DOCUMENT RESUME

ED 387 007 HE 028 588

AUTHOR	Ronco. Sharron L.
TITLE	How Enrollment Ends: Analyzing the Correlates of Student Graduation, Transfer and Dropout with a Competing Risks Model. AIR 1995 Annual Forum Paper.
PUB DATE	May 95
NOTE	24p.; Paper presented at the Annual Forum of the Association for Institutional Research (35th, Boston, MA, May 28-31, 1995).
PUB TYPE	Reports - Research/Technical (143) -- Speeches/Conference Papers (150)
EDRS PRICE	MF01/PC01 Plus Postage.
DESCRIPTORS	*Academic Persistence; *College Graduates; *College Transfer Students; Dropouts; Enrollment Influences; Higher Education; High Risk Students; *Institutional Research; Models; Predictor Variables; *Student Attrition; Student Characteristics
IDENTIFIERS	*AIR Forum; *Competing Risks Model

ABSTRACT

This study applied the methodology of competing risks survival analysis to determine the probability that a student's first enrollment in the university will end in graduation. transfer, or withdrawal. The risk factors associated with each mode of exit were assessed, with attention to factors such as admission status, full-time or part-time enrollment, major, grade point average (GPA), and ethnicity. The ways that the risk factors exert different influences at different times were also addressed. The analyses were based on the cohort of 1,635 first-time-in-college students entering the university in fall 1987 and followed through spring 1994. Results showed that the risk of transfer to a two-year college was almost as high as the risk of dropout throughout the enrollment period, and that provisionally-admitted students and those with low GPAs were at greatest risk. Almost one-third of the cohort graduated. and almost as many dropped out. The next largest group transferred to a two-year college. By studying the timing of exit, it was learned that what originally was thought to be a high dropout rate after the second semester, especially for Hispanic and provisional students, was, at least in part, a significant movement to the community college. (Contains 34 references.) (SW)

HOW ENROLLMENT ENDS:

ANALYZING THE CORRELATES OF STUDENT GRADUATION, TRANSFER AND DROPOUT WITH A COMPETING RISKS MODEL

by

Sharron L. Ronco, Ph.D.
Director, Institutional Studies

University of Texas at El Paso
500 University Ave.
El Paso, Texas 79968-0512
(915) 747-5207 voice
(915) 747-5415 fax
ae05%utep@utepvm.utep.edu

Paper presented at the 35th Annual Forum of the Association for Institutional Research, Boston, MA, May 1995

for Management Research, Policy Analysis, and Planning

This paper was presented at the Thirty-Fifth Annual Forum of the Association for Institutional Research held at the Boston Sheraton Hotel & Towers, Boston, Massacusetts, May 28-31, 1995. This paper was reviewed by the AIR Forum Publications Committee and was judged to be of high quality and of interest to others concerned with the research of higher education. It has therefore been selected to be included in the ERIC Collection of Forum Papers.

Jean Endo
Editor
AIR Forum Publications

ABSTRACT

Students terminate their association with a postsecondary institution by graduating, transferring, or dropping out. These three modes of exit can be viewed as unique events which "compete" with each other to end a student's enrollment. This study applies the methods of survival analysis to the outcomes of an entering freshmen class in order to demonstrate: 1) the risk over time associated with each mode of exit; and 2) the role of factors such as admission status, full- or part-time enrollment, major, grade point average, and ethnicity in determining how a student will leave the institution. Results showed that the risk of transfer to a two-year college was almost as high as the risk of dropout throughout the enrollment period, and that provisionally-admitted students and those with low GPA's were at greatest risk. Studying the influence of a particular predictor on risk is complicated by its differential effect over time, a factor which can be examined by this methodology. The competing risks model is a promising research tool for conducting meaningful studies of student enrollment behavior.

How Enrollment Ends: Analyzing the Correlates of Student Graduation, Transfer and Dropout with a Competing Risks Model

Students end their association with a particular postsecondary institution in one of three ways: They graduate, they transfer to another institution, or they drop out. The manner in which they make their exit is of no trivial importance to their institution, which is increasingly being pressed to account for their departure. Competing demands for public dollars and the taxpayers' recalcitrance to pay higher taxes is helping to redefine higher education as a strategic investment (Ewell, 1994). With this shift in perspective has come a new kind of accountability, one based on demonstrable return on investment, and calling for better and more detailed public information about performance.

But performance, even in relatively straightforward terms like graduation and retention, eludes our attempts to measure it. Students no longer march lockstep through four years of college to graduation. The educational model of the new millennium will likely be characterized more by lifelong learning, where students move among various kinds of higher education institutions, stopping in and out as their lifestyles and educational needs dictate. Enrollment patterns like these make indicators like four or even six-year graduation rates for first-time, full-time freshmen largely irrelevant. Transfer students deprive both the sending and receiving institution of retention and graduation credit. Even graduation, the expected outcome of college matriculation, is beginning to require validation through measures like employer satisfaction and preparation for graduate study.

The futility of forcing institutions to conform to outmoded performance models is evidenced by the Federal government's tenacious, but as yet unsuccessful efforts to require institutions to report graduation rates under the 'Student Right-to-Know Act', attempts which continually dissolve under the burden of trying to standardize cohort definitions and account for the diverse paths that students take through higher education. Some states are moving to an appropriations system for higher education which distributes funds based on performance measures. The performance funding solution selects those measures on which data is most readily obtainable, regardless of its actual link to performance, and converts them into bounties, rewards or dividends (Ashworth, 1994). This State, for example, awards $97.64 in performance funding payback per graduating senior (and almost five times that amount per minority graduate!). This kind of formula penalizes institutions whose students may transfer out for reasons completely unrelated to the worthiness of the sending school, perhaps prompting these schools to wonder to what extent they are preparing students to become somebody else's performance funding.

Since the political momentum for accountability and societal return on investment is probably permanent, it is unrealistic to expect that pressure to produce evidence of performance will disappear, and dangerous to assume that it will. Thus, it is in our best interest to understand the progress of today's students through our higher education systems using all of the analytical tools available to us, and use this information to demonstrate why some of the current performance indicators may be tenable while others may be completely unreliable.

Studying Student Enrollment Behavior

Much is known about the major causes of student withdrawal (dropout) from institutions of higher education: Academic failure, poor adjustment to college, uncertainty about goals, lack of social integration, finances, external commitments (Tinto 1975, 1987, 1990; Bean, 1980; Pascarella & Terenzini, 1991). Grade point average (GPA) is the single most important indicator of whether a student will persist to graduation (Bean & Metzner, 1985). The variables indicating college readiness, such as high school rank and precollege scores on standardized tests of academic ability, like the SAT, show moderate correlations with academic success (Astin, 1993). Students who commute or attend college part-time are less likely to be successful because of less integration into the institution and reduced student-to-student and student-to-faculty contact. Racial/ethnic differences in academic success are largely mediated though strong negative influence on GPA due to the comparatively poorer preparation of ethnic minorities at the secondary level (Bean & Metzner, 1985). Some studies have found that majoring in the hard or technical sciences, as opposed to education and the social sciences, positively affects educational attainment, even when controls are made for other factors (Thomas & Gordon, 1983), whereas other studies have found that overall, evidence on the net influence of academic major on educational attainment is inconclusive (Pascarella & Terenzini, 1991). Although age and gender are not considered primary factors in attrition, some correlates of these variables, such as family responsibility and hours of employment, may be significantly associated with part-time enrollment, poor academic performance, and eventual dropout.

Factors associated with student transfer are less studied (Kraemer, 1995), but it is known that students transfer in order to find a better fit with the institutional environment, whether that environment is defined in terms of academic program offerings, course availability, academic standards, finances, or institutional culture. Transferring may also penalize students. The weight of the evidence suggests that, overall, transfer tends to have a negative effect on educational attainment (Pascarella & Terenzini, 1991).

Multivariate retention designs have become more common with the availability and ease of use of computer packages containing statistical procedures for multiple regression, discriminant analysis and structural equation modeling. These designs, especially those based on well-established models for college attrition like those developed by Tinto, Bean & Metzner, and Terenzini & Pascarella (1980), are valuable in disentangling the complex factors that explain student movement. What these kinds of studies don't address, however, are questions about the timing and duration of enrollment events. How long do students spend at this institution before leaving, via dropout, transfer or graduation? When are students at greatest risk for experiencing these events? What are the risk factors associated with each mode of exit, and does the effect of these risk factors fluctuate over time?

The unique design and analytical difficulties posed by research questions about time are addressed by a collection of techniques known broadly as event history analysis. The present study applies the methodology of competing risks survival analysis to determine the probability that a student's first enrollment in this institution will end in graduation, transfer or dropout; identify the risk factors associated with each mode of exit; and explore how the risk factors exert different influences at different points in time.

METHODS

Data

The analyses are based on the cohort of 1,635 first-time-in-college students entering this university in fall 1987, and followed through spring 1994. Since this State has the capability for statewide tracking, the ID numbers of students who disappeared without graduating were matched against enrollment records of other state public two-year and four-year schools. Students were designated 'two-year transfers' if their next college enrollment was at a junior or community college. and 'four-year transfers' if they next enrolled in a four-year college or university. An exception was made for those students who transferred from this university to the area community college for one semester, then returned to the university; they were treated as if they'd never left. Students who were enrolled during the same semester at both a four-year and a two-year school were considered four-year enrolles. 'Persisters' were those students from the entering cohort who were still enrolled here as of the 1993-94 academic year. Those students who did not fit into any of the other categories were designated 'dropouts.'

At this urban, commuter institution. 'stopout', where students voluntarily interrupt their enrollment for one or more semesters, is a common phenomenon. Treating students as dropouts who actually returned to school or transferred after a spell out of school would greatly distort the analysis. Therefore, stopout spells were ignored, making the 'time' variable in this analysis the number of long (fall or spring) semesters each student was enrolled, rather than chronological time. Summer terms were omitted from the analysis. Foreign students were also omitted since, for many reasons, their enrollment behavior is atypical.

Analytical Strategies

In retention studies. data collection must end at some arbitrarily-defined period without some of the subjects having experienced the target event. As Astin (1993) points out, for example. the only perfect measure of retention is one in which everyone has either already earned the baccalaureate degree or has died. This phenomenon, called right-censoring, means that the researcher has incomplete information about event occurrence, which is the very question of interest (Willett & Singer, 1993a). A relatively new method for studying the relationship between the occurrence of events and selected predictors is event history analysis, also known as survival analysis or hazard modeling. These methods, originally developed by biostatisticians studying clinical lifetime data, have several advantages over traditional OLS regression methods. First. they are able to incorporate both uncensored and censored events in a single analysis. Second. survival analysis has the ability to study time-varying predictors, those whose values change from one semester to the next during the observation period. Survival methods allow the effects of these variables to fluctuate over time, thus modelling dynamic processes dynamically. Finally. by documenting variation in risk over time, survival analysis permits researchers to disentangle the effects of predictors on events. The time frame becomes an integral part of the answer by highlighting, rather than obscuring, variation over time (Singer & Willett, 1993).

The hazard function, which is the fundamental dependent variable in event history data analysis, summarizes the risk of event occurrence in each time period (Allison, 1984). The hazard probabilities shown in Table 2 illustrate the proportion of all students at risk of experiencing a terminating event who experienced a particular outcome in that time period. In discrete time survival analysis, where time is measured not continuously but in intervals like years or semesters, hazard is defined as the conditional probability that a randomly-selected individual will experience the target event in time **j**, given that he or she did not experience the event prior to **j** (Singer & Willett, 1993). Event occurrence is inherently conditional because an individual can experience a target event once and only once. (Repeated occurrences of a single event can be analyzed by adjusting for the number and type of successive occurrences. For details, see Willett & Singer, 1993b; Ronco, 1994; Yamaguchi, 1991).

The relationship between the conditional probabilities and predictors are estimated in much the same way as in ordinary regression models. Following the model developed by Cox (1972), hazard probabilities can be reparametized so that they have a logistic dependence on the predictors and the time periods (log-odds). This is necessary because probabilities can only range from 0 to 1, a result that is assured by the logit transformation (Allison, 1984). A logistic regression is similar to OLS except that the dependent variable is dichotomous; in this case, a ratio of the probability of having a particular outcome to the probability of all other outcomes (hazard). Assuming that the predictors are linearly associated with the logistic transformation of hazard (logit-hazard) would yield:

$$\text{logit } h(t) = [d_1 + d_2S_2 + d_3S_3 + \dots d_{15}S_{15}] + B_1\text{PROV}$$

where S is a time variable like semester, the logistic regression parameters d_2 through d_{15} measure deviations of the baseline hazard from an initial value of d_1, PROV is the time-invariant predictor indicating a student's initial enrollment status, and B_1 captures its effect on hazard (Willett & Singer. 1991b). Estimates for the parameters $d_1 \dots d_j$ and $B_1 \dots B_j$ are obtained by the method of maximum likelihood. Maximum likelihood assumes that the underlying relationship between an independent variable and a dichotomous dependent variable follows the specified logistic distribution. It differs from OLS regression in that it seeks to choose those estimates that yield the highest likelihood of having obtained the observed probability of the dichotomous dependent variable, rather than minimizing the sum of squared errors between observed and predicted outcomes (Cabrera, 1994).

Parameter estimates associated with predictors represent the change in the log-odds (or elevation in the logit-hazard profiles) corresponding to a predictor variable one unit apart. Interpretation of the log-odds form is not intuitive, so the parameter estimate associated with the predictor variable is antilogged. The odds-ratio then indicates how much more likely the terminating event is when the predictor variable is one than when it is zero.

Fitting of discrete time hazard models requires that the data first be restructured into a person-period data set, where each individual under study has a number of separate records equal to the number of time periods under consideration. Willett & Singer (1991a; Singer & Willett, 1993) provide details and SAS code. Statistical packages such as SPSS-X and SAS have logistic procedures which provide analyses of maximum likelihood estimates and provide odds-ratios.

Competing risks

Survival methods can be extended to situations where each individual can occupy one of several states, as long as the states are mutually exclusive and exhaustive. In this study, the target event is exit from the institution; the difference is how that exit is made. The risks associated with each mode of exit 'compete' with each other to end a student's enrollment. 'Competing risks' is sometimes conceptualized as a race between competing independent processes in which the first place winner is recorded (but not the loser) (Tuma, 1984).

Competing risks survival analysis begins with the construction of separate hazard models for each mode of exit. This allows predictors of risk for students who graduate, for example, to differ from those associated with other modes of exit. Persisters, who have not yet experienced a target event, are censored. Once predictors of the competing risks are identified, the combined profile which includes all cases and all factors associated with each risk is assembled. This allows the same predictor to have a different effect depending on the event being modeled.

Different definitions of censoring account for the competing risks. When modeling graduation, for example, all other outcomes are considered censored, since a person who graduates from this institution is no longer in danger of dropping out or transferring.

Variables

The independent variables included in the analysis were selected on the basis of prior research and theoretical considerations as important risk factors associated with student dropout, transfer and graduation. Because this was a retrospective study, it was limited to information on file as reported to the State Higher Education Coordinating Board. Initially, these variables were included in the study: Race/ethnicity, sex, provisional (vs. regular) admission, age, semester grade point average (GPA), program of study (major), and full- or part-time enrollment. It was hypothesized that the 'risk' of ending enrollment by graduation might depend on factors such as GPA or major, while the risk of another outcome, such as transfer, might well depend on something else, such as full- or part-time enrollment status. OLS regression was run first to select the variables for the logistics model. As a result, the age variable was dropped, but all others were retained.

The variables retained in the model included both time-invariant and time-varying variables. The time-invariant variables are those whose values remain constant across all semesters of enrollment. These included ethnicity, sex, and whether the student was initially admitted provisionally for not meeting regular admissions criteria. The time-varying variables were allowed to take on different values for each semester of enrollment. These included enrollment status (full/part-time), GPA and major. The categories of majors highlighted in this study included science, engineering and math (SEM), business, and liberal arts. These, in turn, were compared with all other majors, which also included smaller numbers of education and nursing majors. Due to the nature of the statistical analysis, all variables were categorized and dichotomized even when their underlying scales were interval-type. For example, three levels of GPA were investigated in the analysis: High (3.00 +) Mid (2.00 - 2.99) and Low (under 2.00). When High GPA was tested in the model, it took on a value of '1', with all other GPA's designated '0'. The time variables measure the number of long semesters enrolled at this institution before the target event was experienced.

Table 1. Distribution of mode of exit by selected variables

	Censored		Mode of Exit							
	Persisters		Dropouts		Two-year Transfer		Four-year Transfer		Graduate	
Variables	Number	Percent	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Gender										
Female	84	50%	249	52%	208	55%	32	43%	306	57%
Male	85	50%	226	48%	171	45%	43	57%	231	43%
Ethnicity										
White	25	15%	167	35%	80	21%	42	56%	125	23%
Hispanic	134	79%	274	58%	286	76%	30	40%	360	67%
All others	10	6%	34	7%	13	3%	3	4%	52	10%
Admit Status										
Provisional	33	20%	117	25%	159	42%	12	16%	71	13%
Regular	136	80%	358	75%	220	58%	63	84%	466	87%
Major[1]										
SEM	468	23%	308	18%	237	17%	81	25%	1299	23%
Business	593	29%	374	22%	312	23%	85	26%	1370	25%
Liberal arts	622	31%	615	36%	394	29%	113	35%	1719	31%
All others	355	17%	417	24%	428	31%	47	14%	1186	21%
GPA[1]										
below 2.00	744	37%	924	54%	912	67%	101	31%	745	13%
2.00 to 2.99	805	39%	523	31%	343	25%	130	40%	2294	41%
3.00 plus	489	24%	267	16%	116	8%	95	29%	2535	45%
Enrollment Status[1]										
Full-time	900	44%	878	51%	583	43%	220	67%	4267	77%
Part-time	1138	56%	836	49%	788	57%	106	33%	1307	23%
Total Observations	169		475		379		75		537	
Percentage of Total Cohort	10.3%		29.1%		23.2%		4.6%		32.8%	

[1] Number of person-semesters

The distribution of exit modes by variables shown in Table 1 provides background information important to the context of the data analysis. Almost one-third of this cohort ended its association with this institution through graduation, but almost as many dropped out. The next largest group transferred to a two-year college. Because of the small sample size for four-year transfers, few significant differences between categories of variables were detectable. Ten percent of the original fall 1987 cohort was still enrolled during 1993-94.

Table 2. Hazard probabilities by mode of exit and number of long semesters enrolled

Number of semesters enrolled	Total at risk-all exits	Dropout			Two-year Transfer			Four-year Transfer			Graduate		
		Number in risk set at start of semester	Number who dropped	Hazard	Number in risk set at start of semester	Number who transferred	Hazard	Number in risk set at start of semester	Number who transferred	Hazard	Number in risk set at start of semester	Number who graduated	Hazard
1	1,635	475	92	.056	379	79	.048	75	4	.002	537	0	.000
2	1,460	383	123	.084	300	92	.063	71	16	.011	537	0	.000
3	1,228	260	57	.046	208	57	.046	55	10	.008	537	0	.000
4	1,170	203	64	.058	151	44	.040	45	17	.015	537	0	.000
5	974	139	36	.034	107	29	.030	28	10	.010	537	2	.000
6	896	106	38	.042	78	27	.030	18	6	.007	535	2	.000
7	821	68	24	.029	51	11	.013	12	3	.004	533	14	.017
8	761	44	21	.028	40	17	.022	9	4	.005	519	57	.075
9	655	23	13	.020	23	8	.012	5	0	.000	462	86	.131
10	543	10	7	.013	15	6	.011	5	3	.000	376	146	.269
11	369	3	3	.008	9	3	.008	2	1	.000	230	86	.233
12	268	---	---	---	6	4	.015	1	1	.000	144	85	.317
13	162	---	---	---	2	1	.000	---	---	---	59	29	.179
14	108	---	---	---	1	0	.000	---	---	---	30	28	.000
15	141	---	---	---	1	1	.000	---	---	---	2	2	.000

13

14

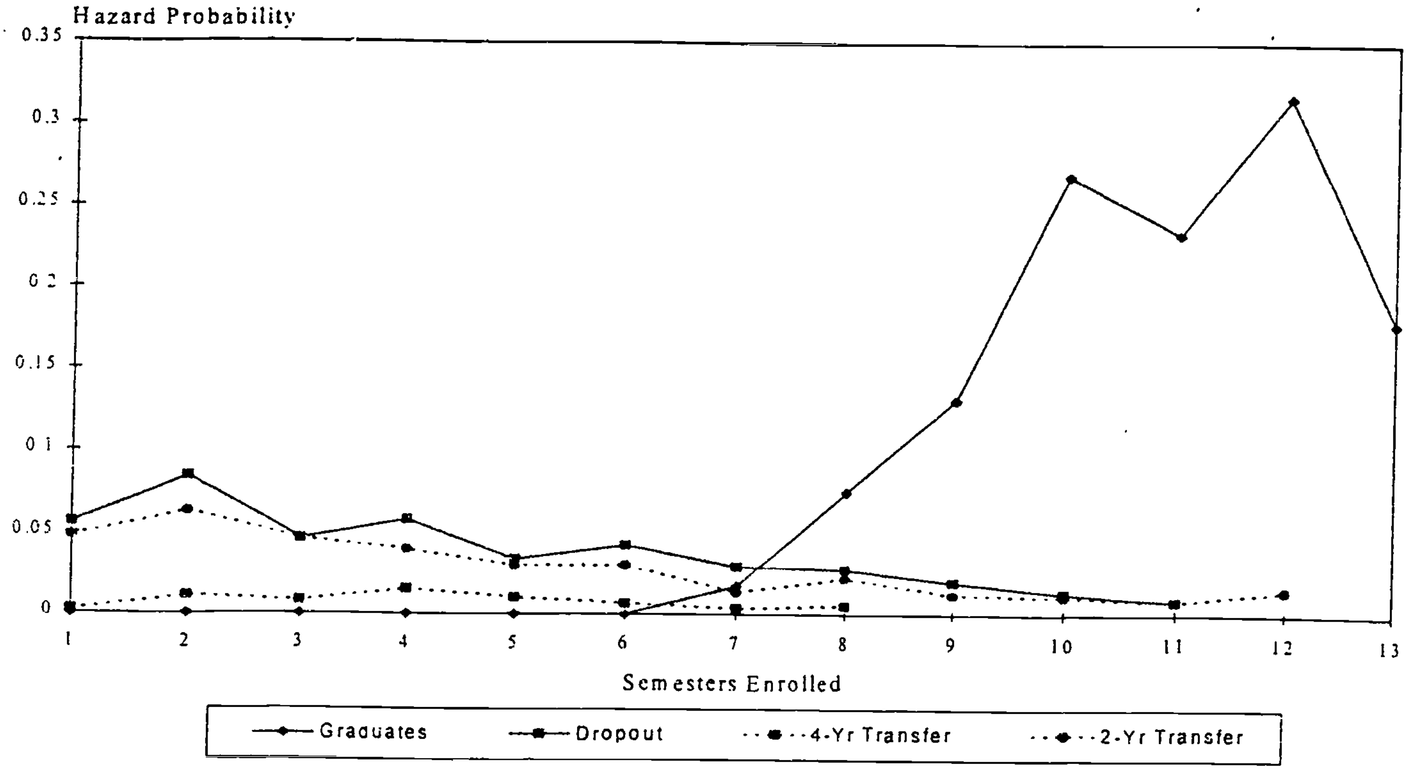

Figure 1: **Risk over time of leaving the university via four modes of exit**

RESULTS

Hazard probabilities shown in Table 2 are computed using each semester's risk set, which consists of all students still enrolled at the university. The risk of experiencing a particular event, such as dropout, consists of the number of students who dropped out after that particular semester, divided by the total number at risk of experiencing any event. The total at-risk number includes persisters (not shown), whose outcomes are censored. We see that risks of exiting via any route other than graduation are highest after the second semester of enrollment. Risk of dropout remains relatively high until about the seventh semester of enrollment. The risk of graduation begins at that time, and peaks after 12 semesters. The larger probabilities for graduate hazard are a function of the declining risk set for all modes of exit. The number of semesters varies by exit mode as well; the last dropouts left after their eleventh semester of enrollment, the last four-year transfers after 12 semesters. The hazard functions of the four modes of exit are plotted in Figure 1.

Main effects

In survival analysis, the effect of substantively interesting predictors can be investigated by comparing pairs of fitted models. The initial model containing the time indicators only is fitted first, indicating the risk of a specific event occurrence in each time period net of any additional

Table 3. Estimated effects of variables on the probability of leaving the university via four modes of exit.

Variables	Dropout	Two-year Transfer	Four-year Transfer	Graduate
Ethnicity				
Hispanic (vs. all others)	0.60***	1.42**	0.30***	0.63***
Sex				
Female (vs. male)	0.95	1.05	0.63	1.23*
Admit Status				
Provisional (vs. regular)	1.62***	3.08***	0.81	0.67**
Enroll Status				
Full-time (vs. part-time)	0.59*	0.57***	1.56	2.33***
Academic Status				
High GPA (vs. all others)	0.24***	0.17***	1.03	2.84***
Mid GPA (vs. all others)	0.31**	0.26***	0.84	0.65***
Low GPA (vs. all others)	6.50***	8.52***	1.15	0.32***
Major				
SEM (vs. all others)	0.79*	0.78	1.15	0.96
Business (vs. all others)	0.81*	0.63***	1.00	0.85
Liberal arts (vs. all others)	1.04	0.77*	1.30	1.06

Note: Effects are expressed as antilogs of the estimated parameters. An odds-ratio of 1.00 means that the variable has no effect on the probability of exit.
Significance tests are improvements in goodness-of-fit of extended model, df=1
*$p<.05$ **$p<.01$ ***$p<.001$

predictors. Additional variables, either singly or in groups, are then added, and their contribution assessed by comparing the goodness of fit of the extended to the original model, using standard decrement-to-chi-square testing (Singer & Willett, 1993).

Table 3 shows the analysis of a single predictor on all four modes of exit. Ethnicity was the only time-invariant variable significantly associated with all modes of exit. Hispanic students were less likely to transfer to another four-year school, to graduate, or even to drop out, but they were 1.4 times more likely than non-Hispanic students to transfer to a two-year institution. The low dropout risk and high two-year transfer odds suggest that Hispanic students enrolled here are intent on continuing their education, but may seek a better institutional fit than is currently being provided by our university. The lower graduation odds for Hispanic students is deceptive, however, since this predictor showed a significant interaction with time. As with any regression analysis, interaction suggests that the model's main effects do not have a straightforward interpretation. Interaction is further discussed below.

Admission status, as expected, influenced mode of exit, with provisionally-admitted students over three times more likely to transfer to a two-year school than regular-admit students, and 62% more likely to drop out. Provisional students were about two-thirds as likely to graduate. suggesting that it is possible for some students to overcome initial academic deficiencies. The nonsignificant four-year transfer difference between provisional and regular-admit students is probably due to sample sizes too small to detect significant differences among categories of students.

Gender played only a small role in predicting mode of exit, with female students slightly more likely to graduate than male students. Enrollment status had an expected effect on mode of exit. Full-time students were significantly less likely to drop out or transfer, and over twice as likely to graduate, at least within the time frame of this study. It is probable that correlates of part-time attendance, such as outside employment and family responsibilities are directly associated with higher dropout, and that these students may choose to do lower division coursework at the community college. which offers a more flexible schedule of classes.

The importance of GPA as a predictor of outcomes is confirmed in this analysis. Few students with high GPA's drop out or transfer to a two-year school, while about three times as many graduate as with lower GPA's. Students who exit through dropout or two-year transfer are most likely to do so because of the immediate impact of a GPA below 2.0. Students with failing GPA's are 6.5 times more likely to drop out, and 8.5 times more likely to transfer. That some low GPA's manage to graduate is the result of students having weathered some bad semesters. Effects for the hard science majors of science, engineering and math were limited to a slightly lower risk for dropout. Business majors were especially less inclined to transfer to a two-year school.

Although time-varying variables can be easily incorporated into the hazard models, the interpretation of these effects is not so straightforward. For example, the values for full- or part-time attendance can fluctuate from semester to semester, but the elevated risk of dropout or transfer for part-timers is present only during those semesters when the student attends part-time. Willett & Singer (1993b) suggest that to ease interpretation, only individuals whose academic careers were composed of all full-time semesters be compared against those whose attendance

Table 4. Summary of effects of variables on mode of exit

Variable	Dropout	Two-year Transfer	Four-year Transfer	Graduate
Hispanic	(-)	(+)*	(-)	(-)*
Female	0	0	0	(+)
Provisional	(+)*	(+)*	0	(-)
Full-time	(-)	(-)	0	(+)*
High GPA	(-)	(-)	0	(+)*
Mid GPA	(-)	(-)	0	0
Low GPA	(+)	(+)	0	(-)
SEM major	(-)	0	0	0
Business major	(-)	(-)	0	0
Liberal arts major	0	(-)*	0	0

Note: (-) Parameter estimates negative. $p < .05$
(+) Parameter estimates positive, $p < .05$
0 Parameter estimates not significant
* Interaction with time variable. $p < .05$

was entirely part-time. The hazard functions produced by these extremes will form the boundaries within which all students with mixed semesters of full and part-time enrollment will fall. Table 4 summarizes the effects for all variables on modes of exit.

Effects of predictors over time: Interaction

In addition to having values which vary over time, predictors can have a different impact on hazard at different time periods. One such predictor is provisional status. We would expect that a student entering on provisional status would be at much greater risk of dropout in the first two semesters of enrollment than after the provisional hurdle is cleared. The models examined above assume that the predictor has an identical effect in every time period. This assumption is known in survival analysis as the proportional hazards assumption. But nonproportional hazards, in which the logit-hazard profiles are not parallel, is the rule rather than the exception, and researchers should assume that nonproportionality exists until proven wrong. The proportionality assumption is tested by forming cross-products in the person-period data set between the time indicators and the chosen predictor, and including those cross-products, along with the relevant main effects, as predictors in the hazard model (Singer & Willett, 1993).

The asterisks in Table 4 indicate which of the predictors in this study had differential effects over time, several of which are graphed in Figure 2. The effect of provisional status on dropout is greatest in the first four semesters, and especially after the second semester (Figure 2a).

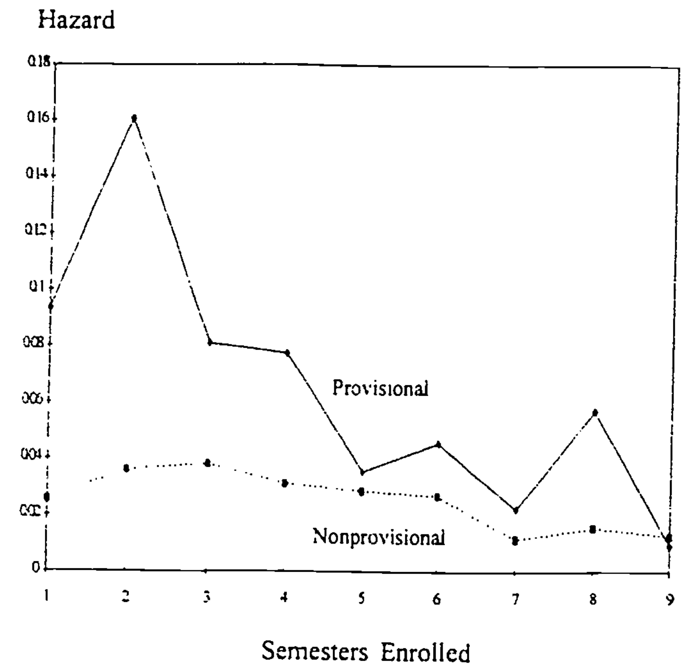

Figure 2a: Effect of provisional admission status on risk of dropout

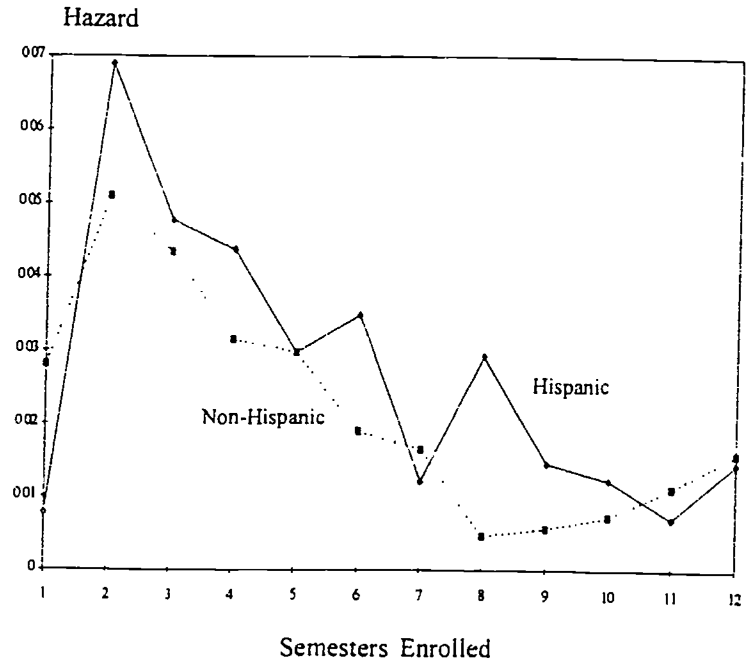

Figure 2b: Effect of ethnicity on risk of two-year transfer

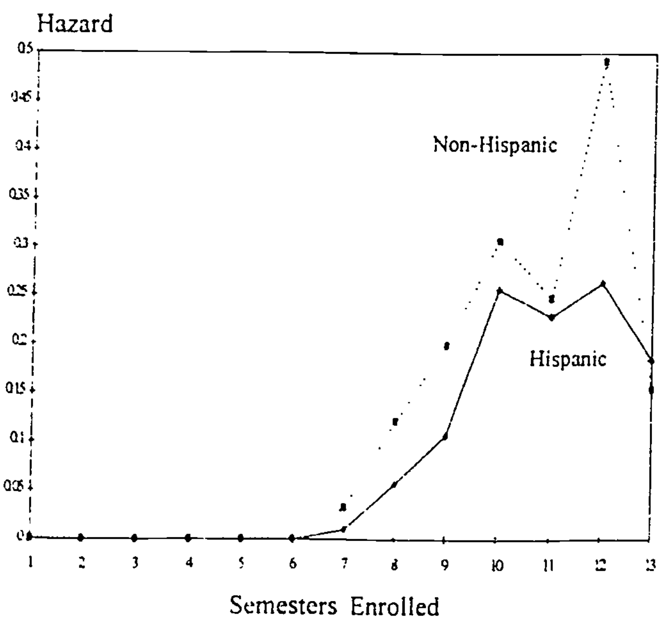

Figure 2c: Effect of ethnicity on risk of graduation

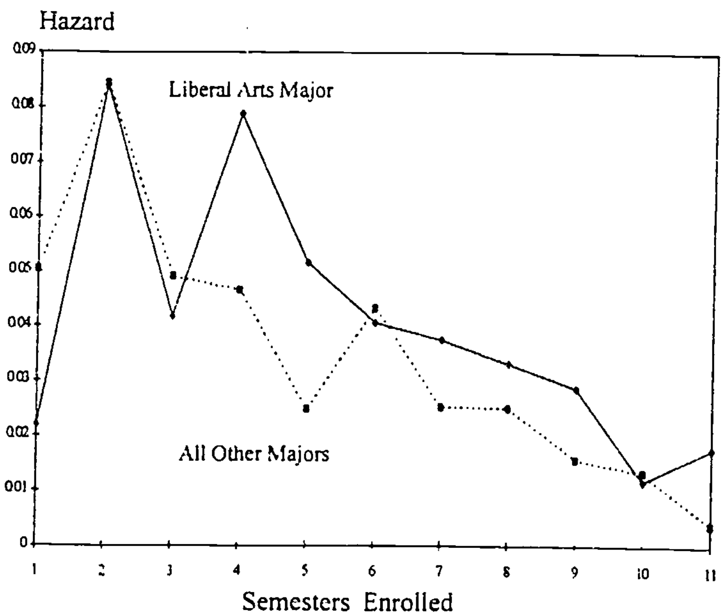

Figure 2d: Effect of having a liberal arts major on risk of dropout

Hispanic students are at a higher risk for two-year transfer, but this risk is by no means constant; it is most pronounced afte- the second and eighth semesters of enrollment (2b). The lower odds for Hispanic student graduation is explained by the time interactions in Figure 2c. The disproportionate risk is entirely accounted for by the high rate of non-Hispanic student graduation after the twelfth semester (sixth year), whereas Hispanic students may take longer to reach graduation. Even predictors whose overall effect on hazard is nonsignificant should be checked for interaction with time. The effect of a liberal arts major on dropout was not significant, but further investigation revealed that these majors do have elevated risks of dropout relative to other majors after the fourth and fifth semesters of enrollment (Figure 2d). In all of these cases, if the time interaction variable had been ignored, conclusions about the risk of these predictors would have been misleading.

DISCUSSION

The purpose of this analysis has been to explore the important contributions that a competing risks model can make to our understanding of student enrollment behavior. Through it we have seen that students who end their association with one institution have not necessarily abandoned higher education. By counting only those students who graduated from this university, this cohort would have a 33% graduation rate after seven years, not a particularly stellar performance. But if persisters and transfers are not considered failures, over 70% of this cohort found its way to a 'successful' outcome, at least upon their first separation from this institution. The percentage is probably even higher since some 'dropouts' undoubtedly have enrolled in private and out-of-state institutions where they could not be located.

By studying the timing of exit we learned that what we originally thought was a high dropout rate after the second semester, especially for Hispanic and provisional students, was, at least in part, a significant movement to the community college. Moreover, the dropout and two-year transfer rates compete about equally to end the students' association with this university over time. The timing of graduation was instructive as well. Although the graduation rate peaks after about six years, it remains high relative to other modes of exit when this data collection ended, suggesting that the 'censored' persisters are at more risk for eventual graduation than for leaving.

Examining the correlates of each mode of exit confirmed much of what we already know about student retention. Students who are academically prepared, who attend full-time, and perform well in college are more likely to graduate. This is hardly surprising since these are the traditional kinds of students that colleges are set up to accommodate. What is more interesting is the apparent mismatch for students who were admitted to this university initially, but found a better institutional fit elsewhere after one, two or more semesters of enrollment here. What could have been done to increase their chances of success here? Should they have enrolled here in the first place? It would be particularly useful to further explore the characteristics that distinguish two-year transfers from dropouts.

The investigation into four-year transfer was disappointing because the small number of these transfers relative to other modes of exit made it difficult to detect significant effects of predictors. It would have been interesting, for example, to see how many of the four-year transfers left to pursue a major not available at this university. Although a larger data set encompassing four years of entering cohorts was available, the conversion to the person-period data set greatly increases data storage requirements and the computer resources needed to run iterative algorithms, making it impractical to use more than a single cohort.

One limitation of this study was that it modeled only the risk of first exit. In a sense, the outcomes of any students other than graduates are censored. Dropouts could return to the university or transfer elsewhere; four-year transfers could persist to graduation or transfer again; two-year transfers might return here, go on to another school, and so on. A second stage of this analysis could be undertaken to follow first-transfer students to their next outcome.

Analytical models like competing-risks survival analysis can help inform institutions about the educational destinations of students and which factors lead to those destinations. This information can be used to prevent unwanted exits. It can also help focus the accountability discussion away from performance measures which do little more than document nontraditional student enrollment behavior, and toward indicators which will measure what students master during their enrollment in a particular institution.

REFERENCES

Allison, Paul D. (1984). Event history analysis: Regression for longitudinal event data. Newbury Park, CA: Sage Publications.

Ashworth, Kenneth H. (1994). Performance-based funding in higher education: The Texas case study. Change, 26, No. 6, 8-15.

Astin, Alexander W. (1993). What matters in college: Four critical years revisited. San Francisco: Jossey-Bass Publishers.

Bean, John P. (1980). Dropouts and turnover: The synthesis and test of a causal model of student attrition. Research in Higher Education, 12, 155-187.

Bean, John P. and Metzner, Barbara S. (1985). A conceptual model of nontraditional undergraduate student retention. Review of Educational Research, 55, 485-540.

Cabrera, Alberto F. (1994). Logistic regression analysis in higher education: An applied perspective. In John C. Smart (ed.) Higher Education: Handbook of Theory and Research, 10, 225-256.

Chirikos, Thomas N. and Nestel, Gilbert (1991). Occupational differences in the ability of men to delay retirement. Journal of Human Resources, 26, 1-26.

Cox, D.R. (1972). Regression models and life tables. Journal of the Royal Statistical Society, 34, Series B, 187-202.

Ewell, Peter T. (1994). A matter of integrity: Accountability and the future of self-regulation. Change, 26, No. 6, 25-29.

Hachen, David S., Jr. (1988). The competing risks model: A method for analyzing processes with multiple types of events. Sociological Methods & Research, 17, 21-54.

Hosmer, David W. & Lemeshow, Stanley (1989). Applied Logistic Regression. New York: John Wiley & Sons.

Kalbfleisch, J.D. and Prentice, R.L. (1980). The statistical analysis of failure time data. New York: John Wiley & Sons.

Koenigsberg, Judy et al. (1994). The effect of family on the job exits of young adults. Work and Occupations, 21, 33-63.

Kraemer, Barbara A. (1995). Factors affecting Hispanic student transfer behavior. Research in Higher Education, 36, 303-322.

Mensch, Barbara S. & Kandel, Denise B. (1988). Dropping out of high school and drug involvement. Sociology of Education, 61, 95-113.

Murdnane, Richard J., Singer, Judith D. & Willett, John B. (1988). The career paths of teachers: Implications for teacher supply and methodological lessons for research. Educational Researcher, 17, 22-30.

Pascarella, Ernest T. and Terenzini, Patrick T. (1991). How college affects students. San Francisco: Jossey-Bass Publishers.

Ronco, Sharron L. (1994). Meandering ways: Studying student stopout with survival analysis. Paper presented at the annual forum of the Association for Institutional Research, New Orleans, LA.

Singer, Judith D. & Willett, John B. (1988). Detecting involuntary layoffs in teacher survival data: The year of leaving dangerously. Educational Evaluation and Policy Analysis, 10, 212-224.

Singer, Judith D. & Willett, John B. (1991). Modeling the days of our lives: Using survival analysis when designing longitudinal studies of duration and timing of events. Psychological Bulletin, 110, 268-290.

Singer, Judith D. & Willett, John B. (1993). It's about time: Using discrete-time survival analysis to study duration and timing of events. Journal of Educational Statistics, 18, 155-195.

Terenzini, Patrick T. and Pascarella, Ernest T. (1980). Towards the validation of Tinto's model of college student attrition: A review of recent studies. Research in Higher Education, 12, 271-282.

Thomas, G. & Gordon, S. (1983). Evaluating the payoffs of college investments for black, white and hispanic students (Report No. 344). Baltimore: Johns Hopkins University, Center for Social Organization of Schools.

Tinto, Vincent (1975). Dropout from higher education: A theoretical synthesis of recent research. Review of Educational Research, 45, 89-125.

Tinto, Vincent (1987). Leaving college. Chicago: University of Chicago Press.

Tinto, Vincent (1990). Principles of effective retention. Journal of the Freshman Year Experience, 2, 35-48.

Tuma, Nancy B. and Hannan, M.T. (1984). Social dynamics, Orlando, FL: Academic Press.

Willett, John B. & Singer, Judith D. (1991a). How long did it take? Using survival analysis in educational and psychological research. In L. Collins and J. Horn (Eds.). Best methods for the analysis of change: Recent advances, unanswered questions, future directions (pp. 310-327). Washington DC: American Psychological Association.

Willett, John B. & Singer, Judith D. (1991b). From whether to when: New methods for studying student dropout and teacher attrition. Review of Educational Research, 61, 407-450.

Willett, John B. & Singer, Judith D. (1993a). Investigating onset, cessation, relapse and recovery: Why you should, and how you can, use discrete-time survival analysis to examine event occurrence. Journal of Consulting and Clinical Psychology, 61, 952-965.

Willett. John B. & Singer, Judith D. (1993b). It's deja-vu all over again: Using multiple-spell discrete time survival analysis. Submitted to the Journal of Educational Statistics. Copy available from authors.

Yamaguchi, Kazuo (1991). Event history analysis. Newbury Park, CA: Sage Publications.

Yamaguchi, Kazuo and Kandel, Denise B. (1987). Drug use and other determinants of premarital pregnancy and its outcome: A dynamic analysis of competing life events. Journal of Marriage and the Family, 49, 257-270.

Zatz, Marjorie S. (1985). Los cholos: Legal processing of Chicano gang members. Social Problems, 33, 13-30.