Survival of the Fittest: What Do Early Behaviors Tell Us About Student Outcomes?

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We posited student behaviors observed during the recruitment process may reveal a student's commitment to our institution and their initial motivation to succeed, which influences their level of integration and decision to leave college or remain. In particular, we examined the impact of participating in a college fair, visiting the campus before enrollment, and attending Welcome Weekend on stop-out times of students. Our findings suggest students who participate in these activities are significantly more likely to succeed. The time enrolled increases by 33.0% for college fair participants, 6.5% for campus visitors, and 18.0% for participants of Welcome Weekend.

Nearly one half of all entering first-time college students at a 4-year institution will not complete their degree at the institution they first enrolled in, and nearly 40% will never graduate. Ability and motivation together determine whether students drop out of college. The most motivated student might be forced to drop out when the ability to meet the academic burden is lacking, whereas a high-ability student may choose to drop out when the experience is unfulfilling. Researchers have a good theoretical understanding that motivation and ability influence dropouts; yet predicting who at a particular institution of higher education is at risk is not always clear. For the most part it is easy for admissions officers to determine students' academic ability by evaluating their applications. High school grades, achievement test scores, and Advanced Placement courses completed are all good indicators of academic ability and are readily available to policy makers. Based on this it would seem as if we have half the pieces to the puzzle. Unfortunately this is not the case, because on many campuses, especially those with high admissions standards, we observe only small differences in observed ability across the student body; that is, student bodies tend to be rather homogeneous in terms of their observed ability. The limited variation in ability can explain only a small fraction of the variation in dropout behavior. Policy makers are left with trying to explain why students with similar levels of ability in some cases drop out and in other cases do not. The missing piece needed to solve this puzzle is motivation. *Motivation* in this context reflects a student's desire to commit to academic goals, such as finishing college, along with a commitment to the institution.

Motivation, unlike ability, is inherently difficult to measure. The challenge is to determine an objective measure of someone's motivation. Many college applications require students to provide a statement of purpose explaining why they want to attend a particular institution. Unfortunately, students do not have an incentive to reveal their true motivation level, thus their responses may reveal little objective information. The alternative we considered is whether certain

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student interactions with the institution observed prior to the start of classes reflect a student's initial motivation to attend our institution. Interactions with our institution include whether a student met with our representatives at a college fair, completed a campus visit, and attended Welcome Weekend. These activities are unlikely to directly impact student outcomes, but they may help to identify students who are more motivated. Participants in these activities are seen as more motivated, and, all else being equal, should be more likely to succeed at our institution. Our empirical findings support this expectation. Participation in Welcome Weekend increased a student's length of enrollment at our University by 18.0%, while those who meet with us at a college fair stay 33.0% longer, and those who made a campus visit stay 6.5% longer on average.

INTEGRATION AND DROPOUT BEHAVIOR

Interactions between college students and the institutions where they choose to enroll are at the heart of Tinto's (1975) theoretical model of college dropout. The model uses psychology to draw comparisons between the internal factors that cause someone to commit suicide or drop out from an institution of higher education. In each context, individuals suffer from a lack of integration, which is caused by having individual values that differ from their environment and insufficient interaction within their environment. College is made up of both social and academic environments, thus students may drop out due to lack of integration in one or both areas. To understand when and why certain students choose to drop out, Tinto suggests differences in individual characteristics, educational expectations, and the motivation to meet expectations must be accounted for. Individual characteristics, such as ability, family background, and past experience with education, influence both expectations and motivation to achieve educational goals.

Goals are important because they affect performance. Locke and Latham (2002) outlined four mechanisms in which goals influence performance. Having goals serves to direct attention to goal-relevant activities and away from nonrelevant activities. More difficult goals also serve to induce greater effort. Lastly, goals have an indirect effect by causing individuals to use their goal-relevant knowledge to develop successful strategies to achieve their goals. It has been shown that the relationship between goals and performance is strongest when people are committed to their goals (Klein, Wesson, Hollenbeck, Wright, & DeShon, 2001). Influencing the commitment to goals are factors such as recognition that a goal is achievable and clearly identifiable outcomes (Locke & Latham, 2002). Institutions can create external incentives to support goals and influence student expectations; though this effect is mitigated by personal goals. Personal goals, Locke (1991) notes, are often the most immediate motivational determinants of action. Tinto (1975) believes commitment to educational goals "helps specify the psychological orientations the individual brings with him into the college setting—orientations that are important predictors of the manner in which individuals interact in the college environment" (p. 93). These differences across individuals influence dropouts.

According to Tinto's (1975) model, students enroll in college with different backgrounds that shape their commitment to goals and to the institution. Students vary in obvious ways, such as gender and ethnicity, but also vary in terms of academic ability (as reflected in achievement test

scores), family structure (parental income, education, and marital status), and their past experience with education (high school grades). These differences, while directly influencing academic performance, also shape students' commitment to succeeding in college and being part of the institution they attend. Students' levels of commitment are also shaped by their interactions with the institution. Student interactions with faculty and other students lead to what Tinto referred to as *social integration*, which is formed as students become part of the university community by joining campus organizations, attending campus events, and more generally spending time on campus. This type of integration is said to further contribute to whether students commit to meet the institution's expectations. Academic integration is also believed to be an important factor influencing students' goals at the institution. Students become integrated into the academic community by performing well in their courses and expanding their knowledge base, which increase the commitment to achieve academic goals, such as graduating from college. It is the "interplay" between these commitments which Tinto (1975, p. 96) notes largely determines whether a student drops out.

In Tinto's (1975) model, variations in the background characteristics of students contribute to variations in initial commitment, which lead to variations in performance and interaction with the institution. These variations then explain differences in social and academic integration, which further influence commitments over time and subsequently the decision to drop out. The empirical question is whether students enrolled at a particular school are sufficiently heterogeneous in terms of their observed characteristics to fully explain variations in their dropout rates. Fuller, Manski, & Wise (1982) have shown that students generally enroll in a college where the ability of the student body is similar to their own. One benefit of this matching is increased graduation rates (Light & Strayer, 2000). Institutions differentiate themselves by their selectivity, which is determined by the academic ability of their students; therefore the typical model, which focuses on background characteristics, can only explain a small fraction of the variations in persistence. Perrine and Spain's (2008) study is one such example where the Nagelkerke R^2 of their first-year retention model is .10, controlling for the demographic variables of high school GPA, ACT score, gender, age, number of transfer credits, race, and number of remedial courses. Adding a measure that proxies for motivation to the specification may improve prediction.

Motivation can be thought of in terms of personal preferences. Students who are motivated to be integrated into the campus community will prefer activities that support this goal. The simplest way to measure a student's motivation and preferences towards something is to simply ask. Data collected from surveys of student attitudes and activities will reveal their stated preferences, but they do not always reflect reality. It is easy to say one thing and then do another, particularly when it involves social norms. The importance of studying is a strong norm on college campuses, so students often overstate how much they study in order to appear to meet the perceived norm. Allen (1999) used survey data from Noel and Levitz's College Student Inventory to capture the impact of student motivation on first-year GPA and retention at a medium-sized, public, 4-year school in the Southwest US. Motivation measures a desire to finish college and is a composite of 6 items from the survey. Allen's findings indicate that motivation, as measured by desire to finish college, had no impact on GPA and only impacted the persistence of minority students. The lack of a definitive link between

motivation and outcomes may be due in part to the bias of stated preferences.

An alternative is to use revealed preferences, which are based on the actions that individuals actually take. The goal is then to observe actions that reveal the underlying motivation level of students. This can be difficult given the need to record actual and not hypothetical actions; therefore in many situations we only observe actions that indirectly capture an individual's preferences. Ishitani and Snider (2006), for example, suggest students who participate in various programs to assist in the college application process are thereby more committed to higher education: students who are more motivated, as demonstrated by participation in certain programs, are more likely to succeed in college. The authors' duration model did find that students who participate in test prep courses are significantly less likely to drop out, as are students whose parents were contacted by the high school to discuss college selection. Interestingly, students who received assistance completing their financial aid applications were more likely to drop out. Further, students who received assistance writing their admissions essays or whose high school counselor contacted a college on their behalf had similar dropout rates as those who did not. Clearly the unobserved relationship between a student's actions and preferences varies substantially as does the observed impact of these actions on outcomes.

Students may be motivated to graduate college and yet may not be motivated to graduate from the particular college where they first enrolled. The former reflects goal commitment, while the latter reflects a lack of institutional commitment. Students who are not committed to the institution may voluntarily drop out and transfer elsewhere. Ishitani and Snider's (2006) measures of motivation capture goal commitment. *Institutional commitment* describes whether a student's "educational expectations involved any specific institutional components which predispose him toward attending one institution (or type of institution) rather than another" (Tinto, 1975, p. 93). The motivation to attend a particular institution could be influenced by the availability of a preferred major, geographic location, size, financial aid, academic ranking, athletics, and facilities of the institution. For example, Berger and Braxton (1998) used students' choice ranking of the institution to measure initial institutional commitment, where students who enroll in their first choice are most committed. Their results show students' initial level of institutional commitment is positively correlated with their subsequent commitment, but they are unable to identify a direct effect on intent to return. Allen (1999) was also unable to find a link between institutional impression and student outcomes. Neither GPA nor retention was related to a composite measure determined by a student's impression of the institution's social life, student body, entertainment, shopping, facilities, faculty, and athletics. In both Berger and Braxton (1998) and Allen (1999), institutional commitment was measured using stated preferences based on survey data. Perhaps an analysis of observed interactions between students and a particular institution will reveal enough variation in institutional motivation to significantly influence student outcomes.

PREENROLLMENT INTERACTIONS BETWEEN STUDENT AND INSTITUTION

Every institution of higher education engages in a number of different activities to recruit new students and retain existing ones. Previous research has shown that preenrollment activities with an institution are associated with college student behaviors. Goenner and Pauls (2006) found that of those students who inquire into

their institution, students who make campus visits are significantly more likely to enroll. A campus visitor is nearly 1 percentage point more likely to enroll than a nonvisitor, which is quite substantial given 13% of their inquiring students subsequently enroll. Kealy and Rockel (1987) also found students who visited their campus, Colgate University, were significantly more likely to have positive perceptions of their institution's academic quality, social atmosphere, location of campus, and athletic quality. Of the large number of factors they considered, a visit to campus was the most important factor influencing perceptions of social atmosphere and the second-most important factor for academic quality. Interestingly, Kealy and Rockel's findings show what students did during their visit to campus—taking a tour, having an overnight stay with an undergraduate host, and meeting with faculty—did not have an impact on perceptions, when controlling for the visit. Based on this, it may be that students who make visits to campus have an a priori positive perception of the campus's quality; and for the majority, the visit only serves to reinforce their impressions. In another study, Murtaugh, Burns, and Schuster (1999) examined the impact of a first-year orientation program on the retention of students at Oregon State University. Their results from a multivariate proportional hazards model indicated participants of the program were 21% less likely to drop out. Again the program may have had an impact on retention, or it may have been the underlying motivation of those who participated that is the cause of improved outcomes.

Our interest was to examine whether students at our institution who participated in three particular activities prior to the start of classes were retained longer than those who did not. The activities included meeting with our representatives at a college fair, visiting the campus, and attending Welcome Weekend.

Our university participates in over 200 local, regional, and national college fairs each year. These events attract college-bound students who interact with recruitment personnel from our university and other colleges. Our staff members are trained to build relationships with prospective students to help them understand the benefits of attending our institution and ultimately assess the degree to which we are a good fit. The expression of personal interest in our university prompts future targeted recruitment efforts and communication throughout the recruitment cycle. For example, if a student's individual academic interests are known, the student's contact information is shared with the appropriate academic department to initiate further contact.

The Office of Enrollment Services at our university offers campus visitors the benefit of a personalized campus visit tailored to meet individual needs and interests; therefore, students and families who visit the Office of Enrollment Services do not generally receive large-group presentations or large-group campus tours. Visiting students and their families typically have an appointment with an Enrollment Services representative who highlights the admission process, the benefits of attending the university, as well as costs and scholarship information. Approximately 75% of all visiting students elect to meet with at least one academic department representative while on campus.

Welcome Weekend is scheduled each year from Friday through Monday prior to the beginning of the fall semester. Its agenda is filled with activities focused around 6 learning outcomes believed to enhance student success:

1. Our campus is a place where I know I'll be welcomed.
2. Our campus is a place where I'll make great friends.

3. I know that I'll get academic support and help if I need it.
4. Being involved in student organizations, etc., is a great way to enhance my student experience.
5. Faculty at our institution care about me and my success in their classrooms.
6. I made the right choice when I chose to attend our university.

More than 430 faculty, staff, and students focus their efforts to welcome new students to campus and seek to affirm each student's belief in these 6 outcomes. Activities include participation in a structured "Meet Your Neighbors" event where resident assistants and student ambassadors help facilitate the initial phase of student relationship-building. Another event involves small group interaction among new students, student ambassadors, and faculty to help students frame short-term and long-term goals for the semester. A number of social activities are also scheduled to welcome students to life on campus.

Students who voluntarily participate in these activities learn more about the social and academic benefits and norms of our campus. These interactions between students and the institution may also reveal whether a student is motivated to attend college and our college in particular. Participation in these activities demonstrates students are, at least initially, willing and able to take initiative to form beneficial interactions with our institution. We would thus expect students who interact with our institution by participating in these activities to have better student outcomes, such as improved retention. Our goal is to empirically determine whether this is the case and, if evident, to quantify the impact.

A MODEL OF DURATION

Students are most at risk of dropping out of college after their first year. Getting past this hurdle is a necessary first step towards ultimately graduating from college. Therefore understanding the factors that influence students' initial success when they first arrive on campus is also crucial to future outcomes. We predicted students who interacted with our institution prior to the start of classes were likely to have a higher initial motivation towards attending our college and were thus more likely to survive their first year and return for their second year, taking ability and demographic factors into consideration. Our analysis focused on determining when students will experience their first break in enrollment, which is referred to as a *stop-out*.

To model the duration of a student's stay in college we used the tools of survival analysis (Hosmer, Lemeshow, & May, 2008; Kiefer, 1988). A survival model is appropriate in cases where the dependent variable measures the time until the occurrence of an event. We examined the time until a student stopped out after enrolling at our university. This represents single-spell data, which means once individuals stopped out they were no longer followed. Our data set contains first-time, first-year students who enrolled at our institution during the fall semesters of 2006, 2007, and 2008. Similar to most survival studies, students did not enter the data set at the same time, but were accrued over a period of time (Cantor, 2003, p. 5). Student outcomes were followed each semester after entry through the fall semester of 2009. Survival analysis distinguishes between two measures of time. Students, as noted, entered the institution and were observed at different dates (academic semesters). Survival analysis is based on the period of time a student is at risk, which is measured relative to the time of entry; thus first-year students who entered in different fall terms and stopped out after their second semester have the same duration of survival. Another key feature of our data is censoring, which survival models are equipped

to handle. Individuals are *right censored* when they are no longer observed in our sample, but have not yet stopped out. For example, individuals who were part of the 2008 first-year class were only followed through the fall of 2009, thus students who had not already stopped out would have been censored after two semesters. Our censoring times are known constants as we analyzed durations through the fall of 2009.

We let T denote the time to stop out (failure), which is a continuous random variable with cumulative density function (CDF) given by $F(t) = \Pr(T \leq t)$ and probability density (PDF) given by $f(t) = dF(t)/dt$. In survival analysis there are two common ways of describing the distribution of T. One is via the survivor function S(t) which is the probability a student enrolls (survives) for at least t consecutive semesters. $S(t) = 1 - F(t) = \Pr(T > t)$. The other function we use is the hazard function $\lambda(t)$ which represents the probability of failure at a point in time, given failure has yet to occur. Mathematically the hazard and survivor functions are related to each other by $\lambda(t) = f(t)/S(t)$. The hazard function is a conditional probability as it equals the probability of failure at a point in time, conditioning on not yet having failed. A hazard function is said to have positive (or negative) duration dependence if its slope is positive (or negative). Positive dependence implies as time passes the duration is more likely to end, whereas negative dependence indicates momentum is increasing with time.

In Table 1 we report nonparametric estimates of the hazard and survival rates for our data set. Following Kiefer (1988), the sample estimate of the hazard function is given by $\hat{\lambda}_t = h_j / n_j$, which equals the number of failures at time t_j divided by the number of observations at risk at time t_j. The number of observations at risk accounts for the number neither completed nor censored at time t_j. For our data set, the first-semester hazard rate is equal to 454/5,583 = .0813; the second-semester hazard rate is 905/5,129 = .1764. The empirical survival function estimates are given by $S(t_j) = \prod_{i=1}^{j}(1-\hat{\lambda}_i)$ where $\hat{\lambda}_i$ are our hazard estimates. The empirical hazard function has a hump shape, increasing substantially from the first to second semester and then generally declining with time. From Table 1 we can see why first-year retention rates are typically emphasized: the greatest risk of stopping out is after the spring semester of the first year is completed. Getting past this hurdle is clearly important to student success. We can also see that there still remains a significant level of risk after the first year.

Our goal was to understand how the background characteristics of students and their interactions with the institution influenced their predicted time to stop out. In our analysis

TABLE 1.
Empirical Hazard and Survival Estimates

Semester	Beginning Total	Stop Outs	Censored	Hazard Rate	Survival Rate
1	5,583	454	0	0.0813	0.9187
2	5,129	905	1,443	0.1764	0.7566
3	2,781	178	0	0.0640	0.7082
4	2,603	233	1,208	0.0895	0.6448
5	1,162	39	0	0.0336	0.6231
6	1,123	82	1,041	0.0730	0.5776

we use a parametric model of stop out time, T, which is a function of our control variables, X. To ensure that T is nonnegative we model the natural log of the stop-out time as a linear function of our controls and an error term:

$$log\ T_j = X_j\beta + \varepsilon$$

The vector X includes the control variables (background characteristics and student interactions), β is a vector of coefficients, and ε is the error term which is assumed to have a normal distribution with standard deviation equal to σ. This model is known as the *lognormal model* and was chosen in part due to its hump-shaped hazard rate. Other distributions for ε could be used, resulting in a different model; the lognormal was chosen here because it best fits the data (as discussed below). The lognormal model with covariates X has the survival and hazard functions at time t given below:

$$S(t;x) = 1 - \Phi\left(\frac{\log(t) - x\beta}{\sigma}\right), \text{ where } \Phi \text{ is the standard normal CDF.}$$

$$\lambda(t;x) = \psi\left(\frac{\log(t) - x\beta}{\sigma}\right)/\sigma t, \text{ where } \psi(z) = \frac{\phi(z)}{1-\Phi(z)}$$

Estimates of β and σ can be found using maximum likelihood estimation with the Stata procedure STREG.

A parametric duration model, similar to ordinary regression models, can only explain part of the variation in failure times across observations. We found that some observations failed more quickly despite having the same observed characteristics. This unexplained variation is referred to as *overdispersion* and can be caused by omitted variables and other misspecifications of the model. To allow for overdispersion unobserved heterogeneity can be introduced into the model. The assumptions are the heterogeneity (a) is independent of the regressors, (b) has a known distribution, and (c) influences the hazard function multiplicatively (Wooldridge, 2002, p. 701). In our model we allowed the heterogeneity to vary for each observation, which is referred to as a *nonshared frailty*. Heterogeneity in our model follows an inverse Gaussian distribution with mean equal to 1 and variance equal to θ, where θ is a measure of overdispersion. An alternative is to allow the heterogeneity to follow a gamma distribution. In our data set, the inverse Gaussian distribution better fit the data slightly, but the choice did not significantly influence our results. The hazard and survival functions with gamma distributed heterogeneity are equal to:

$$S_\theta(t,x) = \exp\left\{\frac{1}{\theta}(1-[1-2\theta \ln S(t,x)]^{1/2})\right\}$$

$$\lambda_\theta(t,x) = \lambda(t,x)[1-2\theta \ln S(t,x)]^{-1/2}$$

Estimation of the model in Stata using the frailty option with STREG generates the coefficients and an estimate of θ. The likelihood ratio test, which is reported by Stata, can then be used to determine whether heterogeneity across observations is significantly different than zero.

Similar to the coefficient estimates from logistic and probit regression models, survival model estimates must be transformed to interpret their meaning. In survival methods the marginal effect of a variable is often measured by comparing how a change in the variable influences the median survival time. The median survival time, with controls X and parameter estimates β, σ, θ, is found by setting the survivor function in equation 3 equal to .5 and solving for t using equation 2 along the way.

$$t = \exp(\sigma A + X\beta) \text{ where } A = \Phi^{-1}[1\text{-}\exp\left(\frac{2\ln(.5) - (\ln(.5))^2\theta}{2}\right)]$$

The marginal impact of a binary variable, x_1, on the median time to failure is found by computing the median time to failure with $x_1 = 1$ and for $x_1 = 0$, holding the other X values the same, and then taking their ratio, which is simply $\exp(\beta_1)$. If the estimate of

β_1 is .6931, then a student with $x_1 = 1$ has a median survival time twice that of a student with $x_1 = 0$: exp(.6931) = 2. This is equivalent to a $(\exp(\beta_1) - 1)\times 100$ percent difference in time of stay. The effect of a nonbinary variable is equal to $\exp(\Delta\times\beta_1)$, where Δ is equal to the change in the covariate.

EMPIRICAL ANALYSIS OF INSTITUTION STOP-OUT BEHAVIOR

We followed the enrollment history of first-time, first-year students who enrolled at our university in the fall semesters of 2006, 2007, and 2008 through the fall semester of 2009. The university is a public institution and is classified as a high research activity institution by the Carnegie Foundation for the Advancement of Teaching. Approximately 13,000 undergraduate and graduate students in 218 fields of study are on campus. The University is located in a vibrant college-town community of 50,000 people. The dependent variable in our study, time to stop-out, measures the number of consecutive fall and spring semesters a student was enrolled at our university without a break in enrollment. Students with a break in enrollment were removed from the sample.

Two types of control variables were used in our empirical model to explain the duration of student stop-out times. The first set of variables includes many of the typical controls used in the literature to analyze student outcomes. This set includes students' high school GPA, ACT score, gender, ethnicity, residency, parental education, and family income. These variables reflect the background characteristics of students, which are said to influence both the motivation and aptitude of students towards college. Previous research by Ishitani and DesJardins (2002) has shown academic ability, measured by high school GPA and entrance test scores, increased the time to stop-out, thus improving retention. Ishitani (2003) and Murtaugh et al. (1999) also found higher high school GPA increased the time to stop-out. Gender and ethnicity were included to determine whether outcomes vary by demographic characteristics. The empirical impact of these variables has been unclear. Ishitani and DesJardins (2002) and Ishitani and Snider (2006), for example, found gender was insignificant to stop-out time, whereas Ishitani (2003) found female students were more likely to stop out. With respect to ethnicity, Ishitani and DesJardins (2002) and Ishitani (2003) both find minority students have stop-out times similar to White students; though Asian students are less likely to stop out than Whites in studies by Ishitani and Snider (2006), DesJardins, Ahlburg, and McCall (1999) and Murtaugh et al. (1999). Ishitani and Snider (2006) found that Black students were more likely to stop out, whereas Murtaugh et al. (1999) found they were less so.

State residency lowers tuition rates at most public schools, which may have an influence on the ability to remain in college (DesJardins et al., 1999; Murtaugh et al., 1999). Students who are first-generation college students are expected to have less family support for college and thus are more likely to stop out, which is confirmed by Ishitani (2003) and Ishitani and Snider (2006). Students from families with a higher income are expected to provide more support, allowing students to become more integrated into the social and academic environment of the institution, improving outcomes. Ishitani and DesJardins (2002), Ishitani (2003), and Ishitani and Snider (2006) found higher family income improved retention.

Many of the variables we used in our analysis are binary outcomes. The variable ethnicity takes a value equal to 1 if a student is White and 0 otherwise. Gender takes a value of 1 for female students and 0 for males. Residency equals 1 for residents of our state and 0 otherwise. We transformed high

school GPA into four groups, which were approximately quartiles: the reference group was students with a GPA less than 3.25; the other students were grouped with GPAs 3.25–3.49, 3.50–3.74, and 3.75 and above. Family income was similarly broken into quartiles: the reference group was students with family income less than $50,000; others were grouped with family incomes $50,000–74,999, $75,000–99,999, and $100,000 and above. These transformations allowed us to easily compare the effects across different income and ability groups. Parental education equals 1 if both parents did not attend college and 0 if either or both did. The student population in our sample, where complete data is available, was 95% White, 44% state residents, 49% female, 22% first-generation college students with the average high school GPA of 3.5, ACT score of 23, and family income of $50,000.

The other set of variables we examined were concerned with measuring the interactions between students and the institution prior to their enrollment. Our hypothesis was that students who take the time to interact with our institution will demonstrate motivation for becoming part of our academic and social community resulting in improved student outcomes for those students. We examined three different methods of student interaction with Enrollment Services—participation at a college fair, making a campus visit, and participation at Welcome Weekend. Each of these three variables was binary, taking a value of 1 in cases when students participated and 0 when they did not. Of the students who enrolled at our university 5% attended college fairs, 57% had made a campus visit, and 69% participated in Welcome Weekend.

For both sets of variables the values remained constant for a particular student over time. It is possible that parental education and family income could have changed while a student was enrolled in college (e.g., a parent loses a job and goes back to school), but in most cases these changes were few and minor. Recall for our measure of family income to change it must move to another quartile; thus only a significant change in income is likely to change the binary measure used. One reason we held these two variables constant is due to the data source for both variables: each was obtained from FAFSA forms that students filled out annually to receive financial aid. The best case then would be an annual observation of family income and parental education for each individual for each year they were enrolled. In our data set students often had a break in filing for financial aid, therefore rather than lose observations, we simply used the family income and parental education data available from the first year to fill in the values for each year. Another reason for this assumption is the difficulty associated with introducing time-varying covariates into the type of parametric duration model used here (Cox & Oates, 1984).

RESULTS

Table 2 reports the estimated coefficients of our empirical model and their standard errors, the corresponding marginal effect on median survival time of a 1-unit change in each variable, and parameter estimates for θ and σ. The median length of stay for the typical student was 7.6 semesters. The average student was male, White, has an ACT score of 23, has a high school GPA of 3.50, family income of $50,000, is a nonresident, is not a first-generation college student, did not attend a college fair, but participated in a campus visit and Welcome Week. The magnitude of the marginal effect of a 1-unit change in each variable, holding the other values constant, is provided in Table 2. Students with high school GPAs below the 25th percentile were

substantially less likely to be retained than those in higher quartiles. A student with a GPA 3.75 or above (highest quartile) was found to stay 60% longer than students in the lowest quartile. With respect to family income, two of the three higher income groups outperformed the reference group, whereas students with a family income of $50,000–74,999 (third quartile) did not, indicating a nonlinear effect. Similar to many studies, we found that first-generation students were at a significant disadvantage—staying in college 13% less than otherwise. The magnitude of student interactions with Enrollment Services also varied across activities. The 5% of students who participated in a college fair were likely to stay 33% longer than those who do not. Attending Welcome Weekend lengthened enrollment by 18.0%, and a campus visit lengthened it by 6.5%.

The impact students' backgrounds and their interactions with our institution have on the risk of their stopping out for each semester they are enrolled was also considered. We calculated the hazard rate for a typical student and semester using equations 2 and 3 and selected values of the covariates along with our coefficient and parameter estimates from Table 2. We examined the risk profiles of two student groups—one with a low-risk background and the other with a high-risk background. Both students are male, White, and state residents. The low-risk student was not a first-generation college student, had an

TABLE 2.
Time to Stop-Out Estimates

	Coefficient	*SE*	*p*	Marginal Effect %
Female	–0.0517	0.0357	.148	–5.04
White	0.0233	0.0757	.758	2.36
ACT Score	0.0157	0.0054	.004	1.58
High School GPA 3.25–3.49	0.1408	0.0491	.004	15.12
High School GPA 3.50–3.74	0.2966	0.0520	< .001	34.53
High School GPA 3.75+	0.4727	0.0547	< .001	60.43
Family Income $50,000–74,999	0.1027	0.0471	.029	10.82
Family Income $75,000–99,999	0.0680	0.0479	.155	7.04
Family Income $100,000+	0.1216	0.0477	.011	12.93
State Resident	0.0770	0.0350	.028	8.00
First-Generation	–0.1365	0.0401	.001	–12.76
Welcome Weekend	0.1621	0.0376	< .001	17.60
Campus Visit	0.0633	0.0343	.066	6.53
College Fair	0.2874	0.0809	< .001	33.29
Constant	0.2014	0.1537	.190	
σ	0.4930	0.0440		
θ	9.0012	2.8493		
Observations	12,932			
Log Likelihood	–2978			

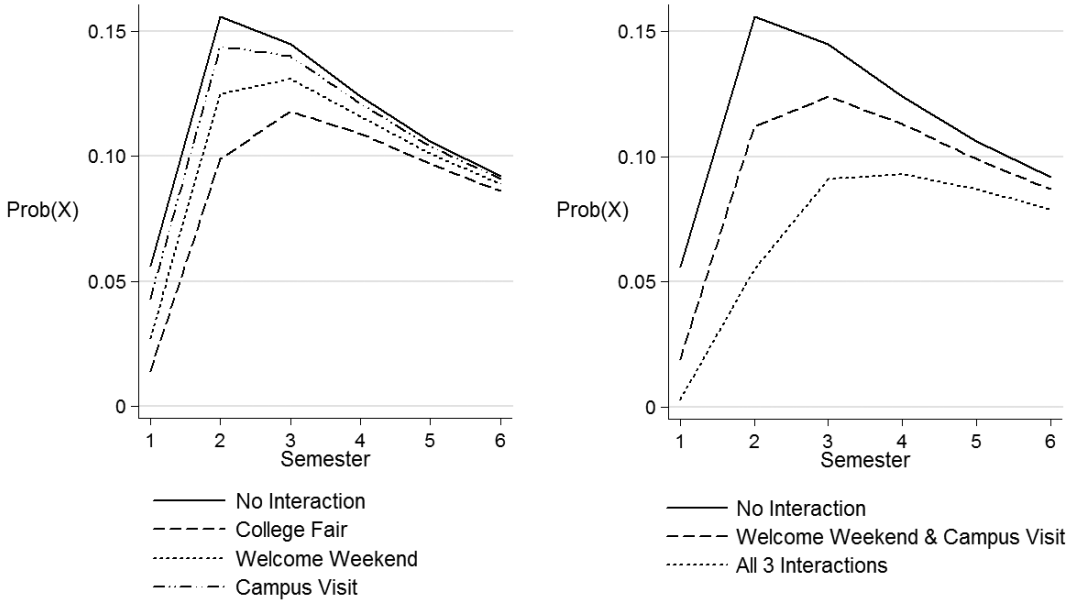

FIGURE 1a. Probability of Stopping Out: Low-Risk Student

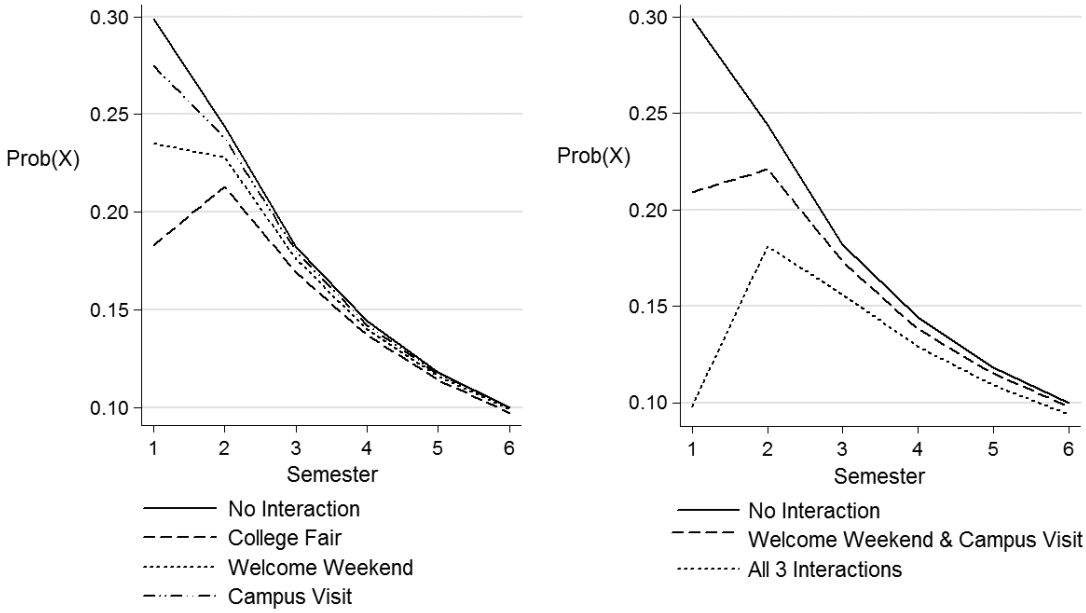

FIGURE 1b. Probability of Stopping Out: High-Risk Student

ACT score of 23 with a high school GPA and family income above the 75th percentiles. The high-risk student was a first-generation college student with an ACT score of 19 (approximately one standard deviation below the mean)with a high school GPA and family income below the 25th percentiles. Figure 1a shows the corresponding hazard rates for the low-risk group under different interactions with the institution. The left graph displays the

effect without interactions, interaction via a college fair, interaction via a campus visit, and interaction via Welcome Weekend. The right graph adds the shared effects of a campus visit and Welcome Weekend, and the effect of all three methods recorded. Figure 1b shows the hazard rate for the high-risk group.

The results in Figure 1 highlight several interesting findings. Comparing the results from the low-risk and high-risk groups, when neither interacted with the institution, the typical student, who is similar to the low-risk student, has a hump-shaped hazard rate. For this student the probability of stopping out increases from the first semester to the second semester and then declines slowly over time. This reflects the typical notion that students are most at risk of stopping out after the second semester of their first year of enrollment. For the high-risk students the risk is highest in their first semester and then more steadily declines with time. The difference between the high-risk and low-risk students was also striking: a low-risk student had a 5.6% chance of stopping out after the first semester relative to a 30.0% chance for the high-risk student. The high-risk student was more than 5.0 times as likely to stop out after the first semester and 1.5 times more likely after the second semester. The longer they remained in college, students we classified at entry as low-risk and high-risk based on their background characteristics had similar risks of stopping out. This is not because high-risk students were misclassified, but because many of the high-risk students had already stopped out. Hazard rates measure a conditional probability. Conditioning on who remained in the pool after the second year, we found that high-risk and low-risk students had similar behaviors with regards to stopping out. In a sense, only the fittest of the high-risk students, perhaps in terms of unobserved motivation, remained enrolled.

Examining the impact of the three forms of student interaction, we found each had a significant impact on the risk of stopping out for both risk groups during their first year. As noted earlier, participating in a college fair had the biggest impact. The probability of stopping out after the first semester for a low-risk student who attended a college fair was 1.4%, relative to 5.6% for one who did not; 18.0% for a high-risk student who attended a college fair and 30.0% for one who did not. Participating in all three activities also had a dramatic impact on stop-outs. Among low-risk students there was a 5.5% chance of stopping out after the first year; for high-risk students 18.0%. Compare this latter finding to low-risk students who did not interact with the institution for whom there was a 24.0% chance of stopping out. Clearly students who interacted significantly reduced their likelihood of stopping out during their first year.

DISCUSSION OF FINDINGS

A potential concern is whether the log normal parametric model used here fits our data. Hosmer et al. (2008) note the most frequently used method to test model fitness compares the estimates of the cumulative hazard function from the parametric model with those of the nonparametric model estimated using Kaplan–Meier. Cox–Snell residuals, which are produced by Stata after estimating the lognormal model, equal the cumulative hazard function for our parametric model. The nonparametric estimate of the cumulative hazard function uses the Cox–Snell residuals as the time variable and the same original censoring variable. If our parametric model is correct, then the plot of the two cumulative hazard functions should lie on a 45° line starting at the origin. Figure 2 reveals that our model fits the data quite well. The deviation from the 45° line on the right side is expected due to the "reduced effective sample caused by prior failures and censoring"

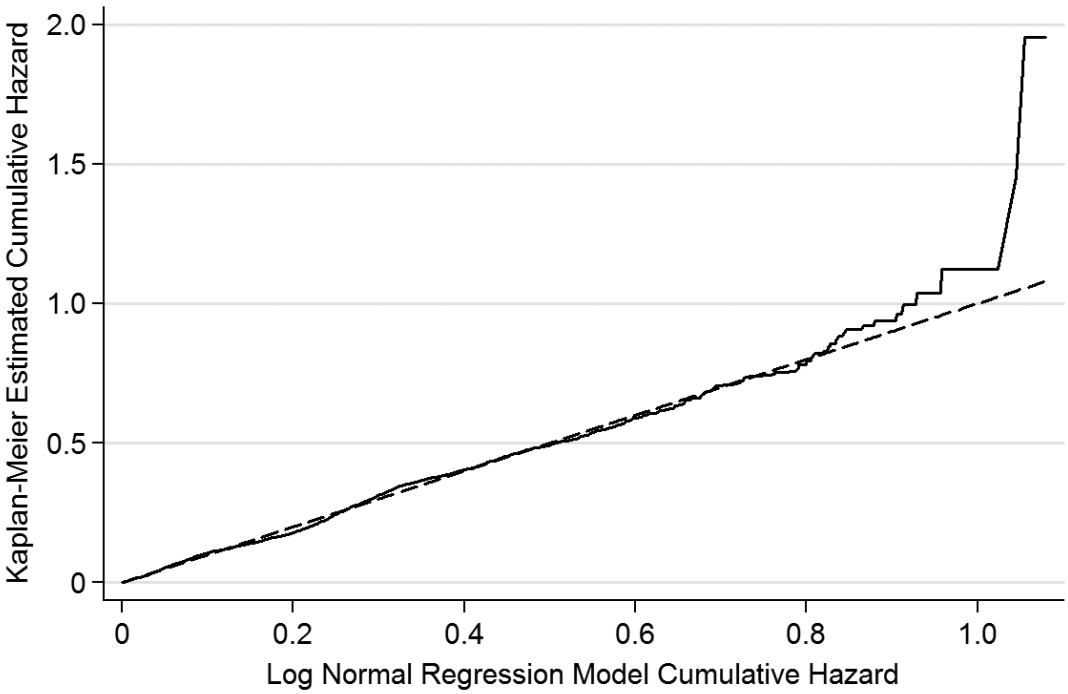

FIGURE 2. Log Normal Model Fit

(Cleves, Gould, Gutierrez, & Marchenko, 2008, p. 216). Another way in which we confirmed our model's fit was to compare the Akaike information criterion (AIC) statistic from the lognormal model we used to that of the Weibull, and log-logistic. The AIC for the lognormal model is 5991, Weibull model is 6180, and log-logistic is 6023. The lowest value, which is the preferred model, coincides with our lognormal model. The frailty we introduced into our lognormal model also appears to be appropriate. The likelihood ratio test, $\chi^2(1) = 112$, $p < .001$, strongly rejects the null hypothesis of θ(frailty) equal to 0.

Of the three forms of student interaction, participation in college fairs had the largest impact. This finding is interesting, as noted by an anonymous referee, because the time and effort it takes for students to participate in a college fair is typically less than that involved with a campus visit. It may be that students who attend college fairs are highly motivated to attend college and are perhaps more likely to thoroughly research different colleges prior to making their decision to enroll, resulting in a better fit and positive outcomes. It is possible though that an omitted variable may be the underlying cause. Unlike the other two forms of interaction, college fair participation involves a choice made by the institution. Our institution chooses to hold college fairs in high schools and other locations where past experience has shown there to be more promising prospective students. Thus it may be characteristics of the schools visited, such as better counselors and teachers, which result in both college fair participation and improved outcomes.

We tested for this potential effect in two ways. To control for our institution's choice of high schools we visited, we included in our specification above a variable that indicates whether we visited a student's high school. The estimates in Table 3 reveal students whose high school we visited were not significantly

more likely to succeed, and the impact on the marginal effects of student interactions was negligible. The second method we used adds fixed effects to our prior specification, which allowed us to control for the different high schools that our students attended. In total, our students attended approximately 1,500 different high schools, over 1,000 of which were unique observations. To limit the effects of multicollinearity we limited our sample to observations of students from high schools with 10 or more students enrolled during the period. This reduced the number of high schools examined to 114 and the number of observations to 7,731. Results of the fixed effects analysis revealed that the coefficients of the dummy variables were jointly significant as the likelihood ratio test statistic equals –2(–1762.55 + 1676.44) = 172.22, which is distributed $\chi^2(113)$, p=.0003. The marginal effect of Welcome Weekend (15.0%) and campus visit (9.3%) were similar to before, whereas the magnitude of college fair increased substantially to 69.0%. In both methods examined here, the three forms of interaction had a significant impact on student outcomes.

Students chose whether to participate in the activities that we examined and thus were not randomly selected. Padgett, Salisbury, An, and Pascarella (2010) note in this case

TABLE 3.
Time to Stop-Out Estimates: Controlling for High School

	High School Visit		Fixed Effects[a]	
	Marginal Effect %	*p*	Marginal Effect %	*p*
Female	–5.25	.133	–2.72	.547
White	1.71	.824	–4.57	.657
ACT Score	1.54	.005	1.42	.052
High School GPA 3.25–3.49	15.27	.004	13.20	.048
High School GPA 3.50–3.74	35.12	< .001	39.90	< .001
High School GPA 3.75+	61.92	< .001	72.44	< .001
Family Income $50,000–74,999	10.36	.037	12.03	.068
Family Income $75,000–99,999	6.63	.181	7.73	.231
Family Income $100,000+	12.33	.016	16.96	.015
State Resident	6.60	.081	0.81	.961
First-Generation	–12.63	.001	–9.53	.064
Welcome Weekend	17.92	<.001	15.27	.005
Campus Visit	6.93	.053	9.31	.053
College Fair	34.86	< .001	69.25	.001
High School Visit	4.47	.222		
σ	0.4976	0.0444	0.3715	0.0578
θ	8.7072	2.7723	17.3545	8.4033
Observations	12,932		7,731	
Log Likelihood	–2978		–1676	

[a] Coefficients for the fixed effects are suppressed but available from authors on request.

one "cannot unequivocally claim that the program effect is attributable to the program experience or to an amalgam of factors that may have influenced the student's decision to participate" (p. 30). The concern is that there may be a systematic imbalance in the characteristics of those who select to participate (treated group) and those who do not (control group). Certain characteristics may cause students to participate in programs and also influence student outcomes, which if not controlled for can bias estimates of a program's effects. A matching model attempts to eliminate this potential bias by pairing an observation receiving treatment (participant) with another that does not and in which other characteristics are similar. Propensity score matching (PSM) is a method of matching that describes the similarity of observations by a single measure, referred to as the *propensity score*: the probability that an observation in the combined sample of treated and untreated observations receives the treatment, given a set of observed variables. Matching treated observations with control observations based on propensity score allowed us to compare the difference in outcomes to isolate the effect of treatment. The techniques we used to implement PSM are based on Guo and Fraser (2010). The process is rather straightforward to implement and involves three steps.

The first step involves using logistic regression to estimate a model that explains whether a student will participate in a particular activity (i.e., receives treatment). We modeled each activity (college fair, campus visit, Welcome Week) independently of the others. The controls we used were guided by theory and are similar to those used to analyze student outcomes. In each model specification we included ACT scores, high school GPA, family income, gender, age, parental education, and residency interacted with high school GPA and family income. We also included race in the model of campus visits because we identified a significant difference in the race of those who made campus visits and those who did not, which is discussed further below. These results are available from the authors on request. Each specification was then used to generate the propensity score, which describes each observation's likelihood of being treated for a particular activity. The propensity score for an individual is equal to the $\log[(1-p)/p]$, where p is the predicted probability estimated from the selection model. Guo and Fraser (2010) discuss the logit is used in place of the predicted probability because the logit is approximately normally distributed.

In the second step, the propensity score is used to match control and treated observations. We used nearest-neighbor matching within a caliper of $.25\sigma_p$ to match observations, where σ_p is the standard deviation of the propensity score. A number of alternative matching algorithms also exist. After matching, our sample size was reduced as cases outside the common support were removed. These were cases where there were no matches due to treated cases with low propensity scores and untreated cases with high propensity scores. We then needed to ensure that the match led to balanced covariates across samples. Independent sample t tests can be used to determine whether significant differences in the sample remain after matching. Prior to matching there were a number of statistically significant differences between the treated and untreated groups, which potentially influenced student outcomes. For example, White students were more likely than non-White students to participate in a campus visit. After using propensity scores to match observations, we were able to remove all of the significant differences in the covariates between the treated and untreated groups for each activity. A table of these comparisons is also available from the authors on request.

The final step involved estimating our

original duration model specification of length of stay using the matched sample. Estimates of the marginal effects for each specification, prematching and postmatching, appear in Table 4. The results indicate there is some variation in the effect of participation, controlling for selection. The effect of Welcome Weekend increased from 18% to 22% as did the effect of college fair participation, which increased from 31% to 48%. The effect of campus visit was reduced from 9% to 8%. Overall, the results are in line with our earlier conclusions, but should still be interpreted with caution. Matching is only able to reduce the bias due to observable differences that influence selection. There may still be a number of unobserved factors that are important to selection and influence outcomes, which could have introduced bias to our results. Further, in our model of college fair participation the size of the matched sample was significantly reduced due to the small number of participants and thus might not reflect the entire sample.

TABLE 4.
Marginal Effects: Prematching and Postmatching

	College Fair		Campus Visit		Welcome Week	
	PRE[a] Effect %	POST[b] Effect %	PRE Effect %	POST Effect %	PRE Effect %	POST Effect %
Female	–2.92	–7.09	–3.38	–5.35	–4.79	–4.74
White	4.76	45.16	3.18	0.91	2.92	12.93
ACT Score	1.81	1.27	1.69**	1.16*	1.58**	0.87**
High School GPA 3.25–3.49	13.20	19.36	13.03*	11.97*	14.76**	16.20**
High School GPA 3.50–3.74	33.46	40.93*	31.18**	31.46**	34.82**	42.16**
High School GPA 3.75+	60.47**	115.50**	57.74**	61.54**	60.19**	62.03**
Family Income $50,000–74,999	11.86**	60.68**	10.39*	11.89*	10.51*	11.73*
Family Income $75,000–99,999	7.57**	67.13**	6.00	4.65	6.32	1.80
Family Income $100,000+	16.53**	68.64**	13.70**	12.96*	12.42*	21.42*
State Resident	4.62	–16.72	4.17	5.30	5.64	1.43
First-Generation	–12.56**	–7.61	–12.85**	–15.87**	–12.84**	–10.50**
Welcome Weekend					18.21**	22.23**
Campus Visit			8.98**	8.04*		
College Fair	31.19**	48.22**				
Observations	12,932	1,447	12,932	9,998	12,932	7,832
Log Likelihood	–2992	–283	–2994	–2368	–2978	–1908

[a] PRE = Prematching; results from an unmatched sample.

[b] POST = Postmatching; results from using nearest neighbor matching to match treated and control observations.

*$p < .05$. **$p < .01$.

CONCLUSION

Students who are better prepared and more motivated are more likely to succeed after they enroll in college. Our duration model has clearly shown the former to be empirically true and suggests that the latter is also true. Students who voluntarily participated in certain activities with our institution demonstrated motivation towards succeeding at our institution. We found students who participated in a college fair, campus visit, or Welcome Weekend were less likely to stop out. The magnitudes of the effects are quite substantial relative to background characteristics. Based on our results one might conclude that student interactions with an institution cause improved student outcomes. The implication of this causal claim is that institutions should be able to reduce stop-outs by increasing the number of students who interact with the institution. One way to do this would be by requiring students to attend Welcome Weekend. Unfortunately, such interactions may not be the underlying cause, but instead are likely correlated with unobserved motivation, which influenced participation and student outcomes. The point is students who are motivated towards attending our university were more likely to interact with the institution prior to enrolling; thus requiring students to participate may not have the desired impact on student outcomes if students who willingly participate have different motivation than those required to do so.

Motivation and ability both influence student outcomes; therefore failing to control for motivation incorporates a bias into the results, making it difficult to explain why students with similar abilities succeed in some instances and fail in others. Understanding the factors that influence motivation in some cases can help to reduce most of the bias (Steiner, Cook, Shadish, & Clark, 2010). The difficulty is with measuring student motivation. As DesJardins et al. (1999) note, using surveys to measure motivation is costly and can significantly reduce the original sample, resulting in a population of participants significantly different from nonparticipants, which introduces a selection bias; the use of institutional data avoids both issues. Our results show that policy makers can use data on their interactions with students to improve their understanding of student outcomes. Students self-select whether to participate in the activities we examined, and selection is based on their underlying motivation. This information allows an institution to determine which students are most at risk, given their motivation and ability, and then to target appropriate interventions to specifically improve outcomes of high-risk students. Interventions could include activities specifically designed to improve student outcomes, such as mandatory advisement, tutoring sessions, and restrictions on enrollment for these students.

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