Identifying Students at Risk: Utilizing Survival Analysis to Study Student Athlete Attrition

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Abstract - The goal of the study was to develop a practical application to help a large doctoral research extensive public university promote student athlete success by identifying at-risk student athletes. A longitudinal model using survival analysis was used to identify factors that impact a student athlete's ability to persist and graduate.

1 Introduction

Student retention/graduation has become more important then ever to institutions in terms of accountability and rankings and recent national initiatives have focused on collegiate academic outcomes. It is also clear from the preliminary reports from the Commission on the Future of Higher Education that accountability of institutions of higher education will be measured, in part, by graduation rates (Field, 2006). For student athletes, the focus on retention and graduation has been even more intense. Changes in NCAA legislation focusing on student athlete academic outcomes at Division IA institutions (Academic Performance Rates, ARP) are aimed at improving academic success (i.e., graduation rates).

As part of an overriding strategic positioning process at the institution of study, a task force focused on the academic support and performance of student athletes was formed to examine the academic progress and success of student athletes. This effort, partnered with the merging of athletic databases into the University central student record system, has greatly aided in the reporting and analyses of athletic related data. Historically, the graduation rates of certain subgroups of students have been low; in particular, the graduation rates of intercollegiate athlete students in the revenue producing sports (e.g., football, basketball, etc.). Student athletes face many of the same pressures that any student faces, but many are unique. The time spent in practice and travel and not on academic work, but also the personal concerns arising from the anxiety of being injured, dealing with team mates and coaches, and maintaining your eligibility (Scott, 2006). The study was conducted for the practical application to help decision makers develop better policies for student athletes. Questions to be answered by the study:

What characteristics of student athletes help predict success or departure?
When is a student athlete at greatest risk of not succeeding?
Does the profile of risk differ across subgroups of athletes (e.g. revenue vs. non-revenue sports)?

2 Overview of the Research

There are a number of student retention models beyond Tinto's (1975) student integration model. But, Tinto was the first to lay out a detailed longitudinal model of student persistence that described the interconnections between the student and institution to the path of student success (i.e., graduation) over time. In a recent review of the state of student retention research and its potential future directions, Tinto argues what really is important is, "… not our theories per se, but how they help institutions address pressing practical issues of persistence." (Tinto, 2006, p. 6).

The attrition studies on student athletes, up to this point, have examined attrition in relation to effective educational practices and academic and student service programs (Umbach, Palmer, Kuh and Hannah, 2006; Hollis, 2001) and/or have been primarily focused on a subgroup of athletes (e.g. African

American male athletes), (Hyatt, 2003; Pearson and LeNoir, 1997). The methodologies in these previous studies have been primarily descriptive in nature or limited to time invariant statistical techniques. None of these studies has implemented a survival analysis approach to examine the longitudinal effect of these factors over time on student athlete attrition. The use of survival analysis modeling to study student retention (Ishitani & Snider, 2006; Ishitani, 2003; DesJardins, Ahlburg, and McCall, 1994; DesJardins, McCall, Ahlburg, & Moye, 2002; DesJardins, & Moye, 2000; Murtaugh, Burns & Schuster, 1999) and student stopout behavior (Ishitani & DesJardins, 2002; DesJardins, Ahlburg & McCall, 1994; Ronco, 1994; Willett & Singer, 1991) is now well established.

DesJardins et al. (1994) used a general athlete variable (athlete or not) in their survival analysis of stopouts in a general population of students. They found that athletes were significantly less likely to stopout during their first four years, but were at higher risk of withdrawal in their 5th and succeeding years (perhaps the loss of eligibility after four years). No other studies have utilized survival analysis techniques focused entirely on student-athlete attrition. The incorporation of explanatory variables related solely to the athletic experience will enhance our understanding of the attrition behavior of this particular subgroup of students.

3 Data

The data sample consisted of all 564 student-athletes at a large, Midwestern Carnegie Doctoral-extensive university who entered as first-time freshmen anytime during the 1999 thru 2001 academic years. The event under study varied slightly depending on when the student matriculated into the university. For students who entered in the 1999-2000 academic year, the outcome observed was whether or not the student had graduated by the sixth year. For students entering in 2000-2001 and 2001-2002, the event was whether or not the student had graduated or was still enrolled after four and five years, respectively. This simplified outcome variable could be justified, if one argues that many student athletes continue through their first four years (i.e., in order to remain eligible to play) and then make the decision to continue or not. The variable used to account for duration of time for the event under analysis was total credits completed at the university. Credits successfully completed corresponds more closely to progress toward a degree than simply the number of terms attended, and also allows for identifying important transitions in a student's career, such as major declaration and the shift from lower to upper division coursework. The model developed focused on: student background characteristics, demographics, financial aid, and end of first term performance indicators. It is not in particular, theory driven, though an attempt to use and operationalize readily available data from the institution's student record system loosely follows Tinto's model of student persistence.

As table 1 illustrates the sample was composed of 53.7% male athletes, 17% students of color (SOC). In-state students comprise the reference group for tuition residency at 55.6% of the cohort, the remaining portion are from states with tuition reciprocity agreements (17.4%), non-reciprocity states (23.6%) and international students (3.4%). Slightly more then an half received some amount of athletic financial aid their first year, that is, were tendered athletes (54.1%). The vast majority of the athletes were in non-revenue sports (70.9%), with the remaining in the revenue producing sports, for purposes of this study defined as men's football, men's and women's basketball, men's and women's hockey and women's volleyball. About 24% of the student-athletes were PELL eligible, in addition to PELL eligibility, the amount of federal unmet need was used as a proxy measure of socioeconomic status. Only about 4% of student athletes lived off-campus their first year. A number of first semester academic progress variables were included. The ratio of credit hours earned toward a degree to credit hours attempted for the first semester (sans course withdrawals) was calculated as one measure of academic progress. The number of C's, and D's earned during the first semester was also collected to assess academic progress, since these grades do count toward the progress to a degree but indicate borderline/marginal performance. The number of first-semester course withdrawals was also collected to augment academic progress.   Of the 564 student-athletes studied, 31.4% were not successful, that is, had not graduated or persisted from the University during the time-frame under investigation.

Table 1. Descriptive Statistics of the Sample (N=564)

Variable	Values	Mean	SD	Variable Description (type of variable)
Departure*	0-1	0.314	0.464	If not successful at the U (response variable)
Credits**	0-203	102.4	40.4	Total credits earned while at the U (timing variable)
Ratio	0-1	0.963	0.118	Ratio of first term credits earned to attempted
C’s earned	0-4	0.741	0.886	Number of C grades earned first semester
D’s earned	0-2	0.150	0.386	Number of D grades earned first semester
W’s earned	0-3	0.050	0.244	Number of W grades earned first semester
ACT Composite	14-36	23.263	4.015	ACT composite score
Remedial	0-3	0.387	0.687	Number of remedial courses taken first semester
Tendered	0-1	0.541	0.499	If tendered (dummy)
Sport Group	0-1	0.709	0.456	If Non-revenue sport group (dummy)
Male	0-1	0.537	0.499	If Male (dummy)
Student of Color	0-1	0.170	0.376	If Black, Hispanic, Asian, Native Am. (dummy)
Reciprocity	0-1	0.174	0.379	If Tuition reciprocity state (dummy)
Non-Reciprocity	0-1	0.236	0.425	If Tuition non-reciprocity state (dummy)
International	0-1	0.034	0.181	If International student (dummy)
Federal Unmet need	$0-$24,194	$4,741	$6,15	Total amount of estimated unmet financial need
Pell	0-1	0.239	0.427	If Pell grant eligible (dummy)
Off-campus Housing	0-1	0.041	0.198	If not living on-campus first term (dummy)

* Response variable

** timing variable

3 Methods

Survival models, also known as event history models or failure-time models are used to estimate the timing of events. These techniques have their origins in biostatistics, in which “survival” was often very much a literal description of the phenomena in question. Survival models have also been used extensively in economics, and are seeing expanded use across the social sciences (Box-Steffensmeier and Jones, 2004). The ability to explicitly model the dynamic nature of events is a powerful tool, as “when?” is frequently at least as important a question as “why?”. This is certainly true in student retention research. Retention is not an instantaneous event, but rather a prolonged process (Tinto, 1987). Understanding the dynamic nature of that process is critical to shaping effective intervention programs and policies.

In modeling the timing of student departure, there is a particular source of heterogeneity in student behavior that is of fundamental importance. Standard survival models assume that all cases will eventually fail, if given sufficient time. Observations will be “censored”, or no longer observable, upon graduation, but the model will still attempt to determine their likely duration of enrollment. Schmidt and Witte (1988) faced a similar difficulty in studying recidivism among released prisoners. While many would commit future crimes and return to prison, many others would not, no matter how long the period of observation. Further, it was important to be able to distinguish the characteristics which led to the occurrence of recidivism from the timing of it, to separate the "whether" from the "when". To answer these two questions, they developed the split-population survival framework.

To understand the structure of the split-population survival model, let F represent an unobserved variable that equals one for those students who eventually depart from the institution, and zero for those who either graduate or persist beyond the period of observation. Further, let the probability of departure be represented as $P(F = 1) = \delta$. The probability of success (graduation or retention beyond observation) is therefore $P(F = 0) = 1 - \delta$. The value of δ substantively represents the departure rate and $1 - \delta$ represents the success (graduation/retention) rate. Since this variable represents a probability, predictions must be constrained between zero and one, so ordinary least squares regression is inappropriate. Instead, methods designed for dichotomous dependent variables must be used, such as logit or probit (Maddala, 1983). For those students predicted to depart, a cumulative distribution function of the time until departure $G(t|F=1)$ is assumed, where t represents time, measured in this study as the number of credits completed. The survivor function, representing the proportion of students who are expected to depart but are still enrolled as of time t can therefore be written as $S(t|F=1) = 1 - G(t|F=1)$. Predictor variables can be incorporated into the model by parameterizing the distribution function. In this case, analysis of the shape of the data on departure times suggested a log-logistic distribution was appropriate. The survivor function can therefore be written as:

$$S(t \mid F = 1) = \frac{1}{1 + (\lambda t)^{1/\gamma}}$$

where λ_j is parameterized by exp(-xB), where x represents the observed value of each variable and B represents the estimated coefficient for each variable, and the scale parameter γ, which represents the shape of the distribution, is estimated from the data. The parameters can be estimated using maximum likelihood estimation procedures.

4 Results

The split-population survival model produces simultaneous equations of the probability of failure and the timing of those failures that are predicted to occur, along with an estimate of gamma, a parameter indicating the shape of the estimated log-logistic distribution of failure times. The model correctly predicted 72% of the students' departure decisions (Table 2). While this is only a slight improvement in accuracy over assuming all students would succeed (69% of the cohort did not drop out), we are more concerned with accurately identifying students who will drop out than those who will succeed. Of the 172 students from the cohort who dropped out by the end of the study period, the model correctly identified over two-thirds of them as drop-outs. These students can be targeted for interventions by student services to improve retention.

Table 2. Predicted and Actual Student Departure

	Predicted Departure		
Actual Departure	Retained	Departed	Total
Retained	278	101	379
Departed	56	116	172
Total	334	217	551

The most statistically powerful predictors of student athlete retention were measures of academic preparation and first-term academic performance (Table 3). The ratio of credits completed to attempted,

Table 3. Split-Population Survival Model Parameter Estimate

Logit (depart)	Coef.	Std Error	z	Sig.	P>|z|
Ratio	-5.7003	1.8063	-3.16	***	0.002
C's earned	0.4245	0.2046	2.07	**	0.038
D's earned	-0.6208	0.4672	-1.33		0.184
W's earned	1.5497	0.5812	2.67	***	0.008
Remedial	1.3247	0.4650	2.85	***	0.004
ACT Composite	-14.7164	6.7375	-2.18	**	0.029
Tendered	0.1546	0.3787	0.41		0.683
Sport Group	-0.4302	0.4110	-1.05		0.295
Male	-0.1573	0.3802	-0.41		0.679
Student of Color	-0.9631	0.5267	-1.83	*	0.067
Reciprocity	0.1224	0.5704	0.21		0.830
Non-Reciprocity	0.9348	0.4616	2.02	**	0.043
International	2.0597	1.7109	1.20		0.229
Federal Unmet Need	0.1452	0.0819	1.77	*	0.076
Pell	-0.2625	0.4517	-0.58		0.561
Off-Campus Housing	-1.6218	0.8458	-1.92	*	0.055
Constant	8.1469	3.0103	2.71		0.007

Duration (credits)	Coef.	Std Error	z	Sig.	P>|z|
Ratio	1.2664	0.5270	2.40	**	0.016
C's earned	0.0018	0.0909	0.02		0.984
D's earned	-0.5393	0.1869	-2.89	***	0.004
W's earned	-0.6827	0.2129	-3.21	***	0.001
Remedial	0.2123	0.1166	1.82	*	0.069
ACT Composite	-5.9107	3.3046	-1.79	*	0.074
Tendered	0.0185	0.2110	0.09		0.930
Sport Group	0.1503	0.2091	0.72		0.472
Male	-0.1605	0.2005	-0.80		0.423
Student of Color	-0.5720	0.2302	-2.48	**	0.013
Reciprocity	0.1881	0.3347	0.56		0.574
Non-Reciprocity	0.2334	0.2059	1.13		0.257
International	-0.0443	0.6375	-0.07		0.945
Federal Unmet Need	-0.0456	0.0311	-1.47		0.142
Pell	0.1282	0.2133	0.60		0.548
Off-Campus Housing	-0.7673	0.4186	-1.83	*	0.067
Constant	4.4114	1.1301	3.90		-

Shape (gamma)	Coef.	Std Error	z	Sig.	P>|z|
Constant	0.5114	0.0459	11.12	***	0.000

* = p < .10 ** = p < .05 *** = p < .01

Log-likelihood = -1,077.77 p(chi-square) < .0001 the number of W's earned, and the number of remedial courses taken were statistically significant at the .01 level. In addition, the number of C's earned during the first term and the student's ACT composite score were statistically significant at the .05 level. In each case, poorer academic performance during the first term and lower measures of academic preparation led to lower retention probability predictions. In addition to measures of academic preparation and performance, there is evidence that students attending the institution from outside its tuition reciprocity agreement area were less likely to be retained. This measure was also statistically significant at the .05 level.

A few other predictors were statistically significant only at the .10 level. Given the relatively small size of the study and the relative rarity of some of these conditions within the cohort, it is possible that these predictors are informative but not clear enough to attain greater statistical clarity. These results suggest areas that could warrant further study to attempt to clarify the relationships. These include identification as a student of color, unmet financial need, and living in off-campus housing. The results at least tentatively suggest that, all other things equal, students of color and students living off campus were more likely to be retained, and students with unmet financial need were less likely to be retained. While the results for race and financial need square with experience and intuition, the results for off-campus housing do not. Very few freshman student athletes live off-campus, so this may be an unusual subgroup, or it may be serving as a proxy for other, unobserved variables.

For those students predicted to drop out, the most statistically powerful predictors of the timing of departure were again primarily measures of academic preparation and first-term academic performance. The number of D's and the number of W's earned during the first term reduced the time until departure, and were statistically significant at the .01 level. In addition, the ratio of credits completed to credits attempted in the first term was statistically significant at the .05 level, and the number of remedial courses and the student's ACT composite score were statistically significant at the .10 level. Failure to successfully complete courses led to earlier departure, but the direction of the last two effects may be somewhat surprising. Remedial coursework appeared to lead to delayed departure, perhaps signaling that difficulties were not encountered until the transition from remedial to standard courses. Higher ACT composite scores led to earlier departure. It has been observed before at this institution that it loses a number of high-ability students early in their careers. These results provide some moderate support for that observation, and suggest the phenomena bears further analysis.

Two additional variables exhibit interesting patterns that are highlighted by the split-population survival technique. Student athletes of color who leave the institution tend to do so earlier than other similar students. This relationship was statistically significant at the .05 level. However, these students, all other things equal, were more likely to be retained. This suggests that those student athletes of color who the institution loses, it loses early. Likewise, for the relatively rare subgroup of student athletes living off campus, while they are retained at a higher level than comparable students living on campus, those that depart do so more quickly. The ability to distinguish these countervailing trends is the great strength of the split-population approach.

The impacts of these variables can be seen more easily by calculating the retention rates for a "typical" case, and comparing those rates to those produced by modifying the values one by one. To generate a baseline or typical case, all of the dichotomous and count variables were set to zero, and the two continuous variables were set to whole numbers near their mean. This produces a theoretical student athlete who successfully completed all of their first-term courses with grades higher than C, took no remedial coursework, had a composite score of 23 on the ACT, was not tendered and did not play a "revenue" sport, was female, not a student of color, a Minnesota high school graduate, had $500 of unmet financial need, was not eligible for Pell grants, and lived on campus. Each of these characteristics can be altered while holding the rest at these baseline values, showing the impact of a typical change in that one variable (Table 4).

For the logit model, the baseline case is predicted to have a 70% retention rate (defined as graduation or continued enrollment at the end of the study period). The strength of the three academic preparation and performance measures in the logit equation can be clearly seen in their lower predicted graduation/retention rates. Failure to successfully complete one of five courses (a ratio of 0.80) lowers the predicted success rate to 43%. Similarly, earning one C drops the retention rate to 61%, and earning one W drops the retention rate all the way to 34%, less than half that of the baseline case. Taking a single remedial course drops the success rate to 39%. Student athletes from non-reciprocity states would be predicted to succeed at a rate of 48%, all other things equal. By contrast, scoring a composite 27 on the ACT, approximately one standard deviation above the mean, increases the expected success rate to 81%. Student athletes of color are predicted to succeed at a rate of 86%, and student athletes living off campus are predicted to succeed at a rate of 92%. The largest impact in the chart is for international students, who all other things equal would be predicted to have only a 23% success rate. The number of such students is small, and the relationship is very noisy, so this is not a statistically significant relationship. However, given its significant practical impact, this is a subgroup that warrants more detailed study, likely at the level of individual case analysis.

Table 4. Predicted Retention Rates for Alternative Values of Each Variable Holding All Other Variables at Baseline Values

Logit (depart)	**Baseline**	**Alternative**	**Retention**	**Change**
Ratio	1.0	0.8	43%	-27%
C's earned	0	1	61%	-10%
D's earned	0	1	82%	11%
W's earned	0	1	34%	-37%
Remedial	0	1	39%	-32%
ACT Composite	23	27	81%	11%
Tendered	0	1	67%	-3%
Sport Group	0	1	79%	8%
Male	0	1	74%	3%
Student of Color	0	1	86%	16%
Reciprocity	0	1	68%	-3%
Non-Reciprocity	0	1	48%	-22%
International	0	1	23%	-47%
Federal Unmet Need	$500	$2,500	64%	-6%
Pell	0	1	76%	5%
Off-Campus Housing	0	1	92%	22%
		Baseline:	**70%**	**0%**

In similar fashion, the impact of each variable on the timing of departure can be more easily interpreted by examining the impact of a deviation from the baseline case on the predicted survival function. For the baseline case, 85% of the student athletes are predicted to have been retained after the completion of 30 credits. By 60 credits, that percentage has declined to 60%. At 90 credits, it is predicted to be 40%, and by 120 credits, it drops to 28%. These percentages are for those students who are predicted to drop out at some point during their careers. This means that of students with the baseline values who will not complete their education, 15% (100%-85%) will have discontinued before reaching 30 credits, and 40% (100%-60%) will have done so before reaching 60 credits. The most statistically significant predictors of the timing of departure were the number of D's and the number of W's earned the student's first term. The practical significance of these factors can be seen in their impact on the survival function. A student athlete predicted to drop out who earned a single D their first term would have only a 67% chance of continuing to be enrolled after 30 credits. By 120 credits, that percentage would have dropped to 12%. Likewise, a student athlete predicted to drop out who earned a single W in their first term would have a 60% chance of being enrolled after 30 credits, and only a 9% chance after

120 credits. As noted above, student athletes of color who were predicted to drop out appear to do so earlier in their careers than other similar student athletes. Of those students athletes of color predicted to drop out, only 65% are estimated to still be enrolled at 30 credits, and by 120 credits that percentage has dropped to 11%. Those who did not successfully complete all of their courses their first term are also more likely to depart early. A student athlete who is predicted to drop out and who successfully completes 80% of their first-term courses would have a probability of being retained past 30 credits of 78%, dropping to 19% by 120 credits. Students living off campus show one of the fastest declines in the duration of attendance, with only 56% of those predicted to drop out still enrolled after 30 credits.

Table 5. Predicted Survivor Function for Alterative Values of Each Variable Holding All Other Variables at Baseline Values

			Survivor Function			
Duration (credits)	**Baseline**	**Alternative**	**30 credits**	**60 credits**	**90 credits**	**120 credits**
Ratio	1.0	0.8	78%	47%	29%	19%
C's earned	0	1	85%	60%	40%	28%
D's earned	0	1	67%	34%	19%	12%
W's earned	0	1	60%	28%	15%	9%
Remedial	0	1	90%	69%	50%	37%
ACT Composite	23	27	78%	48%	30%	19%
Tendered	0	1	86%	61%	41%	28%
Sport Group	0	1	89%	67%	47%	34%
Male	0	1	81%	52%	33%	22%
Student of Color	0	1	65%	33%	18%	11%
Reciprocity	0	1	89%	68%	49%	36%
Non-Reciprocity	0	1	90%	70%	51%	38%
International	0	1	84%	58%	38%	26%
Federal Unmet Need	$500	$2,500	83%	55%	36%	24%
Pell	0	1	88%	66%	46%	33%
Off-Campus Housing	0	1	56%	25%	13%	8%
		Baseline:	**85%**	**60%**	**40%**	**28%**

5 Discussion

The results of the analysis provide guidance on the issues impacting the academic success of student athletes and suggest possible routes for improvement. The most powerful predictors of both the likelihood of student athlete departure and its timing for the cohorts in the study were levels of academic preparation and first-term academic performance. Worth noting was the lack of evidence that either tendered status or sport type was significantly related to student athlete departure after controlling for academic preparation and first-term academic performance. Vigilance and support during the first term of enrollment are therefore of critical importance. The study institution has recently created a system of mid-term grade reports for all freshmen, and this data provides opportunities for targeted outreach to students who are struggling academically. Additional attention should also be paid to student athletes from beyond the tuition reciprocity area and to integrating them into the campus community, given the evidence that they are more likely to leave before completing their degrees. Finally, while the institution should be pleased with its retention of student athletes of color, the fact that those who do leave do so early in their careers suggests there could still be benefit to targeted outreach in the first year.

The study also has several implications for future research. Expanding the analysis to all students on campus will help identify characteristics and relationships that are unique to student athletes, as well as provide information for improving general student retention. Repeating the analysis with more recent cohorts will also open up opportunities to connect data that has only recently been collected at the institution, such as the use of recreational sports facilities. Such measures could help with assessing the importance of the social integration of students. Finally, recent advances in the development of split-population survival models include the integration of time-varying covariates, which could be used in future analyses. While working exclusively with first-term data is useful in identifying early warning indicators for interventions during the critical first year of enrollment, the ability to incorporate changing academic performance, financial need, and other measures over the student's career would enrich our understanding of the process of student retention and departure.

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