# Student Swirl at a Single Institution: The Role of Timing and Student Characteristics

**Iryna Y. Johnson**
Associate Director
Office of Institutional Research and Assessment
Auburn University
203 Samford Hall
Auburn, AL 36849-5111
(334) 844-4765
iyj0001@auburn.edu

**William B. Muse**
Associate Professor
Department of Mathematics and Philosophy
Columbus State University
218 University Hall
Columbus, GA 31907
(706) 507-8240
Muse_William@colstate.edu

**Acknowledgements**
The authors are grateful to Drew Clark and David Muse for their numerous valuable comments and suggestions. The authors would also like to thank Sam Lowther and Matthew Campbell for help with data retrieval for the study.

# Student Swirl at a Single Institution:

# The Role of Timing and Student Characteristics

**Abstract**

Back-and-forth enrollment at different institutions—student swirl—and concurrent enrollment at two or more institutions—double-dipping—have become common experiences for students in the United States. However, empirical studies explaining student mobility are rather rare. This study examines how student departures from and returns to a single institution are affected by college attendance elsewhere. The model presented here demonstrates that departure rates are higher for students concurrently attending another college. Return rates, on the other hand, are substantially lower for those students who attend other colleges after departure from the study institution. The effect of multi-institutional attendance differs by college type, with the effect of four-year out-of-state institution attendance being most pronounced. The simultaneous analysis of departures and returns provides the study institution with a more accurate and complete picture of student mobility.

KEY WORDS: student swirl; retention; stopout; transfer; discrete-time hazard model; multilevel model.

**Introduction**

Increasingly complex student attendance patterns have been widely recognized by scholars in higher education. A majority (59 percent) of 1999–2000 college graduates had attended more than one institution. This trend is widespread even among those students who started at four-year institutions—about half (47 percent) of them had attended several colleges (Peter, Cataldi and Carroll 2005). Multi-institution attendance patterns are frequently referred to as “student swirl” for back-and-forth enrollment and “double-dipping” for concurrent enrollment at two or more institutions (de los Santos and Wright 1990; McCormick 2003; Borden 2004).

On a positive side, by swirling between institutions, students can lower their overall tuition costs or graduate from a more selective institution than they could have entered based on their high school performance alone. On a negative side, student transfer has been associated with longer times to complete degrees, larger student debt, and more financial aid spent on duplicate courses (Mullane 2005). From the institutional perspective, student swirl is also associated with losses of tuition. Financially it is more cost efficient for institutions to retain current students than to recruit more students to replace those who leave prior to receiving a degree. Further, at a public institution with different tuition rates for residents and non-residents and declining state appropriations, it might be also important to look into patterns of swirl by residency status, since attrition of non-resident students leads to even greater losses in tuition revenues. Maximizing retention might also help maintain enrollments in upper-division classes. If students are not retained, they are generally replaced with incoming freshmen who will take lower-division classes. Low retention rates may cause individual programs to become unsustainable due to insufficient number of graduates. In addition to its financial and enrollment management importance, retention is also a political issue. Institutions of higher education are held accountable and frequently criticized by external entities because of low persistence rates.

Swirl and double-dipping are important factors of student departure from the single institution examined in this study. However, with a few exceptions (Herzog 2005; Porter 2002, 2003; Ronco1996), institutional attrition studies do not distinguish between students who dropped out from college altogether and those who transferred to another college. Furthermore, existing institutional attrition studies typically do not consider multiple institution attendance other than straightforward student transfer, yet it is common for students to attend more than one institution concurrently or to complete credits elsewhere with the intent of return to their home institution. McCormick (2003) indicates that not all swirling and double-dipping students transfer decisively between institutions: “among students who graduated from the same institution where they began their college education, one in five have enrolled elsewhere during their college career” (p.17).

Separating transfer students from students who leave the educational system is complicated by the timing of enrollment at another institution. Not all transfer students enroll at their destination institution right after they leave their home institution. McCormick (1997) indicates that, on average, students who transferred from a four-year institution took about seven months off before enrolling elsewhere. Some students take several terms off and re-enroll back at their home institutions. Horn (1998) indicates that among students who left the four-year sector before the beginning of their second year 64 percent returned within five years—that is, they stopped out. Of these “stop out” students, about 42 percent returned to the same institution, while 58 percent transferred elsewhere. Possibilities for students who do not attend their home institutions continuously and exclusively include: concurrent enrollment at multiple institutions, transferring to another institution, stopping out or completing credits elsewhere then returning to their home institution, stopping out then transferring later, or leaving the educational system altogether. These enrollment behaviors may differ substantially by the type of institutions a student chooses to attend—two-year or four-year, same state or different states—and by the student's type of enrollment—full-time or part-time. Examining all these enrollment behaviors simultaneously provides a more complete picture of student enrollment patterns.

Existing studies of student swirl are primarily concerned with non-traditional students—students underprepared for college-level work, first generation students or students who delay their matriculation and have obligations of work and family in addition to school (Wang and Pilarzyk, 2009). Undergraduates at the study institution traditionally fit the profile of an 18-year-old high school graduate with college educated parents. These students are frequently expected to attend the university full-time and continuously. Hence, it is important to show the significant mobility and a possible need to accommodate student swirl for these traditional students.

The purpose of this study is to examine enrollment patterns of undergraduates entering a single institution. We combine two behaviors of swirling students—multi-institutional attendance and stopout—into a single model of student departures and returns. We ask the following questions:

- What are the departure and return rates at different time points of students' college careers? How do different student characteristics affect the probability of departure and return at a single institution?
- What are the rates of enrollment elsewhere, and when do students enroll at other institutions after the departure from the study institution?
- Do students who enroll elsewhere return at higher or lower rates than those who did not enroll elsewhere after leaving the study institution? Do return rates differ by the other institution's type or by the student's type of enrollment—full-time or part-time—at the other institution?

Overall, this study seeks to advance understanding of interrupted enrollment patterns, multi-institutional attendance, and reasons for attrition at the study institution. Among student characteristics included in this study, special attention is given to in-state and out-of-state residence status. Loss of out-of-state tuition revenues is of special interest to campus administrators.

**Conceptual Issues**

Institutional studies of retention are important campus planning tools, but they typically do not reflect the overall student experience, because they underestimate retention by not considering student stopout and transfer. Using National Student Clearinghouse data, Porter (2002, 2003) and Herzog (2005) found significant differences between factors affecting dropout, stopout and transfer. Herzog (2005) also measured the impact of concurrent enrollment—the simultaneous enrollment at another post-secondary institution—on student persistence. Based on the data from the 1990/94 Beginning Postsecondary Survey, Stratton, O'Toole, and Wetzel (2008) assert that failure to recognize differences between long-term dropout and short-term stopout behavior biases the results of standard attrition models.

Prior studies of dropout vs. transfer vs. stopout have examined student departure during the first year of college but have not explored the timing of transfer. This approach does not take into account students who leave the institution later in their educational careers. Separating non-returning students into transfers and departures might be also misleading without timing dimension as some students might enroll at another institution right after the departure from home institution, while others might delay their re-enrollment for several years. Furthermore, DesJardins and McCall (2010) caution that inferences made using cross-sectional data techniques "may provide ambiguous results because they only explain the net differences in outcomes, but do not explain how change occurs over time" (p.515).

Porter (2002, 2003) and Herzog (2005) did not look into subsequent enrollment patterns of students who stopped out or transferred. DesJardins, Ahlburg, and McCall (2006), Johnson (2006), and Ronco (1994) explored subsequent enrollment patterns of students who stopped out for several terms, but did not look into student swirl or double-dipping. Student swirl combines two enrollment behaviors—multi-institutional attendance and stopout—that should be examined simultaneously. By modeling a sequence of events—departures and returns—and including enrollment at other institutions as a predictor, the presented study incorporates multi-institutional attendance into the model of institutional stopout and provides a more accurate and complete picture of student mobility at the study institution.

Students usually transfer from two- to four-year institutions. These students might intend to complete a bachelor's degree all along but decide to attend a community college first to save tuition, room and board costs; or they might enroll at a two-year institution to complete general education coursework, or they simply might wish to develop their academic skills. This common transfer behavior is referred to as *upward* or *vertical* transfer, and its determinants have been extensively studied. For a detailed discussion of this and other types of transfer from community colleges, see Bahr (2011). Transfer from a four-year institution is less common but not unusual. According to McCormick (1997), about one out of four students (28 percent) who began at a 4-year institution transferred: 16 percent to another four-year institution, and 13 percent to a less-than-four-year institution. Moving between four-year institutions is referred to as *horizontal*, while moving from four- to a two-year institution is referred to as a *reverse* transfer. It is logical to assume that these two types of transfers have different effects on the probability of return to the study institution. We hypothesize that compared to horizontal transfers, students who leave the study institution and enroll at two-year college are more likely to come back to the study institution later.

Adelman (1999) indicates that about 40 percent of students who attended more than one institution crossed state lines in the process. These students tend to be more successful—their degree completion rates are higher than for those students who transferred within the state. From our study's perspective, one of the likely reasons for transfer to an out-of-state institution is student return to their home states to lower their overall educational costs. Therefore, it is important to distinguish between in-state and out-of-state transfer effect on the probability of return to the study institution.

Two models of student enrollment decisions are considered here. The first model estimates the rate of enrollment at other institutions after departing from the home institution. The main purpose of this model is to look into timing and student characteristics associated with transfer to another institution. (While modeling types of institutions students are likely to transfer to is beyond the scope of this study, we describe the proportions of students enrolled elsewhere by institution type and by certain student characteristics, such as residence status and college grade performance.) The second model examines the effect of enrollment at other institutions on departures from and returns to the study institution. We assume that concurrent enrollment is associated with an increased probability of departure; while student swirl negatively affects the probability of return to the study institution. We also assume that these effects might differ by institution type—two-year in-state, two-year out-of-state, four-year in-state, and four-year out-of-state. The effects of concurrent enrollment on the probability of departure and the effect of enrollment at another institution on the probability of return are expected to be less pronounced if a student is enrolled at a two-year or in-state institution.

Our selection of control variables is guided by prior research, with certain limitations related to data availability from the central records of the study institution. Prior research indicates that ethnicity (Wells 2009), gender (Stage 1988; Stage and Hossler 1989; Peter, Horn, and Carroll 2005; Conger and Long 2010), and high school performance (Pascarella and Terenzini, 1980; Kahn and Nauta 2001) are important determinants of student persistence. Because the proportion of nonwhite students at the study institution is small, we do not consider all ethnic groups separately and instead include an indicator of other than Caucasian ethnicity here. Certain college experiences, such as part-time enrollment (Stratton, O'Toole, and Wetzel 2007) or college grade performance (Pascarella and Terenzini 1991), have also been shown to be significantly related to persistence. We expect that college experience has a substantial effect on student persistence with students enrolled part time being more likely to leave and students who have a college GPA of 2.00 or higher being less likely to leave the study institution. The effect of membership in fraternities and sororities may depend on the institutional culture (Pike 2003). Based on prior institutional findings we expect that members of fraternities and sororities are more likely to stay at the study institution. We remain agnostic about effects of college experience at the study institution on the odds of return to the study institution or transfer to another institution.

At the study institution, out-of-state students pay two to three times higher tuition than the in-state students. Further, the study institution enrolls a significant number of out-of-state students, and the additional tuition revenue is helpful in supporting its costs. It is expected that out-of-state students are more likely to experience financial difficulties and leave the study institution. Student residence status has been shown to have a significant effect on transfer behavior at other institutions: in-state residents are less likely to transfer (Porter 2002). Hence, we expect that out-of-state students are more likely to enroll elsewhere after departure. Since a high-student-aid strategy could remedy the effects of higher tuition rates, it is also important to include financial aid variables—grants, scholarships, loans, and work-study. Studying student financial aid is complicated by omitted variables bias: "because the neediest students receive the most financial aid, it is difficult to separate the likely benefits of aid from the educational outcomes associated with being from a low-income family" (Goldrick-Rab., Harris, and Trostel 2009, p.10). Despite the omitted variables bias, typical findings from prior research still show that increase in amounts of all types of financial aid decreases the odds of departure (Hossler, Ziskin, Gross and Kim 2009). Since out-of-state students might need higher financial aid amounts to cover their expenses, we also test for interaction effects of financial aid variables and residency status. We expect positive effects of all types of financial aid on persistence; and we hypothesize that the effect of financial aid is less pronounced for out-of-state residents.

**Data and Method**

The institution studied is a public Research University (high research activity) with a total enrollment of about 25,000 students. Over four-fifths of these students are undergraduates. The data for this study contains eleven semesters of fall and spring enrollments, originating with fall 2004 and 2005 new freshmen cohorts of undergraduate students. Data from National Student Clearinghouse are used to trace student enrollments at other institutions.

Because the data structure presumes up to eleven semester observations per student, the models are multilevel. The underlying data structure is referred to as discrete-time survival data or person-period-data. Willett and Singer (1995) provided an example of such data structure and its analysis in their multi-episode analysis of teacher attrition. The underlying premise is that students can experience multiple states, episodes, or spells of enrollment and non-enrollment. Departure from the study institution leads to a transition from the state of enrollment to the state of non-enrollment. After experiencing departure, a student is not at risk of another departure unless she later returns to the study institution. During the periods of non-enrollment a student is “at risk,” so to speak, of return to the study institution. Similarly, return leads to a transition from the state of non-enrollment to the state of enrollment, and the process can repeat again and again. Thus, during the periods of enrollment, the dependent variable is departure from the study institution. During the periods of non-enrollment, the dependent variable is return to the study institution.

When several outcomes—departure and return—are incorporated into one model and differ depending upon a period, the data set should include indicators of such a period or state, which is commonly referred to as a spell (Willett and Singer 1995) or an episode (Johnson 2006). Two such indicators are included in the model. The first indicator distinguishes between episodes or spells of enrollment and non-enrollment. The second indicator distinguishes between the first and any repeated spell. The dependent variable is the event or binomial indicator that equals one if a student left or returned to an institution following the semester of observation. The initial stopout model estimating the log-odds of the event depending upon a semester and an episode is:

$$\ln\left(\frac{P_{Y_{ij}=1}}{1-P_{Y_{ij}=1}}\right)=\beta_{0j}+\beta_{1j}\times t_i+\beta_{2j}\times spell\_out+\beta_{3j}\times spell\_repeat$$

Level 1 Model

$$\beta_{0j}=\gamma_{00}+u_{0j}$$

$$\beta_{1j}=\gamma_{10}$$

$$\beta_{2j}=\gamma_{20}$$

$$\beta_{3j}=\gamma_{30}$$

Level 2 Model

For the spells of enrollment (i.e., *spell_out=0*), *Y* represents departure; for spells of non-enrollment (i.e., *spell_out=1*), *Y* represents return; *i* denotes terms or semesters in spells and *j* denotes students, $\beta_{0j}$ is the intercept for a student $j$, $\gamma_{00}$ is the grand intercept, and $u_{0j}$ is the grand intercept residual for a student *j*. Residuals from the grand slopes, $\beta_{1j}$, $\beta_{2j}$ and $\beta_{3j}$, are constrained to zero.

Even though we use discrete-time survival data, it is still possible to treat the predictor $t_i$ (semester in spell) as though it was a continuous variable (Singer and Willett 2003). By including a single semester variable $t_i$ the model above assumes linear representation of time, which, based on prior stopout studies (Johnson 2006), might not fit the data well. Following Singer's and Willett's (2003) discussion of alternative specifications of time in discrete-time hazard models, constant, linear, quadratic, cubic, and three stationary points representations of terms are considered for models presented here. Selection among different timing specifications is guided by principle of parsimony, which implies that including an additional parameter should be justified by better model fit.

The relative goodness-of-fit criteria—the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)—are used for model comparison. The models with lower AIC or BIC indicate a better fit. AIC is calculated by adding twice the number of parameters to the deviance statistic. BIC is calculated by adding the product of the natural logarithm of the sample size and the number of parameters to the deviance statistic. In multilevel models it is not clear whether the first-level or second-level sample should be used, which could explain why BIC differs by choice of software program (O'Connell and McCoach 2008: 253). For timing characteristics, we take a more conservative approach to inclusion of parameters in the model by using the first-level sample size. Based on prior stopout research findings (Johnson 2006), in addition to different representations of term we also test the inclusion of such timing variables as prior spell duration and indicator of a spring semester.

The description and descriptive statistics of variables included in the model are provided in Table 1. The *time-varying predictors* of student stopout included in the model are: cumulative GPA; hours earned at the study institution; part-time enrollment at the study institution for episodes of enrollment); amounts of grants, scholarships, work study, and loans received (in $1,000s) for episodes of enrollment; and attendance of another college, with differentiation between in-state and out-of-state, two- and four year, and part-time and full-time enrollment. The student-level or *time-invariant predictors* are: gender, ethnicity, residency status, high school grade point average, ACT or SAT equivalent test scores, and Greek membership. Because information about membership in fraternities and sororities was not available on a term-by-term basis, we included information about Greek membership as of the first semester of enrollment at the study institution. Since change in residency status is a rare event, we treated this variable as time-invariant. It is logical to assume that the effects of study variables vary depending upon the outcome—departure or return. Therefore, the interaction effects of substantive predictors and an indicator of episode of non-enrollment were tested using BIC criterion described above.

A separate model is estimated to explore the timing and student characteristics of student enrollment at other institutions. Descriptive statistics in Table 1 indicate that concurrent enrollment is rather rare: less than half of 1 percent of students are concurrently enrolled at other institutions. Therefore, timing and student characteristics associated with enrollment at other institutions are explored only for the episodes of non-enrollment. Because there might be more than one episode of non-enrollment at the study institution for students who left, returned and left again, the repeated spell indicator—a binomial indicator that equals one if this is not the first time a student left the study institution—is also included here. Apart from exclusion of the effect of episodes of non-enrollment, the initial logit model of enrollment at other institutions depending upon a semester and an episode is the same as the initial stopout model above.

In order to receive a degree from the study institution one must have a 2.00 or higher grade point average on all course work. Academic warning occurs at the end of any semester for which the student's cumulative GPA on the study institution’s course work is below 2.00. Since a cumulative GPA of at least 2.00 indicates satisfactory academic progress toward graduation, a binomial indicator that equals 1 if the student has a cumulative GPA of 2.00 or higher is included in models presented here. Numerous prior studies (Pascarella and Terenzini 1991, 2005; Tinto 1975) show that grades reflect success in making the transition to college and significantly affect persistence. McCormick (2003) also indicates that students with low grades at their first institution have higher rates of multiple-institution attendance. Descriptive statistics in Table 1 align with these findings. Thus the share of students with a cumulative GPA of 2.00 and higher is significantly lower among students who experienced episodes of non-enrollment than among all students in the study sample.

Consistent with our expectations, descriptive statistics in Table 1 indicate that members of fraternities and sororities are less likely to leave the study institution. The share of members of Greek organizations is substantially lower among students who experienced episodes of non-enrollment. Compared to all students in the cohorts under study, students who experienced episodes of non-enrollment are also less likely to be female, Caucasian, or have higher high school GPA or ACT scores (see Table 1). Therefore, one might assume that female students, Caucasian students, or students with higher high school GPA or test scores are more likely to persist. Similarly, since the proportion of state residents is the same for all students and students who experienced the episode of non-enrollment, one might conclude that state residents are just as likely to leave the study institution as those students who come from out of state. As we will see later, these hypotheses do not always hold. Since female students and out-of-state students at the study institution are more likely to receive a cumulative GPA of 2.00 or higher, the effects of gender and state residence change after control for cumulative GPA.

**STUDENT ENROLLMENT AT OTHER INSTITUTIONS**

Student enrollment at other institutions is explored only for episodes of non-enrollment at the study institution. The primary reason for excluding episodes of enrollment was the rare occurrence of concurrent enrollment—in any given term concurrent enrollment did not reach one percent of all students. For the episodes of non-enrollment, on the other hand, enrollment at another institution is very common—in any given term of non-enrollment at the study institution, enrollment at another institution could frequently reach over a half of students.  Based on descriptive statistics in Table 1, after a departure from the study institution, about half of the students are enrolled elsewhere. A little less than half (46%) of the students who are enrolled elsewhere (or 23% of all students who left the study institution) go to another institution within the state and a quarter (or 12% of all students who left) go to two-year colleges. About one fifth of students enrolled elsewhere are part-time students.

While a college choice model predicting the likelihood of enrollment at different institution types is beyond the scope of the study, we provide a descriptive analysis of student characteristics that are most noticeably associated with different transfer behaviors. Fig. 1 provides proportions of enrollment at two- and four-year in-state and out-of-state institutions in the third semester of the first episode of non-enrollment by two student characteristics—residence status and cumulative GPA. (As illustrated later, the proportion of students enrolled at other institutions is highest in the third semester of the first episode of non-enrollment.) Fig. 1 illustrates that after two semesters of non-enrollment at the study institution, the vast majority (81%) of out-of-state students with a cumulative GPA of 2.00 or higher enrolled elsewhere. About 72% of out-of-state students with a cumulative GPA of 2.00 or higher chose out-of-state four-year institutions, most likely in an attempt to lower their tuition. In-state residents with cumulative GPA of 2.00 or higher are also likely to enroll elsewhere after two semesters of non-enrollment at the study institution; 74% of them did enroll at other institutions with four-year in-state institutions being the most popular destination. Students whose likely reason for departure is academic are somewhat less likely to re-enroll at other institutions after the departure. About 57% of out-of-state and 43% of in-state students with a cumulative GPA below 2.00 enroll elsewhere after two semesters of non-enrollment. Out-of-state students with a cumulative GPA below 2.00 frequently enroll in out-of-state four-year institutions (31%) and out-of-state two-year institutions (22%). In-state students who left with a cumulative GPA less than 2.00 often enroll in two-year in-state (21%) and four-year in-state (17%) institutions. Overall, these descriptive statistics suggest that out-of-state students and students who did not incur academic warning are more likely to transfer elsewhere after the departure from the study institution. And their likely destinations are four-year in-state institutions for state residents and four-year out-of-state institutions for non-residents. Students who enroll at two-year institutions are either "true undergraduate reverse transfers" (Adelman, 2005) who might have found the academic rigor of the study institution too challenging or "drop-ins" who enroll to a community college to raise their grade point averages.

**Timing of Enrollment at Other Institutions**

As mentioned earlier, separating students who transfer elsewhere from those who leave the educational system altogether is complicated by the timing of their enrollment at another institution. Some students might re-enroll elsewhere immediately after departing from their original institution, while others might take several terms off prior to re-enrollment. The average duration of the period of non-enrollment for students who started at a four-year institution and transfer to another institution is about seven months (McCormick, 1997). Since students do not always re-enroll immediately after leaving their home institution, enrollment at other institutions is examined by term. The first term is a fall or spring term immediately following the departure from the study institution. In our dataset a student can have a maximum non-enrollment spell of ten terms if she left the study institution after the first term and never returned.

Following Singer's and Willett's (2003) discussion of alternative specifications of time in discrete-time hazard models, we consider constant, linear, quadratic, cubic, and three stationary points representations of terms of enrollment at another institution. The first model in the Table 2 completely eliminates the effect of time, assuming that the odds of enrollment at another institution are constant across all terms. Model 2 adds the effect of a term. Comparison of deviance, AIC, and BIC statistics for Model 1 and 2 clearly indicates a superior fit of Model 2. After adding the main effect of term, the deviance drops from 51,605 to 51,279: $\chi^2(1)=326$, significant at the .01% alpha level. As compared to Model 1, Model 2 also has lower AIC and BIC statistics, which penalize the deviance statistic for the presence of the additional parameter. Similarly, Model 3—quadratic representation of timing—has a superior fit compared to Model 2, and Model 4—cubic representation of timing—has a superior fit compared to Model 3. Adding term in the fourth degree in Model 5—the "three stationary points" representation of timing—leads to a further drop in deviance from 50,757 to 50,753; and the $\chi^2(1)=4$, significant at the 5% alpha level. While Model 5 has a significantly lower deviance, it also has a higher BIC statistic. Singer and Willett (2003) indicate that "the specification with lowest, or nearly lowest, AIC or BIC is often the most attractive" (p.416). Based on BIC, among four timing representations—linear, quadratic, cubic, and three stationary points—we select the cubic representation.

Other timing dimensions considered in the present study were: the indicator of repeated episode of enrollment; the indicator of spring semester; and the variable representing previous episode duration or duration of enrollment at the study institution. With the exception of spring semester, these timing variables significantly improved model fit and were included in the final model of timing of transfer (see

Model 6 of Table 2). Thus, Model 6 shows that students who were enrolled longer at the study institution are less likely to enroll elsewhere in the event they leave: the effect of previous spell duration is negative and statistically significant. For instance, if a student was enrolled at the study institution for two semesters, her odds of enrollment elsewhere are 21% $\left(1-\frac{\mathrm{e}^{-0.59\times\ln(2+1)}}{\mathrm{e}^{-0.59\times\ln(1+1)}}\right)$ lower than if she was enrolled at the study institution for only one semester. If a student was enrolled at the study institution for three semesters, her odds of enrollment elsewhere are 16% $\left(1-\frac{\mathrm{e}^{-0.59\times\ln(3+1)}}{\mathrm{e}^{-0.59\times\ln(2+1)}}\right)$ lower than if she was enrolled at the study institution for two semesters. Model 6 in Table 2 also indicates that students who already experienced stopout and returned to the study institution before are less likely to enroll elsewhere in the event they leave again: the effect of the indicator of repeated enrollment spell is negative and statistically significant.

The likelihood of student enrollment at another institution by episode (first or repeated) and term is illustrated in Fig. 2. The fitted probabilities presented in Fig. 2 are based on Model 6 of Table 2. A substantial proportion of students who leave the study institution enroll elsewhere shortly after departure. Students who did not return to the study institution within the first two terms of their first non-enrollment episode have a 0.69 fitted likelihood of enrollment elsewhere. (This likelihood becomes substantially lower [0.26] for the second episode of non-enrollment.) High likelihoods of enrollment elsewhere demonstrate the inefficiency of traditional institutional retention summaries. Such summaries significantly underestimate the overall student retention as those students who leave one institution are likely to enroll elsewhere shortly after.

**Enrollment at Other Institutions: Student Characteristics**

Student characteristics—gender, minority indicator, residence status, high school academic performance, college cumulative grade point average, hours earned at the study institution, and membership in Greek organizations—are added to timing predictors in the Table 3 model. Consistent with prior descriptive analysis of student enrollment at other institutions by residence and academic performance, having a cumulative GPA of 2.00 or greater and resident status have significant effects on the log-odds of enrollment at another institution. Compared to nonresidents, residents have 37% $(1 - e^{-0.47})$ lower odds of enrollment elsewhere. Non-resident higher transfer rates were also noted in prior studies separating departure and transfer. For instance, Herzog (2005) and Porter (2002) indicate that students from out of state are more likely to transfer than students who are state residents. Students with a cumulative GPA below 2.00 have 59% lower odds of enrollment elsewhere after the departure from a study institution. Greater odds of enrollment elsewhere for students who leave for non-academic reasons make sense. Students who are unhappy with their experience at a study institution or experience financial difficulties are more likely to look for a better fit or a better priced alternative elsewhere.

Nonwhite students are less likely to transfer. Based on the Table 3 model, nonwhite students have 23% lower odds of enrollment elsewhere compared to white students. According to Herzog (2005), men are less likely to transfer than women. Our study also shows that, compared to males, female students have 1.28 times the odds of enrollment elsewhere. Because males are more likely to leave for academic reasons and poor college grade performance leads to lower odds of transfer after the departure, it is quite logical that they are less likely to transfer.

The model also indicates that members of fraternities and sororities are more likely to enroll at another institution. Greek affiliation, while having a negative effect on cognitive development and academic performance, raises the level of social integration on campus (Pike & Askew, 1990). Therefore, one would expect Greek members to have lower probabilities of departure and higher likelihood of return to the study institution. At the same time, a higher likelihood of enrollment elsewhere after departure was rather an unexpected finding.

Hours earned reflect the exposure to and the time spent at the study institution. Students who earned more hours at the study institution are less likely to enroll elsewhere after the departure.

## STUDENT STOPOUT AT THE STUDY INSTITUTION

### Timing of Departures and Returns

The timing dimension is essential for understanding the complex longitudinal nature of student enrollment patterns. Existing stopout studies (e.g., Johnson 2006; DesJardins, Ahlburg, and McCall 2006) indicate that the odds of departures and returns are highly correlated with timing and prior episode durations. Similarly to models of timing of enrollment at other institutions in Table 2, models of timing of departures and returns in Table 4 start with a flat hazard rate. Thus, the first model in Table 4 completely eliminates the effect of term and assumes that the probability of departures and returns is constant across all terms. The only variable included in the first model is the indicator of episodes of non-enrollment that allows separation between events—departures and returns. Since the effect of an episode of non-enrollment is negative, return is less likely than departure. The odds of return are 0.45 times ($e^{-0.79}$) the odds of departure. Model 2 in Table 4 adds the effects of term and interaction of term and episode of non-enrollment, which leads to a significant drop in the deviance from 170,126 to 168,317: $\chi^2(2)=1,809$, significant at the .01% alpha level. It also leads to smaller AIC and BIC values. Models 3, 4, and 5 lead to further drops in deviance and AIC values. However, compared to Model 4, Model 5 does not lead to a decrease in BIC. And the effects of interactions of term squared, term cubed and term in the forth degree with the episode of non-enrollment become insignificant. Therefore, the cubic representation in Model 4 was chosen among four timing representations considered here. While not presented here, other timing representations that did not include interactions of episodes of enrollment and terms were considered and rejected due to poor model fit. Please note that, as a result of adding interactions of timing and episodes of non-enrollment, the sign of the main effect of episode of non-enrollment became positive. At the same time, Fig. 3 illustrates that average fitted probabilities of return are lower than the average fitted probabilities of departure for most terms and episodes. The exception is the first semester of first episode of enrollment and first episode of non-enrollment, when the likelihood of departure (.04) is lower than the likelihood of return (.22).

DesJardins, Ahlburg, and McCall (2006) and Johnson (2006) indicate that previous spell duration and indicator of a repeated spell have a significant effect on stopout. Students are also more likely to leave and return after the spring semester. Consistent with these findings, several variables showed a significant association with stopout and led to further improvement in model fit. Based on Model 6 in Table 4, students are more likely to return to the study institution if they were enrolled in it for a longer period of time in the first place—the interaction effect of spells of non-enrollment and the natural logarithm of their previous spell duration is positive and statistically significant. This reinforces our prior finding that students who leave the institution earlier in their educational careers are more likely transfer elsewhere as opposed to returning to the study institution. The effect of spring semester is significant and positive, thus indicating that students are more likely to leave and return after a spring semester or in fall. (Adding the interaction effect of spring semester and episode of non-enrollment did not lead to a significant drop in the deviance.) Finally, the odds of departure are substantially higher for the repeated episode; but the odds of return are only slightly higher for the repeated episode. The interaction effect of episode of non-enrollment and repeated spell attenuates the main effect of repeated spell.

Average fitted probabilities in Fig. 3 show that the likelihood of departure in the first episode of enrollment is less than a third of the likelihood of departure in the repeated episode across all semesters. For example, in the first and second semesters the likelihood of departure is 6.0 and 3.1 times higher in the repeated episode of enrollment compared to the first episode of enrollment. The differences between the first and second episode of non-enrollment are less pronounced.

Fig. 3 also indicates close to zero fitted probabilities of return after three semesters of non-enrollment. This means that the effects of our substantive predictors on the probabilities of return become negligible if a student stayed out for over three terms. Due to properties of logistic regression, as predicted probabilities get close to zero (or one) the effect of independent variables on probabilities becomes smaller. (Odds and log odds do not depend on initial probabilities.)

**Departures and Returns: Student Characteristics**

The stopout model in Table 5 clearly demonstrates that attending other colleges has a substantial and statistically significant effect on enrollment patterns at the study institution. Herzog (2005) indicates that "concurrent enrollment at another post-secondary institution cuts the dropout risk by half and reduces the transfer-out risk considerably during the first and second semester" (p. 916). Contrary to this finding, the stopout model presented here shows that departure rates are higher for students concurrently attending another college. Return, on the other hand, is substantially lower for those students who attend other colleges. The model also demonstrates that the effect of other college attendance differs by college type. For example, students who do not attend other colleges have 95% or $\left(1-\frac{1}{e^{2.97}}\right)$ lower odds of departure and 8.2 or $\left(\frac{1}{e^{2.97-5.08}}\right)$ times the odds of return compared to students attending four-year *out-of-state* colleges. Compared to students attending four-year *in-state* colleges, students who do not attend other colleges have 88% lower odds of departure and 5.5 times the odds of return. The effect of concurrent enrollment in the *two-year* college is similar to the effect of concurrent enrollment in the *four-year* college. (The interaction effect of another college attendance and two-year college type is small and statistically insignificant.) At the same time, two-year college type does attenuate the effect of enrollment at another institution on the odds of return. (The interaction effect of another college attendance, two-year college type, and episode of non-enrollment is positive and statistically significant.) Students who do not attend other institutions have 1.5 or $e^{-(2.97-5.08-.88+1.28-.03+1.31)}$ times the odds of return compared to students attending two-year in-state institutions.

While concurrent attendance at other colleges has significant effect on the odds of departure, its overall impact on retention rates is less substantial due to low incidence of concurrent enrollment at the study institution. As indicated earlier, on average less than half of a percent of students—0.19% in the first semester of first episode of enrollment, 0.11% in the second semester of enrollment and so on—are concurrently enrolled at other institutions. By contrast, college attendance elsewhere after the departure from the study institution involves a substantial number of students (see average fitted probabilities of enrollment elsewhere in Fig. 2) and has substantial effect on return rates at the study institution.

Fig. 4 illustrates the average fitted probabilities of returns for the first three semesters of the first episode of non-enrollment by attendance of other institutions. While over a third of students who leave and do not enroll elsewhere are expected to return within a semester after their departure, this expected proportion decreases substantially if a student does enroll elsewhere. If a student attends a two-year college, this proportion drops to .25 and .17 for in-state and out-of-state colleges. If a student chooses another four-year institution, the return rate drops to .07 and .04 for in-state and out-of-state. The differences in fitted probabilities are significantly lower for the second and third semester of non-enrollment as the overall return rates go down significantly with time.

The National Student Clearinghouse dataset also provides the indicator of *public* versus *private* institution. This indicator is not included in the final model presented here, because it was not significant and did not lead to improvement of model fit both in terms of deviance and AIC/BIC criteria. The indicator of matriculation term was also not included in the model due to lack of model improvement.

Part-time status attenuates the effect of attending another institution. A student who attends another institution part time, has 81% lower odds of departure and 1.7 times the odds of return compared to a student who attended another institution full time. Compared to students who do not attend other institutions, students attending other four-year out-of-state institutions part time have 3.7 times the odds of departure and 80% lower odds of return.

As expected, grade performance significantly affects persistence. Students with a cumulative GPA of 2.00 or higher are less likely to leave. Compared to students with unsatisfactory grade performance, students with satisfactory GPA have 0.17 times the odds of departure. This finding agrees with many prior studies showing higher departure rates for students with unsatisfactory academic progress. For instance Ronco (1996) indicates that students who dropout or transfer to a two-year college are most likely to do so because of the impact of the GPA below 2.00. The effect of grade performance on the odds of return has not been studied before. Our analysis indicates that the odds of return to a home institution are lower for students with satisfactory grades: they have 0.85 times the odds of return compared students with unsatisfactory grades. The lower odds of return for students with satisfactory grades reinforces the earlier finding of a higher likelihood of enrollment elsewhere after the departure from the study institution for this group of students. The model also shows a significant effect of hours earned at the study institution on the odds of departure but no effect of hours earned on the odds of return. One should interpret this particular finding with caution, as hours earned are expected to correlate strongly with previous spell duration and other timing indicators.

Consistent with prior studies, part-time students are more likely to leave. O'Toole, Stratton, and Wetzel (2003) indicate that only 2 in 10 of those attending exclusively full time are observed stopping out, but over 4 in 10 of those ever attending part time are observed stopping out. Thus, students who attend college part time have 2.7 times the odds of stopout compared to students who attend college full time. Our model shows that in any given semester, part-time enrollment increases the odds of departure 1.8 times.

Hossler, Ziskin, Gross and Kim (2009) indicate that "constructing longitudinal studies of the effects of financial aid is often impossible because of limitations in data sets" (p.395). Use of institutional datasets in our and several prior studies (DesJardins, Ahlburg, and McCall, 2002; Singell and Stater, 2006) had the advantage of availability of financial aid information by year or term. The findings of our study are consistent with typical findings of prior research (for review of prior research see Hossler et al., 2009): all types of financial aid have a small but positive effect on student persistence. Since student residence status is associated with substantially lower tuition rates, it was important to explore interaction effects of residence status and financial aid on the odds of departure. We considered interaction effects of grants, loans, scholarships, and work study and residence status on odds of departure. Only interaction term of loans and residence status was included in the final model, because inclusion of other interaction effects neither significantly decreased the deviance nor led to lower AIC or BIC. The model shows that receiving $1,000 in grants leads to a 6% decrease in odds of departure; $1,000 in loans is associated with a 4% decrease in odds of departure for out-of-state students and a 10% decrease for state residents; $1,000 in scholarship aid is associated with a 21% decrease in odds of departure; and $1,000 in work-study is associated with a 22% decrease in odds of departure. As expected, the same dollar amount of loan has a more noticeable impact on residents, as their tuition is significantly lower. Overall, these findings of financial aid effects should be interpreted with caution, as unobserved student characteristics might affect both the likelihood of receiving financial aid and the likelihood of attrition. For example, Pell Grant recipients might have "risk" characteristics that suggest greater chances of dropping out of college (Wei and Horn, 2009).

Higher departure rates for nonresidents are frequently reflected in traditional retention reports. However, traditional reports do not reflect lower return rates among nonresidents. Fig. 5 illustrates that the differences in fitted probabilities of departure are statistically significant but rather small and range from one to two percent for the first episode of enrollment. At the same time, return rates are significantly lower for nonresidents both statistically and substantively. Compared to nonresidents, residents are 1.6 times as likely to return after one semester of stopout and 1.8 times as likely to return after two semesters of stopout. There are several possible explanations of higher attrition among nonresidents. On the one hand, students’ residency status may affect their social integration. Students who enroll from out-of-state are less likely to have friends who are attending an institution and, therefore, might feel isolated or homesick (Caison 2007). On the other hand, in-state residency status is typically rewarded by lower tuition. In the case of the study institution it is likely to be the latter reason. Evidence from an institutional survey of non-returning students shows that non-resident students more frequently indicate that their major reasons for non-return were high tuition and fees, not receiving financial aid, or receiving financial aid that was not sufficient. The differences between shares of residents and nonresidents who indicated feeling isolated or homesick were not statistically significant.

Greek membership reflects the level of social integration and positively affects persistence at the study institution. Compared to students who are not affiliated with Greek organizations, members of fraternities and sororities have 0.5 the odds of departure and 1.4 the odds of return. After control for other characteristics, female students have 1.2 the odds of departure and 0.8 the odds of return. As indicated earlier, greater odds of departure for females do not agree with descriptive findings of higher persistence rates for females. This is because females are more likely to earn and maintain a cumulative GPA of 2.00 or higher and the effect of gender changes after control for cumulative GPA. White students are significantly less likely to experience both departures from and returns to the study institution. (The interaction effect between ethnicity indicator and episode of non-enrollment neither decreased the deviance nor lowered AIC or BIC.) The odds of departures and returns are 17% lower for white students.

**Limitations**

The model of student enrollment at other institutions presented here shows the timing and student characteristics associated with enrollment elsewhere. A college choice model predicting the likelihood of enrollment at different institution types is beyond the scope of the study. This study is restricted to a descriptive analysis of student characteristics that are most noticeably associated with different transfer behaviors. The multinomial logit model of different transfer behaviors—non-transfer, two-year in-state, two-year out-of-state, four-year in-state, and four-year out-of-state—is not considered here because of its restrictive assumption of the independence of irrelevant alternatives (IIA). This assumption means that if one of alternatives, such as transfer to out-of-state two year institution, is removed from the choice set, the probability of a student choosing any of the remaining alternatives—non-transfer, two-year in-state, four-year in-state, and four-year out-of-state—increases proportionally. This assumption is unreasonable for our choice set. Some solutions to this problem require additional data on the choice attributes (see, for example, Porter 2002), which are not available. A college choice model that includes both college- and student- level characteristics would advance the understanding of student transfer from the study institution.

The analysis is based on data from a single moderately large research institution. Persistence patterns and student characteristics affecting stopout, dropout, and transfer out vary across institutions, and the findings presented here might not apply to other institutions and institution types.

**Implications**

Our analysis shows that the vast majority of students who leave the study institution and do not return shortly after eventually transfer elsewhere. Most of the students who leave enroll elsewhere by the third semester of staying out. This includes those who leave for academic reasons. Hence, traditional institutional retention reports significantly underestimate student success or rate of progress towards degree.

Concurrent enrollment has a statistically significant negative effect on persistence. And this effect varies by enrollment status at another institution—part- or full-time—and types of institutions students chose to attend concurrently—four- or two-year, in-state or out-of-state. Students might take classes offered through distance education, especially if their institution of concurrent enrollment is located out of state. It could be important to explore classes students prefer to take at other institutions and reasons why they prefer to take those classes outside of the study institution. The study institution might consider dual enrollment programs with a less selective in-state institution to differentiate its mission, improve cost-effectiveness, and admit more in-state students. Some universities have already established dual enrollment programs that enable student swirl and promote college persistence (Bontrager, Clemetsen, and Watts 2005).

While concurrent enrollment is rather unusual for the study institution, student enrollment elsewhere after departing from the study institution is very common. Such enrollment negatively affects the probability of return to the study institution, and its effect varies by enrollment status and types of institutions. The effect of other college attendance on return rates becomes very small after a few terms of non-enrollment at the study institution (see Fig. 4). This is because the overall return rates become extremely low in the later terms of stopout and because the relationships between independent variables and probabilities are nonlinear and nonadditive. (Because of low return rates after the third semester of stopout, the effect of all student characteristics on probabilities become minimal.) Overall, including other institution attendance in the stopout model provides a more accurate and complete picture of student mobility in and from the study institution.

Another important finding is the association between out-of-state residency and persistence. Traditional retention summaries might overestimate retention for nonresidents, because they do not account for return rates and do not control for other student characteristics, such as college grade performance. Higher attrition rates among nonresidents are likely caused by differences in tuition rates. From the institutional perspective, loss of out-of-state students might mean a significant loss in revenues. With a significant decrease in state appropriations in recent years, the study institution experienced the decline in share of state appropriations in the main campus operating budget from 45 percent to 32 percent. During the same period of time, the ratio between out-of-state and in-state tuition remained practically the same. Because the study institution relies on out-of-state tuition, in case of continuing decline in state appropriations it might not be economically viable to keep the current tuition ratio. At the same time, raising tuition to market levels for state residents would generate political pressure “to limit future tuition increases or even to roll back previous increases” (Ehrenberg 2005: 6). Furthermore, charging resident students higher tuition or attracting out-of-state and other full-pay students might leave the study institution out of reach for students from in-state low and moderate-income families. Some states and public universities attempted to distribute state appropriations proportionally among in-state students. Miami University of Ohio approached this problem by charging resident and nonresident students the same nominal tuition and offering resident students grants in the amount of state appropriation per student. The College Opportunity Fund (COF), introduced in Colorado, presumes vouchers as the financing mechanism for all resident undergraduate students attending the state's public institutions. However, transitions to these innovative approaches to financing public higher education do not always go smoothly (Prescott 2010). Recent studies (e.g., Toutkoushian and Shafig 2009) indicate that in order to maximize student participation in postsecondary education states need to provide need-based financial support to students rather than appropriations to state colleges. If state appropriations continue to decline either absolutely or as a share of all revenues, the study institution might need to consider alternative tuition practices for in-state students.

Evidence of substantial mobility in the beginning of student educational careers emphasizes the importance of shared general education outcomes, such as a robust set of "Essential Learning Outcomes" proposed by the National Leadership Council for Liberal Education and America’s Promise (2007).

From the methodological standpoint, our study demonstrates the possibilities of analysis of multiple episodes of enrollment and non-enrollment at a single institution. The model of enrollment at other institutions handles repeated spells—first and subsequent non-enrollment spells—simultaneously. The stopout model handles multiple enrollment states—enrollments and non-enrollments at the study institution—and repeated states—first and subsequent episodes—simultaneously. Handling repeated events and states separately might have the advantage of simplicity. For example, instead of one model of enrollment at other institutions, we could have built separate models for the first episode of non-enrollment, second episode of non-enrollment, etc. Similarly, instead of having one model of departures and returns, we could have built a model of departure for the first episode of enrollment, a model of return for the first episode of non-enrollment, a model of departure for the second episode of non-enrollment, and so on. Steele (2005) provides review of studies that illustrate inefficiencies of separate analysis of repeated events and multiple states. For example, separate models do not test the hypothesis of differentiating effect of student characteristics for departures and returns or for the first or repeated episodes. Within a single stopout model, this study answers multiple institution-level attrition questions such as: are higher departure rates for out-of-state students associated with their enrollments elsewhere; do students who leave, eventually return; or are students who are enrolled elsewhere more likely to return than those who do not enroll at other institutions. Application of multiple-episode discrete-time logistic regression model for stopout behavior in this study is a step towards development of what McCormick referred to as a "more sophisticated understanding of the various ways that students combine enrollment at multiple institutions—one that takes us well beyond simple descriptions of transfer behavior" (p.22).

**References**

Adelman, C. (1999). *Answers in the toolbox: Academic intensity, attendance patterns, and Bachelor's degree attainment.* Washington, D.C.: U.S. Department of Education.

Adelman, C. (2005). *Moving into town—and moving on: The community college in the lives of traditional-age students*. Washington, DC: U.S. Department of Education.

Bahr, P.R. (2011). Student flow between community colleges: Investigating lateral transfer. *Research in Higher Education*, in print.

Bontrager, B., Clemetsen, B. and Watts, T. (2005). Enabling student swirl: A community college/university dual enrollment program. *College and University Journal, 80(*4): 3-6.

Borden, V. M. H. (2004.) Accommodating student swirl: When traditional students are no longer the tradition. *Change 36(*2): 10–17.

Caison, A.L. (2007). Analysis of institutionally specific retention research: A comparison between survey and institutional database methods. *Research in Higher Education 48(*4): 435–451.

National Leadership Council for Liberal Education and America's Promise (2007). *College Learning for the New Global Century*. America Association of American Colleges and Universities, Washington D.C.

Conger, D. and Long, M. (2010). Why are men falling behind? Gender Gaps in college performance and persistence. *The Annals of the American Academy, 627*: 184-214.

De los Santos, A., Jr., and Wright, I. (1990). Maricopa's Swirling Students: Earning One-Third of Arizona State's Bachelor's Degrees. *Community, Technical, and Junior College Journal, 4(*6): 32-34.

DesJardins, S. L., Ahlburg, A. A., and McCall, B. P. (2002). Simulating the longitudinal effects of changes in financial aid on student departure from college. *Journal of Human Resources 37(*3): 653–679.

DesJardins, S. L., Ahlburg, A. A., and McCall, B. P. (2006). The effects of interrupted enrollment on graduation from college: Racial, income, and ability differences. *Economics of Education Review, 25*: 575–590

DesJardins, S.L. and McCall, B.P. (2010). Simulating the Effects of Financial Aid Packages on College Student Stopout, Reenrollment Spells, and Graduation Chances. *The Review of Higher Education, 33,(*4), 513-541.

Ehrenberg, R.G. (2005). The perfect storm and the privatization of public higher education. *Working Papers*, *59*. Retrieved on April 15, 2011 at http://digitalcommons.ilr.cornell.edu/workingpapers/59

Goldrick-Rab, S., Harris, D.N. and Trostel, P.A. (2009). Why financial aid matters (or does not) for college success: toward a new interdisciplinary perspective. Smart, J.C. (Ed.) *Higher Education: Handbook of Theory and Research, Vol. XXIV*: 389-426.

Herzog, S. (2005). Measuring determinants of student return vs. dropout vs. transfer: A First-to-Second Year Analysis of New Freshmen. *Research in Higher Education 46(*8): 883-928.

Horn, L. (1998). *Stopouts or stayouts? Undergraduates who leave college in their first year* (NCES 1999–087). Washington, DC: U.S. Government Printing Office.

Hossler, D., Ziskin, M., Gross, J. P.K., and Kim, S. (2009). Student aid and its role in encouraging persistence. Smart, J.C. (Ed.) *Higher Education: Handbook of Theory and Research, Vol. XXIV*: 389-426.

Johnson, I. Y. (2006). Analysis of stopout behavior at a public research university: The multi-spell discrete-time approach. *Research in Higher Education 47(*8): 905-934.

Kahn, J. H. and Nauta M. M. (2001). Social-cognitive predictors of first-year college persistence: The importance of proximal assessment. *Research in Higher Education, 42(*6): 633-652.

McCormick, A.C. (1997). *Transfer Behavior among Beginning Postsecondary Students: 1989-94*. Washington, DC: U.S. Department of Education.

McCormick, A.C. (2003). Swirling and double-dipping: New patterns of student attendance and their implications for higher education. *New Directions for Higher Education, 121:* 13-24.

Mullane, L. (2005). *Taking Transfer Credit Beyond Traditional Boundaries.* Americal Council on Education. Retrieved on April 12, 2011 at http://www.acenet.edu/AM/Template.cfm?Section=Home&TEMPLATE=/CM/ContentDisplay.cfm&CONTENTID=12215 .

National Leadership Council for Liberal Education and America's Promise (2007). *College Learning for the New Global Century*. America Association of American Colleges and Universities, Washington D.C.

O'Connell, A. A., McCoach, D. B. (2008). *Multilevel Modeling of Educational Data*. Information Age Publishing, Inc.

O'Toole, D.M., Stratton, L.S. and Wetzel, J.N. (2003). A longitudinal analysis of the frequency of part-time enrollment and the persistence of students who enroll part time. *Research in Higher Education, 44(*5), 519-537.

Pascarella, E. T., and Terenzini, P. (1980). Predicting freshman persistence and voluntary dropout decisions from a theoretical model. *Journal of Higher Education 51(*1), 60–75.

Pascarella, E. and Terenzini, P. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco: Jossey-Bass.

Pascarella, E. and Terenzini, P. (2005). *How college affects students, A Third Decade of Research*. Vol. 2, San Francisco: Jossey-Bass.

Peter, K., Cataldi, E.F., and Carroll C.D. (2005). *The Road Less Traveled? Students Who Enroll in Multiple Institutions*. Washington, DC: U.S. Department of Education.

Peter, K., Horn, L., and Carroll C.D. (2005). *Gender Differences in Participation and Completion of Undergraduate Education and How They Have Changed Over Time*. Washington, DC: U.S. Department of Education.

Pike, G. R., & Askew, J. W. (1990). The impact of fraternity or sorority membership on academic involvement or learning outcomes. *NASPA Journal, 28*, 13-19.

Pike, G. R. (2003). Membership in a fraternity or sorority, student engagement, and educational outcomes at AAU public research universities. *Journal of College Student Development, 44(*3), 369-382.

Porter S. (Winter, 2002). Including transfer-out behavior in retention models: Using the NSLC enrollment search data. *IR Professional File,* 82.

Porter S. (2003). Understanding Retention Outcomes: Using multiple data sources to distinguish between dropouts, stopouts, and transfer-outs. *Journal of College Student Retention, 5(*1), 53-70.

Prescott, B.T. (2010). Is Colorado's voucher system worth vouching for? *Change*, July-August. Retrieved on April 15, 2011 at http://www.changemag.org/Archives/Back%20Issues/July-August%202010/Colorado-voucher-full.html .

Ronco, S.L. (1994). *Meandering Ways: Studying Student Stopout with Survival Analysis.* Paper presented at the 34th Annual Conference of the Association for Institutional Research, New Orleans, LA.

Ronco, S.L. (1996). How enrollment ends: Analyzing the correlates of student graduation, transfer and dropout with a competing risks model. *AIR Professional File,* 61.

Singell, L. and Stater, M. (2006). Going, going, gone: the effects of aid policies on graduation at three large public institutions. *Policy Sciences, 39(*4): 379-403.

Singer, J.D., and Willett, J.B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. New York: Oxford University Press.

Stage, F. K. (1988). University attrition: LISREL with logistic regression for the persistence criterion. *Research in Higher Education 29(*4), 343–357.

Stage, F., and Hossler, D. (1989). Differences in family influences on college attendance plans for male and female ninth graders. *Research in Higher Education 30(*3), 301–315.

Steele, F. (2005). *Event History Analysis*. A National Centre for Research Methods Briefing Paper. University of Bristol, Bristol, UK. Retrieved on April 29, 2011 at http://eprints.ncrm.ac.uk/88/1/MethodsReviewPaperNCRM-004.pdf .

Stratton, L.S. , and O'Toole, D.M., and Wetzel, J.M. (2007). Are the factors affecting dropout behavior related to initial enrollment intensity for college undergraduates? *Research in Higher Education, 48(*4), 453-485.

Stratton, L.S. , and O'Toole, D.M., and Wetzel, J.M. (2008). A multinomial logit model of college stopout and dropout behavior. *Economics of Education Review 27*, 319-331.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research 45(*1), 89-125.

Toutkoushian, R.K. and Shafiq, M.N. (2010). A conceptual analysis of state support for higher education: Appropriations versus need-based financial aid. *Research in Higher Education, 51(*1), 40-64.

Wang, Y., and Pilarzyk, T. (2009). Understanding student swirl: The role of environmental factors and retention efforts in the later academic success of suspended students. *Journal of College Student Retention, 11(*2), 211-226.

Wells, R. (2009). Social and cultural capital, race and ethnicity, and college student retention. *Journal of College Student Retention: Research, Theory & Practice, 10(*2): 103-128.

Wei, C.C., and Horn, L. (2009). *A Profile of Successful Pell Grant Recipients: Time to Bachelor's Degree and Early Graduate School Enrollment* (NCES 2009-156). Washington, DC: U.S. Government Printing Office.

Willett, J.B. ,and Singer, J.D. (1995). It's Déjá Vu all over again: Using multi-spell discrete-time survival analysis. *Journal of Educational and Behavioral Statistics 20(*1), 41–67.

**TABLE 1. Variable Description and Descriptive Statistics**

| Variable | Variable description | Mean (SD) Episodes of enrollment | Episodes of non-enrollment | All episodes |
|---|---|---|---|---|
| *Level-1: Time-varying variables* | | | | |
| Event | Dependent variable: equals 1 if a student left or returned | 0.07 (0.25) | 0.06 (0.24) | 0.07 (0.25) |
| *Timing and episodes* | | | | |
| Term | Semester in a spell (only fall and spring semesters included) | 4.16 (2.56) | 4.45 (2.64) | 4.38 (2.63) |
| $Term^2$ | Semester squared | 23.85 (24.90) | 26.76 (27.13) | 26.06 (26.64) |
| $Term^3$ | Semester cubed | 160.93 (223.3) | 188.38 (257.8) | 181.82 (250.2) |
| $Term^4$ | Semester in the fourth degree | 1,188.6 (2013.6) | 1,452.4 (2479.7) | 1,389.2 (2379.2) |
| Episode of non-enrollment | Equals 1 when a student is not enrolled at the study institution | - | - | 0.24 (0.43) |
| Repeated episode | Equals 1 for episodes other than first | 0.12 (0.32) | 0.05 (0.23) | 0.07 (0.25) |
| Spring semester | Equals 1 for spring semesters | 0.46 (0.50) | 0.47 (0.50) | 0.47 (0.50) |
| Previous spell duration | Natural logarithm of previous spell duration plus 1, ln(d+1) | 1.21 (0.41) | 0.05 (0.21) | 0.33 (0.57) |
| *College attendance elsewhere* | | | | |
| Attending another college | Equals 1 if a student attends a college other than home college | 0.004 (0.064) | 0.49 (0.50) | 0.12 (0.33) |
| ... × in-state college | Equals 1 if a student attends another in-state college | 0.003 (0.052) | 0.23 (0.42) | 0.06 (0.23) |
| ... × two-year college | Equals 1 if a student attends two-year college | 0.002 (0.047) | 0.12 (0.33) | 0.03 (0.17) |
| ... × part-time | Equals 1 if a student attends another college part time | 0.003 (0.051) | 0.10 (0.30) | 0.03 (0.16) |
| ... × public | Equals 1 if a student attends another public institution | 0.004 (0.061) | 0.45 (0.50) | 0.11 (0.31) |
| *Other student-period characteristics* | | | | |
| GPA 2.00 or higher | Equals 1 if a student's cumulative GPA is 2.00 or higher | 0.84 (0.37) | 0.44 (0.50) | 0.74 (0.44) |
| Enrolled part-time* | Equals 1 if a student's attempted hours are less than 12 | 0.06 (0.24) | - | 0.05 (0.21) |
| Hours earned | Hours earned at the study institution | 55.80 (39.93) | 37.10 (22.59) | 42.45 (42.19) |
| Grant ($1,000s)* | Amount of grants received in $1,000s | 0.20 (0.67) | - | 0.15 (0.59) |
| Loan ($1,000s)* | Amount of loans received in $1,000s | 1.59 (3.26) | - | 1.21 (2.92) |
| Scholarship ($1,000s)* | Amount of scholarship received in $1,000s | 0.52 (1.41) | - | 0.40 (1.25) |
| Work/study ($1,000s)* | Amount of work study received in $1,000s | 0.02 (1.41) | - | 0.02 (0.16) |
| *Number of student-period observations* | | *56,227* | *17,688* | *73,915* |
| *Level-2: Student characteristics or time-invariant variables* | | | | |
| Female | 1 if female; 0 otherwise | 0.52 (0.50) | 0.47 (0.50) | 0.52 (0.50) |
| Non-white | 1 if ethnicity is non-white; 0 otherwise | 0.12 (0.32) | 0.22 (0.42) | 0.12 (0.32) |
| State resident | 1 if state resident; 0 otherwise | 0.59 (0.49) | 0.59 (0.49) | 0.59 (0.49) |
| High School GPA | High School GPA | 3.69 (0.43) | 3.35 (0.47) | 3.69 (0.43) |
| ACT or SAT Equivalent | ACT or SAT Equivalent | 25.87 (3.48) | 23.37 (3.45) | 25.87 (3.48) |
| Greek membership | | 0.32 (0.47) | 0.22 (0.41) | 0.32 (0.47) |
| *Number of student-level observations* | | *7,768* | *2,862* | *7,768* |

* Indicator of part-time enrollment at the study institution as well as financial aid information is available only for episodes of enrollment.

**TABLE 2. Enrollment at other institutions: Timing representations**

| *B (SE)* | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Constant | -0.19 (0.03)*** | 0.13 (0.04)*** | -0.45 (0.05)*** | -0.78 (0.07)*** | -0.93 (0.1)*** | 0.04 (0.13) |
| Term | | -0.09 (0.01)*** | 0.27 (0.03)*** | 0.61 (0.06)*** | 0.82 (0.13)*** | 0.65 (0.06)*** |
| $Term^2$ | | | -0.04 (0)*** | -0.12 (0.01)*** | -0.2 (0.05)*** | -0.13 (0.01)*** |
| $Term^3$ | | | | 0.01 (0.00)*** | 0.02 (0.01)** | 0.01 (0)*** |
| $Term^4$ | | | | | -0.00 (0.00) | |
| Repeated episode of non-enrollment | | | | | | -0.58 (0.08)*** |
| Previous spell duration: ln(d+1) | | | | | | -0.59 (0.07)*** |
| Variance component | 2.99 | 3.36 | 3.39 | 3.42 | 3.42 | 3.11 |
| Deviance | 51,605 | 51,279 | 50,816 | 50,757 | 50,753 | 50,633 |
| Number of parameters | 2 | 3 | 4 | 5 | 6 | 7 |
| AIC | 51,609 | 51,285 | 50,824 | 50,767 | 50,765 | 50,647 |
| BIC (based on level-1 sample size) | 51,625 | 51,308 | 50,855 | 50,806 | 50,811 | 50,701 |

*Significant at the 10% alpha level; **Significant at the 5% alpha level; *** Significant at the 1% alpha level.

*Note:* Population-average estimates with robust standard errors are presented here. Model 1 eliminates the effect of timing; Model 2 is a linear representation of timing; Model 3 is a quadratic representation of timing; Model 4 is a cubic representation of timing; Model 5 is a three stationary points representation of timing; and Model 6 is a cubic representation of timing that accounts for repeated episodes and previous spell duration.

**TABLE 3. Enrollment at other institutions: Student characteristics**

| | *B (SE)* |
|---|---|
| Constant | -0.81 (0.34)** |
| Term | 0.70 (0.06)*** |
| $Term^2$ | -0.14 (0.01)*** |
| $Term^3$ | 0.01 (0.00)*** |
| Repeated episode of non-enrollment | -0.19 (0.13) |
| Previous spell duration: ln(d+1) | -0.22 (0.15) |
| Cumulative GPA of 2.00 or higher | 0.88 (0.07)*** |
| Hours earned at the study institution | -0.01 (0.00)*** |
| State resident | -0.47 (0.06)*** |
| Non-white | -0.26 (0.08)*** |
| Female | 0.25 (0.06)*** |
| High School GPA | 0.11 (0.08) |
| ACT or SAT Equivalent | 0.01 (0.01) |
| Greek membership at the study institution | 0.20 (0.08)** |
| Variance component | 2.61 |
| Deviance | 50,228 |
| Number of parameters | 15 |
| AIC | 50,258 |
| BIC (based on level-1 sample size) | 50,396 |

*Significant at the 10% alpha level; **Significant at the 5% alpha level; *** Significant at the 1% alpha level.
*Note:* Population-average estimates with robust standard errors are presented here.

**TABLE 4. Stopout: Timing representations**

| *B (SE)* | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Intercept | -2.51 (0.02)*** | -2.16 (0.03)*** | -2.27 (0.05)*** | -2.99 (0.08)*** | -3.50 (0.13)*** | -3.19 (0.08)*** |
| Term | | -0.11 (0.01)*** | -0.03 (0.02) | 0.70 (0.06)*** | 1.39 (0.15)*** | 0.61 (0.06)*** |
| $Term^2$ | | | -0.01 (0.00)*** | -0.19 (0.01)*** | -0.46 (0.05)*** | -0.17 (0.01)*** |
| $Term^3$ | | | | 0.01 (0.00)*** | 0.05 (0.01)*** | 0.01 (0.00)*** |
| $Term^4$ | | | | | 0 (0)*** | |
| Episode of non-enrollment | -0.79 (0.07)*** | 1.13 (0.10)*** | 1.88 (0.13)*** | 2.83 (0.23)*** | 2.69 (0.47)*** | 1.43 (0.29)*** |
| Repeated episode | | | | | | 0.71 (0.30)** |
| Spring semester | | | | | | 0.45 (0.030)*** |
| Previous spell duration (ln(d+1)) | | | | | | -0.27 (0.34) |
| Term × episode of non-enrollment | | -0.75 (0.05)*** | -1.47 (0.09)*** | -2.51 (0.25)*** | -2.14 (0.69)*** | -2.44 (0.24)*** |
| $Term^2$ × episode of non-enrollment | | | 0.11 (0.01)*** | 0.38 (0.06)*** | 0.16 (0.29) | 0.37 (0.06)*** |
| $Term^3$ × episode of non-enrollment | | | | -0.02 (0.00)*** | 0.03 (0.04) | -0.02 (0.00)*** |
| $Term^4$ × episode of non-enrollment | | | | | 0.00 (0.00) | |
| Repeated episode × episode of non-enrollment | | | | | | -0.53 (0.36) |
| Previous spell duration (ln(d+1)) × episode of non-enrollment | | | | | | 1.31 (0.36)*** |
| Variance component | 0.91 | 0.50 | 0.51 | 0.52 | 0.52 | 0.52 |
| Deviance | 170,126 | 168,317 | 168,210 | 168,053 | 168,033 | 167,469 |
| Number of parameters | 3 | 5 | 7 | 9 | 11 | 14 |
| AIC | 170,132 | 168,327 | 168,224 | 168,071 | 168,055 | 167,497 |
| BIC (based on level-1 sample size) | 170,159 | 168,373 | 168,289 | 168,154 | 168,156 | 167,626 |

*Significant at the 10% alpha level; **Significant at the 5% alpha level; *** Significant at the 1% alpha level.

*Note:* Population-average estimates with robust standard errors are presented here. Model 1 eliminates the effect of timing; Model 2 is a linear representation of timing; Model 3 is a quadratic representation of timing; Model 4 is a cubic representation of timing; Model 5 is a three stationary points representation of timing; and Model 6 is a cubic representation of timing that accounts for repeated episodes, previous spell duration, and an indicator of spring semester.

**TABLE 5. Stopout: Student characteristics**

| | B (SE) |
|---|---|
| Intercept | -2.11 (0.19)*** |
| Term | 0.86 (0.08)*** |
| $Term^2$ | -0.13 (0.02)*** |
| $Term^3$ | 0.01 (0.00)*** |
| Episode of non-enrollment | 1.78 (0.25)*** |
| Repeated episode | 1.63 (0.20)*** |
| Spring semester | 0.47 (0.03)*** |
| Previous spell duration (ln(d+1)) | 0.04 (0.20) |
| Term × episode of non-enrollment | -2.57 (0.21)*** |
| $Term^2$ × episode of non-enrollment | 0.31 (0.06)*** |
| $Term^3$ × episode of non-enrollment | -0.01 (0.00)*** |
| Repeated episode × episode of non-enrollment | -1.84 (0.25)*** |
| Previous spell duration (ln(d+1)) × episode of non-enrollment | 0.42 (0.25)* |
| Cumulative GPA of 2.00 or higher | -1.80 (0.04)*** |
| Cumulative GPA of 2.00 or higher × episode of non-enrollment | 1.64 (0.09)*** |
| Enrolled part-time at the study institution × episode of enrollment | 0.58 (0.07)*** |
| Hours earned at the study institution | -0.03 (0.00)*** |
| Hours earned at the study institution × episode of non-enrollment | 0.03 (0.00)*** |
| Grant ($1,000s) × episode of enrollment | -0.06 (0.03)** |
| Loan ($1,000s) × episode of enrollment | -0.04 (0.01)*** |
| Scholarship ($1,000s) × episode of enrollment | -0.23 (0.03)*** |
| Work/study ($1,000s) × episode of enrollment | -0.25 (0.14)* |
| *College attendance elsewhere* | |
| Attending another college | 2.97 (0.33)*** |
| Attending another college × episode of non-enrollment | -5.08 (0.37)*** |
| Attending another college × in-state college | -0.88 (0.39)** |
| Attending another college × in-state college × episode of non-enrollment | 1.28 (0.44)*** |
| Attending another college × two-year college | -0.03 (0.43) |
| Attending another college × two-year college × episode of non-enrollment | 1.31 (0.46)*** |
| Attending another college × part-time attendance | -1.67 (0.46)*** |
| Attending another college × part-time attendance × episode of non-enrollment | 2.18 (0.49)*** |
| *Level-2 variables* | |
| State resident | -0.11 (0.05)** |
| Non-white | 0.19 (0.05)*** |
| Female | 0.22 (0.04)*** |
| High School GPA | -0.01 (0.04) |
| ACT or SAT Equivalent | 0.003 (0.006) |
| Greek membership | -0.60 (0.05)*** |
| *Cross-level interactions* | |
| State resident × episode of non-enrollment | 0.22 (0.09)** |
| Female × episode of non-enrollment | -0.50 (0.08)*** |
| Greek membership × episode of non-enrollment | 0.95 (0.09)*** |
| Loan ($1,000s) × state resident × episode of enrollment | -0.06 (0.01)*** |
| Variance component | 0.05 |
| Deviance | 162,834 |
| Number of parameters | 41 |
| AIC | 162,916 |
| BIC (based on level-1 sample size) | 163,293 |

Significant at the 10% alpha level; **Significant at the 5% alpha level; *** Significant at the 1% alpha level.
*Note:* Population-average estimates with robust standard errors are presented here.

**FIG. 1.** Proportions of students enrolled at other institutions two terms after the departure from the study institution by residence, grade performance, and transfer institution type.

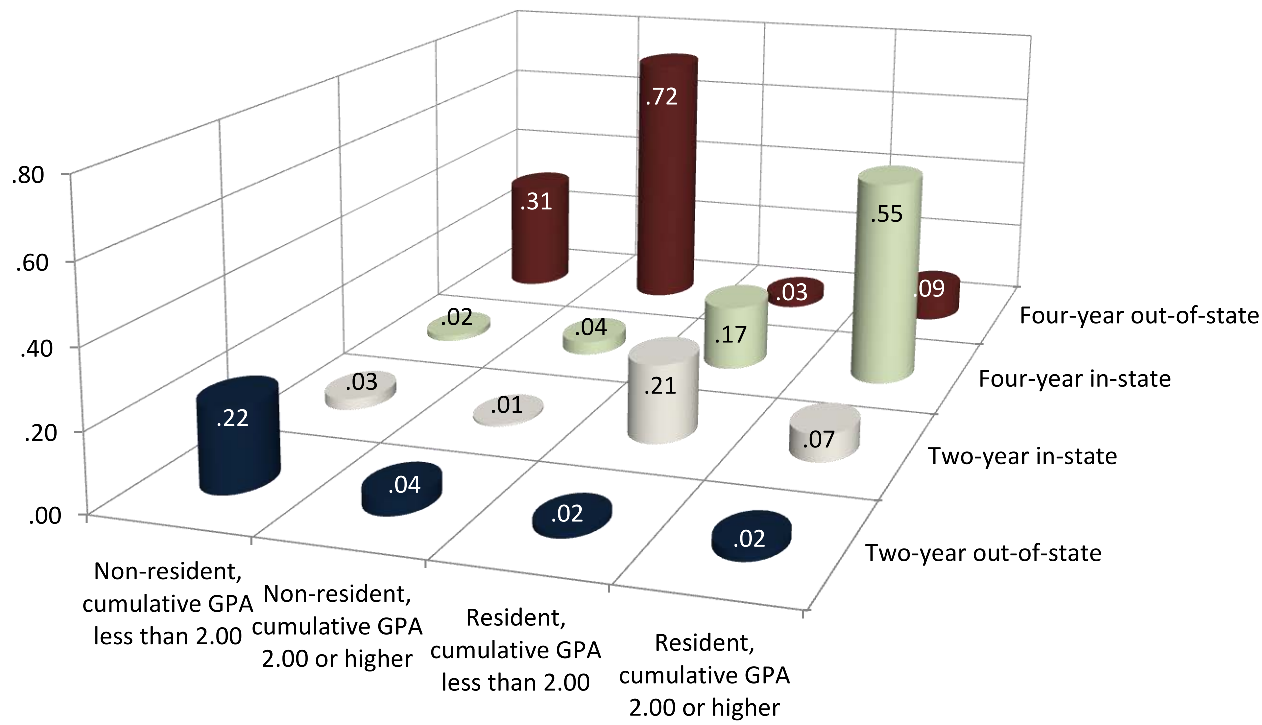
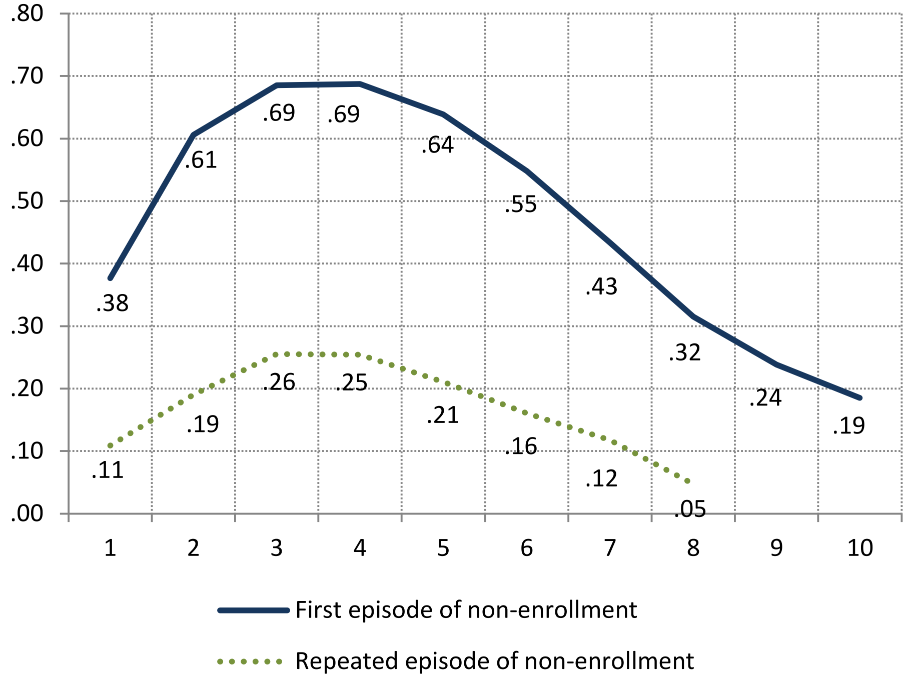
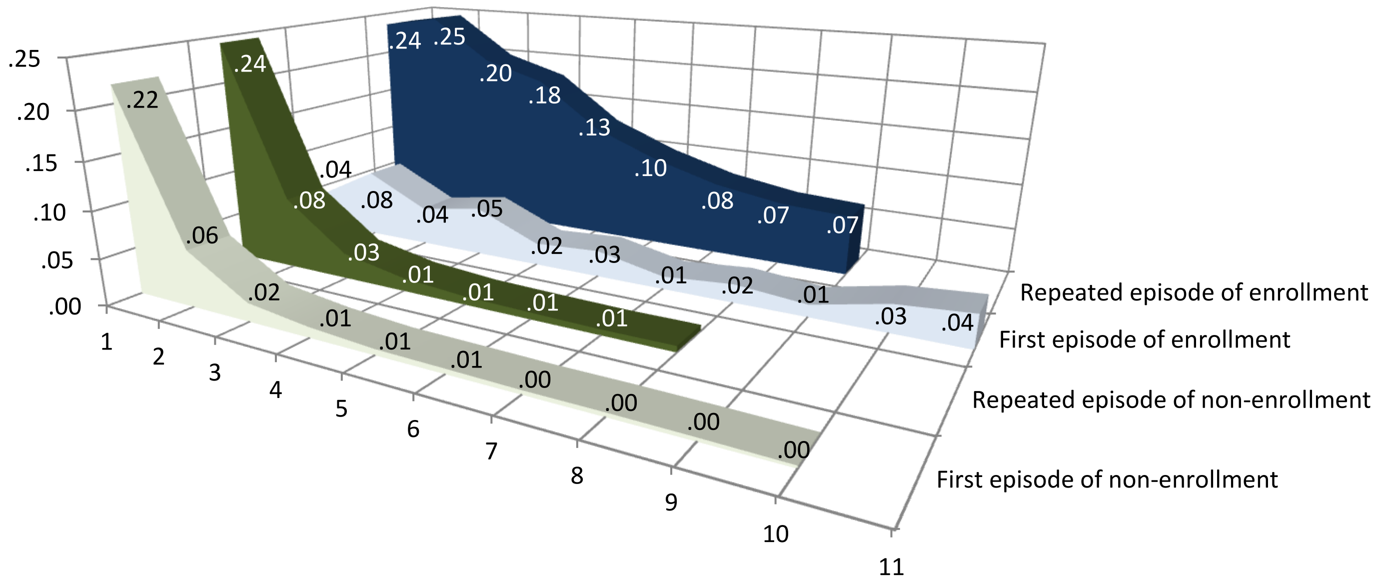


**FIG. 2.** Average fitted probabilities of enrollment at another institution by term and episode of enrollment.



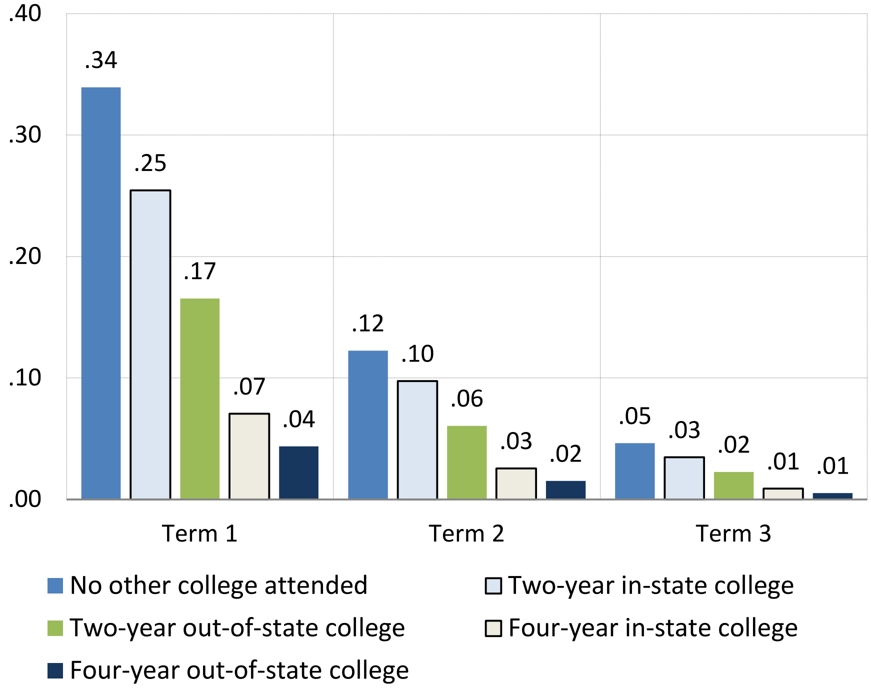

*Note:* Fitted probabilities are predicted probabilities for the observed responses under the Model 6 in Table 2.

**FIG. 3.** Average fitted probabilities of departures and returns by term and episode of enrollment or non-enrollment.



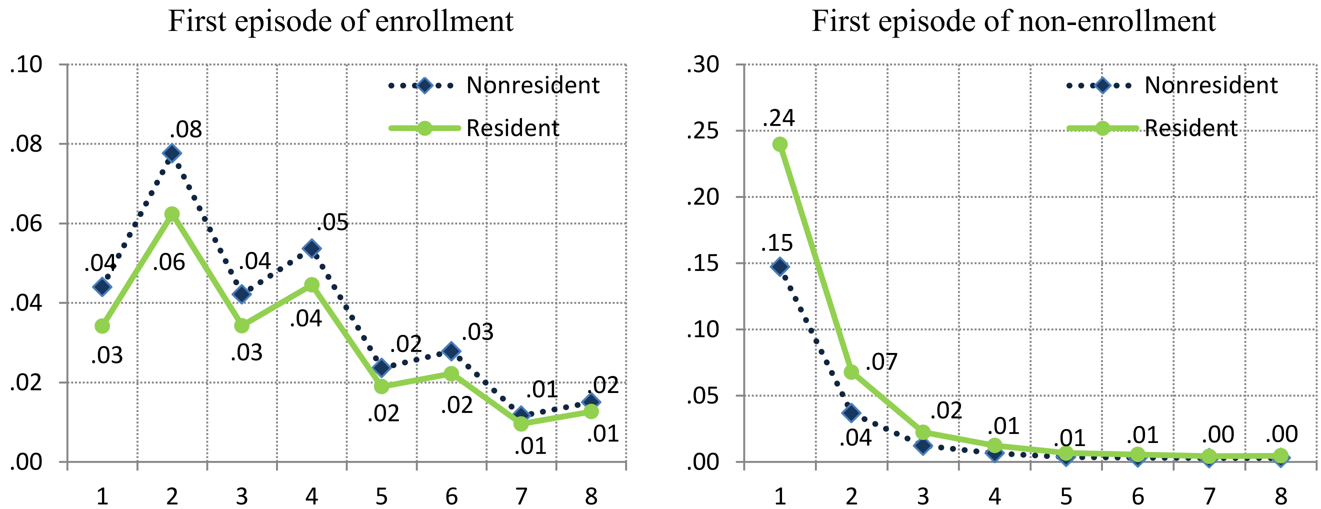

*Note:* Fitted probabilities are predicted probabilities for the observed responses under the Model 6 in Table 4.

**FIG. 4.** Average fitted probabilities of returns for first three semesters of the first episode of non-enrollment by attendance of other institutions.




*Note:* Fitted probabilities are predicted probabilities for the observed responses under the Model in Table 5.

**FIG. 5.** Average fitted probabilities of departures and returns for first episode of enrollment and first episode of non-enrollment by residence status.




*Note:* Fitted probabilities are predicted probabilities for the observed responses under the Model in Table 5.