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

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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 4-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.

Keywords 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%) of 1999–2000 college graduates had attended more than one institution. This trend was widespread even among those students who started at 4-year institutions—about half (47%) of them had attended several colleges (Peter et al.

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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 an institutional perspective, student swirl is also associated with losses of tuition. 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 (Noel et al. 1985). 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. By maximizing retention, reductions in student swirl and double-dipping 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 and graduation rates (Cook and Pullaro 2010).

Swirl and double-dipping are important factors in student departure from an institution. 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 forms of 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 4-year institution took about 7 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 4-year sector before the beginning of their 2nd year, 64% returned within 5 years— that is, they stopped out. Of these "stop out" students, about 42% returned to the same institution, while 58% 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, returning to their home institution after stopping out or completing credits elsewhere, transferring after stopping out, or leaving the educational system altogether. These enrollment behaviors may differ substantially by the type of institutions a student chooses to attend—2-year or 4-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 a university full-time and continuously. Hence, it is important to show the extent of 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 departure and return rates at different time points of 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 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 another institution?

Overall, this study seeks to advance understanding of interrupted enrollment patterns, multi-institutional attendance, and reasons for attrition at the study institution. In our study we also illustrate how institutional patterns of multiple episodes of enrollment and non-enrollment can be examined simultaneously within a single statistical model. Models presented here can be of interest to institutional researchers, because they are well suited for the analysis of retention data, where some predictors vary over time and observations are made in discrete units of time—semesters or years.

Conceptual Issues

Becker (1964) viewed education as an investment in human capital. Human capital is a set of knowledge, skills, abilities, and attitudes that increase individual productivity and lifetime earnings. A student finds the decision to invest in education advantageous if the expected benefit of college outweighs the cost of college attendance—tuition, fees, books, and lost earnings. Manski and Wise (1983) were the first economists who applied human capital theories in higher education (Melguizo 2011). Using data obtained through the National Longitudinal Study (NLS) of the High School Class of 1972, Manski and Wise (1983) examined college enrollment decisions—whether or not to attend college, which college to attend, and whether or not to persist. They found that student attributes that affect attendance—academic aptitude and parents' income—also affect the persistence. Other general factors that determine people's choices after school include cost and aid. Thus, the utility of college enrollment depends on a student's ability and family income as well as on the quality and cost of her best college opportunity. Manski and Wise (1983) acknowledge that their utility model is not perfect—"some nonlinear effects

may be neglected and some utility related factors may be unobserved" (p. 33)—and add not directly observable disturbances or random variables to the model that they referred to as a "random utility model." Despite the liability to the criticism that the assumption of students being rational in their behavior is too simple (e.g., Rabin 1998, quoted in DesJardins and Toutkoushian 2005), human capital theory and random utility model became a conceptual framework for numerous empirical studies that have implications for institutional, state, and federal-level policies (Melguizo 2011). Paulsen (2001) provides an excellent overview of findings and generalizations supported by empirical studies based on human capital theory. Some of these generalizations indicate that the likelihood of student enrollment or re-enrollment is higher if the direct cost of college—tuition, fees, books, and living cost—is lower and scholarships, grants and loans are higher.

St. John et al. (2000) indicate that economic approach in persistence studies "underestimates the role that the institution plays in shaping persistence decisions" (p. 32). Student-institution fit approach has been guided by Tinto's (1975, 1993) interactionalist theory. Based on Tinto's model, pre-college characteristics—family background, individual attributes, and high school performance—affect the student's initial commitment to an institution, which in turn affects a student's academic and social integration within an institution. Academic and social integration positively influence subsequent institutional commitment and therefore the odds of persistence.

Herzog (2005) points out that Tinto's theory as well as various approaches to its revisions offered by Braxton's *Reworking the Student Departure Puzzle* (2000) conceptualize student departure in terms of a single institution. Thus, the theory overlooks student concurrent enrollment at two or more institutions, back-and-forth enrollment between institutions and transfer to another institution. Human capital theory applies to transfer or stopout behavior. "[S]tudents compare the costs and benefits of obtaining an education at a particular institution versus other institutions and immediately participating in the labor market and make the choice that will maximize their utility" (Porter 2002, p. 5). However, empirical studies typically apply human capital theory to initial student choice to attend college or choices among colleges to which they apply or among colleges to which they were admitted (DesJardins et al. 2006a). Empirical studies of student stopout and transfer behavior are rather rare.

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—simultaneous enrollment at another post-secondary institution—on student persistence. Based on the data from the 1990/1994 Beginning Postsecondary Survey, Stratton et al. (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 versus transfer versus stopout have typically examined student departure during the 1st 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 (McCormick 1997; Horn 1998). 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 et al. (2006b), 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 patterns—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 frequently transfer from 2- to 4-year institutions. McCormick (1997) indicates that 43% of students who began at a 2-year institution transferred elsewhere, with 22% transferring to a 4-year institution. These students might intend to complete a bachelor's degree all along but decide to attend a community college first to save on tuition and fees, complete general education coursework, or 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 4-year institution is less common but not unusual. According to McCormick (1997), about one out of four students (28%) who began at a 4-year institution transferred: 16% to another 4-year institution, and 13% to a less-than-4-year institution. Moving between 4-year institutions is referred to as *horizontal*, while moving from 4- to a 2-year institution is referred to as a *reverse* transfer (Bahr 2011). 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 2-year college are more likely to come back to the study institution later.

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 the timing and student characteristics associated with transfer to another institution. (While modeling types of institutions to which students are likely to transfer is beyond the scope of this study, we describe the proportions of students enrolled elsewhere by institutional 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—2-year in-state, 2-year out-of-state, 4-year in-state, and 4-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 2-year or in-state institution.

Our selection of control variables is guided by prior theoretical and empirical research, with certain limitations related to data availability from the central records of the study institution. Human capital theory informs our study of the association between the cost of college and student enrollment decisions. Because of the difference between in-state and out-of-state tuition at public universities, student residence status is an important indicator of the college cost. Student residence status has also been shown to have a significant effect on transfer behavior at other institutions: in-state residents are less likely to transfer elsewhere (Porter 2002). 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, we also include financial aid variables—grants, scholarships, loans, and work-study.

Our analysis does not include variables measuring family income or parents' educational attainment, which complicates the interpretation of the effects of financial aid variables. "[B]ecause 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 et al. 2009, p. 10). When family income variables are not included, typical findings from prior research still show that increase in amounts of all types of financial aid decreases the odds of departure (Hossler et al. 2009). Since out-of-state students might need higher financial aid amounts to cover their expenses, we 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 the same amount of financial aid is less pronounced for out-of-state residents.

Apart from socioeconomic background, financial aid and tuition factors, economic studies of retention account for other important predictors, such as demographic factors, academic ability and achievement, and college performance (St. John et al. 2000). Two demographic characteristics—gender and ethnicity—are included in our study. 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. Age is not included in our models, because the vast majority of new freshmen at the study institution matriculate within a year after graduating from high school.

Academic ability and achievement have been traditionally measured through high school grades and standardized tests (Allen et al. 2008). Several studies found that high school grades and test scores had no direct effect on persistence, but rather affected college performance (Pascarella and Terenzini 1983; Munro 1981; cited in Hoffman and Lowitzki 2005). We expect that the effects of high school grades and tests on retention will not be significant after controlling for college grade point average.

Tinto's (1975, 1993) interactionalist theory informs our study of importance of academic and social integration and institutional commitment. "Extent of academic integration is determined primarily by the student's academic performance" (Pascarella and Terenzini 1980). We expect that student cumulative grade point averages have a significant effect on persistence at the study institution. Wetzel et al. (1999) suggest that social integration and institutional commitment can be measured by such indicators as part-time enrollment or participation in student life by joining a fraternity or sorority: being a part-time student "may make it difficult to develop a 'sense of place'" (p. 48) and being a member of a fraternity or sorority enhances student fit within an institution. We expect that students enrolled part time are more likely to leave and members of fraternities and sororities are more likely to stay at the study institution. We remain agnostic about effects of these college experience variables on the odds of return to the study institution or transfer to another institution.

Prior studies of stopout (DesJardins et al. 2006b; DesJardins and McCall 2010; Johnson 2006) examined the effects of the occurrence and duration of previous stopout spells on subsequent spells. For example, DesJardins and McCall (2010) demonstrate that students who experience one stopout are more likely to experience subsequent spells of non-enrollment, while students with longer spells of enrollment have greater chances of graduation. This could be partially due to a plausible association between the occurrence and duration of stopout spells, on the one hand, and the progress a student made towards attaining a degree on the other. Duration of enrollment spells at a home institution can also affect the odds of enrollment elsewhere after the departure. "[T]he longer a student

remains at a particular institution, the higher is the transaction cost of switching to a competing institution, since there is higher probability of losing more credit hours the longer one stays at the original institution" (Wetzel et al. 1999, p. 45). At the same time, spell occurrence and duration could be deceiving as they do not take into account academic progress (Adelman 1999; Bahr 2009). To account for a student's academic progress at a given time point we include an indicator of credit hours earned at the study institution. We expect that students who earn more hours at the study institution are less likely to leave and transfer elsewhere, because of a higher transaction cost of switching institutions.

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 the model is based on institutional records for the fall 2004 and 2005 new freshmen cohorts of undergraduate students. Data from the National Student Clearinghouse are used to trace student enrollments at other institutions. If a student enrolled at an institution that does not participate in Clearinghouse, this information would be missing from the study. Taking into account that Clearinghouse member institutions represent 93% of all students enrolled in U.S. postsecondary education (Cook and Pullaro 2010), we anticipate that the occurrence of such not-accounted-for enrollments would be rather rare in our study.

Of 7,768 students who matriculated in fall 2004 and 2005, 4,906 students persisted for twelve semesters without stopping out, dropping out, or transferring elsewhere. The remaining 2,862 students left the study institution at some point during their studies. Students who left the institution are included in the model that estimates the rate of enrollment at other institutions after departure from the home institution. All first-time freshmen are included in the model of departures and returns at the study institution. Each student had up to eleven semester observations in the model of departures and returns (for a total of 73,915 student-semester observations) and up to ten semester observations in the model of enrollment at other institutions after departure from the study institution (for a total of 17,688 student-semester observations), see Table 1.

Student choice between enrollment at a particular institution, enrollment at another institution, or participating in labor market varies with time. "The student retention decision is continually updated with the arrival of new information, such as academic status, grades, and satisfaction with the social life or student peer group, i.e. information not present in the initial enrollment decision" (Wetzel et al. 1999, p. 45). It is important that the chosen method of analysis handles timing and time varying variables as well as different choices—such as departures and returns. Therefore, in our study, we use a discrete-time logit model. First, this model handles observations that are made in discrete units of time—semesters. Second, this model can be used to handle repeated events and multiple episodes or spells. Third, including time varying covariates is straightforward with these models. Finally, logistic function is favored over alternative link functions for ease of interpretation (Stewart 2010).

Because the data structure presumes up to eleven semester observations per student, the models are multilevel. Multilevel discrete-time models rely on certain assumptions, including the conditional independence assumption and the noninformative covariates assumption. Conditional independence assumption implies that, conditional on our independent variables and random effect, the dependent variables at different time points are

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)
... × 2-year college	Equals 1 if a student attends 2-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[a]	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 ($1,000 s)[a]	Amount of grants received in $1,000 s	0.20 (0.67)	–	0.15 (0.59)
Loan ($1,000 s)[a]	Amount of loans received in $1,000 s	1.59 (3.26)	–	1.21 (2.92)
Scholarship ($1,000 s)[a]	Amount of scholarship received in $1,000 s	0.52 (1.41)	–	0.40 (1.25)

Table 1 continued

Variable	Variable description	Mean (SD)		
		Episodes of enrollment	Episodes of non-enrollment	All episodes
Work/study ($1,000 s)[a]	Amount of work study received in $1,000 s	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

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

Table 2 Student-semester-spell data arrangement	Student	Term	Episode of non-enrollment	Repeated episode	Event
	A	1	0	0	0
	A	2	0	0	1
	A	1	1	0	1
	A	1	0	1	0
	A	2	0	1	1
	A	1	1	1	0
	B	1	0	0	0
	B	2	0	0	0
	B	3	0	0	0
	B	4	0	0	0
	B	5	0	0	0

independent. Noninformative covariates assumption implies that our random effect is not correlated with independent time-varying variables. Barber et al. (2000) provide a detailed discussion of these assumptions for multi-level discrete-time models.

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. When a student enrolls at an institution, she is at risk of departure. Departure from the study institution marks 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 marks a transition from the state of non-enrollment to the state of enrollment when a student is once again at risk of departure. This 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 such spell and any further or 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. Table 2 illustrates a hypothetical example of the data arrangement for two students. Student A left an institution after the second semester—the variable *event* equals 1 for the second semester of the first spell of enrollment. The next observation for this student is the first semester of spell of non-enrollment (the variable *episode of non-enrollment* equals 1) in which she experiences another *event* or returns to an institution. Then this student transitions to the repeated enrollment spell (*episode of non-enrollment* equals 0 and *repeated episode* equals 1) and leaves again after the second semester to enter into the repeated spell of non-enrollment (*episode of non-enrollment* equals 1 and *repeated episode* equals 1). Student B, on the

other hand, did not experience an event and moved from one semester to another in a single enrollment spell. The initial stopout model estimating the log-odds of the event depending upon a semester and an episode is:

$$\ln\left(\frac{P_{Y_{ij}=1}}{1 - P_{Y_{ij}=1}}\right) = \beta_{0j} + \beta_{1j} \times t_i + \beta_{2j} \times episode\_of\_non\_enrollment + \beta_{3j}$$

$$\times repeated\_episode \qquad \text{(Level 1 Model)}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30} \qquad \text{(Level 2 Model)}$$

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

One can use different specifications of time in discrete-time models. The most straightforward and easily interpretable specification is so-called general specification which presumes including dummy variable for each time period. However, Singer and Willett (2003) point out that such specification might lack parsimony and lead to erratic results, which is why they recommend exploring other alternatives if a study involves many time periods or if event occurrence or the number of observations are small for some periods. While there are numerous possible specifications of time in discrete-time models, we will consider the ordered subset of polynomials described by Singer and Willet (2003)—constant, linear, quadratic, cubic, and three stationary points. 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 (Singer and Willett 2003, pp. 120–122). 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, p. 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 (DesJardins et al. 2006b; DesJardins and McCall 2010; 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 $1,000 s) for episodes of enrollment; and attendance of another college, with differentiation between in-state and out-of-state, 2- and 4 year, and part-time and

full-time enrollment. Independent time varying variables are lagged by one point. For example, attendance of another college affects the log-odds of departure or return in the semester that follows. 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 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 among students at the study institution: on average, less than half of 1% of students are concurrently enrolled at other institutions in each given term of enrollment at the study institution. 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 grade point average of 2.00 or higher on all course work. Academic warning occurs at the end of any semester for which the student's cumulative GPA on course work taken at the study institution 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 a student has a cumulative GPA of 2.00 or higher is included in the 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. The descriptive statistics in Table 1 align with these findings. Thus, the share of students with a cumulative GPA of 2.00 and higher is, on average, substantially lower during episodes of non-enrollment.

Consistent with our expectations, the 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, and 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. For example, 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 1% 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.

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. Figure 1 provides proportions of enrollment at 2- and 4-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.) Figure 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 were enrolled elsewhere. About 72% of out-of-state students with a cumulative GPA of 2.00 or higher chose out-of-state 4-year institutions, most likely in an attempt to lower their tuition. In-state residents with a 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 4-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 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 4-year institutions (31%) and out-of-state 2-year
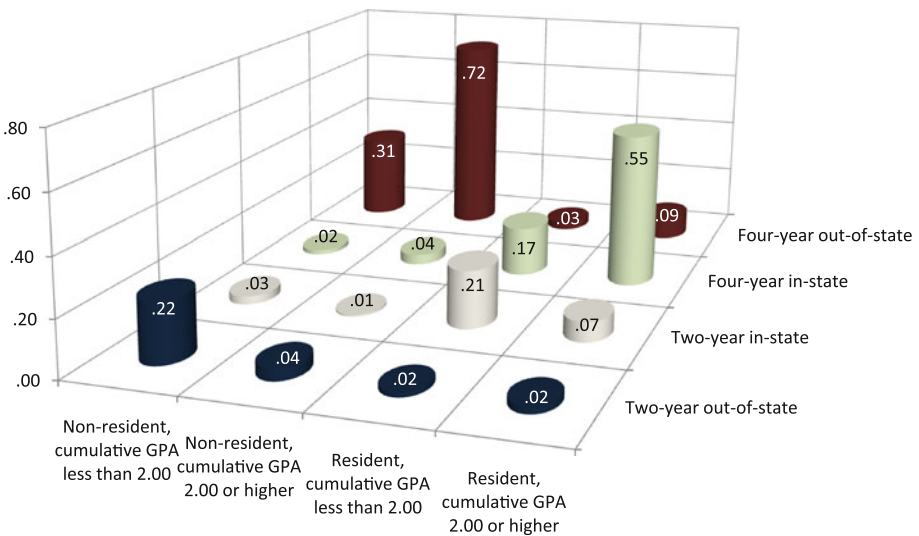

Fig. 1 Proportions of students enrolled at other institutions two terms after departure from the study institution by residence, grade performance, and transfer institution type

institutions (22%). In-state students who left with a cumulative GPA less than 2.00 often enroll in 2-year in-state (21%) and 4-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 their departure from the study institution. And their likely destinations are 4-year in-state institutions for state residents and 4-year out-of-state institutions for non-residents. Students who enroll at 2-year institutions are either "true undergraduate reverse transfers" who might have found the academic rigor of the study institution too challenging or "drop-ins" (Adelman 2005) 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 4-year institution and transfer to another institution is about 7 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 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 3 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—which uses a quadratic representation of timing—has a superior fit compared to Model 2, and Model 4—which uses a cubic representation of timing—has a superior fit compared to Model 3. Finally, 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. However, 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, which is also referred to as a third order polynomial that has two stationary points—a peak and a trough. Because the effect of term is positive, the trajectory initially goes up. But due to a negative effect of term squared, the rising value diminishes with each new term until the trajectory starts to decline. Finally, a positive effect of the term cubed leads to another rise of the trajectory later on.

Other timing dimensions considered in the present study were: an indicator of a repeated episode of enrollment; an indicator of spring semester; and the variable representing the

Table 3 Enrollment at other institutions after departure from the study institution: 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

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

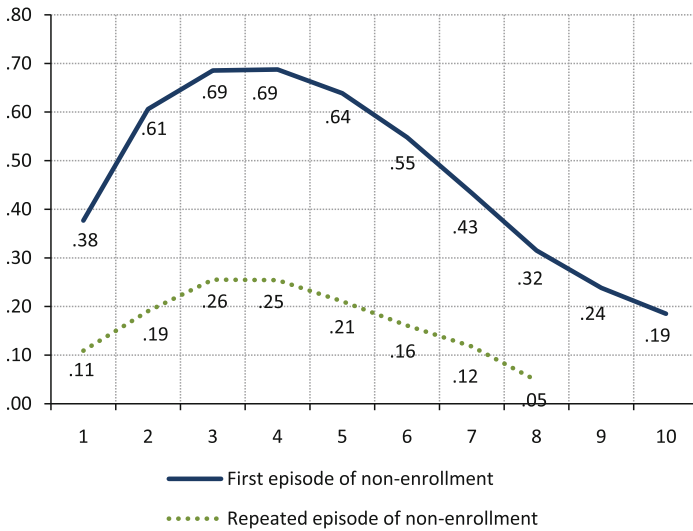* Significant at the 10% alpha level; ** significant at the 5% alpha level; *** significant at the 1% alpha level

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 3

duration of the previous episode or the duration of enrollment at the study institution. With the exception of the spring semester indicator, these timing variables significantly improved model fit and were included in the final model of timing of enrollment at another institution (see Model 6 of Table 3). 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 $21\% \left(1 - \frac{e^{-0.59 \times \ln(2+1)}}{e^{-0.59 \times \ln(1+1)}}\right)$ 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% $\left(1 - \frac{e^{-0.59 \times \ln(3+1)}}{e^{-0.59 \times \ln(2+1)}}\right)$ lower than if she was enrolled at the study institution for two semesters. This finding aligns with our expectation that students who spent more time at their home institution are less likely to transfer, because they are likely to lose more credit hours in the process of transition. Model 6 in Table 3 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 3. 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

Table 4 Enrollment at other institutions after departure from the study institution: 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

Population-average estimates with robust standard errors are presented here

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

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 4 model. Consistent with prior descriptive analysis of student enrollment at other institutions by residence and academic performance (see Fig. 1), 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. After departure from the study institution students with satisfactory academic progress towards graduation—cumulative GPA 2.00 or above—have 2.41 times greater odds of enrollment elsewhere. Thus, students who leave the study institution for non-academic reasons 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 4 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.

The model also indicates that members of fraternities and sororities are more likely to enroll at another institution. Because Greek affiliation raises the level of social integration on campus (Pike and Askew 1990), we expected that members of fraternities and sororities have lower probabilities of departure from the study institution. At the same time, a higher likelihood of enrollment elsewhere among those Greek members who left the study institution was rather an unexpected finding.

Earlier we suggested that students who earned more hours at the study institution might lose more hours in the process of transfer to another institution and therefore be less likely to transfer elsewhere. In line with these expectations, students who earned more hours at the study institution are less likely to enroll elsewhere after 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 et al. 2006b) indicate that the odds of departures and returns are highly correlated with timing and prior episode durations. Like models of timing of enrollment at other institutions in Table 3, models of timing of departures and returns in Table 5 start with a flat hazard rate. Thus, the first model in Table 5 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 flat hazard rate model is the indicator of episodes of non-enrollment that allows separation between events—departures and returns. Based on coefficients of this model, the average expected probability of departure is 0.08 $\left(\frac{e^{-2.51}}{1+e^{-2.51}}\right)$ and the average probability of return is 0.04 $\left(\frac{e^{-2.51-0.79}}{1+e^{-2.51-0.79}}\right)$. The negative effect of the episode of non-enrollment indicates that return is less likely than departure. Model 2 in Table 5 adds the effects of term and interaction of term and episode of non-enrollment, which leads to a 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 non-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 the 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 et al. (2006b), DesJardins and McCall (2010), 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.

Table 5 Student departures and returns at the study institution: 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

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

* Significant at the 10% alpha level; ** significant at the 5% alpha level; *** significant at the 1% alpha level
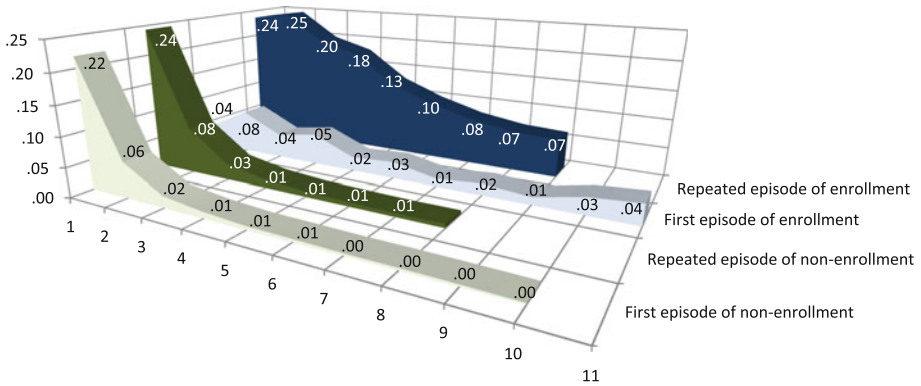
Fig. 3 Average fitted probabilities of departures and returns by term and episode of enrollment or non-enrollment. *Note*: Fitted probabilities are predicted probabilities for the observed responses under the Model 6 in Table 5

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 5, students are more likely to return to the study institution if they were enrolled there 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 a repeated episode. The interaction effect of episode of non-enrollment and repeated spell attenuates the main effect of a 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, the likelihood of departure is 6.0 times higher in the first semester and 3.1 times higher in the second semester of a repeated episode of enrollment compared to the first episode of enrollment. The differences between the first and repeated episode of non-enrollment are less pronounced.

Figure 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 6 clearly demonstrates that attending other colleges has a substantial and statistically significant effect on enrollment patterns at the study institution.

Table 6 Student departures and returns at the study institution: 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 ($1,000 s) × episode of enrollment	−0.06 (0.03)**
Loan ($1,000 s) × episode of enrollment	−0.04 (0.01)***
Scholarship ($1,000 s) × 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 × 2-year college	−0.03 (0.43)
Attending another college × 2-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)***

Table 6 continued

	B (SE)
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

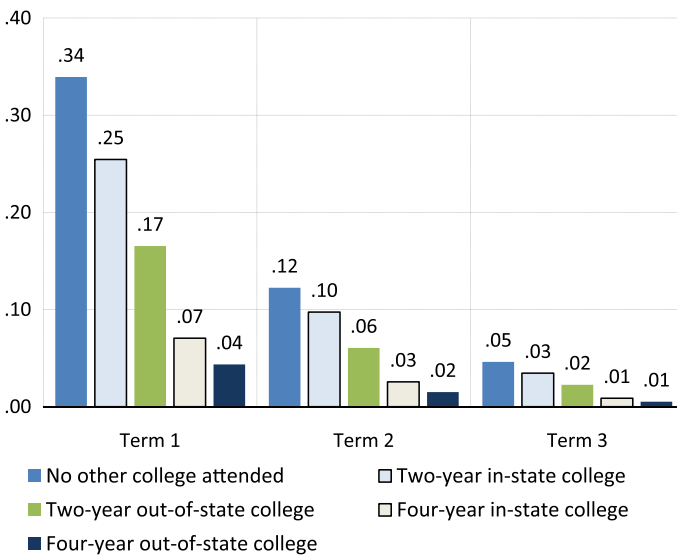*Note:* Population-average estimates with robust standard errors are presented here

Fig. 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 6

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 Herzog's finding, the stopout model presented here shows that departure rates are actually 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. This effect is more pronounced if a student attended 4-year out-of-state college. For example, compared to students attending 4-year *out-of-state* colleges, 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 4-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

2-year college is similar to the effect of concurrent enrollment in the *4-year* college. (The interaction effect of another college attendance and 2-year college type is small and statistically insignificant.) At the same time, 2-year college type does attenuate the effect of enrollment at another institution on the odds of return. (The interaction effect of another college attendance, 2-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 2-year in-state institutions.

While concurrent attendance at other colleges has a 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 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.

Figure 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 2-year college, this proportion drops to .25 for in-state colleges and .17 for out-of-state colleges. If a student chooses another 4-year institution, the return rate drops to .07 for in-state and .04 for 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. Compared to a student attending another institution full time, a student who attends another institution part time has 81% lower odds of departure and 1.7 times the odds of return at the study institution.

As expected, grade performance significantly affects persistence. Students with a cumulative GPA of 2.00 or higher are less likely to leave or, to put it differently, have 83% lower odds of departure compared to students with GPA below 2.00. This finding agrees with many prior studies showing higher departure rates for students who are making unsatisfactory academic progress. For instance, Ronco (1996) indicates that students who dropout or transfer to a 2-year college are most likely to do so because of the impact of a 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 the home institution are lower for students with satisfactory grades: they have 15% lower odds of return compared students with unsatisfactory grades. The lower odds of return for students with satisfactory grades reinforce the earlier finding of a higher likelihood of enrollment elsewhere after 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
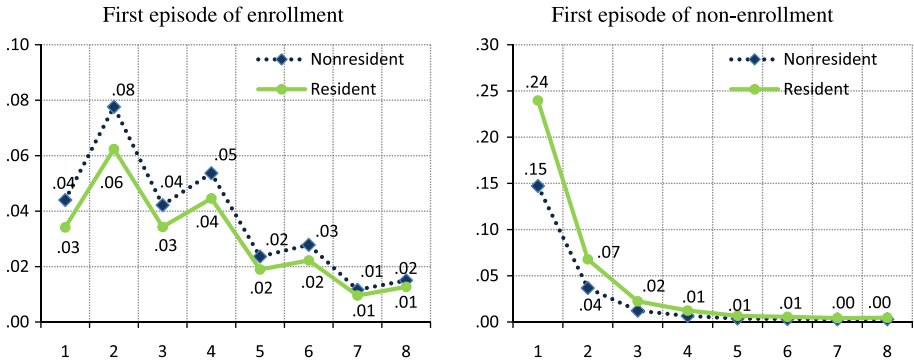
Fig. 5 Average fitted probabilities of departures and returns for first episode of enrollment and first episode of non-enrollment by residence status. *Note*: Fitted probabilities are predicted probabilities for the observed responses under the Model in Table 6

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, students attending the study institution part time are more likely to leave. According to O'Toole et al. (2003), students who are enrolled 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 at the study institution increases the odds of departure 1.8 times.

Hossler et al. (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 et al. 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 positive effect on student persistence.

Since student residence status is associated with substantially lower tuition rates, it was also 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 the odds of departure. Only an 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 the odds of departure; $1,000 in loans is associated with a 4% decrease in the 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 the odds of departure; and $1,000 in work-study is associated with a 22% decrease in the 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. Figure 5 illustrates that the differences in fitted probabilities of departure are statistically significant but rather small and range from one to 2% 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 the study institution and, therefore, might feel isolated or homesick (Caison 2007). On the other hand, at a public institution in-state residency status is 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 the 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

Our model of student enrollment at other institutions does not distinguish between enrollment at 2-year in-state, 2-year out-of-state, 4-year in-state, or 4-year out-of-state institutions. This study is restricted to a descriptive analysis of student characteristics that are most noticeably associated with these different transfer behaviors. Due to the ease of computations and wide availability of software packages, the majority of existing choice studies apply the multinomial logit model (Hensher et al. 2005). However, the multinomial logit model assumes the independence of irrelevant alternatives (IIA). This assumption means that if one of the alternatives, such as transfer to an out-of-state 2-year institution, is removed from the choice set, the probability of a student choosing any of the remaining alternatives—non-transfer, 2-year in-state, 4-year in-state, and 4-year out-of-state—increases proportionally. This assumption is unreasonable for our choice set. More advanced models—such as multinomial probit or mixed logit—relax the assumption of the independence or irrelevant alternatives but are beyond the scope of this study.

The analysis is based on institutional records from a single moderately large research institution. Use of institutional data has several advantages. It ensures that this study can be replicated at another institution. Institutional records have also been shown to be more

accurate than self-reported data (Cole and Gonyea 2010). However, the use of institutional records also leads to limited variable selection. Adding certain survey items to the model could provide additional insights into enrollment patterns at the study institution. Furthermore, 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. Findings of this analysis can be extrapolated only to the study institution or similar relatively large, doctorate-granting public institutions with comparable student entering characteristics.

Finally, the model presented here does not address the problem of endogeneity. Certain independent variables—such as membership in a Greek organization or full-time enrollment—might appear to have an effect on persistence due to self-selection. Some recent studies have demonstrated use of instrumental variable approach to address the self-selection bias; see for example Pike et al. (2011).

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. Students who enroll elsewhere are more likely to have higher grade point averages and fewer credit hours earned at their home institution. Our model provides student characteristics associated with enrollment elsewhere, but does not separate such enrollment by the type of institution students are going to—2-year or 4-year, in-state or out-of-state. Further research that utilizes multinomial probit or mixed logit would advance the understanding of student enrollment elsewhere after departure from their home institution.

Concurrent enrollment has a statistically significant negative effect on persistence. And this effect varies by the student's enrollment status at another institution—part- or full-time—as well as on the types of institutions students chose to attend concurrently—four- or 2-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. Concurrent enrollment is rare among students at the study institution. Further research is needed on effects of concurrent enrollment at institutions where concurrent enrollment is more common. Institutions with significant concurrent enrollment might consider dual enrollment programs to improve cost effectiveness, enable student swirl, and promote college persistence. Some universities have already established such dual enrollment programs (Bontrager et al. 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 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 becomes minimal.) Overall, including attendance at other institutions in the stopout model provides a more accurate and complete picture of student mobility in and from an institution.

Another important finding is the association between out-of-state residency and persistence. Traditional retention summaries might overestimate retention for nonresidents, because these summaries 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. Like many other public institutions, the study institution experienced a decrease in state appropriations in recent years. 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, p. 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 (Ehrenberg 2005). However, transitions to these innovative approaches to financing public higher education do not always go smoothly (Prescott 2010). Recent studies (e.g., Toutkoushian and Shafiq 2010) 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.

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, the 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 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 a 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 (2003) 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).

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