models, respectively. Only the time-invariant and time-varying models are presented as the baseline model contained no predictors and in all cases the time-invariant and time-varying models provided significantly better fit based on change in the log likelihood. To provide a reference point for comparison of the percent correctly classified, the 'naïve' percent is presented in parenthesis following the model's percent correctly classified. The 'naïve' percent represents the percent correctly classified if it were assumed that all students persevered.

In order to interpret the odds ratios, a discussion of the variable coding is necessary. Perseverance was coded as a 1 in the semester the student the student experienced the event, i.e., had zero earned hours, and 0 if they persevered through the semester. For the dichotomous independent variables, females were coded as 1, each ethnicity category was coded as 1 for yes, remedial math course was coded as 1 if they took the course, financial aid was coded as a 1 if they received aid, on campus housing was coded as a 1 if they lived on campus, and undeclared was coded as a 1 if they did not have a major declared. SAT Math and Verbal score were divided by 10 to aid interpretation.

Table 4

Logistic Model for Perseverance through 3rd Semester

Parameter	Time-Invariant	Time-Varying
Gender	.882	.904
SAT Math	.994	1.001
SAT Verbal	1.003	1.024*
Ethnicity/Black	.977	1.160
Ethnicity/Hispanic	.836	.830
Ethnicity/Asian	.397***	.458*

Ethnicity/Other	1.271	1.769
Remedial Math Course	1.623*	1.346
High School GPA	.511***	
Lagged GPA		.240***
Financial Aid		.644**
On Campus Housing		.270***
Undeclared		.961
Log Likelihood	3,757	1,804
Percent Classified Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified Semester 2	94.1 (94.1)	96.9 (96.9)
Percent Classified Semester 3	91.6 (91.6)	97.6 (97.6)
Percent Classified All Semesters	94.4 (94.4)	97.4 (97.4)

*p<.05, **p<.01, ***p<.001

For the time-invariant logistic model, Asian ethnicity, remedial math course and high school GPA were significant predictors of perseverance through the third semester. For the time-varying model, SAT verbal, Asian ethnicity, lagged GPA, financial aid and on campus housing were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for both models is no better or worse than the naïve model. In nearly every semester both models predict all students to persevere and do not predict students not persevere. Given the significance of the time-varying predictors and their consistency with the literature, the significant change in the log likelihood function, and the lack of difference in predictive classification, the time-varying model was chosen as the best model.

Table 5

Survival Model for Perseverance through 3rd Semester

Parameter	Time-Invariant	Time-Varying
Gender	.881	1.102
SAT Math	.942	1.014
SAT Verbal	1.026	1.217**
Ethnicity/Black	.976	.711*
Ethnicity/Hispanic	.835	.797
Ethnicity/Asian	.395**	.411***
Ethnicity/Other	1.279	1.296
Remedial Math Course	1.266	1.095
High School GPA	.509***	
Lagged GPA By Semester 1, 2, 3		.322***, .213***, .327***
Financial Aid By Semester 1, 2, 3		.545*, 1.054, .953
On Campus Housing By Semester 1, 2, 3		.243***, .375***, 4.634***

Undeclared		.908, .868
By Semester 1, 2, 3		1.089
Log Likelihood	1,879	1,548
Percent Classified Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified Semester 2	94.1 (94.1)	94.5 (94.1)
Percent Classified Semester 3	91.6 (91.6)	87.0 (91.6)
Percent Classified All Semesters	94.4 (94.4)	93.2 (94.5)

**p*<.05, ***p*<.01, ****p*<.001

For the time-invariant survival model, Asian ethnicity and high school GPA were significant predictors of perseverance through the third semester. For the time-varying model, SAT verbal, Black and Asian ethnicity, lagged GPA in all semesters, financial aid in the first semester and on campus housing in all semesters were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. In addition, the odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 4.6 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for the time-varying model is slightly less than the naïve model as a result of poor prediction in the third semester. In nearly every semester, the time-invariant model predicts nearly all students to persevere while the time-varying model has predicted values for perseverance and non-perseverance. Given the significance of the time-varying predictors and their general consistency with the literature, the significant change in the log likelihood function, and the small difference in predictive classification, the time-varying model was chosen as the best model.

Table 6

Latent Growth Model for Perseverance through 3rd Semester

	Slope (Intercept)	
Parameter	Time-Invariant	Time-Varying
Gender	.954 (.738)	1.127 (.956)
SAT Math	.751 (1.169)	.931 (1.125)
SAT Verbal	1.088 (.950)	1.094 (1.078)
Ethnicity/Black	.997 (.947)	.533** (1.644)
Ethnicity/Hispanic	.497 (1.429)	.538 (1.718)
Ethnicity/Asian	.252 (.542)	.732 (.614)
Ethnicity/Other	.208 (6.841)	.240** (5.270***)
Remedial Math Course	.890 (2.098)	.730 (1.614)
High School GPA	.579 (.355)	
Lagged GPA By Semester 1, 2, 3		.233***, .239***, .296***
Financial Aid By Semester 1, 2, 3		.450**, 1.128, 1.009

On Campus Housing		.212***, .399***,
By Semester 1, 2, 3		5.089***
Undeclared		.842, .941
By Semester 1, 2, 3		1.057
Log Likelihood	1,869	1,537
Percent Classified		
Semester 1	98.4 (97.5)	97.6 (97.6)
Percent Classified		
Semester 2	92.2 (94.1)	94.1 (94.1)
Percent Classified		
Semester 3	100 (91.6)	91.8 (91.6)
Percent Classified		
All Semesters	96.8 (94.4)	94.6 (94.5)

*p<.05, **p<.01, ***p<.001

For the time-invariant latent growth model, there were no significant predictors of perseverance through the third semester. For the time-varying model, Black and Other ethnicity, lagged GPA in all semesters, financial aid in the first semester and on campus housing in all semesters were significant predictors. The odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 5.1 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for the time-varying model is slightly less than the naïve model as a result of poor prediction in the third semester. The time-invariant model has perfect prediction in the third semester. As can be seen in later tables, the time-invariant latent growth model has perfect prediction in the last semester in each of the different time periods in the study. Even though the percent classified for all semesters is better in the time-invariant model than the time-varying model, the time-varying model was chosen as the best model based on the predictor's general consistency with the literature and the significant change in the log likelihood function.

Table 7

Logistic Model for Perseverance through 4th Semester

Parameter	Time-Invariant	Time-Varying
Gender	.921	.882
SAT Math	.995	.998
SAT Verbal	1.003	1.021*
Ethnicity/Black	1.000	1.028
Ethnicity/Hispanic	1.001	.775
Ethnicity/Asian	.387***	.338**
Ethnicity/Other	1.561	1.700
Remedial Math Course	1.314**	1.287
High School GPA	.461***	
Lagged GPA		.252***
Financial Aid		.731*
On Campus Housing		.286***
Undeclared		1.003

Log Likelihood	5,000	2,200
Percent Classified Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified Semester 2	94.1 (94.1)	96.9 (96.9)
Percent Classified Semester 3	91.6 (91.6)	97.6 (97.6)
Percent Classified Semester 4	93.4 (93.4)	98.3 (98.3)
Percent Classified All Semesters	94.3 (94.3)	97.6 (97.6)

*p<.05, **p<.01, ***p<.001

For the time-invariant logistic model, Asian ethnicity, remedial math course and high school GPA were significant predictors of perseverance through the fourth semester. For the time-varying model, SAT verbal, Asian ethnicity, lagged GPA, financial aid and on campus housing were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for both models is no better or worse than the naïve model. In nearly every semester both models predict all students to persevere and do not predict students not persevere. Given the significance of the time-varying predictors and their consistency with the literature, the significant change in the log likelihood function, and the lack of difference in predictive classification, the time-varying model was chosen as the best model.

Table 8

Survival Model for Perseverance through 4th Semester

Parameter	Time-Invariant	Time-Varying
Gender	.895	1.119
SAT Math	.942	1.019
SAT Verbal	1.031	1.204**
Ethnicity/Black	.997	.818
Ethnicity/Hispanic	.981	1.090
Ethnicity/Asian	.326**	.393***
Ethnicity/Other	1.818	1.578
Remedial Math Course	1.408	1.162
High School GPA	.395**	
Lagged GPA		.339***, .216***,
By Semester 1, 2, 3, 4		.333***, .246***
Financial Aid		.527**, 1.016,
By Semester 1, 2, 3, 4		.917, .531***
On Campus Housing		.241***, .371***,
By Semester 1, 2, 3, 4		4.471***, .800
Undeclared		.908, .875
By Semester 1, 2, 3, 4		1.090, 1.243
Log Likelihood	2,500	2,065
Percent Classified		

Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified		
Semester 2	94.1 (94.1)	94.5 (94.1)
Percent Classified		
Semester 3	91.6 (91.6)	86.8 (91.6)
Percent Classified		
Semester 4	93.4 (93.4)	93.3 (93.4)
Percent Classified		
All Semesters	94.3 (94.3)	93.2 (94.5)

*$p<.05$, **$p<.01$, ***$p<.001$

For the time-invariant survival model, Asian ethnicity and high school GPA were significant predictors of perseverance through the fourth semester. For the time-varying model, SAT verbal, Asian ethnicity, lagged GPA in all semesters, financial aid in the first and fourth semesters and on campus housing in the first three semesters were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. In addition, the odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 4.5 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for the time-varying model is slightly less than the naïve model as a result of poor prediction in the third semester. In nearly every semester, the time-invariant model predicts nearly all students to persevere while the time-varying model has predicted values for perseverance and non-perseverance. Given the significance of the time-varying predictors and their general consistency with the literature, the significant change in the log likelihood function, and the small difference in predictive classification, the time-varying model was chosen as the best model.

Table 9

Latent Growth Model for Perseverance through 4th Semester

	Slope (Intercept)	
Parameter	Time-Invariant	Time-Varying
Gender	1.033 (.725)	1.124 (.924)
SAT Math	.875 (1.094)	.963 (1.093)
SAT Verbal	1.065 (.955)	.995 (1.306)
Ethnicity/Black	1.040 (.909)	.946 (.777)
Ethnicity/Hispanic	.972 (.964)	1.318 (.582)
Ethnicity/Asian	.337** (.553)	1.005 (.316)
Ethnicity/Other	-.871 (1.722*)	-.532 (5.110)
Remedial Math Course	1.120 (1.713*)	.845 (1.550)
High School GPA	.500*** (.478**)	
Lagged GPA		.070***, .160***,
By Semester 1, 2, 3, 4		.264***, .194***
Financial Aid		.342*, 1.336,
By Semester 1, 2, 3, 4		.794, .580*
On Campus Housing		.052***, .256***,

By Semester 1, 2, 3, 4		4.364***, .823
Undeclared		.783, .988
By Semester 1, 2, 3, 4		.913, 1.680
Log Likelihood	2,497	2,069
Percent Classified Semester 1	95.2 (97.5)	99.8 (97.6)
Percent Classified Semester 2	86.5 (94.1)	97.3 (94.1)
Percent Classified Semester 3	94.0 (91.6)	91.6 (91.6)
Percent Classified Semester 4	100 (93.4)	96.9 (93.4)
Percent Classified All Semesters	93.7 (94.3)	96.4 (94.5)

*p<.05, **p<.01, ***p<.001

For the time-invariant latent growth model, Asian ethnicity and high school GPA were significant predictors of perseverance through the fourth semester. For the time-varying model, lagged GPA in all semesters, financial aid in the first and fourth semesters and on campus housing in the first three semesters were significant predictors. The odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 4.4 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification in all semesters for the time-varying model is slightly better than the naïve model and the time-invariant model is slightly worse. Given the significance of the time-varying predictors and their general consistency with the literature, the significant change in the log likelihood function, and the slightly better predictive classification, the time-varying model was chosen as the best model.

Table 10

Logistic Model for Perseverance through 5th Semester

Parameter	Time-Invariant	Time-Varying
Gender	.938	.882
SAT Math	.999	.998
SAT Verbal	.998	1.021*
Ethnicity/Black	.946	1.028
Ethnicity/Hispanic	.888	.775
Ethnicity/Asian	.447***	.338**
Ethnicity/Other	1.823*	2.283*
Remedial Math Course	1.376***	1.287
High School GPA	.456***	
Lagged GPA		.252***
Financial Aid		.731*
On Campus Housing		.286***
Undeclared		1.003
Log Likelihood	6631	2200
Percent Classified		
Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified		

Semester 2	94.1 (94.1)	96.9 (96.9)
Percent Classified		
Semester 3	91.6 (91.6)	97.6 (97.6)
Percent Classified		
Semester 4	93.4 (93.4)	98.3 (98.3)
Percent Classified		
Semester 5	89.6 (89.6)	97.1 (97.1)
Percent Classified		
All Semesters	93.4 (93.4)	97.5 (97.5)

*$p<.05$, **$p<.01$, ***$p<.001$

For the time-invariant logistic model, Asian and Other ethnicity, remedial math course and high school GPA were significant predictors of perseverance through the fifth semester. For the time-varying model, SAT verbal, Asian and Other ethnicity, lagged GPA, financial aid and on campus housing were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for both models is no better or worse than the naïve model. In nearly every semester both models predict all students to persevere and do not predict students not persevere. Given the significance of the time-varying predictors and their consistency with the literature, the significant change in the log likelihood function, and the lack of difference in predictive classification, the time-varying model was chosen as the best model.

Table 11

Survival Model for Perseverance through 5th Semester

Parameter	Time-Invariant	Time-Varying
Gender	.985	1.102
SAT Math	.986	1.034
SAT Verbal	1.031	1.124**
Ethnicity/Black	.945	.751**
Ethnicity/Hispanic	.884	.943
Ethnicity/Asian	.431**	.437***
Ethnicity/Other	1.895	1.906**
Remedial Math Course	1.398**	1.121*
High School GPA	.440***	
Lagged GPA		.345***, .218***,
By Semester 1, 2, 3, 4, 5		.336***, .248***, .415***
Financial Aid		.531**, 1.028,
By Semester 1, 2, 3, 4, 5		.923, .535***, 1.051
On Campus Housing		.246***, .377***,
By Semester 1, 2, 3, 4, 5		4.536***, .813, 1.287
Undeclared		.898, .861
By Semester 1, 2, 3, 4, 5		1.088, 1.238, 2.112**
Log Likelihood	3,315	2,830
Percent Classified		
Semester 1	97.5 (97.5)	97.6 (97.6)
Percent Classified		

Semester 2	94.1 (94.1)	94.3 (94.1)
Percent Classified		
Semester 3	91.6 (91.6)	89.4 (91.6)
Percent Classified		
Semester 4	93.4 (93.4)	93.4 (93.4)
Percent Classified		
Semester 5	89.6 (89.6)	88.7 (89.5)
Percent Classified		
All Semesters	93.4 (93.4)	92.9 (93.4)

*p<.05, **p<.01, ***p<.001

For the time-invariant survival model, Asian ethnicity, remedial math course, and high school GPA were significant predictors of perseverance through the fifth semester. For the time-varying model, SAT verbal, Asian and Other ethnicity, remedial math course, lagged GPA in all semesters, financial aid in the first and fourth semesters and on campus housing in the first three semesters, and undeclared major in the fifth semester were significant predictors. The odds ratio for SAT verbal is counter to research as its directional indication is that as the score increases a student is more likely to experience the event. In addition, the odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 4.5 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification for the time-varying model is slightly less than the naïve model as a result of slightly lower predictive accuracy in the third and fifth semester. In nearly every semester, the time-invariant model predicts nearly all students to persevere while the time-varying model has predicted values for perseverance and non-perseverance. Given the significance of the time-varying predictors and their general consistency with the literature, the significant change in the log likelihood function, and the small difference in predictive classification, the time-varying model was chosen as the best model.

Table 12

Latent Growth Model for Perseverance through 5th Semester

	Slope (Intercept)	
Parameter	Time-Invariant	Time-Varying
Gender	1.095 (.735)	1.029 (1.029)
SAT Math	1.029 (.998)	1.006 (1.017)
SAT Verbal	.952 (1.054)	.949 (1.274*)
Ethnicity/Black	.939 (1.036)	.891 (.980)
Ethnicity/Hispanic	.848 (1.276)	.926 (1.121)
Ethnicity/Asian	.619* (.221*)	1.024* (.409*)
Ethnicity/Other	1.053 (3.059)	1.052 (1.713)
Remedial Math Course	1.120 (1.713)	1.018 (1.160)
High School GPA	.591** (.339**)	
Lagged GPA		.334***, .259***,
By Semester 1, 2, 3, 4, 5		.259***, .308***, .408***
Financial Aid		.518**, 1.264,
By Semester 1, 2, 3, 4, 5		.726*, .657**, 1.059

On Campus Housing		.236***, .424***,
By Semester 1, 2, 3, 4, 5		4.093***, .888, 1.340
Undeclared		.914, .995
By Semester 1, 2, 3, 4, 5		.875, 1.460, 2.072**
Log Likelihood	3,329	2,844
Percent Classified Semester 1	86.9 (97.5)	97.6 (97.6)
Percent Classified Semester 2	84.6 (94.1)	94.5 (94.1)
Percent Classified Semester 3	85.1 (91.6)	91.6 (91.6)
Percent Classified Semester 4	90.3 (93.4)	93.4 (93.4)
Percent Classified Semester 5	100 (89.6)	89.3 (89.6)
Percent Classified All Semesters	88.9 (93.4)	93.4 (93.4)

*p<.05, **p<.01, ***p<.001

For the time-invariant latent growth model, Asian ethnicity, remedial math course intercept, and high school GPA were significant predictors of perseverance through the fifth semester. For the time-varying model, SAT verbal intercept, lagged GPA in all semesters, financial aid in the first and fourth semesters and on campus housing in the first three semesters, and undeclared in the fifth semester were significant predictors. The odds ratio for SAT verbal is counter to previous research as its directional indication is that as the score increases a student is more likely to experience the event. In addition, the odds ratio for housing in the third semester is counter to previous research, indicating that student's who were in on campus housing were 4.1 times more likely to not persevere than student not in on campus housing. Based on the change in the log likelihood ratio, the time-vary model fits the data better. Predictive classification in the first four semesters and for all semesters for the time-invariant model is moderately worse than the naïve model. Given the significance of the time-varying predictors and their general consistency with the literature, the significant change in the log likelihood function, and the better predictive classification, the time-varying model was chosen as the best model.

The time-varying models were chosen as the best model for all three methods for all three time horizons. Using the parameter estimates from the models, predicted group classification was calculated for the hold out sample. Tables 13 through 15 present a comparison of the logistic, survival and latent growth percent classified correctly for the three time horizons, through the third, fourth and fifth semesters, respectively. The classification of logistic models was consistently equal to the naïve model. The classification for all semesters of the survival models was consistently slightly below the naïve model due to poor classification in the third semester. The classification for all semesters of the latent growth models was consistently slightly higher than the naïve model.

Table 13

Time-varying models through 3rd Semester for hold out sample

Time Period	Logistic	Survival	Latent Growth
Percent Classified Semester 1	97.2 (97.2)	97.9 (97.9)	97.9 (97.9)
Percent Classified Semester 2	94.0 (94.0)	94.9 (94.4)	94.4 (94.4)
Percent Classified Semester 3	92.1 (92.1)	88.5 (91.8)	92.4 (91.9)
Percent Classified All Semesters	94.5 (94.5)	93.9 (94.8)	95.0 (94.9)

Table 14

Time-varying models through 4th Semester for hold out sample

Time Period	Logistic	Survival	Latent Growth
Percent Classified Semester 1	97.2 (97.2)	97.9 (97.9)	100 (97.9)
Percent Classified Semester 2	94.0 (94.0)	94.9 (94.4)	97.9 (94.4)
Percent Classified Semester 3	92.1 (92.1)	87.8 (91.8)	90.0 (91.9)
Percent Classified Semester 4	93.4 (93.4)	94.6 (94.1)	99.0 (94.1)

Percent Classified All Semesters	94.3 (94.3)	93.9 (94.7)	96.8 (94.7)

Table 15

Time-varying models through 5th Semester for hold out sample

Time Period	Logistic	Survival	Latent Growth
Percent Classified Semester 1	97.2 (97.2)	97.9 (97.9)	97.9 (97.9)
Percent Classified Semester 2	94.0 (94.0)	94.5 (94.4)	94.4 (94.4)
Percent Classified Semester 3	92.1 (92.1)	90.2 (91.8)	91.8 (91.8)
Percent Classified Semester 4	93.4 (93.4)	94.5 (94.1)	94.8 (94.1)
Percent Classified Semester 5	88.4 (88.4)	88.9 (88.3)	88.3 (88.3)
Percent Classified All Semesters	93.0 (93.0)	93.4 (93.6)	93.7 (93.6)

Chapter 5

Discussion and Conclusion

This study examined the use of latent growth modeling within the traditional event history analysis (or hazard) context and compared model performance between the two techniques. The hypothesis was that latent growth modeling provided more accurate prediction and better model fit of the change from student perseverance to non-perseverance. More specifically, the analyses were designed to answer the four research questions of this study:

1. Does the best statistical technique vary depending on the time frame of perseverance under study, e.g., into the 3rd, 4th, or 5th semester?
2. Which statistical technique provides the best predictions of the change from student perseverance to non-perseverance?
3. Are the predictors and parameter estimates of student perseverance different between techniques?
4. What are the distinct advantages and disadvantages of each technique with regard to data requirements, assumptions, ease of use, and interpretation?

The remainder of this chapter provides a discussion of the results for each of the research questions and is followed by limitations of the study, implications for future research and some conclusions from this study.

Best Model by Time Frame

Examining the results by each time frame showed more similarities than differences. Time-varying models were chosen as the best models for the logistic, survival and latent growth techniques in each of the three time frames. As can be seen in Tables 13, 14, and 15, the classification for the hold out sample in each of the three time frames was equal to the naïve model for the logistic method, minimally less than the naïve model for the survival method, and minimally more than the naïve model for LGM. Which variables were significant and the magnitude of the odds ratios was also quite consistent across time frames for the logistic and survival models and moderately consistent for LGM, as can be seen in Appendices A, B, and C.

Time frame does not appear to be relevant in choosing a best model. The additional information on parameter estimates that are available from the survival model and LGM provide an advantage over the logistic technique, which will be further discussed in addressing the fourth research question.

Predictive Classification

Based on the out of sample results from Tables 13, 14, and 15, there was no meaningful difference between the logistic, survival and latent growth models with regard to percent classified correctly. It is worth noting that since parameter estimates for the time-varying predictors are uniquely estimated for each time period in survival and LGM, the large switch in the parameter estimate from the second to third semester for on campus housing results in poor predictive performance for the third semester. The survival and latent growth models also resulted in predicted values of event occurrence, whereas the logistic model predicted nearly all students to persevere. Having models that result in predicted values in both categories of the dependent measure can potentially yield additional insight if misclassifications were analyzed.

Differences in Predictors and Parameter Estimates

The parameters that were significant predictors of student perseverance were mostly consistent between models and with previous research. Table 16 presents the odds ratios for the logistic, survival, and latent growth models for predicting perseverance through the 5th semester. The five period time frame was chosen for illustrative purposes since it represents the most complete data. For LGM, both the slope and intercept odds ratios are presented, with the intercept in parentheses. The most direct comparison between the logistic and survival model odds ratios is with the slope odds ratio in LGM .(L. K. Muthen, 2007; L. K. Muthen & Muthen, 2006).

As can be seen in Table 16, gender was not a significant predictor in any of the models. Asian ethnicity was a significant parameter in all the models (DesJardins et al., 1999) while Black ethnicity was significant for the survival model only (Murtaugh et al., 1999). While the Other ethnic category was significant in two of the models, the category represented slightly less than one percent of the students and therefore the stability of the estimates was questionable. Lagged GPA, which included high school and college GPA was a significant predictor for all models in all time periods (Berger & Braxton, 1998; Cabrera et al., 1993; DesJardins et al., 1999, 2002b; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999; Pascarella & Chapman, 1983). On campus housing and financial aid were significant predictors in all models (DesJardins et al., 1999; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999; Stage, 1988), though only in the first and third semesters for the survival and latent growth models.

There were two instances where the significant parameters were different between models. Undeclared major was a significant predictor for the survival and latent growth models in the fifth semester but not for the logistic model. Taking a remedial math class was significant for the survival model, but not the logistic and latent growth models.

There were two instances where the odds ratios were not consistent with prior literature. The first is SAT Verbal (DesJardins et al., 1999; Ishitani & DesJardins, 2002-2003; Murtaugh et al., 1999), which was a significant for all three models. The odds ratios is greater than one, which means that students who have higher SAT Verbal scores are more likely to experience the event, e.g., no longer persevere. The second is the odds ratio for on campus housing in the third semester for the survival and latent growth model, which indicates that student who are in on campus housing are over 4 times more likely to experience the event that those who are not in on campus housing. This finding could be a statistical artifact from the dramatic drop off in the number of student who are in on campus housing in the third semester compared to the first two semester (18 percent versus 68 and 64 percent).

Table 16

Odds Ratios for Time-varying models through 5th Semester

Parameter	Logistic	Survival	Latent Growth
Gender	.882	1.102	1.029 (1.029)
SAT Math	.998	1.034	1.006 (1.017)
SAT Verbal	1.021*	1.124**	.949 (1.274*)
Ethnicity/Black	1.028	.751**	.891 (.980)
Ethnicity/Hispanic	.775	.943	.926 (1.121)
Ethnicity/Asian	.338**	.437***	1.024* (.409*)
Ethnicity/Other	2.283*	1.906**	1.052 (1.713)
Remedial Math	1.287	1.121*	1.018 (1.160)
Lagged GPA By Semester	.252***	.345***, .218***, .336***, .248***, .415***	.334***, .259***, .259***, .308***, .408***
Financial Aid By Semester	.731*	.531**, 1.028, .923, .535***, 1.051	.518**, 1.264, .726*, .657**, 1.059
On Campus Housing By Semester	.286***	.246***, .377***, 4.536***, .813 1.287	.236***, .424***, 4.093***, .888, 1.340
Undeclared By Semester	1.003	.898, .861 1.088, 1.236 2.112**	.914, .995 .875, 1.460, 2.072**

Further analysis on Asian ethnicity for the other significant predictors in the model (see Table 17) revealed that students of Asian ethnicity had significantly higher lagged GPA in all but the 5th semester and lower SAT Verbal scores compared to non-Asians. Undeclared major in the 5th semester, housing in the first 2 semesters and financial aid in the first semester were not significantly different. The higher GPAs for students of Asian ethnicity are likely the reason for the significance of the ethnicity predictor.

Table 17

Differences for Select Predictors for Asian Ethnicity

Parameter Mean (SD)	Asian	Non-Asian
High School GPA***	3.29 (.57)	3.14 (.52)
Semester 1 GPA*	2.75 (.91)	2.61 (.95)
Semester 2 GPA***	2.71 (.95)	2.46 (1.01)
Semester 3 GPA**	2.75 (.88)	2.58 (.99)
Semester 4 GPA	2.81 (.87)	2.70 (.92)
SAT Verbal**	512 (103)	529 (85)
Undeclared Major, 5th Sem.	.05 (.23)	.05 (.21)
Housing, 1st Sem.	.67 (.47)	.67 (.47)
Housing, 2nd Sem.	.68 (.47)	.68 (.47)
Housing, 3rd Sem.*	.17 (.38)	.22 (.41)
Financial Aid, 1st Sem.	.70 (.46)	.72 (.45)

*p<.05, **p<.01, ***p<.001

The university in the study has a policy that guarantees all first time, full time freshman on campus housing for their first year. Due to an overall lack of housing to accommodate all student requests, there is a lottery system in place for students in their second year and beyond who are seeking on campus housing. The large positive odds ratio for the third semester results from the precipitous drop (from 64 to 18 percent) from the second to third semester. In looking at the other significant predictors in the model (see Table 18), students with on campus housing in the third semester had significantly lower SAT Verbal scores and a lower percentage were Asian. There was no significant difference for lagged GPA. These mixed results indicate that the large swing in the odds ratio is a result of the drop in percentage with on campus housing. In hindsight, housing should have been modeled as two separate phenomena.

Table 18

Differences for Select Predictors for 3rd Semester Housing

Parameter Mean (SD)	On Campus	Off Campus
Semester 2 GPA	2.60 (.86)	2.61 (.92)
SAT Verbal***	513 (90)	534 (86)
Asian Ethnicity*	.08 (.27)	.11 (.31)

*$p<.05$, **$p<.01$, ***$p<.001$

Further analysis on undeclared majors in the 5th semester for the other significant predictors in the model (see Table 19) revealed that they had significantly lower lagged GPA and higher SAT verbal scores. There was no significant difference in Asian ethnicity. The large mean GPA difference is likely the contributor to the significance of the undeclared group.

Table 19

Differences for Select Predictors for Undeclared Major in 5th Semester

Parameter Mean (SD)	Undeclared	Declared
Semester 4 GPA***	2.17 (.83)	2.87 (.78)
SAT Verbal**	510 (94)	532 (88)
Asian Ethnicity	.13 (.33)	.11 (.32)

*p<.05, **p<.01, ***p<.001

Advantages and Disadvantages of Methods

The logistic, survival, and latent growth models were relatively similar in their data requirements, assumptions, and ease of use. The survival and latent growth models, however, had strong advantages when it came to interpretation. All three models used maximum likelihood estimation which resulted in parameter estimates that can be converted to odds ratios for ease of interpretation. Converting the data to a person-period data set for the logistic regression model required only a few lines of code and did not present any issues. While there are some differences in assumptions between the logistic regression and SEM framework, pragmatically the only difference is that the error term can be a parameter in SEM. Once familiar with the syntax of Mplus and with a reasonable understanding of the SEM framework, writing the syntax for the survival and latent growth models was only moderately more involved than using SPSS for logistic regression.

The advantage that the SEM framework, and therefore both the survival and latent growth models, had over the logistic regression model involved the nature of the person-period versus person-level data structure. With the person-period data structure, only one estimate was available even for the time-varying predictors. With the person-level structure in SEM, estimates were uniquely calculated for each time period. Looking at financial aid in Table 16, we can see that the estimate was significant for the logistic model, but the survival and latent growth models indicate that financial aid was significant in the first and fourth semester time periods. As another example, undeclared major showed as not significant for the logistic model, but as significant in the fifth semester for the survival and latent growth models.

LGM has the advantage of being able to include latent constructs and structural relationships compared to the survival model. Whether the survival or LGM model is the better model to use depends on the literature and research question. If theory does not necessitate the testing of latent constructs or structural relationship than the survival model is preferable as it is a simpler solution.

Limitations

There were several limitations to this study. Since the sample included only one large urban university, and the university in the study also had a higher first year, and lower second year, retention rate compared to its peer institutions, generalizations to all colleges and universities would not be appropriate. In addition, the study was specific to students initially enrolled in 2001 and 2002. As higher education admission policies change, student characteristics and motivations also change. The study also excluded stopouts, which limited generalization. Lastly, the variables under study were limited to those collected by the university and there were variables that would enhance model specification, such as measures of student integration or commitment. The limited number of variables in the study, along with the lack of integration and commitment measures, could result in misspecified models.

Conclusions

While no one method outperformed the others in terms of predicting correct classification, the results were still informative. Parameter estimates as odds ratios were quite consistent across models. Appendix D presents 95 percent confidence intervals for the 5 semester model to show the overlap. Parameter estimates also were mostly consistent with previous research. The survival method (discrete-time hazard using Mplus) appears to be a very promising alternative to logistic since one can model error terms and examine the differential effects of predictors at each time period. While the LGM can handle much more complex relationships, the survival model presents research with a relatively simple way to estimates the differential effects of time-varying predictors than provides much more useful information than using logistic regression with the person-period data structure.

While LGM did not outperform the other methods in predictive classification, the study demonstrated it can be used for event occurrence analysis to test more complex theories. LGM offers a host of additional capabilities that are not available using the survival or logistic models. With LGM, multi-sample tests can be set up to analyze the differences in parameter estimate for different samples, specific parameter estimates for a given model can be constrained for null hypothesis testing, and monte carlo simulations can be modeled to propose what the true population coefficients are. Lastly, LGM can model both latent constructs and measurement error, which allows for the testing of structural relationships that is the hallmark of SEM analysis.

Implications for Future Research

There are several implications for future research. The study demonstrated that obtaining time period specific estimates for both time-invariant and time-varying predictors is readily accessible through the SEM framework for longitudinal studies. The discrete-time hazard model using standard logistic regression programs provided a single parameter estimate for time-varying predictors. Using the SEM framework, both the discrete-time hazard (survival model) and LGM models provided specific estimates for each time period for the time-varying predictors. In addition, SEM has the flexibility to estimate the effect of the time-invariant predictors for each time period. This would allow researchers to examine whether time-invariant characteristics such as ethnicity have differential effects over time in addition to showing the differential effects of time-varying variables such as financial aid.

The study also demonstrated that LGM is a feasible alternative to model event occurrence as the dependent measure. This suggests two implications for future research. The first is the use of latent constructs. While not included in this study, future research can test theories that include more complex relationships using the SEM framework than are available through path analysis or logistic regression. The second implication is that the method also could be applied to similar issues such as teacher retention or high school drop out rates.

Another implication for future research is exploring the use of LGM with time-invariant predictors. In each of the three time frames in the study, the LGM model with time-invariant predictors was 100 percent accurate in its classification in the last semester. Post hoc analysis indicated that this was true for all time periods in the hold out sample as well. Classification in the semesters prior to the last semester was often below the naïve model, however. This particular model specification should be tested with a different cohort of freshmen using to provide further evidence for its predictive accuracy. With only using time-invariant predictors, the LGM is optimizing parameter estimates on the status in the last time period. To the extent the model remains accurate, the time-invariant predictors are more readily available and less time consuming to collect.

A final implication for future research involves the operational definition of student departure from college. The study used perseverance, which was defined as successfully completing coursework at the end of the semester, rather than the traditional definition of persistence that uses enrollment at the beginning of the semester. Future research should examine if there are differences between students who leave college during the semester and students who complete the semester but do not return the following semester. Stopouts, who were excluded from this study, is another area to explore. Greater understanding of the factors that affect students ability or desire to remain in college is needed in order to ultimately lead to higher graduation rates (Hagedorn, 2006).

Implications for Practice and Policy

With the high level of focus on student outcomes in education, the current working definition of student persistence, defined as enrollment at the beginning of a semester, is not as consistent with the concept of student outcomes, or as accurate, as it could be. This study defines student perseverance as completion of a coursework in a semester, which is consistent with graduation rates and the idea of student outcomes or success. The results show that the significant predictors of perseverance are very similar to those of persistence, so the body of research built thus far is still applicable, but with a better defined dependent measure.

While this study was limited in the variables that were available for modeling and in the type of population studied, databases from the National Center for Education Statistics (NCES), such as the Beginning Postsecondary Students Longitudinal Survey (BPS) and National Education Longitudinal Survey (NELS), offer a much richer collection of information to use in testing student persistence, or perseverance, theory. Individual institutions interested in researching perseverance would be well served to try and collect additional psychological constructs such as commitment, engagement and interest variables from surveys such as the National Survey of Student Engagement. As the underlying causes of non-perseverance are identified, program and policy decision-makers can implement, and subsequently evaluate, programs that increase graduation rates.

There are several practical ‘take away’ messages from the results of the current study. The first is that when results are communication to decision-makers, relative risk rather than the odds ratio should be used to indicate the magnitude of effect. Odds ratios, while required to appropriately interpret statistical results, are often misrepresented and relative risk is more easily understood and presents a more realistic estimate of the effect. The second is how programmatic decisions can manifest themselves in the data. As stated previously, the university in the study guarantees housing to all incoming freshmen, which results in less available housing for students past the first year and the odds ratio of non-perseverance in the third semester for student’s in on-campus housing to reverse direction. The non-significant parameter estimates in the 4th and 5th semester warrant further analysis to see if there is an unintended trade-off being made with for students who want, but cannot get housing in their second and subsequent years. The third point is that students who still have an undeclared major going into their 5th semester are at greater risk for not persevering.

Finally, the results of the benefits of financial aid are mixed depending on the semester. Given limited aid available to be disbursed, the timing of the aid to students could be an important factor to increasing perseverance. In addition, the use of perseverance address matters related to financial aid much better than persistence. Aid given to a student who starts school but does not earn any credit hours is aid that could have been given to a student who perseveres. Policy makers and those doling out scarce resources should focus on actual student success.

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Appendices

Appendix A: Coefficient Estimates and Standard Errors for Logistic Models

Table A1

Time-invariant Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender	-.126 (.100)	-.082 (.086)	-.064 (.074)
SAT Math[1] / 10	-.006 (.008)	-.005 (.007)	-.001 (.006)
SAT Verbal[1] / 10	.003 (.007)	.003 (.006)	-.002 (.005)
Ethnicity/Black	-.024 (.119)	.000 (.103)	-.056 (.089)
Ethnicity/Hispanic	-.180 (.247)	.001 (.199)	-.118 (.179)
Ethnicity/Asian	-.924*** (.237)	-.950*** (.207)	-.805*** (.162)
Ethnicity/Other	.240 (.378)	.445 (.301)	.601* (.248)
Remedial Math Course	.233* (.114)	.273** (.097)	.319*** (.083)
High School GPA	-.671*** (.102)	-.774*** (.089)	-.785*** (.076)

*$p<.05$, **$p<.01$, ***$p<.001$

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Table A2

Time-varying Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender	-.101 (.148)	-.126 (.135)	-.147 (.121)
SAT Math[1] / 10	.001 (.011)	-.002 (.010)	.000 (.009)
SAT Verbal[1] / 10	.024* (.010)	.021* (.009)	.014* (.008)
Ethnicity/Black	.148 (.190)	.028 (.174)	.000 (.157)
Ethnicity/Hispanic	-.186 (.407)	-.254 (.377)	-.151 (.322)
Ethnicity/Asian	-.781* (.356)	.-948** (.335)	-.806** (.364)
Ethnicity/Other	.571 (.484)	.531 (.441)	.826* (.364)
Remedial Math Course	.297 (.163)	.252 (.150)	.225 (.136)
Lagged GPA	-1.427*** (.096)	-1.378*** (.083)	-1.235*** (.072)
Financial Aid	-.440** (.147)	-.314* (.134)	-.361* (.119)
Campus Housing	-1.308*** (.160)	-1.252*** (.153)	-1.260*** (.147)
Undeclared	-.040 (.162)	.003 (.149)	-.017 (.141)

*$p<.05$, **$p<.01$, ***$p<.001$

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Appendix B: Coefficient Estimates and Standard Errors for Survival Models

Table B1

Time-invariant Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender	-.127 (.106)	-.111 (.129)	-.069 (.083)
SAT Math[1] / 10	-.006 (.008)	-.006 (.008)	-.001 (.006)
SAT Verbal[1] / 10	.003 (.007)	.003 (.007)	-.002 (.005)
Ethnicity/Black	-.024 (.120)	-.003 (.126)	-.057 (.094)
Ethnicity/Hispanic	-.180 (.251)	-.019 (.243)	-.123 (.191)
Ethnicity/Asian	-.928** (.237)	-1.120** (.467)	-.841** (.266)
Ethnicity/Other	.246 (.353)	.598 (.567)	.639 (.350)
Remedial Math Course	.236 (.132)	.342 (.197)	.335** (.121)
High School GPA	-.675*** (.183)	-.930** (.354)	-.822*** (.223)

**p*<.05, ***p*<.01, ****p*<.001

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Table B2

Time-varying Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender	.097 (.102)	.112 (.087)	.097 (.074)
SAT Math[1] / 10	.001 (.008)	.002 (.007)	.003 (.056)
SAT Verbal[1] / 10	.020** (.007)	.019** (.006)	.012** (.005)
Ethnicity/Black	-.341* (.141)	-.201 (.115)	-.286** (.097)
Ethnicity/Hispanic	-.227 (.272)	.086 (.203)	-.059 (.184)
Ethnicity/Asian	-.888*** (.238)	-.933*** (.208)	-.827*** (.164)
Ethnicity/Other	.259 (.447)	.456 (.326)	.645** (.256)
Remedial Math Course	.091 (.120)	.150 (.098)	.200* (.084)
Lagged GPA Sem. 1	-1.103*** (.278)	-1.082*** (.278)	-1.065*** (.279)
Lagged GPA Sem. 2	-1.545*** (.106)	-1.532*** (.106)	-1.526*** (.106)
Lagged GPA Sem. 3	-1.117*** (.092)	-1.099*** (.092)	-1.090*** (.092)
Lagged GPA Sem. 4		-1.403*** (.101)	-1.395*** (.101)
Lagged GPA Sem. 5			-.879*** (.086)
Financial Aid Sem. 1	-.607* (.244)	-.640** (.243)	-.632** (.243)
Financial Aid Sem. 2	.053 (.180)	.016 (.179)	.028 (.179)
Financial Aid Sem. 3	-.048 (.161)	-.087 (.161)	-.080 (.160)
Financial Aid Sem. 4		-.632*** (.174)	-.626*** (.174)
Financial Aid Sem. 5			.050 (.147)
Campus Hous. Sem. 1	-1.416*** (.246)	-1.424*** (.246)	-1.402*** (.246)
Campus Hous. Sem. 2	-.980*** (.166)	-.990*** (.165)	-.975*** (.165)
Campus Hous. Sem. 3	1.533*** (.153)	1.498*** (.152)	1.512*** (.151)

Campus Hous. Sem. 4		-.233 (.226)	-.207 (.225)
Campus Hous. Sem. 5			.252 (.185)
Undeclared Sem. 1	-.096 (.275)	-.097 (.275)	-.108 (.275)
Undeclared Sem. 2	-.141 (.199)	-.134 (.199)	-.150 (.199)
Undeclared Sem. 3	.085 (.181)	.086 (.181)	.085 (.181)
Undeclared Sem. 4		.217 (.224)	.214 (.224)
Undeclared Sem. 5			.748** (.232)

*p<.05, **p<.01, ***p<.001

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Appendix C: Coefficient Estimates and Standard Errors for Latent Growth Models

Table C1

Time-invariant Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender			
Intercept	-.304 (.391)	-.322 (.238)	-.308 (.296)
Slope	-.047 (.335)	.032 (.157)	.091 (.104)
SAT Math[1] / 10			
Intercept	.020 (.027)	.009 (.018)	-.000 (.022)
Slope	-.029 (.040)	-.013 (.012)	.003 (.008)
SAT Verbal[1] / 10			
Intercept	-.005 (.017)	-.005 (.014)	.005 (.018)
Slope	.008 (.020)	.006 (.010)	-.005 (.007)
Ethnicity/Black			
Intercept	-.054 (.315)	-.095 (.271)	.035 (.346)
Slope	-.003 (.295)	.039 (.184)	-.063 (.123)
Ethnicity/Hispanic			
Intercept	.357 (.706)	-.037 (.493)	.244 (.679)
Slope	-.699 (1.025)	-.028 (.359)	-.165 (.237)
Ethnicity/Asian			
Intercept	-.613 (.757)	-.593 (.504)	-1.508* (.640)
Slope	-1.378 (2.405)	-1.088** (.369)	-.479* (.232)
Ethnicity/Other			

Intercept	1.923 (2.173)	1.373* (.608)	1.118 (.754)
Slope	-1.572 (1.526)	-.138 (.564)	.052 (.356)
Remedial Math Course			
Intercept	.741 (.785)	.544* (.273)	.523 (.341)
Slope	-.117 (.354)	.113 (.181)	.224 (.133)
High School GPA			
Intercept	-1.037 (.983)	-.783** (.261)	-1.083** (.343)
Slope	-.546 (1.353)	-.694*** (.188)	-.526** (.164)

*p<.05, **p<.01, ***p<.001

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Table C2

Time-varying Models

Variable	Through 3rd Semester	Through 4th Semester	Through 5th Semester
Gender			
Intercept	-.045 (.228)	-.079 (.328)	.029 (.169)
Slope	.120 (.154)	.117 (.159)	.029 (.061)
SAT Math[1] / 10			
Intercept	.012 (.018)	.009 (.025)	.002 (.013)
Slope	-.007 (.012)	-.004 (.012)	.000 (.005)
SAT Verbal[1] / 10			
Intercept	.008 (.014)	.027 (.024)	.024* (.011)
Slope	.009 (.010)	-.000 (.011)	-.052 (.040)
Ethnicity/Black			
Intercept	.497 (.270)	-.252 (.481)	-.020 (.201)
Slope	-.629** (.193)	-.056 (.231)	-.115 (.077)
Ethnicity/Hispanic			
Intercept	.541 (.547)	-.542 (.995)	.114 (.402)
Slope	-.619 (.414)	.2766 (.466)	-.077 (.149)
Ethnicity/Asian			
Intercept	-.488 (.497)	-1.151 (.692)	-.894* (.381)
Slope	-.312 (.338)	.005 (.328)	.024* (.126)
Ethnicity/Other			
Intercept	1.662 (.575)	1.631 (1.460)	.538 (.429)
Slope	-1.427 (.579)	-.631 (.725)	.051 (.168)

Remedial Math Course			
Intercept	.479 (.262)	.438 (.396)	.148 (.191)
Slope	-.315 (.176)	-.158 (.192)	.018 (.070)
Lagged GPA Sem. 1	-1.501*** (.318)	-2.652*** (.542)	-1.097*** (.220)
Lagged GPA Sem. 2	-1.433*** (.131)	-1.832*** (.224)	-1.352*** (.118)
Lagged GPA Sem. 3	-1.216*** (.183)	-1.333*** (.084)	-1.349*** (.085)
Lagged GPA Sem. 4		-1.640*** (.188)	-1.179*** (.090)
Lagged GPA Sem. 5			-.897*** (.140)
Financial Aid Sem. 1	-.799** (.272)	-1.704* (.502)	-.659** (.250)
Financial Aid Sem. 2	.121 (.191)	.289 (.260)	.234 (.185)
Financial Aid Sem. 3	.008 (.168)	-.231 (.156)	-.320* (.156)
Financial Aid Sem. 4		-.544* (.242)	-.420** (.1694)
Financial Aid Sem. 5			.057 (.148)
Campus Hous. Sem. 1	-1.551*** (.300)	-2.955*** (.719)	-1.444*** (.265)
Campus Hous. Sem. 2	-.920*** (.202)	-1.362*** (.286)	-.858*** (.191)
Campus Hous. Sem. 3	1.627*** (.274)	1.473*** (.158)	1.409*** (.159)
Campus Hous. Sem. 4		-.195 (.301)	-.118 (.237)
Campus Hous. Sem. 5			.293 (.190)
Undeclared Sem. 1	-.171 (.297)	-.244 (.553)	-.089 (.287)
Undeclared Sem. 2	-.061 (.202)	-.012 (.264)	-.005 (.201)
Undeclared Sem. 3	.056 (.192)	-.092 (.184)	-.134 (.186)
Undeclared Sem. 4		.519 (.306)	.378 (.204)
Undeclared Sem. 5			.728** (.242)

*p<.05, **p<.01, ***p<.001

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Appendix D: 95 Percent Confidence Intervals for 5 Semester Model

Variable	Logistic	Survival	Latent Growth
Gender	-.389, .095	-.051, .245	-.093, .151
SAT Math[1] / 10	-.018, .018	-.109, .115	-.010, .010
SAT Verbal[1] / 10	-.002, .030	.002, .022	-.132, .028
Ethnicity/Black	-.314, .314	-.480, -.092	-.269, .039
Ethnicity/Hispanic	-.795, .493	-.427, .309	-.375, .221
Ethnicity/Asian	-1.534, -.078	-1.155, -.499	-.228, .276
Ethnicity/Other	.098, 1.554	.133, 1.157	-.285, .387
Remedial Math Course	-.047, .497	.032, .368	-.122, .158
Lagged GPA	-1.379, -1.091		
Lagged GPA Sem. 1		-1.623, -.507	-1.537, -.657
Lagged GPA Sem. 2		-1.738, -1.314	-1.588, -1.116
Lagged GPA Sem. 3		-1.274, -.906	-1.519, -1.179
Lagged GPA Sem. 4		-1.597, -1.193	-1.359, -.999
Lagged GPA Sem. 5		-1.069, -.725	-1.177, -.617
Financial Aid	-.599, -.123		
Financial Aid Sem. 1		-1.118, -.146	-1.159, -.159
Financial Aid Sem. 2		-.330, .386	-.136, .604
Financial Aid Sem. 3		-.400, .240	-.632, -.008
Financial Aid Sem. 4		-.974, -.278	-.758, -.082
Financial Aid Sem. 5		-.244, .344	-.239, .353
Campus Housing	-1.554, -.966		
Campus Hous. Sem. 1		-1.894, -.910	-1.974, -.914
Campus Hous. Sem. 2		-1.305, -.645	-1.240, -.476
Campus Hous. Sem. 3		1.210, 1.814	1.091, 1.717
Campus Hous. Sem. 4		-.657, .243	-.592, .356
Campus Hous. Sem. 5		-.118, .622	-.087, .673

Undeclared	-.299, .265		
Undeclared Sem. 1		-.658, .442	-.663, .85
Undeclared Sem. 2		-.548, .248	-.407, .397
Undeclared Sem. 3		-.277, .447	-.506, .238
Undeclared Sem. 4		-.148, .576	-.030, .786
Undeclared Sem. 5		.284, 1.212	.244, 1.212

1/ - SAT Math and Verbal score were divided by 10 to aid interpretation.

Researcher Vitae

Richard Mohn was born on April 3, 1965 in Lebanon, Pennsylvania. He graduated from Annville-Cleona High School in Annville, Pennsylvania in 1983. Richard received his Bachelor of Arts in Psychology and English from Lock Haven State University in 1987 and his Master of Arts in Psychology from the University of Richmond in 1992.

Following completion of his degree, Richard worked for several agencies in the Commonwealth of Virginia, including the Departments of Education, Corrections, and Planning and Budget. For almost 15 years, he worked at the Federal Reserve Bank of Richmond where he was involved in financial and strategic planning. Richard is currently an Assistant Professor of Research and Statistics in the Department of Educational Leadership and Research at the University of Southern Mississippi.