Analysis of Stopout Behavior at a Public Research University: The Multi-Spell Discrete-Time Approach

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Abstract

Using multi-spell discrete time binary logistic regression, this study examined sequential occurrences of students' departures and returns over the period of six years. The model included time-invariant (gender, ethnicity, parents' educational attainment, family income, timing of matriculation, high school performance, and geographic origin) and time-varying (part-time attendance and college grade performance) predictors. The departure was strongly associated with poor college grade performance and part-time enrollment. Parents' educational attainment, SAT scores, and geographic origin predicted the probability of return. It was also shown that the duration of a spell affected the odds of departures and returns in a spell immediately following.

Introduction

College persistence has been a continuing concern for campus administrators, institutional researchers, policymakers, and society at large. In response to this concern, a substantial number of empirical and theoretical studies have sought to examine the factors associated with student attrition. Persistence studies usually focus on a students' first departure without considering subsequent enrollment patterns of individuals who stop out for several terms. However, there is growing evidence that stopout constitutes a substantial part of attrition. Horn (1998) indicates that the majority (64 percent) of students who left the 4-year sector before the beginning of the second year returned within 5 years.[1] According to O'Toole, Stratton, and Wetzel (2003), about 30% of the college going population stopped out during some non-summer term. This evidence of stopout activity suggests that considering attendance patterns after the first departure and factors contributing to student return would provide a more informative description of attrition.

Previous studies differentiating between stopout and dropout (e.g., Herzog, 2003, Horn, 1998, Stratton, O'Toole, and Wetzel, 2003) found significant differences between those who returned and did not return. However, most of these studies were limited to the first early departure (leaving before the second year of college) and did not consider the timing of departures and returns. Using fixed time frames in studies of stopout behavior lead to the possibility of a classification error (Stratton et al., 2003): some of those classified as having stopped out may return for one term and then leave permanently; some of those classified as dropouts might return later; and some of those classified as persisters might leave later. Capturing the timing of departures and returns reduces classification error and reveals the longitudinal character of stopout behavior.

Studies exploring the times at which students are at risk of leaving college (e.g., DesJardins, Ahlburg, and McCall, 1994, 1999, Ronco, 1995) typically focused on the first departure and did not extend their analysis to subsequent enrollment episodes (exception is Ronco, 1994). The earlier application of multi-spell analysis to stopout study (Ronco, 1994) illustrated the possibilities of the method. However, Ronco's study used only two substantive predictors (ethnicity and part-time enrollment) and did not explore the effects of spells' length on subsequent episodes. The study herein extends the application of multi-spell analysis in several ways. It considers the effect of stopout duration on subsequent departure and the effect of departure timing on the probability of return, incorporates several substantive predictors to the stopout model, and offers a model with fewer timing parameters without a substantial decrease in model fit. The focal questions of the study are:

- When are students more likely to leave and return after the departure
- How different students' characteristics affect the risk of departure and the chance of return at different semesters of spells
- Do effects of students' characteristics change over time
- Does enrollment duration affect return after the departure
- Does stopout duration affect future enrollment episodes

Overall, exploring multiple episodes of departures and returns in this study provides insight into interrupted enrollment patterns at a particular institution. The results of this study can be used to provide more accurate forecasts for future enrollments and to distinguish between students at risk of dropout and students at risk of stopout.

Conceptual Framework

Two theoretical models have dominated attrition research for the past three decades: Tinto's Student Integration Model (1975) and Bean's Student Attrition Model (1980, 1982).

Both models commonly viewed the departure from college as a longitudinal process, where students' decision to persist is determined by the quality of ongoing interactions between precollege characteristics and institutional environments. Many empirical studies attempted to validate these models (e.g. Bean, 1980, 1982, Braxton, Duster, and Pascarella, 1988, Pascarella and Terenzini, 1983, Stage, 1988). Cabrera, Nora, and Castaneda (1993) merged these two models and developed an integrated model to refine these two attrition theories. Although the attrition studies cited above tremendously contributed to the understanding of factors explaining student attrition, these studies failed to incorporate a timing dimension. Using one arbitrary point of time, typically first-to-second year stage, to assess departure status in these studies did not allow examining differences in departure behavior that may exist at any given time.

Event history modeling applied in more recent studies of college persistence (e.g., DesJardins, Ahlburg, and McCall, 1994, 1999, Ronco, 1994, 1995) remedied the limitations of earlier research by incorporating a timing dimension, and extending the analysis of student persistence beyond the freshman year. In these studies, the "risk" of departure at a given point of time is predicted with the set of certain variables (typically, pre-college, demographic characteristics, college performance, institutional, and financial variables). Two major advantages of event history approach in the studies of student attrition include: (1) controlling for censored observations, and (2) incorporating predictors that change their value during the observation period in the model (i.e. time-varying variables[2]). By employing event history approach in retention studies, institutional personnel gain a better understanding of the longitudinal nature of student departure. However, as stated earlier, these studies (e.g., DesJardins et al., 1994, 1999, Ronco, 1995) typically analyzed the first departure and did not extend their analysis to subsequent enrollment episodes.

This study explores multiple episodes (spells) of departures and returns (i.e., stopout), that extends the scope of the existing application of event history modeling in attrition research. Figure 1 is provided to illustrate four episodes of stopout: (1) a first spell in school, (2) a first spell out of school, (3) a second spell in school, and (4) a second spell out of school. The outcome variable reflects event occurrence. Depending on a spell, event reflects either departure, or return. Departure refers to students who leave the institution and either return or do not return (i.e. either stop or drop out). The analysis was carried out from an institutional perspective. Therefore, a student who transfers to another institution is referred to as a leaving/departing student.[3] Solid arrows in the Figure 1 depict the main effects of substantive predictors (student characteristics) and timing variables (spells and semesters) hypothesized in the model. Dashed arrows represent student's progression to the next semester or spell. Students experiencing an event progress to the first semester of a spell immediately following. Otherwise, students progress to the following semester in a current spell. Students who graduate are censored at the semester when they attain their degree. Students who do not experience an event at a particular spell are censored at the end of the observation period (that might correspond either to the last semester of the first spell in, or to any semester in one of the subsequent spells).

The selection of variables in the model was guided by previous research employing event history modeling.[4] The model included gender, ethnicity, parents' educational attainment (more precisely, first generation to attend college), family income, timing of matriculation (direct or delayed), high school performance indicators (high school percentile and SAT total or ACT equivalent), and geographic origin as predictors of students' departures and returns. College GPA and full- or part-time status were considered as predictors of departure, changed their value at each semester of enrollment periods, and were treated as time-varying predictors. As it will be discussed later, interaction effects of timing and substantive predictors were essential for the model, since they allowed accounting for time-varying and spell-varying effects of substantive predictors.

Empirical Methodology

Data

The institution studied is a Midwest public Research II university enrolling eleven to twelve thousand students each year. About 11% of these students are from out-of-state and 4% are international students. The data for the study contained 12 semesters of fall and spring enrollments of two fall cohorts of undergraduate students (1997 (N=1,819) and 1998 (N=1,960)).[5]

Initially, the data set provided up to four episodes of departures and returns.[6] However, since the number of students departing and returning more than twice was rather small, the study covers the first and second episodes of departures and returns.

Descriptive statistics for time-invariant variables used in the models estimated here are presented in Table 1. Time-varying predictors are presented in Table 2.

Empirical Methodology and Data Arrangement

Time in attrition studies is expressed in discrete units (semesters/years). Therefore, they employ discrete-time event history analysis, particularly its alternatives, the discrete-time equivalent of the proportional hazards model[7] and the logit model (Yamaguchi, 1991; Allison, 1995).

The logit model used in this study was introduced in education related research by Singer and Willett (1991, 1993). Their original one-episode application of logit models was later developed into a multi-episode analysis of teacher attrition (Singer and Willett, 1995). Ronco (1994) applied multi-episode logit analysis to the study of student stopout behavior at a single institution.

Proportional hazards models and logit models require different data arrangements, *person-level* and *person-period* data respectively. In a person-level data set each individual has one record, while in a person-period data set each individual has multiple records – one for each time period (Singer and Willett, 1991, 1993, 2003; Willett and Singer, 1993). Thus, a student who was observed for 12 semesters would have 12 records in the data set. Multi-episode applications of logit models also require variable(s) identifying episodes (spells, cycles). Table 3 presents an example of a *person-period-spell* dataset for the multi-episode application of a logit model. Student 1 dropped out after the second semester of studies and never reenrolled. Student 2 stopped out and returned two times and had four spells lasting one semester each. The variable *EVENT* in this table represents a student's transition from one state to another, i.e. from enrollment to departure and from stopout to return. It equals 1 for the semesters and spells when such transition occurs. Spells are represented by the variables *SPELLIN (SI)*, *SPELLOUT (SO)*, and *SPELLREPEAT (SR)*[8].

The group of students at risk of departure/return for each semester and spell consists of those who did not graduate by the time under consideration and, with the exception of the first spell, experienced an event (departure or return) in the preceding spell. Discrete-time hazard in semester *j* of spell *k* is:

$$h(t_j s_k) = \frac{n_{events(jk)}}{n_{atrisk(jk)}} \tag{1}$$

The general shape of the hazard profile can be estimated depending upon spell and semester using logit model (Willett and Singer, 1995; Ronco, 1994):

$$\begin{aligned}\ln\left(\frac{h(t_j s_k)}{1-h(t_j s_k)}\right) &= \alpha_1 t_{1k} + \alpha_2 t_{2k} + \ldots + \alpha_{12} t_{12k} + \gamma_1 SO + \\ &+ \gamma_2 (SO * \ln(t_j)) + \gamma_3 SR + \gamma_4 (SO * \ln(t_j)),\end{aligned} \tag{2}$$

Where SO is the dummy variable representing spells out and SR is the dummy variable representing repeated spells. The main effect of a semester (t_j) is represented by 12 dummy predictors. This specification yields easily interpretable and consistent with observed hazard rates model. However, the analysis involves many time periods, and some time periods have small risk sets and/or close to zero hazards. Singer and Willett (2003, pp. 408-409) suggested that under these conditions, identifying more parsimonious temporal specification should be seriously considered. The study herein considered linear, logarithmic, quadratic, cubic, and three stationary points' representations of terms and years for four spells to identify the general shape of hazard profile (see Table 4). *Akaike Information Criterion* (AIC) and *Bayesian Information Criterion* (BIC) served as criteria for the selection among different specifications:

$$AIC = -2LL + 2(\text{number of model parameters}) \quad (3.1)$$

$$BIC = -2LL + (\ln(N))(\text{number of model parameters}), \quad (3.2)$$

where ln(N) is the natural logarithm of the sample size (Singer and Willett, 2003, pp.121-122).

After identifying the general shape of the hazard profile, this study examined the effect of each student's characteristic on risks of departures and probabilities of returns. It was logical to assume that the effects of students' characteristics can be different for spells in and spells out, repeated spells, and different semesters of spells. Therefore, three sets of hypotheses were tested for each of the substantive predictors under consideration. The first set of hypotheses was represented by interaction terms of a substantive predictor and spells in and out. The second set was represented by interaction of a substantive predictor, spells in and out, and repeated spells. And, the third set was represented by interaction of a substantive predictor, spells in and out, and a semester (more precisely a natural logarithm of a semester). Thus, the model with a substantive predictor (SP) would include the following parameters:

$$\ln\left(\frac{h(t_j s_k)}{1-h(t_j s_k)}\right) = \text{[parameters identifying the general shape of hazard profile]} +$$

$$+ \beta_1 (SP*SI) + \beta_2 (SP*SO) + \qquad [1^{st} \text{ set/block}]$$

$$+ \beta_3 (SP*SI*SR) + \beta_4 (SP*SO*SR) + \qquad [2^{nd} \text{ set/block}] \qquad (4)$$

$$+ \beta_5 (SP*SI* \ln(t_j)) + \beta_6 (SP*SO* \ln(t_j)) \qquad [3^{rd} \text{ set/block}]$$

The forward (likelihood ratio) stepwise method was used to screen possible effects. Parameters were included by blocks. After including initial parameters identifying the general shape of hazard profile, the first set of variables was screened. After including parameters of hazard profile and parameters of the first set that significantly decreased model deviance, the second set was screened, and so on. The effects of student characteristics were explored both in separate models (including a single substantive predictor) and in the model including multiple substantive predictors (final model). The forward (likelihood ratio) stepwise method was also used to construct the final model including all substantive predictors under consideration. Significance of each effect was examined and coefficients from the final model were compared to the coefficients from the models including one substantive predictor as suggested by Hosmer and Lemeshow (1989, pp. 87-88). The "alpha" level chosen in this study was 0.15, since as shown in previous studies, smaller alpha levels often exclude important variables from the model (Hosmer and Lemeshow, 2000, p. 118).

Timing of Departures and Returns

Descriptive Analysis

The general shape of observed hazards for student departures and returns by semesters by spells is illustrated in Figure 2. Comparison of spells in shows that students were more likely to leave in the second spell in: for example, students were 3.08 times (0.40/0.13) as likely to leave in the first semester of the second spell as they were in the first semester of the first spell. At the same time, leaving after the first semester was less likely than leaving after the second semester in the first spell in. The opposite was true for the second spell in when the hazard of leaving for the second semester was lower than the hazard for the first semester. This suggested that students were more likely to leave after the spring semesters. (Taking into account that the study covered fall cohorts, second semester for the first spell in indicated spring semester, while second semester in the rest of spells could indicate either spring or fall.)

Students were more likely to return in the semester following their departure. For example, returning in one semester was 2.80 ($0.14/0.05$) times as likely as returning in two semesters in the first spell out and 2.67 ($0.16/0.06$) times as likely as in two semesters in the second spell out. Overall, the probability of return decreased in time.

Comparing risks of departures and returns showed that the departure was 2.63 times (0.63/0.24, see Table 1) as likely as the return in the initial spells and 2.73 times (0.71/0.26, see Table 1) as likely as the return in the repeated spells.

Overall, descriptive analysis of timing of departures and returns suggested the following hypotheses for the logit model:

- with the exception of later semesters, students were more likely to leave and return in the initial semesters of a spell
- departure was more likely than return
- repeated spell in had higher hazard rates as compared to the initial spell in
- departure was more likely to occur after spring semesters

It was also logical to assume that the timing of departures was related to the probability of return in subsequent spells out, and the duration of stopout had an impact on the departure in the subsequent spell in.

General Shape of Hazard Profile

Initially, the general shape of the hazard profile was estimated depending upon spell and semester using logit model (2) proposed by Willett and Singer (1995) and applied to the study of student stopout by Ronco (1994) (see Table 5, Model A). Overall, this model reflected observed hazard rates. The probability of departures and returns decreased with time with the exception of later semesters, the probability of return was lower than the probability of departure, and the probability of departures and returns was higher in the repeated spells in and out. At the same time, according to Model A, all departures and returns were more likely to occur in the second semester, which was true for the first spell in only. More importantly, such completely general specification of time lacked parsimony. And, adding substantive predictors to such model was problematic, since some of parameters capturing timing became insignificant, while others changed their signs thus indicating that the completely general specification yielded erratic model.

Based on the earlier hypothesis that the departure was more likely to occur after spring semesters, it was assumed that the timing in this model could be better represented with the combination of a year and the binominal indicator for spring semesters. Table 6 displays the comparison of AICs and BICs for different representations of the main effects of a semester and a year.

Not surprisingly, timing of the first departure (i.e. event in the first spell in) was better explained by the completely general representation of a semester. However, quadratic representation of a year yielded similar BIC. The “best” model explaining the timing for the second spell in was the one with quadratic representation of a semester. The “best” representation of a year in this spell was also quadratic. For both spells out, logarithmic representation of a semester explained hazards best. Accordingly with these findings, the discrete hazard model that substituted the initial completely general specification was as follows (see model B (1), Table 5):

$$\ln\left(\frac{h(t_j s_k)}{1-h(t_j s_k)}\right) = \alpha_0 + \alpha_1 y * SI + \alpha_2 y^2 * SI + \alpha_3 SO + \alpha_4 \ln(t) * SO + \alpha_5 SI * SR + \alpha_6 SPR \qquad (5)$$

Model's deviance significantly decreased after including interaction effect of the binominal indicator of a spring semester and $\ln(t_j)$ (model B (2), Table 5) and the previous spell's duration (*$Ln(Spell_{i-1})$*) for spells out and the second spell in (model B (3), Table 5).

Overall, the general shape of the hazard profile was estimated based on the quadratic representation of a year for spells in and the logarithmic representation of a semester for spells out. Based on models' estimates, the risk of departure and the probability of return were higher after spring semesters, and the effect of a spring semester decreased with time. Risks of departure were higher for the repeated spell in as compared to the initial spell in. The odds of return were lower as compared to the odds of departure. Finally, previous spells' durations had a positive impact on the probability of return and a negative impact on the probability of departure for the second spell in. Those who departed later in a previous spell in, were more likely to return and those who returned after a longer period of stopout were less likely to depart again. Figure 3 illustrates reproduced hazards for student departures and returns, based on Model B (3).

Student Attributes Related to Departures and Returns

As indicated earlier, this study explored the effects of the following student characteristics on departures and returns: gender, ethnicity, parent's educational attainment (more precisely, first generation to attend college), family income, timing of matriculation (direct or delayed), high school performance indicators (high school GPA, percentile, and SAT total or ACT equivalent), geographic origin, college GPA, and full- or part-time status as predictors of students' departures and returns. Table 7 displays models for each substantive predictor considered in this study.

Previous studies indicate little or no difference in attrition by gender (e.g. Leppel, 2002[9]). Our analysis showed that women were less likely to leave (0.85 ($e^{-0.16}$) times as likely as men), but women who left were also less likely to return (0.71 ($e^{-0.34}$) times as likely as men). These effects were insignificantly different for repeated spells.

Two major ethnic groups at the study institution were Caucasian and African American. The number of students from other minority groups (Asian, Hispanic, and Native American) was fairly small (less than 2 percent of fall cohorts). Therefore, rather than considering each minority group separately; this study combined minority groups into one category. Although interaction effects of minority group and spells were not significant, the results indicated that minority students were more likely to leave in later terms of spells in (see interaction effect of minority status, SI, and $ln(t_j)$) and less likely to return in later terms of spells out (see interaction effect of minority status, SO, and $ln(t_j)$). These findings were consistent with previous studies indicating time-varying effect of ethnicity (DesJardins et al., 1994, Ronco, 1994).

One of the characteristics of non-traditional students and at-risk students is associated with the delayed postsecondary enrollment. Delayed enrollment not only postpones the economic and social advantages of higher education, but also increases the risk of the departure (Horn, 1996, 1998, Schmitt, 1990). Institutional data of this study confirmed that those who entered the university a year or less after graduation from a high school (direct matriculants) were less likely to depart (0.48 ($e^{-0.73}$)) times as likely as those who delayed their matriculation). Timing of matriculation affected return rates only for the repeated spell out when direct matriculants were more likely to return. Model also showed some evidence of time-varying character of direct postsecondary enrollment (see interactions with $ln(t_j)$). However, interactions indicating time-varying effect of direct enrollment were not significant at 1% level.

Measures of high school performance (SAT total or ACT equivalent and high school percentile) were grouped by quartiles. The lowest quartile students as well as those who did not report a particular indicator were included in the reference group. Students from higher SAT total or ACT equivalent quartiles were less likely to leave. The same tendency was peculiar to high school percentile quartiles. SAT total or ACT equivalent had also a significant impact on the probability of return: the higher the quartile, the higher the probability of return.

Previous studies consistently showed that student persistence was related to parents' educational attainment: first generation students were more likely to depart (e.g., Ishitani, 2003) and to dropout after leaving (e.g., Horn, 1998). In this study, students were considered as first generation if their parents never attended college. Instead of excluding the cases of non-response, the additional variable of non-response was added to the model. The results did not indicate that first generation students were significantly more likely to leave. At that, they were less likely to return after the first departure. Non-response (that was essentially equal to summer orientation session attendance) was positively associated with the departure in the initial semesters of enrollment.

Families with a yearly income of $25,000 or less were referred to as low income families. Similarly to the model distinguishing between first generation and students whose parents attended college, the model distinguishing between low income and other students incorporated non-response variable. Based on this model, students from lower income families were less likely to persist in the first spell in. The effects of non-response variable in this model were similar to the corresponding effect in the model explaining first generation students' stopout behavior.

To relate student's geographic origin and stopout behavior, this study considered two binominal variables: W/IN_CTY (equals 1 if a student came from the county of the institution's location) and W/IN_60M (equals 1 if a student came from a county within 60 miles from the institution). Although within county students were more likely to leave, they were also more likely to return especially in later semesters. Students from counties within 60 miles were also more likely to return in later semesters.

Persistence studies typically treated part-time enrollment as a risk factor or determinant of departure (e.g., Adelman, 1999, O'Toole et al., 2003). Consistently with previous studies, the model including part-time binominal predictor showed that part-time students were more likely to leave. At the same time, this effect was less pronounced for the repeated spell in and for later semesters of spells in.

College grade performance is "both a reflection of the person's ability and the institution's preferences for particular styles of academic behavior" (Tinto, 1975, p.104). In most empirical studies, grade performance at the end of the first term has been shown to be the most important factor in college persistence and eventual degree attainment. Several studies employing event history modeling (e.g., DesJardins et al., 1994, 1999) treated grade performance as the time-varying predictor and showed that its impact varied over time. Binominal variables representing cumulative and semester grade point averages in this study equaled 1 for GPAs 2.00 and higher and varied for different semesters of enrollment. The impacts of both semester and cumulative GPAs were quite similar: students with 2.00 and higher college GPAs were more inclined to persist with less evident effect in the repeated spell in and in later semesters of spells in. Based on models' AICs and BICs it was concluded that the binominal indicator of semester GPA was a better predictor of persistence as compared to the binominal indicator of cumulative GPA.

Overall, models including substantive predictors showed that persistence was “best” explained by college GPA, followed by part-time enrollment and high school performance indicators (see models’ deviances, BICs, and AICs, Table 7). Higher college GPA, full-time enrollment, and higher high school performance were associated with lower risks of departure. Consistently with previous studies, it was also shown that low income students were more likely to leave, first generation students were less likely to return, and delayed enrollment was positively associated with the departure. It was found that the proximity of student geographic origin had an impact on the odds of return. The closer the geographic origin the higher the odds of return with more pronounced effect in later terms of spells out.[10] Female students were less likely to leave, but also less likely to return after the departure. Finally, it was found that minority students were more likely to leave and less likely to return in later terms of spells.

Taking into account that some effects could become insignificant after controlling for other substantive predictors under consideration, parameters that had significant effect on the odds of departures and returns for separate models (with an exception of cumulative college GPA), were included in a single model (see Table 8).

The results of the model with multiple substantive predictors were similar to the results of separate models. At the same time, the effects of timing at matriculation, gender, and low income for spells in became non-significant after controlling for college GPA performance and high school performance. The effect of SAT or ACT equivalent became non-significant for spells in, but remained significant for spells out. Overall, the model with multiple substantive predictors was consistent with models including single predictors.

Conclusion and Implications

Despite the evidence of stopout behavior, attrition studies typically limit their analysis to the first stopout. Based on institutional data containing 12 semesters of fall and spring enrollments of undergraduate students, this study explored four episodes of departures and returns. The multi-spell discrete-time approach used in this study was earlier applied in attrition study at a single institution by Ronco (1994). Following Ronco's model, this study attempted to incorporate both the timing and relevant student characteristics into the model explaining multiple episodes of departures and returns. One of the principal differences between Ronco's and this study lays in the different ways of capturing timing component. Since completely general specification of timing employed in Ronco's model lacked parsimony and did not work after including substantive predictors,[11] such specification was substituted with quadratic representation of a year for spells in and logarithmic representation of a semester for spells out. This study was also different in the way substantive predictors were included in the model: six parameters of substantive predictors' interactions with spells in and spells out, repeated spells in and out, and semesters[12] of spells in and out were screened using the forward (likelihood ratio) stepwise method. Finally, in addition to the analysis of models with single substantive predictors, this study incorporated several substantive predictors into one model.

Major findings were consistent with previous attrition studies. Departure was strongly associated with poor college grade performance, high school performance, and part-time enrollment. The analysis also revealed that in a study institution, first generation and students with lower SAT or ACT equivalent were less likely to return after the departure, while students who came from nearby counties were more likely to return. Female students were less likely to leave and less likely to return. At the same time, after controlling for college grade performance, the impact of gender on the odds of departure became insignificant. Certain effects varied over time. The effects of part-time enrollment and college GPA were less pronounced in later terms and the repeated spell in. Student geographic origin had a stronger impact on the odds of return in later terms. Although in initial semesters of spells minority students were almost as likely to depart and return as Caucasian students, it changed over time: in later terms minority students were more likely to leave and less likely to return. Using multi-spell approach also allowed studying the impact of previous spells' duration on the odds of departures and returns. Students departing later in a previous spell in were more likely to return and those who returned after a longer period of stopout were less likely to depart again.

This study demonstrated possibilities of multi-spell discrete-time approach in the analysis of attrition at a single institution and allowed defining the timing and student characteristics associated with departures and returns. In a practical sense, knowing the timing and student characteristics associated with departures and returns would help institutional researchers to forecast future enrollments more accurately. Gaining a better understanding of stopout behavior would also allow administrators to develop intervention strategies aimed at increasing the number of returning students and minimizing the duration and frequency of stopout episodes. Such interventions would ultimately strengthen institutional effectiveness by preventing students from leaving the institution permanently and by increasing their chances for timely degree completion.

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Endnotes

[1] Among those who returned, 42 percent returned to the same institution, and 58 percent transferred elsewhere.

[2] With the exception of studies utilizing event history modeling, research analyzing attrition behavior typically treated time-varying predictors (predictors that change their value over time) in the same fashion as time-invariant predictors (predictors that are constant over time), e.g. used data from one or two terms to classify a student as part time or full time. At the same time, several researchers (e.g. Adelman, 1999; O'Toole, Stratton, Wetzel, 2003) indicated that a single term's use of data could be inaccurate. In this study, several variables (college GPA and part-time indicator) were treated as time-varying predictors.

[3] Students leaving one institution can continue their studies at another college or university (i.e. to leave an institution, but to remain in the educational system). Since this research used institutional data and the institution under study did not participate in the National Student Clearinghouse or other data exchange programs that track enrollment status of students who left their initial institution, it was problematic to separate transfers out from leavers in this analysis. Thus, this study analyzed stopout behavior from the institutional perspective and did not distinguish between transfers and leavers.

[4] Financial variables were not considered in this study since data was not available on a time-varying basis.

[5] International students were excluded from the analysis. Cohort is defined as a group of students, full- or part-time, enrolling for their first semester during a particular fall. The group does not include transfer students.

[6] Out of 3779 students enrolled for their first semester in fall 1997 or fall 1998, 2399 left but 2382 progressed to the first spell out (i.e. left at least one semester before the end of the observation period). Of these, 560 returned and 542 progressed to the second spell in. Among 387 leavers, 359 progressed to the second spell out. The number of students in the third spell in was 80, the third spell out – 50, the fourth spell in – 12, the fourth spell out – 5, and the fifth spell in – 1.

[7] In the studies of student departures, the discrete-time equivalent of the proportional hazards model is typically generalized to allow for time-varying effects and to include an unobserved heterogeneity variable (e.g. DesJardins, Ahlburg, and McCall, 1994, 1999, DesJardins, 2003).

[8] *SPELLIN* equals 1 for the episodes of enrollment, *SPELLOUT* equals 1 for the episodes of non-enrollment, and *SPELLREPEAT* equals 1 for the repeated episodes.

[9] Although the main effect of gender in Leppel's study was not significant, ethnicity and having children was found to be having a significantly positive impact on women's persistence and a negative impact on men's persistence.

[10] It is reasonable to believe that this particular finding might not be relevant to other institutions, since the study institution serves mainly its regional area.

[11] Some of the parameters capturing timing became insignificant, others changed their sign.

[12] More precisely, logarithms of semesters were used for interaction effects of substantive predictors.

Table 1

Descriptive statistics for time invariant predictors of departures/returns for the first semesters of spells

Mean	1st Spell In	1st Spell Out	2nd Spell In	2nd Spell Out
Event*	0.63	0.24	0.71	0.26
Female	0.56	0.52	0.47	0.42
Minority	0.14	0.17	0.16	0.17
Direct Matriculant	0.91	0.88	0.88	0.89
County	0.18	0.19	0.30	0.31
Within 60 miles	0.31	0.30	0.30	0.31
First Generation	0.27	0.27	0.21	0.19
Low Income (Family Income less than $25,000 a year)	0.16	0.18	0.17	0.16
Nonresponse	0.17	0.20	0.22	0.24
SAT Total: Second through fourth quartiles**				
Quartile 2: 830-940	0.25	0.25	0.24	0.22
Quartile 3: 940-1050	0.21	0.20	0.22	0.21
Quartile 4: 1050 & higher	0.21	0.16	0.20	0.19
High School Percentile: Second through fourth quartiles**				
Quartile 2: 42-60	0.25	0.28	0.27	0.29
Quartile 3: 60-77	0.24	0.23	0.26	0.25
Quartile 4: 77 & Higher	0.24	0.16	0.15	0.11
High School GPA: Second through fourth quartiles**				
Quartile 2: 2.43-2.80	0.24	0.27	0.27	0.28
Quartile 3: 2.80-3.23	0.24	0.23	0.22	0.21
Quartile 4: 3.23 & Higher	0.24	0.15	0.16	0.13
Total # of cases	3779	2382	542	359

*Although event is the time-varying outcome variable, it is included here to provide the percent of departures/returns in each spell.

**Not reported and first quartile were included in the reference group

Table 2

Descriptive statistics for time varying predictors for spells in

		1	2	3	4	5	6	7	8	9	10	11	12
Semester GPA 2.00 or higher	1st Spell In	0.73	0.73	0.77	0.81	0.84	0.89	0.89	0.89	0.86	0.83	0.74	0.75
	2nd Spell In	0.61	0.69	0.66	0.71	0.70	0.81	0.40	0.58	1.00	0.00		
Part-time (11 or less attempted hours)	1st Spell In	0.10	0.11	0.12	0.10	0.10	0.09	0.09	0.11	0.16	0.24	0.33	0.33
	2nd Spell In	0.37	0.29	0.31	0.29	0.28	0.29	0.46	0.17	0.00	0.00		
Total # of cases	1st Spell In	3779	3288	2573	2301	2028	1848	1718	1593	809	479	144	87
	2nd Spell In	542	305	213	147	97	62	27	12	3	1		

Table 3

Structure of the person-period-spell dataset

Student	*SPELLOUT (SO)*	*SPELLIN (SI)*	*SPELLREPEAT (SR)*	*T*	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	*Event*
1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0
1	0	1	0	2	0	1	0	0	0	0	0	0	0	0	1
1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0
1	1	0	0	2	0	1	0	0	0	0	0	0	0	0	0
1	1	0	0	3	0	0	1	0	0	0	0	0	0	0	0
1	1	0	0	4	0	0	0	1	0	0	0	0	0	0	0
1	1	0	0	5	0	0	0	0	1	0	0	0	0	0	0
1	1	0	0	6	0	0	0	0	0	1	0	0	0	0	0
1	1	0	0	7	0	0	0	0	0	0	1	0	0	0	0
1	1	0	0	8	0	0	0	0	0	0	0	1	0	0	0
1	1	0	0	9	0	0	0	0	0	0	0	0	1	0	0
1	1	0	0	10	0	0	0	0	0	0	0	0	0	1	0
2	0	1	0	1	1	0	0	0	0	0	0	0	0	0	1
2	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1
2	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1
2	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1

Table 4

Representations of the main effects of terms and years

	The main effect of the semester	The main effect of a year
Linear	logit $h(t_j) = \alpha_0 + \alpha_1 t_j$	logit $h(y_i) = \alpha_0 + \alpha_1 y_i + \gamma_1$*SPR
Logarithmic	logit $h(t_j) = \alpha_0 + \alpha_1 \ln(t_j)$	logit $h(y_i) = \alpha_0 + \alpha_1 \ln(y_i) + \gamma_1$*SPR
Quadratic	logit $h(t_j) = \alpha_0 + \alpha_1 t_j + \alpha_1 t_j^2$	logit $h(y_i) = \alpha_0 + \alpha_1\ y_i + \alpha_1\ y_i^{\ 2} + \gamma_1$*SPR
Cubic	logit $h(t_j) = \alpha_0 + \alpha_1 t_j + \alpha_1 t_j^2 + \alpha_1 t_j^3$	logit $h(y_i) = \alpha_0 + \alpha_1\ y_i + \alpha_1\ y_i^{\ 2} + \alpha_1\ y_i^{\ 3} + \gamma_1$*SPR
Three Stationary Points	logit $h(t_j) = \alpha_0 + \alpha_1 t_j + \alpha_1 t_j^2 + \alpha_1 t_j^3 + \alpha_1 t_j^4$	logit $h(y_i) = \alpha_0 + \alpha_1\ y_i + \alpha_1\ y_i^{\ 2} + \alpha_1\ y_i^{\ 3} + \alpha_1\ y_i^{\ 4} + \gamma_1$*SPR
Completely general	logit $h(t_j) = \alpha_1 t_1 + \alpha_2 t_2 + \ldots + \alpha_j t_j$	logit $h(y_i) = \alpha_1 y_1 + \alpha_2 y_2 + \ldots + \alpha_j\ y_i + \gamma_1$*SPR

Table 5

Parameter estimates, standard errors, and goodness-of fit statistics for the models explaining the general shape of the hazard profile

MODEL A		MODELB			
	Parameter estimates		Parameter estimates (SE)		
Predictor	(SE)	Predictor	(1)	(2)	(3)
t_1	-1.71 (0.04)	*Intercept*	-1.73 (0.04)	-1.76 (0.04)	-1.77 (0.04)
t_2	-1.45 (0.04)	$SI^* y_i$	-0.86 (0.05)	-0.77 (0.05)	-0.77 (0.05)
t_3	-2.07 (0.06)	$SI^* y_i^{\ 2}$	0.18 (0.01)	0.17 (0.01)	0.17 (0.01)
t_4	-2.10 (0.06)	*SO*	-0.27 (0.06)	-0.34 (0.06)	-1.06 (0.13)
t_5	-2.27 (0.07)	$SO^* \ln(t_j)$	-1.60 (0.06)	-1.49 (0.07)	-1.43 (0.07)
t_6	-2.80 (0.09)	*SR*SI*	0.86 (0.07)	0.83 (0.07)	1.20 (0.16)
t_7	-3.01 (0.11)	*SPRING*	0.34 (0.04)	0.54 (0.07)	0.56 (0.07)
t_8	-2.42 (0.09)	$SPRING^* \ln(t_j)$		-0.19 (0.05)	-0.21 (0.05)
t_9	-2.28 (0.12)	$Ln(Spell_{i-1})^*SO$			0.52 (0.08)
t_{10}	-1.74 (0.12)	$Ln(Spell_{i-1})^*SI^*SR$			-0.39 (0.15)
t_{11}	-1.44 (0.20)				
t_{12}	-1.42 (0.27)				
SO	-0.33 (0.06)				
SR	0.81 (0.08)				
$SO^*\ln(t_j)$	-1.25 (0.07)				
$SR^*\ln(t_j)$	-0.16 (0.10)				
-2LL	20782.78	-2LL	20744.70	20731.58	20683.67
Model χ^2 (df)	34678.70 (16)	Model χ^2 (df)	2711.3 (6)	2724.42 (7)	2772.33 (9)
AIC	20814.78	AIC	20758.70	20747.58	20703.67
BIC	20952.33	BIC	20818.88	20816.35	20789.64

Model A: Initial model for spell and semester (proposed by Ronco (1994))

Model B: Model with quadratic representation of a year of spells in and logarithmic representation of a semester of spells out. Model B (2) adds interaction effect of *SPRING* and $Ln(T_k)$. Model B (3) adds previous spells' duration.

Table 6

Representations for the main effect of SEMESTER and YEAR* in discrete-time hazard models for spells

	First Spell In				First Spell Out				Second Spell In				Second Spell Out			
	# of parameters	-2LL	AIC	BIC	# of parameters	-2LL	AIC	BIC	# of parameters	-2LL	AIC	BIC	# of parameters	-2LL	AIC	BIC
Representations of SEMESTER																
Linear	2	14668.05	14672.05	14687.92	2	4178.68	4182.68	4198.10	2	1622.84	1626.84	1637.34	2	644.00	648.00	658.58
Logarithmic	2	14664.98	14668.98	14684.85	2	4117.04	4121.04	4136.92	2	1604.56	1608.56	1619.06	2	634.39	638.39	648.97
Quadratic	3	14578.42	14584.42	14608.23	3	4129.13	4135.13	4158.94	3	1590.98	1596.98	1612.73	3	634.05	640.05	655.93
Cubic	4	14474.13	14482.13	14513.87	4	4120.23	4128.23	4159.97	4	1589.97	1597.97	1618.97	4	633.23	641.23	662.40
Three Stationary points	5	14366.32	14376.32	14415.99	5	4116.14	4126.14	4165.81	5	1588.01	1598.01	1624.27	5	631.42	641.42	667.88
General	12	14269.03	14293.03	14388.25	11	4113.33	4135.33	4222.62	10	1580.71	1600.71	1653.22	9	624.96	642.96	690.59
Representations of YEAR*																
Linear	3	14567.00	14573.00	14596.81	3	4254.21	4260.21	4283.34	3	1638.20	1644.20	1659.95	3	648.03	654.03	669.91
Logarithmic	3	14494.35	14500.35	14524.16	3	4224.03	4230.03	4253.84	3	1632.50	1638.50	1654.25	3	642.91	648.91	664.78
Quadratic	4	14379.54	14387.54	14419.28	4	4226.32	4234.32	4266.06	4	1623.72	1631.72	1652.72	4	640.50	648.50	669.67
Cubic	5	14369.33	14379.33	14419.01	5	4224.11	4234.11	4273.79	5	1623.61	1633.61	1659.87	5	640.23	650.23	676.69
Three Stationary points	6	14359.44	14371.44	14419.06	6	4221.71	4233.71	4281.32	6	1623.54	1635.54	1667.04	6	638.47	650.47	682.22
General	7	14357.42	14371.42	14426.96	7	4220.54	4234.54	4290.09	6	1623.54	1635.54	1667.04	6	638.47	650.47	682.22

*In addition to representations of YEAR, each of the models included the binominal indicator for spring semesters

Table 7: Parameter estimates, standard errors and goodness-of fit statistics for models with substantive predictors

	Parameter estimates (SE)										
Predictor	FEMALE	MINORITY	DIRECT MATRICULANT	SAT TOTAL	High School Percentile	FIRST GENERATION	LOW INCOME	GEOGRAPHIC ORIGIN	PART-TIME	SEMESTER GPA	CUMULATIVE GPA
Intercept	-1.68 (0.04)**	-1.77 (0.04)**	-1.14 (0.09)**	-1.47 (0.05)**	-1.40 (0.05)**	-1.88 (0.04)**	-1.94 (0.04)**	-1.79 (0.04)**	-2.26 (0.04)**	-0.36 (0.05)**	-0.34 (0.05)**
$SI{*}y_i$	-0.77 (0.05)**	-0.81 (0.05)**	-0.85 (0.08)**	-0.74 (0.05)**	-0.71 (0.05)**	-0.71 (0.05)**	-0.71 (0.05)**	-0.77 (0.05)**	-0.65 (0.05)**	-0.68 (0.06)**	-0.56 (0.06)**
$SI{*}y_i^2$	0.16 (0.01)**	0.17 (0.01)**	0.17 (0.01)**	0.16 (0.01)**	0.15 (0.01)**	0.16 (0.01)**	0.16 (0.01)**	0.16 (0.01)**	0.14 (0.01)**	0.15 (0.01)**	0.13 (0.01)**
SO	-1.04 (0.14)**	-1.06 (0.13)**	-1.80 (0.16)**	-1.62 (0.14)**	-1.54 (0.14)**	-0.91 (0.13)**	-0.97 (0.14)**	-1.19 (0.15)**	-0.62 (0.13)**	-2.49 (0.14)**	-2.55 (0.14)**
$SO{*}\ ln(t_j)$	-1.42 (0.07)**	-1.37 (0.07)**	-1.16 (0.13)**	-1.4 (0.07)**	-1.35 (0.08)**	-1.41 (0.07)**	-1.42 (0.07)**	-1.72 (0.11)**	-1.41 (0.07)**	-1.43 (0.07)**	-1.41 (0.07)**
*SR*SI*	1.27 (0.17)**	1.18 (0.16)**	0.68 (0.26)**	1.11 (0.16)**	1.13 (0.16)**	1.21 (0.16)**	1.26 (0.16)**	1.20 (0.16)**	1.30 (0.17)**	0.80 (0.19)**	0.38 (0.18)**
SPRING	0.56 (0.07)**	0.55 (0.07)**	0.53 (0.07)**	0.57 (0.07)**	0.57 (0.07)**	0.6 (0.07)**	0.60 (0.07)**	0.56 (0.07)**	0.65 (0.07)**	0.60 (0.07)**	0.67 (0.07)**
$SPRING{*}\ ln(t_j)$	-0.21 (0.05)**	-0.21 (0.05)**	-0.21 (0.05)**	-0.21 (0.05)**	-0.21 (0.05)**	-0.22 (0.05)**	-0.22 (0.05)**	-0.21 (0.05)**	-0.23 (0.06)**	-0.19 (0.06)**	-0.23 (0.06)**
$Ln(Spell_{i-1}){*}SO$	0.54 (0.08)**	0.52 (0.08)**	0.57 (0.08)**	0.57 (0.08)**	0.55 (0.08)**	0.54 (0.08)**	0.53 (0.08)**	0.55 (0.08)**	0.52 (0.08)**	0.52 (0.08)**	0.52 (0.08)**
$Ln(Spell_{i-1}){*}SI{*}SR$	-0.38 (0.15)*	-0.37 (0.15)*	-0.39 (0.16)*	-0.38 (0.15)*	-0.39 (0.15)*	-0.43 (0.15)**	-0.44 (0.15)**	-0.40 (0.15)**	-0.48 (0.16)**	-0.27 (0.17)	-0.23 (0.16)
…*SI	-0.16 (0.04)**	-0.07 (0.10)	-0.73 (0.10)**				0.33 (0.06)**		2.65 (0.09)**	-2.62 (0.08)**	-2.47 (0.08)**
...*SO	-0.34 (0.09)**					-0.46 (0.11)**					
... *SI *SR	-0.20 (0.13)		0.58 (0.21)**				-0.28 (0.17)		-1.30 (0.15)**	0.41 (0.15)**	0.88 (0.14)**
…*SO*SR	0.43 (0.19)*		0.40 (0.13)**			0.64 (0.28)*					
$...{*}SI{*}\ ln(t_j)$		0.31 (0.07)**	0.12 (0.07)						-0.48 (0.06)**	0.23 (0.06)**	0.25 (0.07)**
$...{*}SO{*}\ ln(t_j)$		-0.47 (0.17)**	-0.29 (0.13)*								
*NONRESP*SI*						0.61 (0.08)**	0.67 (0.08)**				
*NONRESP*SO*							0.19 (0.10)				
$NONRESP{*}SI{*}\ ln(t_j)$						-0.27 (0.07)**	-0.27 (0.07)**				
*QUARTLE2*SI*				-0.31 (0.05)**	-0.19 (0.05)**						
*QUARTLE2*SO*											
*QUARTILE3*SI*				-0.43 (0.06)**	-0.50 (0.06)**						
*QUARTLE3*SO*				0.25 (0.11)*	0.13 (0.10)						
*QUARTILE4*SI*				-0.73 (0.06)**	-1.01 (0.06)**						
*QUARTILE4*SO*				0.44 (0.11)**							
*QUARTLE2*SO*SR*				0.67 (0.24)**	0.46 (0.22)*						
*QUARTLE3*SO*SR*				0.86 (0.23)*	0.38 (0.24)						
*QUARTLE4*SI*SR*				0.38 (0.16)**							
$QUARTLE2{*}SO{*}\ ln(t_j)$					-0.26 (0.12)*						
*W/IN_CTY*SI*								0.12 (0.05)*			
*W/IN_CTY*SO*								0.53 (0.13)**			
*W/IN_60M*SO*								-0.02 (0.13)			
$W/IN\_CTY{*}SO{*}\ ln(t_j)$								0.52 (0.15)**			
$W/IN\_60M{*}SO{*}\ ln(t_j)$								0.47 (0.15)**			
-2LL	20644.29	20639.84	20602.28	20491.38	20366.23	20602.87	20589.86	20603.42	19055.42	17906.28	18682.86
Model Chi-Square (df)	2811.71 (13)	2816.16 (12)	2853.72 (14)	2964.62 (17)	3089.77 (16)	2853.13 (13)	2866.14 (14)	2852.58 (14)	4400.58 (12)	5549.72 (12)	4773.14 (12)
Change in -2LL (df)[1]	39.38 (4)	43.83 (3)	81.39 (5)	192.29 (8)	317.44 (7)	80.8 (4)	93.81 (5)	80.25 (5)	1628.25 (3)	2777.39 (3)	2000.81 (3)
AIC	20672.29	20665.84	20632.28	20527.38	20400.23	20630.87	20619.86	20633.42	19081.42	17932.28	18708.86
BIC	20792.64	20777.6	20761.23	20682.13	20546.38	20751.22	20748.81	20762.37	19193.17	18044.03	18820.62

* Significant at 5% level, ** Significant at 1% level

[1] All Models are compared to Model B (3), Table 3.

Table 8

Parameter estimates, standard errors and goodness-of fit statistics for the model including multiple substantive predictors

Predictor	Parameter estimates (SE)
Intercept	-0.93 (0.06)**
$SI*y_i$	-0.60 (0.07)**
$SI*y_i^2$	0.13 (0.01)**
SO	-2.05 (0.16)**
$SO*\ln(t_j)$	-1.72 (0.11)**
*SR*SI*	1.16 (0.19)**
SPRING	0.67 (0.07)**
$SPRING*\ln(t_j)$	-0.20 (0.06)**
$Ln(Spell_{i-1})*SO$	0.54 (0.08)**
$Ln(Spell_{i-1})*SI*SR$	-0.33 (0.18)
*FEMALE*SO*	-0.20 (0.08)*
$MINORITY*SI*\ln(t_j)$	0.11 (0.05)*
*SAT_QUARTILE3*SO*	0.29 (0.10)**
*SAT_QUARTILE4*SO*	0.31 (0.11)**
*HSPCT_QUARTILE3*SI*	-0.12 (0.06)*
*HSPCT_QUARTILE4*SI*	-0.24 (0.07)**
*NONRESPONSE*SI*	0.35 (0.10)**
$NONRESPONSE*SI*\ln(t_j)$	-0.19 (0.08)*
*FIRST GENERATION*SO*	-0.34 (0.10)**
*W/IN CTY*SO*	0.50 (0.12)**
$W/IN\ CTY*SO*\ln(t_j)$	0.52 (0.15)**
$W/IN\ 60\ MILES*SO*\ln(t_j)$	0.46 (0.12)**
*PART-TIME*SI*	1.99 (0.10)**
*PART-TIME*SI*SR*	-1.16 (0.16)**
$PART\text{-}TIME*SI*\ln(t_j)$	-0.46 (0.07)**
*SEMESTER GPA*SI*	-2.21 (0.08)**
$SEMESTER\ GPA*SI*\ln(t_j)$	0.22 (0.06)**
-2LL	17094.01
Model Chi-Square (df)	6361.99 (26)
AIC	17148.01
BIC	17380.13

* Significant at 5% level, ** Significant at 1% level

Figure 1
Multi-spell model of student departure

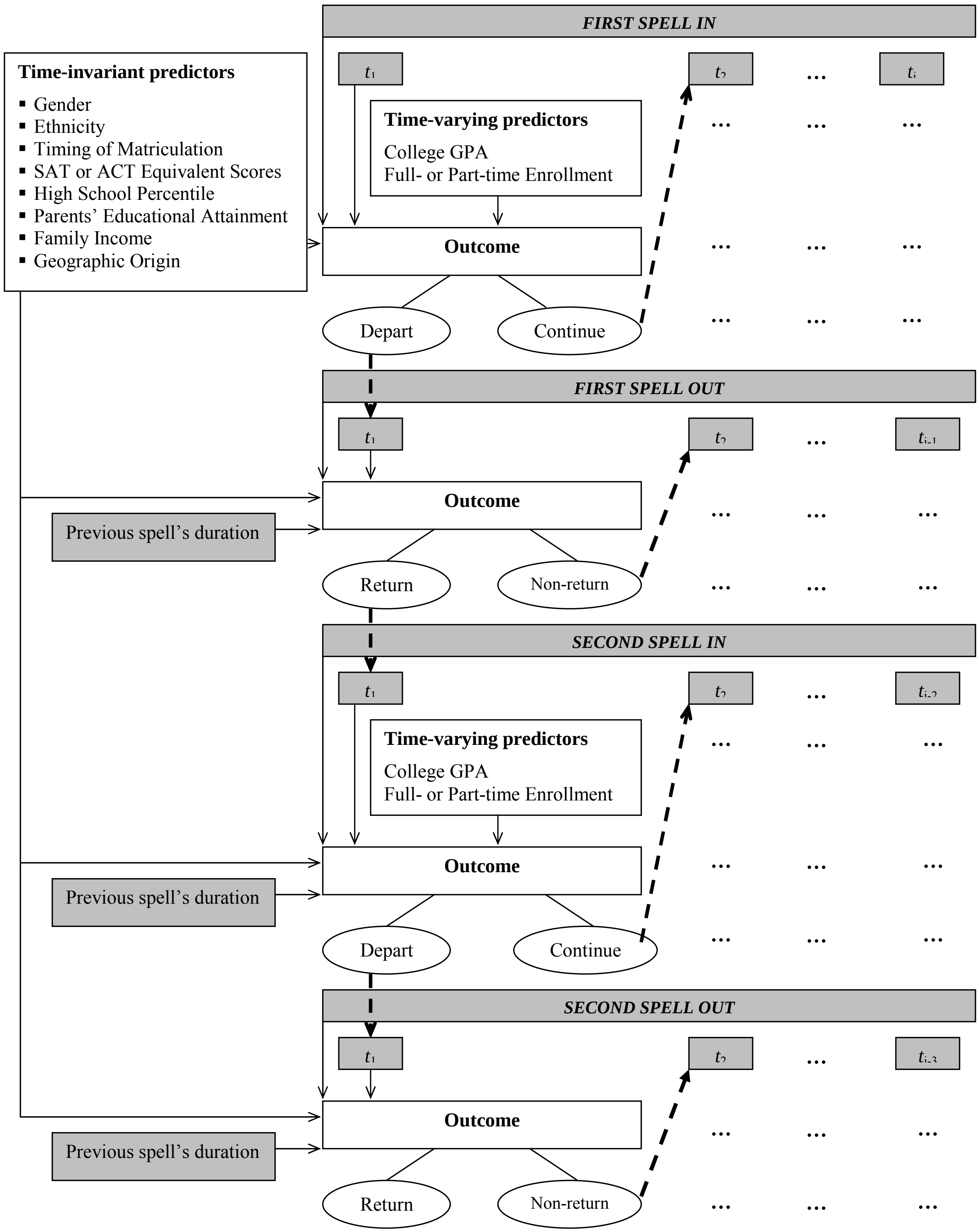
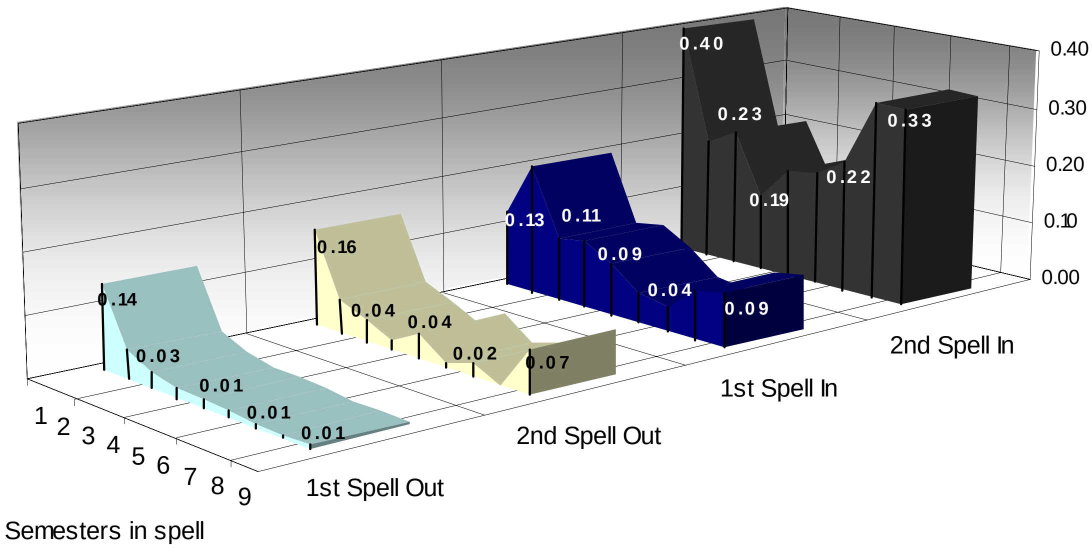
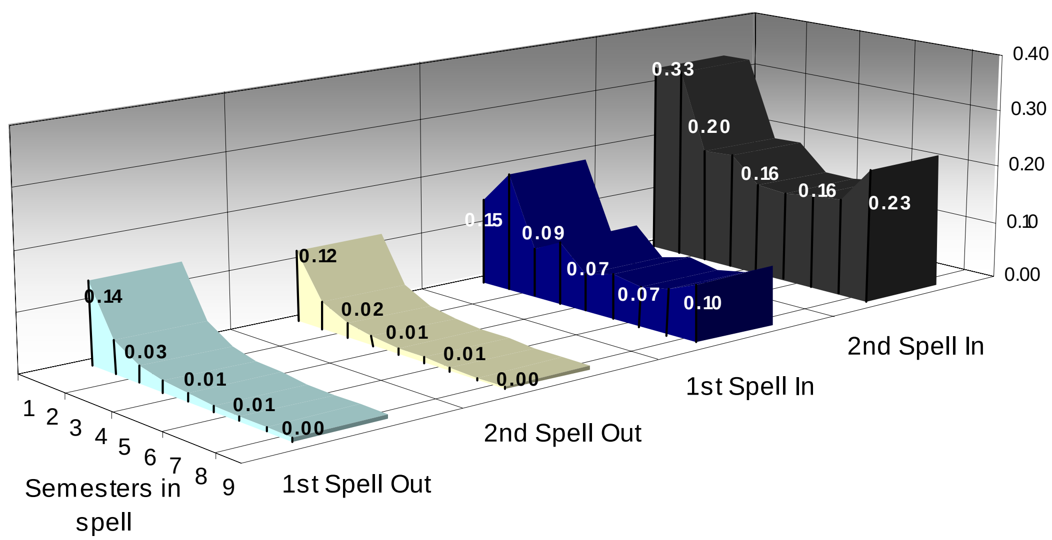


Figure 2
Observed hazards for student departures and returns by semesters by spells



Spells	Semesters								
	1	2	3	4	5	6	7	8	9
2nd Spell In	0.40	0.20	0.23	0.13	0.19	0.19	0.22	0.33	0.33
1st Spell In	0.13	0.22	0.11	0.11	0.09	0.05	0.04	0.08	0.09
2nd Spell Out	0.16	0.06	0.04	0.02	0.04	0.01	0.02	0.00	0.07
1st Spell Out	0.14	0.05	0.03	0.01	0.01	0.01	0.01	0.01	0.01

Figure 3
Reproduced hazards for student departures and returns by semesters by spells (Model B (3), Table 6)



Spells	Semesters								
	1	2	3	4	5	6	7	8	9
2nd Spell In	0.33	0.33	0.20	0.20	0.16	0.15	0.16	0.17	0.23
1st Spell In	0.15	0.21	0.09	0.11	0.07	0.08	0.07	0.08	0.10
2nd Spell Out	0.12	0.05	0.02	0.02	0.01	0.01	0.01	0.00	0.00
1st Spell Out	0.14	0.05	0.03	0.02	0.01	0.01	0.01	0.01	0.00