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A LONGITUDINAL APPROACH TO ASSESSING ATTRITION BEHAVIOR AMONG FIRST-GENERATION STUDENTS: Time-Varying Effects of Pre-College Characteristics

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Although going to college may be viewed as a rite of passage for many students, some groups of students often face unique challenges in their pursuit of a college degree. One group of students that we are trying to gain a better understanding of is "first-generation" students, those whose parents did not graduate from college. This article presents the results of a study that investigated longitudinal effects of being a first-generation student on attrition. Results indicated that first-generation students were more likely to depart than their counterparts over time. After controlling for factors such as race, gender, high school grade point average (GPA), and family income, the risk of attrition in the first year among first-generation students was 71% higher than that of students with two college-educated parents.

KEY WORDS: first-generation students; student attrition; event history modeling.

INTRODUCTION

Over the years, postsecondary institutions have been called on to educate an increasing number of diverse students with a wide range of background characteristics and needs. One group of students that we are trying to gain a better understanding of is "first-generation" students, those students whose parents did not graduate from college. Among the 1.3 million first-time freshmen who took the Scholastic Aptitude Test (SAT) last year, 364,000 were first-generation college students. In fact, the number of first-generation students attending college

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has been increasing. One study (Postsecondary Education Opportunity, 1999) suggested that the chance of attending college among children of high school degreed parents has improved from 1987–1996 by 4.8%. Although going to college may be viewed as a rite of passage for many students, as a college degree becomes a prerequisite for jobs with higher salaries, first-generation students often face unique challenges in their pursuit of a college degree.

Previous studies indicated that first-generation students differed from their peers in many aspects. For example, first-generation students tended to have lower SAT scores and lower high school GPAs (Riehl, 1994). Terenzini, Springer, Yaeger, Pascarella, and Nora (1996) suggested that, compared with their peers, first-generation students had lower critical thinking abilities, less support from their family in attending college, and spent less time socializing with their peers and talking with their teachers in high school. Riehl determined that first-generation students were less confident about their academic performance in college. York-Anderson and Bowman (1991) discovered that first-generation students received less support from their parents in making the decision about college attendance. This finding was also consistent with other studies (Billson and Terry, 1982; Choy, 2001).

Researchers have identified various characteristics of first-generation students after matriculation as well. Nunez and Cuccaro-Alamin (1998) showed lower levels of academic and social integration among first-generation students compared with students with two college-educated parents. Billson and Terry (1982) found that first-generation students tended to have lower grades in college than their peers. However, other findings related to college grades were inconsistent. For example, Strage (1999) discovered no differences in grades between first-generation students and students whose parents had a college degree. Another study (Inman and Mayes, 1999) also indicated no significant differences in first-year college GPAs between first-generation students and their peers.

Although inconsistency was found in the findings regarding college academic performance between first-generation students and students whose parents were college educated, previous studies have concluded that first-generation students were more likely to have lower retention rates than their peers (Horn, 1998; Nunez and Cuccaro-Alamin, 1998; Riehl, 1994). However, these findings were based on comparisons of descriptive statistics between groups of students whose parents did not have college degrees and students with college-educated parents. A study illustrating longitudinal effects on attrition between first-generation students and their counterparts is nonexistent to date. The study proposed herein is to investigate the longitudinal effect of being a first-generation student on attrition, after controlling for other, potentially confounding characteristics. The findings in this study advance our understanding of first-generation students and their attrition behavior.

METHODOLOGIES IN PREVIOUS RETENTION STUDIES

The focus of previous attrition studies has been devoted to testing student departure theories. Structural equation modeling has been one typical approach used in early studies of student departure (Bean, 1983; Braxton, Duster, and Pascarella, 1988; Cabrera, Nora, and Castaneda, 1993; Nora, Attinasi, and Matonak, 1990; Pascarella and Chapman, 1983; Pascarella and Terenzini, 1983). While structural equation models have proved to be valid in describing students' dropout behavior, they lack a more practical implication. For instance, they often failed to incorporate the timing of dropout. Although these authors often noted that student departure was a longitudinal process, arbitrary points were chosen to assess students' enrollment status. For example, a fourth-year snapshot of students' enrollment status does not specify the timing of dropout; that is, it does not allow us to specifically examine how factors affect students who drop out in their second or third year. It is reasonable to suspect that the magnitude of effects of variables influencing dropout behavior may differ among students, and may vary over time. For instance, one's high school GPA may have a very strong influence on dropout behavior early in a student's college career, but this effect may become less pronounced over time.

DesJardins, Ahlburg, and McCall (1999) suggested a new approach to examining the role of time in retention studies. They applied an event history model using data collected from a large public university in the Midwest. With this statistical technique, they were able to focus attention on the time periods when students were most at risk of leaving the institution. Following their lead, in the present study the temporal dimension of attrition behavior among first-generation students is more adequately addressed by using an event history model.

Other advantages of using event history modeling for this study rather than structural equation modeling are: (a) one event history model can incorporate enrollment status information of students from different points of time, instead of one arbitrary point of time typically used in one structural equation model, (b) using the maximum likelihood estimation, event history modeling allows researchers to examine the probability of highly skewed dichotomous dependent variables (i.e., enrollment status), since using the highly skewed dichotomous dependent variable violates the assumption of ordinary least square regression, and (c) event history modeling is suited to investigating various probabilities of student departure at different points of time, instead of addressing significant paths in the specified model using the structural equation approach.

Event history modeling is rather new to the area of educational research, and in fact, using this particular technique to assess attrition behavior of first-generation college students makes this study unique. The focal point of this investigation is to examine whether the effects of independent variables hypothesized to influence student departure behavior vary at different points of a student's academic career.

METHODOLOGY

Censoring

Figure 1 graphically displays the longitudinal process of student enrollment. Five types of outcomes are specified—continue, stopout, dropout, transfer, and graduate—and these events are identified in each discrete time period. Exogenous and time-dependent variables are assumed to affect an individual student's (i) outcome in each time period. Even though the values of exogenous variables are considered to be constant after matriculation, the *effects* of these variables may vary over time. However, the effects and values of time-dependent variables can change over time. Therefore, time-varying variables are depicted in separate boxes in Fig. 1 at each time period.

For students who decide to stay in college (continue) after time period $t1$, a solid arrow indicates their continuation to the next time period ($t2$). For four other types of outcomes (stopout, dropout, transfer, and graduates), students are excluded from the sample at the time when they *experience* one of these outcomes ("randomly censored observations"). For example, students who graduated in the fourth year were retained in the sample until the time they graduated in the fourth year. Another type of censoring occurs when students do not experience any type of outcomes before the observation period ends. Therefore, the outcome of these students is not able to be determined. These students are classified as "right censored observations."

Determinants affecting different types of departure, such as graduation, dropout, stopout, transfer, or academic dismissal, are quite different (Mallette and Cabrera, 1991; Tinto, 1987). However, these different types of censoring are difficult to incorporate into a model when one uses a logistic regression approach (Stage, 1988), since it only allows the specification of one type of censoring in the dependent variable. Event history modeling is well suited to handle different types of censoring. With indicators to identify types of student departure in the data, researchers can address how these different types of departure differ over time using event history modeling, while retaining the subjects with different attrition types in the data. This is the unique advantage of event history modeling over logistic regression modeling, since creation of separate samples may be needed to examine different types of student departure in the logistic regression approach.

Empirical Models

The measurement of time is important in event history modeling. There are two ways to define time: continuous or discrete. For identifying students who departed, institutional personnel may not know exactly when in the semester students left the institution; often they discover the departure by viewing regis-

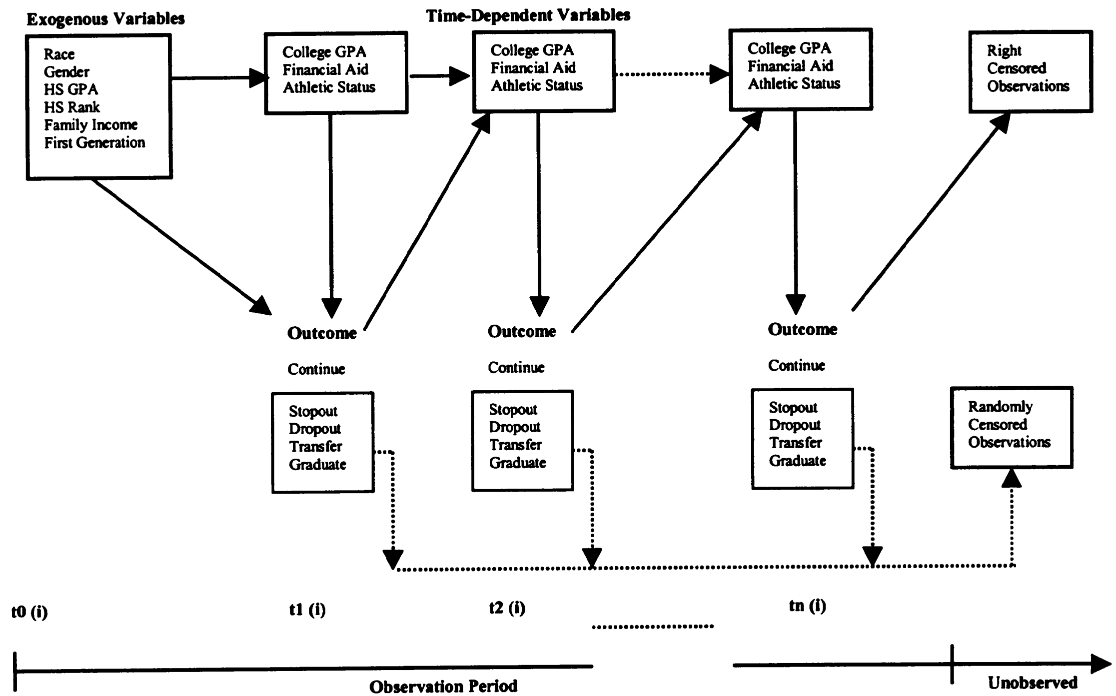

FIG. 1. Conceptual framework of student departure process. Source: Adapted from DesJardins, Ahlburg, and McCall (1999).

tration status of these students in the following semester. This is actually the case for the sample data used in this study. Data specifying exact dates and months of student departure are not available for analysis. However, for a longitudinal analysis focusing on terms or academic years of student attrition, exact dates or months of departure may not be relevant to the objectives of the study. For these reasons, this study uses the discrete-time method, which includes data specifying enrollment status at discrete points of time, such as terms or years.

Survivor function and hazard rate are two central concepts in event history modeling. Survivor function is the proportion of the sample that has not yet departed and is at risk of dropping out at a discrete point in time. The hazard rate is the probability that a dropout occurs to a student at a discrete point in time, given that the subject is at risk at that time. For instance, one has a sample of college students that included 500 freshmen, and 100 students dropped out in the first year. The number of students who are at risk of dropping out ("risk set") in the second year is 400 (500–100). So the survivor function can be computed as 400/500 = 0.800. Let us assume that the hazard rate may vary by academic year but is constant within the same academic year, and additional 50 students dropped out by the beginning of the third year. The hazard rate for dropout in the second year can be estimated as 50/400 = 0.125.

The next step is to assess how specific explanatory (exogenous) variables affect the hazard rate. Let $P(t)$ denote the conditional probability (discrete-time hazard rate) of dropping out at discrete-time interval t, given that dropout did not occur before time t. One can describe $P(t)$ as a linear function of the independent variables:

$$P(t) = a + b_1x_1 \tag{1}$$

where a is a constant coefficient, b is a coefficient for an independent variable, and x is a value associated with that variable. The specification of $P(t)$ is problematic, since it is a probability that cannot be greater than one or less than zero. This problem can be solved by taking the logit transformation of $P(t)$:

$$\log(P(t)/1 - P(t)) = a + b_1x_1 \tag{2}$$

Equation (2) is referred to as the exponential model in the literature. Equation (2) is, however, restrictive since the hazard rate and the effect of b are assumed to be constant over time. Equation (2) can be improved by including the time-varying effects as:

$$\log(P(t)/1 - P(t)) = a(t) + b_1(t)x_1 \tag{3}$$

where the hazard rate depends on the value of b_1 at time t, and the value of a at time t. Equation (3) is sometimes referred to as the piecewise exponential model with period-specific effects. In this study, both an exponential model and a piecewise exponential model with period-specific effects will be estimated to demonstrate how the role of time affects the results.

DATA AND EXPLANATORY VARIABLES

This study uses a sample cohort of college students matriculated in the fall of 1995 at a 4-year comprehensive public university in the Midwest. This sample cohort includes 1,747 students and their fall and spring semester enrollment status for 5 academic years (nine semesters). Attrition in this study is defined as a student's first spell of departure from the institution, which includes different types of departure, such as dropouts, transfers, academic dismissals, and stopouts (i.e., some of departed students may return and resume their enrollment after a certain period of discontinuation). Table 1 displays information on the enrollment status of the sample and the explanatory variables included in this study.

Information on student characteristics used in this study is based on a freshman survey conducted during the 1995 freshman orientation. About 55% of the sample is female ($n = 955$). Gender is operationalized as a dummy variable. Since a majority of students in the sample are Caucasian (89.5%, $n = 1{,}564$), the size of each racial group in the sample becomes small to examine the effects of racial differences. Thus, for this study the effect of race is measured with a dichotomous variable (Caucasian or minority). The sample includes a large number of first-generation students. Approximately 58% of the students are classified as first-generation students ($n = 1{,}016$), that is, neither of their parents has a college degree. About 16% of students ($n = 277$) in the sample have two college-educated parents, while 26% of students ($n = 454$) have at least one parent who graduated from college. This large portion of first-generation students in the student body makes this particular institution where the sample data were collected unique. The study proposed herein becomes vital to institutions with a larger number of first-generation students enrolled to improve their retention efforts and lower attrition among these first-generation college students.

High school GPA is included in this study as an explanatory variable. High school GPA is ranged from 1.46 to 4.00 with the mean of 2.82. Other explanatory variables include family income and the size of subject's hometown. Family income is operationalized as three dummy variables. The first dummy variable includes a group of students with family annual incomes less than $25,000, which is approximately 27% of the sample ($n = 466$). The second dummy variable specifies a group of students whose family incomes ranged from $25,000 to $45,000, which is 33% of the sample ($n = 577$). Missing values are also grouped as the third dummy variable to maintain the sample size (7.6%, $n = 133$). The reference group includes students whose annual family incomes are higher

TABLE 1. Descriptive Statistics of Sample

Overall Enrollment Status for 9 Semesters	Status	Count	Percentage
	Graduated	488	27.9
	Departed (First Spell of Departure)	1,052	60.2
	Still enrolled	207	11.8

Explanatory Variable Exogenous Variable	Label	Count	Percentage
Gender	Female	955	54.7
	Male (Reference Group)	792	45.3
Race	Minority	183	10.5
	Caucasian (Reference Group)	1,564	89.5
Parent's education	First-generation	1,016	58.2
	One parent with a college degree	454	26.0
	Two college-educated parents (Reference Group)	277	15.9
Annual family income	Less than $25,000	466	26.7
	$25,000–$45,000	577	33.0
	$45,000 or higher (Reference Group)	571	32.7
	Missing	133	7.6
Size of hometown	Less than 5,000 residents	465	26.6
	5,000–50,000 residents (Reference Group)	770	44.1
	More than 50,000 residents	512	29.3

		Mean	Range
High school GPA	Continuous	2.82	1.46–4.00

Time-Varying Variable	Label	Count	Percentage
First-year college GPA	Below 2.0	479	27.4
	Above 2.0	1,268	72.6
Second-year college GPA	Below 2.0	428	36.9
	Above 2.0	733	63.1
Third-year college GPA	Below 2.0	177	19.4
	Above 2.0	734	80.6
Fourth-year college GPA	Below 2.0	123	15.8
	Above 2.0	654	84.2
Fifth-year college GPA	Below 2.0	66	26.3
	Above 2.0	185	73.7

than \$45,000 (32.7%, $n = 571$). The size of subject's hometown includes two dummy variables. The first dummy variable is a group of students whose towns have populations of less than 5,000 residents. The second dummy variable contains students who are from cities with more than 50,000 residents. The reference group for this construct is a group of students whose hometowns have more than 5,000 residents but not more than 50,000 residents.

The time-varying variable is assumed to change its value and effect over time. College GPAs are included in this study as a time-varying variable. Operationally, this is a dichotomous variable to indicate a student's last enrolled semester GPA for each academic year (either fall or spring) being above or below 2.0. Inclusion of this time-varying variable is designed to assess the extent of departure conditional on academic performance. Some of the students who attained GPAs below 2.0 and were shown in the institutional record as dismissed in one semester were conditionally granted continuation of attendance in the following semester. Thus, by using this dichotomous variable, this study attempts to examine volunteer departure behavior for a group of students who had good academic standing in each academic year.

RESULTS

Product-Limit Estimation

Figure 2 illustrates survivor functions estimated by the product-limit estimation (the Kaplan-Meier method). Three different lines indicate the survivor functions for the three groups of students with different parental educational backgrounds. As shown in this graph, the dynamics of departure differed among the groups of different parental educational backgrounds. A precipitous decline was already found between first-generation students and their peers in the first semester. This relationship, a lower survival rate for first-generation students and a higher rate for their peers, continued throughout the observation period. A group of students whose both parents had college degrees sustained the highest survival rates till the end of the observation period. The group of students who had one college-educated parent had slightly lower survival rates than the group of students with two college-educated parents in the first and second semesters. However, the gap between these two groups widened through the third to sixth semesters.

Table 2 shows the survivor functions for these three groups of different parental educational backgrounds for the first six semesters. The survival rate for first-generation students in the first semester was about 9% less than that of the group of students with two college-educated parents. However, in the sixth semester, the rate for the first-generation students was 22% less than the one for students with two college-educated parents.

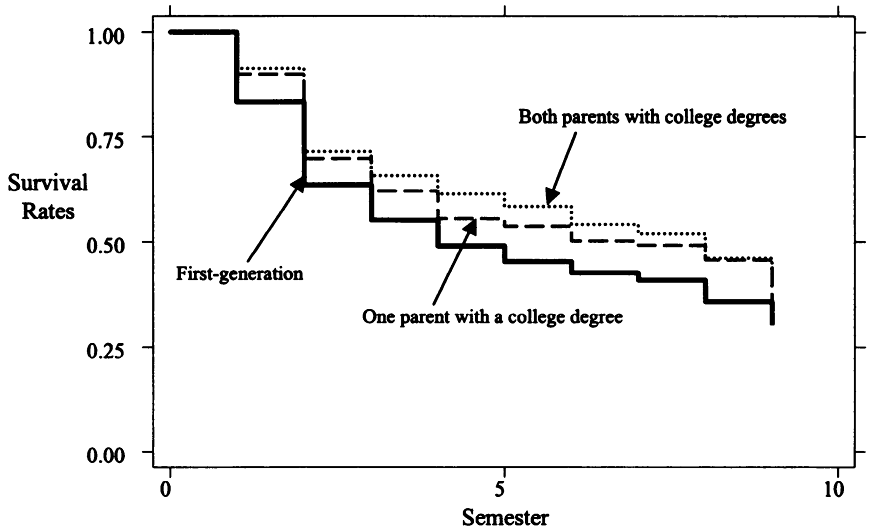

FIG. 2. Survivor functions for students with different parental educational backgrounds.

After testing equality of the survivor functions (Wilcoxon and Peto-Peto-Prentice tests),[1] I rejected the hypothesis that the survivor functions were the same for the three groups. Although cross-sectional analyses from previous studies have proved that first-generation students had higher rates of attrition at particular points in time, the results of the product-limit estimation herein demonstrated that first-generation students indeed had higher rates of attrition over time.

TABLE 2. Survivor Functions for the First Six Semesters

Semester	First-Generation	One College-Educated Parent	Two College-Educated Parents
1	0.833	0.898	0.913
2	0.635	0.698	0.714
3	0.552	0.621	0.657
4	0.491	0.555	0.614
5	0.423	0.537	0.584
6	0.426	0.501	0.541

Exponential Model

Table 3 displays the effects of explanatory variables on attrition behavior estimated by the exponential model. Interpretation of the coefficients produced by the model is made easier by using Eq. (4),

$$\Delta r = (\exp(\alpha_j)^{\Delta A} - 1) * 100\% \tag{4}$$

where $\exp(\alpha_j)$ is the antilogarithm of the unstandardized coefficient (α_j) and is known as the relative risk. ΔA is the change in the variable under consideration, and Δr is, therefore, the percentage change in the relative risk of departure. To demonstrate, the coefficient estimate for first-generation students (from Table 3) was 0.253, indicating that first-generation students had attrition rates higher than did the students with two college-educated parents. Generally, a positive coefficient estimate indicates that the variable increased the relative risk of departure; a negative estimate indicates that the variable reduced the relative risk of departure in this study. Using Eq. (4), one can obtain the relative risk for first-generation students as $\Delta r = (\exp(0.253) - 1) * 100 = (1.288 - 1) * 100 = 28.8$. Thus, first-generation students had the rate of departure that was approximately 29% higher than the reference group.

However, the exponential model was not the most appropriate model to estimate the effects of explanatory variables on attrition behavior discussed in the study herein. As noted earlier, the exponential model assumes that the effects of explanatory variables are constant and change proportionally over time. As shown in Fig. 1, survivor rates changed disproportionately over time. Therefore, it was reasonable to suspect that the effects of the expiatory variables affecting

TABLE 3. Exponential Model

Variable	Label	Coeff.	Sig.
Constant		–0.600	*
Gender	Female	0.142	*
Race	Minority	–0.066	
Parent's education	First-generation	0.253	*
	One parent with a college degree	0.027	
Annual family income	$25,000 or less	0.209	*
	$25,001–$45,000	0.032	
Size of hometown	Less than 5,000	0.051	
	Larger than 50,000	0.017	
High school GPA	Continuous	–0.650	*

*$p < 0.05$.

student attrition might change disproportionately as well. Furthermore, the exponential model herein did not estimate effects of time-varying variables, such as college GPAs, that had different values at different points in time. In the next section, the results estimated by the piecewise exponential model with period-specific effects are discussed.

Piecewise Exponential Model with Period-Specific Effects

Table 4 shows the results of the piecewise exponential model with period-specific effects. This model assumes that effects of explanatory variables are constant within each period but vary across different periods. Fall and spring semesters were aggregated into one period (except for the fifth year) to improve computation efficiency for the explanatory variables included in this study. The inclusion of time-varying college GPAs above or below 2.0 controlled for two types of student departure—voluntary departure and departure possibly related to poor academic performance.

Using the results of the exponential model as a benchmark, the piecewise exponential model revealed how the role of time influenced the explanatory variables. For instance, after controlling for other variables in the study, the estimated coefficient for being a first generation was 0.253 in Table 3. In Table 4, the estimated coefficients were ranged from –0.307 to 0.534. The negative effect of being a first-generation student on retention was the largest in the first year ($\beta = 0.534$). The relative risk of departure in the first year was 71% higher for first-generation students than for students with two college-educated parents. However, the risk of departure among first-generation students was less pronounced in the third year ($\beta = 0.473$). Thus, using the coefficient vector for first-generation yielded by the exponential model for computing the relative risk would underestimate the impact of first-generation on attrition for the first and third years. Statistical insignificance was found in the second, fourth, and fifth years for the effects of first-generation. Perhaps different types of departure, such as transfers, might have contributed to the insignificance of the coefficient estimate for the second year. This may imply that differences in parental educational attainment might have little impact on a student's decision to transfer to other institutions.

The coefficient for gender estimated by the exponential model was 0.142, which was statistically significant. However, the negative effect of gender on retention behavior was found statistically significant only in academic years 3 and 4. After controlling other variables, the relative risk of departure for female students in the third year was approximately 57% higher than that of male students ($\beta = 0.448$). Furthermore, the likelihood of leaving the institution among female students was the highest in the fourth year in this sample, which was 61% higher than male students ($\beta = 0.475$).

The results indicated that minority students had lower attrition rates than their

TABLE 4. Piecewise Exponential Model with Period-Specific Effects

		1st year		2nd year		3rd year		4th year		5th year	
Variable	Label	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Constant		−2.387	*	−2.273	*	−2.768	*	−4.740	*	−2.361	*
Gender	Female	0.236		0.108		0.448	*	0.475	*	0.080	
Race	Minority	−0.557	*	−0.411	*	−0.403		0.228		−0.377	
Parent's education	First-generation	0.534	*	0.138		0.473	*	−0.307		0.227	
	One parent with a college degree	0.050		0.171		0.250		-0.242		0.257	
Annual family income	$25,000 or less	0.400	*	0.229	*	0.261		0.666		−0.076	
	$25,001–$45,000	0.039		0.076		0.091		0.111		−0.061	
Size of hometown	Less than 5,000	0.263		−0.061		−0.251		0.448		−0.102	
	Larger than 50,000	0.226		−0.223	*	0.140		0.186		−0.030	
High school GPA	Continuous	−0.554	*	−0.076		−0.318		0.336		0.278	
Time-varying effect	College GPA less than 2.00	1.356	*	1.345	*	1.391	*	1.752	*	1.036	*

*$p < 0.05$.

counterparts in years 1 and 2. In the first year, minority students were about 43% less likely to leave the institution than Caucasian students ($\beta = -0.557$). Attrition behavior of minority students weakened in the second year; they were 34% less likely to depart than their counterparts ($\beta = -0.411$).

The positive effect of lower income on attrition was found statistically significant in years 1 and 2. Compared with the reference group (students with annual family incomes of $45,000 or more), a group of students whose families had annual family incomes of $25,000 or less had 49% higher risk of leaving in the first year ($\beta = 0.400$). In the second year, the relative risk of departure among students from lower income families decreased, but was still approximately 26% higher than the reference group ($\beta = 0.229$). Using the results from the exponential model ($\beta = 0.209$) would result in underestimating the relative risk of departure for lower income students in academic years one and two.

A group of students from larger towns had a lower probability of departure in the second year. They were 20% less likely to leave the institution in the second year than were students from mid-sized towns ($\beta = -0.223$). As expected, high school GPAs showed its statistically significant positive effect on retention only in the first year ($\beta = -0.554$).

Overall, the outcomes in this study were consistent with the findings from previous studies. The results of the product-limit estimation indicated that first-generation students were more likely to depart than were their peers. However, compared with the previous findings, the results herein exhibited more time-profile detail after controlling for factors such as gender, race, family income, and academic standing. For instance, the risk of departure among first-generation students varied over time. Although computing risks is sensitive to the model specification, the risk of departure among first-generation students was the highest in the first year.

DISCUSSION

The type of analysis presented herein has practical implications for administrators and researchers at institutions of higher education. For example, an application of event history modeling would help researchers examine the probability of student departure based on different student characteristics. Using the results from this study, let us assume that "Student A" had low-risk characteristics of departure, and "Student B" had high-risk characteristics of departure. Student A (B) was a male (female) student from a small town (a large town), who had a family income of $46,000 ($23,000), had two college-educated parents (first-generation). Both Students A and B had a college GPA of 2.0 or above in each semester they attended. One can graphically compare the conditional probability of departure between these two students (Fig. 3). Overall, the high-risk student (Student B) had higher risks of departure than the low-risk student (Student A) through academic years one to five. In academic years 1 and 3, Student B had a much higher risk of departure than that of Student A. But the risk became

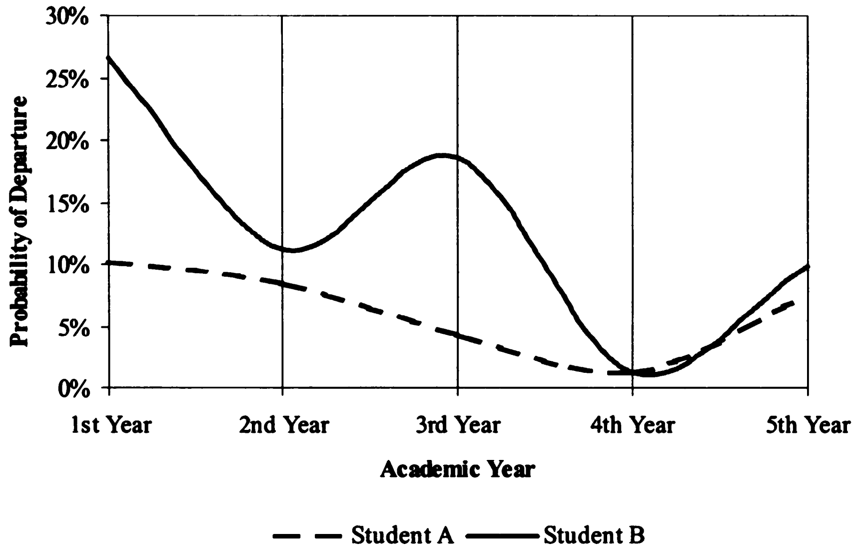

FIG. 3. Comparisons of conditional probability of departure between low- and high-risk students.

smaller for Student B in the second and fourth years. However, Student A had the highest risk of departure in academic year 1, and the risk waned over time until academic year 4. Steep increases in the risk rates in the fifth year for Students A and B may be due to the mathematical artifact that the risk set diminished because of the graduation of the majority of students in the sample. This graph illustrates evidence of the time-varying nature of the factors that affect college student attrition behavior.

Since merely offering first-generation students opportunities to attend college may not guarantee them academic success, knowing the risk periods and the magnitude of the risks over time, illustrated in Fig. 3, would help administrators responsible for retention to develop profiles of at-risk students. This information could then be shared with appropriate departments on campus. This would further help enrollment managers facilitate communication with other institutional administrators for designing policies and initiating interventions to prevent first-generation students from departing. Administrators can also map academic support plans in conjunction with other academic support services even before students arrive on campus. Since lower levels of academic and social integration were found among first-generation students (Nunez and Cuccaro-Alamin, 1998), getting first-generation students with risk factors involved with advisors earlier and more frequently may not only help them with academic issues but may also help them socialize into the higher education environment more easily.

Institutional researchers can incorporate other variables of interests into the event history model and examine their longitudinal effects on student attrition behavior. For example, event history modeling is suitable for assessing how unmet financial need affects student departure behavior. Another example may be how changes in admission policies have longitudinally influenced retention behavior. Alumni offices may use event history modeling to investigate the timing of postgraduate employment based on student characteristics. Institutional development administrators can also study if and when alumni donate to their alma mater based on student information in the institutional database.

At the state level, time to degree is becoming a priority for some legislators and the general public. A number of states have introduced legislation that limits the subsidies to students who exceed a certain time without the completion of a degree (Gorman, 1996). In conjunction with various time-dependent variables, event history models can help to provide empirical evidence about why students are taking more than 4 or 5 years to graduate. For example, the event history technique is an ideal approach to examine how frequent changes in majors or the number of earned credit hours would affect time to degree.

In summary, using the event history technique, student attrition and retention research would move into a more advanced and fruitful stage. Targeting at-risk students during the risk periods makes the institutional retention efforts more efficient and effective. Moreover, an application of event history modeling would assist researchers in examining the role of time for exiting research questions.

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ENDNOTE

1. These are statistic tests to compare survivor functions across groups. They are similar to nonparametric rank tests, which compare the observed and expected number of students who left in each of the groups. The expected number of departed students is obtained under the null hypothesis of no differences in survivor functions across the groups.

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