

Using Institutional Data to Identify Students at Risk for Leaving Community College: An Event

History Approach

By

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A dissertation submitted to the Graduate Faculty in Educational Psychology in partial fulfillment
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This manuscript has been read and accepted for the Graduate Faculty in Educational Psychology
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Abstract

Using Institutional Data to Identify Students at Risk for Leaving Community College: An Event History Approach

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Community colleges have been criticized for having lower graduation rates than four-year colleges, but few studies have looked at non-graduation transfer, in which a student leaves the community college for a four-year college without taking an associate degree. The current study utilizes institutional data and a discrete-time event history model to predict non-transfer attrition in community colleges. The data utilized include five years of institutional data from 21,724 first-time freshmen from the six community colleges of the City University of New York. The study includes students who resided in New York City and its two adjacent suburban counties and who matriculated in the fall of the 2004 and 2005 academic years. Multinomial logistic regression was employed in an event history model of student absence and transfer; models were developed for both the first and second spells. Data on students who transferred were obtained from the National Student Loan Clearinghouse (NSLC). Continuation or type of leaving following each semester constituted the dependent variable. Many of the risk factors for leaving were related to academic performance. Students who were writing- and math- proficient and who had higher GPAs and more credit completion were more likely to remain enrolled or to transfer; students who failed were more likely to leave. Notably, course withdrawal was a greater risk factor for leaving than course failure. Financial aid in the form of grants and loans was associated with a decreased risk for attrition, and weekly travel was associated with an increased risk for leaving as well as an increased risk for transfer. Smaller class size and time spent on campus and especially in class was associated with lower risks for attrition. Three

models were employed, two of these modeled transfer as separate form of leaving; one included transfer together with graduation and continuation as a successful semester outcome. Parameters obtained from the 2004 cohort were applied to the 2005 cohort to assess each model's predictive validity in a naïve dataset. The most successful model for the first spell correctly identified 34.6 percent of the leavers in the semester in which they left, with a 35 percent false positive rate. The most successful model for the second spell identified 49.6 percent of leavers with a 30.8 percent false positive rate. If a false positive rate of 50 percent is allowed, about 60 percent of leavers in the first spell and about 80 percent of the leavers in second spell can be detected. Remedial study does not present a risk, but the data suggest that remedial education may be using too much of a student's grant money. It is suggested that additional study may be needed to determine how to effectively remediate students in math and writing, and that a model for course withdrawal and failure using interim grades be developed. Since withdrawal and failure present acute risks, it is suggested that a student's fitness and prerequisite skills for courses be assessed prior to course enrollment. Since many of the risk factors are interrelated, it is suggested that a structural model may be needed to assess each predictor's relevance.

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Her children arise up and call her blessed; her husband also, and he praiseth her:
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Chapter One: Introduction

It is estimated that roughly half of all students who enter college eventually earn a degree (U.S. Department of Education, 1999). As of 2005, the U.S. Department of Education estimated the graduation rate at four-year institutions at about 56 percent. Low as this may seem, the Department of Education estimates the graduation rate at 2-year community colleges to be much lower at 33% (Knapp, Kelly-Reid, Whitmore & Miller, 2007). For the sake of the student, the institution, and society at large, it is important that college graduation rates improve. On the personal level, a worker with a college degree will earn nearly 80% more than one without (Middle Class Task Force, 2010). On the institution level, colleges are increasingly being held accountable for graduation and retention rates. On the societal level, employment growth is predicted to occur principally in areas that require a postsecondary education (Saunders, 2005). Further, health and civic participation are higher for individuals with more education (Middle Class Task Force, 2010).

Increasingly, colleges are being held accountable for their success or lack of success in retaining and graduating students. Accountability is being demanded by official bodies such as regional accreditation boards, the federal government and state governments, as well as by unofficial arbiters in the popular media, such as US News and World Report, which exercise a great deal of influence over the colleges to which a student will apply. Further, the loss of tuition revenue due to students leaving early is of concern.

This has prompted colleges to develop a number of strategies to increase their success in retaining students. These strategies include declining admission to students who are deemed less likely to succeed and to make the school more attractive to (and thus retain) students who have been admitted. The latter has led to a host of interventions from increasing social functions,

freshman orientation programs and other on-campus programming that will make the college more attractive. Less attention has been paid to everyday features of the student's environment that may influence a student's decision to remain in or leave an institution. No studies have investigated how a poorly designed class schedule might influence a decision to depart. For example, might a student with several courses arranged back-to-back experience fatigue that is so unpleasant that the student avoids future enrollment? Few studies have addressed how the distance that a student needs to travel to get to campus might influence re-enrollment. The current study addresses questions such as these by including institutional data in a predictive model of retention and withdrawal.

There are three main reasons for failure to graduate: Academic dismissal, dropout, and transfer. As Tinto (1982) points out, it is important to distinguish between these, and studies that fail to do so may present contradictory and confusing findings. Tinto (1993) reminds us that the majority of students who leave college do so voluntarily and not because of poor performance. Students may leave an institution because they feel that they are performing poorly, but they may also leave because they are doing well (in the case of transfer from a two-year to a four year institution). The distinction is in the destination: Students who are doing well may leave to pursue their college careers elsewhere, while students who are doing poorly might drop out of college altogether. Adelman (2006) writes that a formal transfer from a community college to a four-year college is positively associated with degree completion. Clearly, this distinction is of significant importance for community colleges in particular, because many students who matriculate there plan to leave for a four year institution, in many cases without the intention of taking a degree (Borglum & Kubala, 2000).

A theory of student leaving has been articulated by Vincent Tinto over the past four decades. Tinto's comprehensive model as presented in his book Leaving College (1993) focuses on the student's integration into the college. Although Tinto's model allows that precollege student characteristics such as aptitude and external influences such as finances may play a role in a student's retention, he regards the institution as playing the central role, and holds that the institution bears considerable responsibility for student retention. Tinto (1975) feels that students who voluntarily withdraw from an institution do so primarily because they do not fit into the institution either academically or socially. Tinto's theory maintains that students who are successfully integrated into college life will be more likely to stay until they graduate. Central to this theme is the importance of interaction between students and other members of the college community including faculty, staff, and other students. Consistent with this theme, he advises colleges to develop programs that would more fully integrate students into college life by facilitating interactions with other members of the campus community. Examples of these include orientation programs, freshman seminars and social events. Tinto (1993) and other researchers allow that this may be somewhat different for non-traditional students, students who do not live on campus, attend part-time, or are older.

As Tinto (1993) notes, a distinction needs to be made between leaving a particular institution for another and leaving higher education altogether. We will refer to these respective processes as transfer and leaving. Relatively few studies make this distinction, possibly because a convenient means for obtaining subsequent enrollment data has only recently been developed. Two exceptions are Porter (2000) and Jones-White, Radcliffe, Huesman, & Kellogg (2010), who used data provided by the National Student Loan Clearinghouse (NSLC) to develop a model to

disentangle leaving due to transfer versus simply dropping out. This study addresses these two different forms of voluntary leaving using NSLC data.

Tinto (1993) notes that leaving college exists along a temporal dimension. Some of the studies focus on the temporal nature of dropping out, noting that the factors that affect dropout differ depending on how many credits the student has earned or how many semesters the student has been in college. Many studies do not do this, focusing only on whether or not the student left without graduating. Several studies focus on the phenomenon of “stopping out”, or non-enrollment following semesters completed, followed by continued enrollment (Stratton, O’Toole & Wetzel, 2004). Time is an important dimension: Students who leave after the first semester cannot be assumed to have made the choice for the same reasons as those who leave after the second, the third, or indeed, after any of the subsequent semesters (Tinto, 1993). Fortunately, the statistical method of event history modeling (often referred to as survival analysis, a name that derives from its development in the medical sciences) provides a means to model an individual’s departure from an institution within a temporal framework (Willet & Singer, 2003). This research aims to generate a model that will predict if and when a student will leave community college, and the variables that are associated with that event.

Bean & Metzner (1985) studied attrition in commuter students and posited that they would be less likely than traditional students to be affected by the campus environment. More recently, Tinto (2006/2007) acknowledges a distinction between the reasons that commuter students leave college and the reasons that traditional students leave college. Further, Tinto (1993) suggests that this will also be different in colleges that are located in urban versus rural or suburban settings. The current study specifically addresses student leaving in six urban commuter community colleges.

The notion that colleges need to spruce up programs such as freshmen seminars and extracurricular activities in order to retain students is something of a one-size-fits-all approach. Tinto (2006/2007) acknowledges that commuter students are likely to spend less time in such pursuits, and recommends that student-faculty interaction in the classroom may be a more fitting focus for such students. Indeed, Tinto (1993) states that it is of extreme importance that retention programs focus on the individual student rather than the group. It is also important to recognize that students face a number of stressors that may be differentially affecting their decision to remain enrolled in higher education and that are not easily addressed by social programs. This is likely to be particularly true for part-time or working students who are not likely to have a great deal of time to spend on extracurricular activities. Spanard (1990) writes that many nontraditional students leave school due to external stressors and subsequently return when those stressors are removed. Among the stressors that she cites are job commitments, home responsibility, lack of money or childcare, and transportation problems.

The literature achieved much in the way of explaining “what students are thinking”, but is unfortunately dependent on many variables that are largely unobservable at worst and unobserved at best. As Tinto (1993) says: “... models which seek to explain why it is that students leave or ‘drop out’ ... [are not] particularly well suited to the needs of institutional officials who seek to retain more students on campus” (p. 84). Research on college attrition that has been conducted for the past forty years has focused on cognitive variables that mediate between environmental variables and behavior. Consider, for example, the question concerning whether a student has successfully integrated into campus life. One indication of successful integration is that the student interacts directly with faculty, staff or other students. To measure this for every student would be financially and logistically burdensome if not impossible. At

best, it might be possible to educate faculty and staff to look for warning signs that a student is not integrated, and then take some corrective action. Even then, it is difficult to say how such an observation of student integration could be made, unless the faculty has contact with students, which of course is the problem to begin with.

While a student's integration into college is undoubtedly of significant importance, it is important to recognize that there are likely other external barriers to remaining enrolled. For example the distance that needs to be travelled might present difficulties in getting to class. Since colleges have at their disposal many indicators of these barriers, it should be possible to construct a predictive model that could use existing data to identify students who are at risk for stopping out. Identified students could then be referred to advisement personnel or faculty before they have made a decision not to re-enroll. Also, such students could have their schedules tailored in such a way that the effect of these barriers might be minimized. For example, even though the college cannot reduce the distance that a student needs to travel to get to the campus, the college might advise a student with travel difficulties to adopt a schedule that requires him to attend more classes per day but fewer days per week.

With the advent of large-scale institutional databases and modern computing equipment and software, many data analysis techniques are readily available as they had not been in the past, and it would make sense to explore the variables that institutions have at their disposal for the identification of students who are at risk for leaving. Lotkowski, Robbins & Noeth (2004) recommend that colleges develop an early warning system to identify students who are at risk for leaving before they do so. They suggest that this system incorporate precollege data such as high school GPA, assessment tests, socioeconomic information and placement tests, as well as other data that are collected for college-level work, such as GPA. Bontrager & Parry (2008) suggest

that colleges make use of existing institutional data to solve the problem of low retention rates. One example of this might include monitoring for course withdrawal as a precursor to institutional withdrawal.

An early warning system would be able to identify students who are at risk for leaving, and assign to each student a risk score based on those variables, and present a report to a college officer who would then be able to intervene. For colleges with dedicated advisement staff, this process could be incorporated into the registration process. This aspect of the system would allow a college to target a subpopulation that is at higher risk for leaving. This would have the economically salubrious effect of saving money and resources for the university, and would make it more likely that those at greatest risk for stopping out be allocated the most time and attention. Optimally, such a system would not only identify students who are at greatest risk, but also the factors that place them at risk, which would allow college officials to advise them on a course of action that would make retention more likely. At a minimum, this system would be able to identify “talking points” for a university official to use in conversation with a student at risk, allowing the official to identify possible stressors that the student might be facing, and to enter into a dialogue whose eventual conclusion would be a schedule that would be amenable to the student’s current situation.

The Current Study

The current study addresses the question concerning which variables already present in a university’s data systems will be useful in predicting which students are at risk for leaving. It is suggested that identification of these variables could eventually lead to a reporting system that would identify students who are highest risk for leaving, perhaps by ranking students at greater risk for leaving highest on a list and assigning risk scores that vary between 0 and 1, zero being

impossibility that students will leave, and one being certainty that a student will leave. It is further suggested that a confidence interval be established around this statistic. The system would also note which variables are placing the student at risk, and serve, as noted above, as a beginning point for a dialogue with the student.

The model assumes that risks for stopping out change temporally, as suggested by Ishitani (2006) and Ishitani & DesJardins (2002), who studied the effects of demographic, social, academic, financial and institutional variables over time.

Chapter Two: Prior Research

There are diverse theories to account for student departure. Tinto (1993) largely focuses on the institution, stating that students who voluntarily withdraw from an institution do so because they do not fit into the institution either academically or socially. Tinto (1975) argues that a student's commitment to the goal of completing an education plays an important role. If the student does not perceive the benefits of a college education, or sees other pursuits as more attractive, he may decide to discontinue his education in favor of pursuing those other goals. Other researchers look to characteristics of individuals, such as demographics, academic ability and financial resources, while still others look to environmental influences that belong neither to the individual nor to the institution per se, but clearly influence student success. Examples of such would be infrastructure that allows a student to get to class, the current labor market which might influence a student's decision to pursue higher education and if so, whether to do so on a full-time or part-time basis. Clearly, all three of these influences interact and influence one another, but it is useful to consider them separately. The review will begin with student-level variables; these include demographics, precollege variables, student characteristics and financial variables. This will be followed with institutional factors, and external variables that provide the context that both the student and the institution inhabit. Considered separately are time-variant variables such as GPA which vary from term to term. Finally, the destinations of students have following institutional withdrawal will be discussed.

Demographic Variables

Gender has been demonstrated to be differentially associated with persistence, often in the presence of other variables. Stratton et al. (2007) showed that females attending on a full-time basis are more likely to drop out than males, but for part-time students, the reverse is the

case. They also demonstrated that age is positively associated with persistence for women, but not for men. They also found that attrition was more likely for full time students when the student was a woman, when the student's parent had not completed college, if the student received a low grade and when the student was a man who married while in college. Using logistic regression, Leppel (2002) shows that the presence of children in the household has a negative effect on men's persistence but a positive effect on women's, she also shows that being black is associated with improved persistence among women but not men. Leppel also shows that being involved in social activities on campus has a greater differential effect for men than for women.

Gender is also differentially associated with other variables that are associated with persistence. Leppel (2005) showed that choice of major leads to different persistence rates for men and women. Using a national data set and employing logistic regression, Leppel showed that men who chose majors in business or engineering were more likely to persist than those who chose majors in education and liberal arts and sciences. Conversely, women who chose majors in education and health were more likely to persist than women who chose majors in liberal arts and sciences. Women choosing business were less likely to persist. Leppel interprets this as persons conforming to roles that are considered traditionally gender appropriate.

Ethnicity has been shown to be related to persistence, but often loses its explanatory value when other variables are considered. In a review article, Bean and Metzner (1985) note that several studies showed that blacks have a lower persistence rate than whites, but this is ameliorated or reversed when other variables including socioeconomic status, past academic achievement, and aspirations are included in the model. Also of interest is the fact that many blacks attend institutions that are predominately white. Hoffman and Lowitzki (2005)

hypothesize that being part of a minority group on a campus is associated with a change in the relationship of other predictor variables and retention. For example, they found that for members of a minority group on campus, standardized test scores were less predictive of persistence but high school records were more predictive. Ishitani & DesJardins (2002), using a hierarchical model, found that the only effect for race was that being Asian was positively related to persistence in the first semester. Stratton et al. (2007) found that full-time students were less prone to attrition when the student was an older female.

A number of researchers, including Tinto (1997), have suggested that the determinants of persistence will differ from person to person, especially given a student's age. Adelman (2007) argues that the traditional freshman will approach college in a much different manner than a student who begins college at middle age. Clearly, as students age they take on responsibilities that will make full-time attendance difficult if not impossible. The most frequently noted correlates of age that might complicate attendance are employment and children. In a study that utilized probit analysis, Liu & Liu (1999) demonstrated that younger students are more likely to be retained than older students. It might not be difficult to see why this may be the case. Bean and Metzner (1984) state that it is likely that correlates of age, rather than age itself that may be of importance to attrition. As people age, they are generally more likely to be encumbered with additional responsibilities of maintaining a home or taking care of children. This necessarily adds a financial burden to the student, who may consider not working to be completely out of the question. Working, in turn, adds to the complexity of the student's schedule, and may make the logistics of attending class all the more burdensome.

Pre-College Predictors

Pre-college variables include academically oriented variables that exist before a student enters college and may indicate the student's preparedness for a successful college career. These include standardized test scores, high school GPA, interest in a particular course of study, and motivation to succeed financially or academically. The most widely used include high school GPA, high school class rank, standardized test scores like the SAT or ACT, and achievement tests such as the various regents exams administered in New York State.

Pascarella, Duby & Iverson (1983) also found that persistence among students at commuter institutions was more likely to be influenced by pre-college characteristics. They found a particularly stronger effect for aptitude as measured by the ACT among students at a commuter institution than previous studies had found among students at a residential institution. Ishitani & DesJardins (2002) found that higher SAT scores were generally helpful to persistence. They found that low GPA was associated with higher levels of dropout in the first three years.

Bean and Metzner (1985) stated that high school academic scores such as high school GPA and class rank "seem to be among the strongest pre-enrollment predictors of persistence" (p. 497). Precollege variables are measured only once, and are presumed to exert more influence in the beginning of the student's career, and will likely lose influence as the student progresses. This would be due to the increased presence of more temporally proximal indicators, such as college GPA, which would figure more immediately in a student's choice to remain enrolled. The rationale behind the precollege academic variables and the direction of the prediction is that students who score on the higher end of these variables have greater opportunity to transfer to a more prestigious program, as well as a greater personal indicator of fitness for such a program. These students may be attending a community college for financial reasons (e.g. the higher cost

of a four-year program). Further, these students may not be considering finishing the degree, but rather earning transferable credits that may be later applied elsewhere.

It is natural to assume that students who score poorly on precollege indicators may be poorly equipped to handle college-level work, and will be more likely to eventually leave, however, this is not always the case. Pascarella, Duby & Iverson (1983), using path analysis, found a significant negative direct correlation between High school GPA and persistence at a commuter institution, but they found a positive correlation between high school grades and academic integration, which was, in turn, positively associated with persistence. Although not mentioned by the authors, one possibility for the confusing negative correlation between high school grades and persistence may be that the students with higher grades may have transferred to another institution. Therefore, all other things held constant, it is expected that students who score in the middle of this spectrum will be more likely to remain at the community college of choice.

Student Characteristics

The traditional first-year student is young; usually 20 or less, is typically enrolled full-time, may live on or near campus, and expects to complete the requirements of a baccalaureate in 4-6 years, and probably works part-time, if at all. She is looking to school not only for an education, but for a social experience as well. The non-traditional student may be older, may work full-time, and perhaps have a spouse and a family. College is likely seen as a means for securing a better or more profitable job, for the prestige of holding a degree, or simply to learn (Spanard, 1990). According to Choy (2002), traditional college students accounted for slightly more than one-quarter of undergraduates in the 1999-2000 academic years; the rest bore one or more characteristics of non-traditional students.

Spanard (1990) declares that personal characteristics such as maturity, motivation, and endurance will have a sizeable impact on a student's likelihood to persist, and that these characteristics fluctuate in intensity over time. She suggests that characteristics may be cyclic and that if institutions could develop interventions that are cycle-sensitive, much progress could be made in helping students persist.

Empirical evidence supports the notion that nontraditional students may form a distinct group that differs in many regards from traditional college students. Bean and Metzner point out that academic preparedness might also be less predictive when considering that non-traditional students have a large variety of other concerns, such as finances, jobs and children. These factors may lead even highly competent students to leave college. Bean & Metzner (1985) posit that commuter students are less likely than traditional students be affected by the campus environment. They declare that the primary interest of a non-traditional student is likely to be academic. This student is not likely to have a social interest in education, as he likely has a circle of friends that has been built up over years. Liu and Liu (1999) found that transfer students were more likely to persist at commuter institutions than were regularly admitted freshmen.

The emergent theme is that the overall approach to higher education should be significantly different for traditional versus non-traditional students. For traditional students, they are in "The College Years", a time of life when their main focus is on education, and they are fully immersed in those pursuits. This is a phase of life that that is cleanly delimited by the end of high school and the start of a career. It is expected to take four years, possibly five or six, but not much longer. When the student is finished, he moves on. For the non-traditional student who has other pursuits, the journey is not so well defined. It should be expected that he will take

more years to finish, but college pursuits will not fill up his entire day. Rather than having “College Years”, the student is likely to have “College Time”, or hours of days that are devoted to attending classes and studying. The degree is a far more distant goal. For the traditional student, getting to classes, studying, and preparing assignments should simply be a matter of getting around to them, but for the non-traditional student, more complicated logistics may be involved. Since this is a long-term pursuit, it is likely that the student will be more successful if going to class is part of a general routine, like going to work, going to lunch, or going to the gym, rather than as a mission to be accomplished. As such, factors in daily life that interfere with the routine are likely to cause trouble. A work schedule that changes from week to week or day to day, being “on call”, having frequent family emergencies, or an arduous commute are likely to make it inconvenient to get class and meet academic requirements, and may lead to dropout, even in students who are academically fit to pursue higher education.

Financial Variables

Research suggests that the reasons behind leaving are manifold. In a qualitative study by Gittell and Steffy (2000), two primary reasons that students gave for dropping out centered on financial, personal and family issues. Among the financially-oriented reasons that students gave for leaving were lack of funds, financial aid difficulties and the need to take a job. Among the personal reasons that were given was a sense of being overwhelmed with other responsibilities, such as family and work.

Tinto (1975) argues that a student’s commitment to the goal of completing an education plays an important role as well. If the student does not perceive the benefits of a college education, or sees other pursuits as more attractive, he may decide to discontinue his education in favor of pursuing those other goals. This argument may be extended to finances when we

consider that a student may perceive the immediate rewards of working to be more attractive than the increased income that will be earned following graduation.

Work, especially on a full-time basis, has generally been seen as having a deleterious effect on persistence. Ehrenberg & Sherman (1986) demonstrated that a student is more likely to drop out of college prior to completion when he works more than 20 hours off-campus. Interestingly, the same result did not hold for on-campus work in junior and senior years. Considering this evidence in conjunction with Tinto's (1993) notion that integration with the campus life is positively associated with persistence, it may be possible that work on campus neutralizes the negative effect of work due to the fact that the work is developing ties between the student and the campus, although not in the traditional academic or social sense. It might also be argued that the typical work-study student is more likely to be a traditional college student, who has few obligations other than school, whereas the student who works off-campus may not consider his role of student as primary. Another possibility is that the student works and studies in the same physical location and this may simplify the logistics of getting to and from work, school and home.

Bean and Metzner (1985) show that many studies agree that work is negatively related to persistence, but note that some studies indicate that this relationship is not as strong in community colleges as it is in four-year schools. Also, one study found that students who worked part-time were more likely to persist than students who were unemployed.

The usual argument is that students will tend to drop out of college because they cannot afford the tuition, but financial variables may play a more complex role in influencing persistence. Financial considerations are likely to be interrelated with age variables presented in the preceding section. One of the most notable influences of financial considerations on college

persistence is that that financial need engenders a necessity for employment, which will in turn compete for a student's time and attention. Financial need will be augmented by the presence of family and other responsibilities, but is not limited to them. Leppel (2005) argues that students' attitude toward financial success plays a dynamic role in the decision whether to remain in college or not. For example, a student may value financial success so highly that the student will be drawn away from college and into the working world in order to begin earning money. On the other hand, a student may recognize the more distal pecuniary rewards of a college education and choose to remain in college in order to maximize them. Further, Leppel argues, students may choose a major based on the eventual earning power of careers to which it leads, and irrespective of fit that the major has with the student's abilities or interests. Using logistic regression, Leppel (2005) found that the perceived importance of money was negatively related to student's decision to persist from the freshman to the sophomore year of a baccalaureate program. Students who did not persist either dropped out or changed schools.

Several financial variables have been posited as influencing a student's decision to drop out of college; these include a lack of financial resources (DesJardins, Ahlburg & McCall, 2002), and working (Paulsen & St. John, 2002). The more hours that working-class students spent on on-campus work/study jobs, the less likely they were to persist (Paulsen & St. John, 2002). Cabrera et al. (1993) found that financial attitudes had a weak effect on academic integration and an even weaker (yet statistically significant) effect on GPA, but they studied student's attitudes toward the various forms of financial assistance that they had received, rather than looking at a student's level of need, or amount or type of assistance received. Stratton et al. (2004) found that except in cases in which it was very low (less than \$20,000 per annum) household income did not have an effect on enrollment semester after semester. Students whose households had very

low income were more likely to drop out. These authors did find that the type of financial aid that was received was useful in predicting whether a student was likely to drop out, stop out, or remain continuously enrolled between 1989 and 1994. They found that work-study aid was associated with lower levels of dropout relative to stopout (leaving temporarily) and lower levels of dropout relative to remaining continuously enrolled. Further, they demonstrated that loan-based aid was associated with higher levels of dropout relative to remaining continuously enrolled, albeit not significantly. Aid in the form of grants was not significantly associated with any change in tendency to remain enrolled semester after semester. The authors note that students may be reacting to the fact that student loans may need to be repaid, and that students may be unwilling to shoulder this additional burden.

Ishitani and DesJardins (2002), using a national sample, found that increased financial aid was positively associated with persistence, and that this relationship's size and strength grew as the student progressed from the freshman through the senior year. This relationship was observed in a model that also included other variables; among them were parental education and family income. Chen and DesJardins (2010) found that financial aid in the form of grants and loans was positively associated with retention.

Institutional Characteristics and Retention

Tinto (1975) feels that students who voluntarily withdraw from an institution do so because they do not fit into the institution either academically or socially. He further claims that large institutions, by virtue of a large and diverse student body and faculty, may provide a student with a network within which socialization is more probable. On the other hand, a student in a large institution may find himself lost in an impersonal crowd.

Tinto (1993) proposes that college leaving may be due to an incongruity between the perceived needs of the student and his perception of what the institution is delivering. Tinto places this incongruence broadly within the “demands of the academic life” (p. 50). As a concrete example, would a lower ability student who elected to take difficult courses find the experience so daunting that he is turned off to college? Conversely, would a student who takes easy courses decide that college is a waste of time? One way to address this problem might be to use data on a student’s ability (for example, test scores and prior academic record) to match the student with courses that would challenge the student, but also allow for a high probability of success given sufficient engagement on the student’s part.

Studies ask what aspects of a college are more likely to influence student persistence. Braxton, Milem & Sullivan (2000) show that teaching style and student involvement in the classroom may improve persistence. Using path analysis and working within the rubric of Tinto’s theory, they show that class discussions and higher order thinking activities are positively correlated with social integration, which is in turn associated with improved intent to persist. Class discussions are also associated with institutional commitment, which is positively associated with intent to persist. They also found that examination questions that deal only with rote memorization are negatively related to institutional commitment as well as to intent to persist. Ishitani & DesJardins (2002) found that talking with an advisor was helpful in the senior year, but not in earlier years.

Strauss and Volkwein (2004) compared institutional commitment in both two year and four year institutions. They found that the variables that predict institutional commitment are largely the same for both types of colleges; among these were student satisfaction, sense of belonging, academic and social interaction, and positive classroom experiences. But they found

that classroom experience is more influential for two-year schools; whereas social integration was more influential in four-year schools. As Spanard (1990) notes, a reasonable hypothesis might be that students at community colleges are more interested in what they can learn rather than in a total experience, which is more closely associated with a four-year school.

A theory of an institution-individual fit was first described by Tinto (1975). In a later theoretical paper, utilizing the language of anthropology, Tinto (1988) describes the stages of a rite of passage as separation, transition and incorporation, a metaphor that he uses to describe a student's assimilation into the college setting. According to this paradigm, separation occurs when a student mentally and physically severs ties to his high school years, leaving friends, family and old ideas behind. Transition occurs when the student interacts with members of the new group, forging ties with new people and new ideas as well as new surroundings. Incorporation, the final stage, occurs when the student becomes a member of these new surroundings, identifying fully with them. Tinto sees dropout as a failure at one of these three stages: A failure to separate from old ways, a failure to establish new ties, or a failure to fully incorporate into the new setting. Tinto identifies dropout as a failure to successfully complete all of these stages, and thus casts persistence and dropout in a longitudinal framework.

Tinto (1993) posits that students may leave an institution because they are not sufficiently integrated into it. He further divides integration into social and academic spheres, and argues that both may need to be satisfied. For example, a student who is socially integrated may spend too much time on the social side which detracts from the academic side, and due to a lack of academic success, will consequently drop out. Alternatively, a student who is very academically integrated may not feel socially connected to the school, and this disconnect will eventually lead to a severance of ties to the school in spite of good grades.

The idea that greater social and academic involvement in college life was involved in persistence was evaluated by Mangold, Bean, Adams, Schwab and Lynch (2002). Mangold et al. showed that students who participate in a program which assigns them to the same classes and promotes social connections between them and their professors are more likely to persist from semester to semester. The study was initially planned as an experiment with the experimental group exposed to various social events and the control group merely given a similar schedule, but owing to circumstances beyond the control of the researchers, the groups were self-selected, and the study fell short of the criteria for an experiment. The authors argued persuasively that in spite of this self-selection the design could be considered successful since on its face the self-selected group should have fared less well in the area of persistence. This was because they had lower High School GPA and ACT Scores, as well as being younger than non-selected groups. On the other hand, since the students were self-selected, it might be the case that those students were interested in a greater amount of social interaction and that this was the operating effect. Not all studies have found that grouping students together is helpful. Potts, Schultz & Foust (2003-2004) found no evidence for learning communities promoting retention.

Tinto (1993) allows that the risk of leaving in community colleges may differ from that of residential colleges. A student who resides on campus needs to establish new ties to his new environment because the old ties have been thoroughly severed by the physical move to a campus, whereas a community college student has not found the need to rapidly sever the ties with his old surroundings. The transition may be easier, but the presence of old associations may prevent the student from establishing new ties in his new surroundings. Interestingly, Bean (1985) found that leaving school in order to be with old friends was strongly related to likelihood to drop out.

Tinto (1997) showed that community college students who are enrolled in a socially and academically integrated program may show improved persistence, as well as improved academic performance and a more positive outlook on the college experience in general. In a combined qualitative and quantitative assessment of the Coordinated Studies Program at Seattle Central Community College, students were enrolled in courses that centered on a general theme. The students were required to participate in cooperative learning communities and to participate in more student-to-student discussions. A logistic regression analysis demonstrated that participation in this program improved persistence even in the presence of other explanatory variables including GPA and hours of study.

It is useful to consider that the students who attend community college are likely doing so out of convenience or financial necessity. They are generally attending a college that is convenient to where they have established their lives (or simply where they were raised), and for many, especially those who have families or jobs, school is an adjunct rather than a main focus. Paulsen and St. John (2002) note that while “most theories on student outcomes assume geographic, social and economic mobility and opportunity” (p.192), in reality, the broader group do not share these advantages, rather they have far fewer choices. This consideration may serve to render Tinto’s argument regarding ties to be somewhat superfluous since the students are not seeking to be immersed in college life, but rather to view it as a commodity that will enhance their future prospects within a sphere that they have already established.

Pascarella, Duby, & Iverson (1983) found that the academic integration aspect of Tinto’s (1975) model worked quite well for commuter institutions, but that social integration had the opposite effect in that students who were socially integrated were more likely to leave the institution. The authors felt that one possible explanation for this is that such students might still

seek out the greater social interaction than is available at a commuter institution, and therefore transfer to a more traditional residential institution. Johnson (1997) found that interaction with faculty and staff may be important in determining whether students are retained or not; she found that retained students rated their interaction with faculty somewhat higher than non-retained students. Interestingly, Johnson (1997) did not find that social interaction was important to students at a commuter institution. This would fall into line with the notion of students who consider their college courses to be an adjunctive as opposed to a central focus of their lives.

Tinto (2006) has proposed that at commuter colleges, student-faculty interaction in the classroom may be the primary way that students integrate into campus life. If this is the case, this interaction will be dependent on class size due to the fact that students in larger classes have less time for interaction with faculty. Consider a student in a 3-hour course with ninety other students. On a weekly basis, the average student can expect at most 2 minutes of interaction with the faculty. In contrast, a student who is in a class of thirty can expect 6 minutes of interaction, three times that amount. A student in a class with 15 students could expect 12 minutes of interaction. Leaving aside the fact for a moment that a professor would spend a good deal of time addressing the class as whole rather than one student in particular, it is easy to see that as class sizes increase, the student can expect a lot less attention from faculty and fail to develop a meaningful relationship that would anchor the student to the college. It could be argued that some students will engage the faculty more, but this simply means that there will be less time for everyone else.

External Factors

Tinto (1975) allowed that urban institutions may not be subject to the same influences of socialization as are the more traditional institutions that are situated in rural or suburban areas.

Students attending urban schools typically do not live on campus, and may in fact live a significant distance from the campus, and are thus not as likely to be as integrated into the social life of the campus as students at the traditional rural college. It is also worth considering that urban institutions, by virtue of their proximity to business districts, may be catering to a larger percentage of non-traditional students who are interested in improving their careers by taking a few courses after, or perhaps in conjunction with their jobs.

Commuter student attrition was studied by Bean & Metzner (1985). The external environment may play a role in separating non-traditional students from college. These authors stated that the external environment would serve as a “rich source of variables for predicting attrition” (pg. 492).

Research that focuses on persistence in the traditional college student, characterized by an individual in his late teens or early twenties and living on campus, may not provide satisfactory explanation for the nontraditional student who may have to spend a substantial amount of time in non-scholastic pursuits. For students who hold a job, have a family, or are engaged in other activities, college may be a side pursuit that must be accommodated, and it can be argued, accommodation of school into an individual’s schedule may be a key to improving persistence among such non-traditional students. For these students, picking a class schedule that will accommodate work and family life may prove to be of importance. For example, a student who holds a job that ends at five p.m. would be ill-advised to take a course at 5:30 pm, if the expected travel time between work and school is less than a few minutes. This is considering that delays are unavoidable, and frequent tardiness would undoubtedly lead to lower grades, ill-feeling between professor and student, and a general climate of being rushed. Similarly, a student with children or other dependents might find it difficult to attend class if

accommodations for childcare cannot be guaranteed when classes meet. Whereas the usual criteria for choosing a class for a traditional student might be level of interest, scheduling conflict with other classes, level of preparation (prerequisites, ability, etc.); for the nontraditional college student, we may need to add the scheduling conflicts associated with the larger realm of work and family.

Bean (1985) found that environmental influences such as outside friends were more likely to affect freshmen dropout symptoms than students at higher levels. This is therefore consistent with Tinto (1988) who declared that these influences were more important in the early part of the process. Further, Bean (1985) showed that institutional commitment is especially important during the sophomore year and somewhat less so during the freshman and junior years, this being roughly aligned with Tinto's notion of Transition.

Consistent with the notion that factors external to the campus may play a significant role in persistence, Cabrera, Nora & Castañeda (1993) note that Bean's model includes external factors that are ignored by Tinto's model. Using structural equations, they demonstrate that external influences, most notably encouragement from family and friends, affect intent to persist through the separate factors of institutional commitment and goal commitment. Intent to persist, in turn, affects persistence itself.

Spanard (1990) focuses largely on older and non-traditional student's decisions to enter or re-enter higher education, and explores paradigms that may explain these decisions. Spanard notes a push-pull mechanism that may be operating, much of it dependent on forces that are external to both the student and the educational system, such as competing responsibilities of family, finances and work. This outlook could also be applied to a student's decision to leave

higher education, for example, a student faced with a growing family, or the possibility of a high-paying job that does not require a college degree.

Stratton, O'Toole & Wetzel (2007), using the Beginning Post-Secondary Survey (BPSS) evaluated the effect of travel distance between the institution and the student's home, and found that part-time students who lived more than 100 miles from the campus were more likely to persist than students who lived closer. Unfortunately, the data only specified whether students lived within 10 miles or further than 100 miles of the campus.

Time-Variant Predictors

Tinto (1993) emphasizes the importance of the temporal nature of the dropout process. Time is an important factor in leaving college that is often ignored, possibly because studies that look at this dimension must either be longitudinal or depend solely on archival data. Tinto notes that most leaving takes place in the early years, and attributes much of this to low levels of integration into college life. Ishitani & DesJardins (2002) studied the effects of demographic, social, academic, financial and institutional variables over time in the likelihood to drop out. Of particular interest was their finding that a low GPA does not predict dropout in the same degree over time. They found that successively lower GPA's are indeed associated with higher risk for dropout in the first and second year of school, but this relationship degrades in year 3 and is non-significant in year 4.

Another time-dependent variable that Bean and Metzner (1985) mention is part-time vs. full-time status, which is subject to change from semester to semester. Most of the studies that they cite demonstrated that part-time students were more likely to drop out.

Similar to precollege variables are academic record variables, with the notable exception that these change over time. In this model, the previous semester's GPA would be used to

predict likelihood of returning in a given term. Both cumulative GPA and semester GPA are being considered because one may temper the other, for example a student with a poor semester GPA might be buoyed up by a respectable cumulative GPA. It is suggested that a very low GPA would be associated with leaving, perhaps because the student has become doubtful of his ability, but a student with a high GPA might become encouraged to pursue academic work at a four-year college.

Finally, other factors may have an influence. Consider Stratton et al. (2007) who found that full-time students were less prone to attrition when the student initially enrolled in the fall term; this may reflect more about the student than anything else since the traditional beginning of the academic year is in the fall. External circumstances that vary with time may also play a role. Stratton et al. (2007) also found that full-time students were less prone to attrition when the prevailing local unemployment rate was low.

Destinations after Leaving

Where do students go when they leave? Karp and Logue (2002) showed that students have several destinations. Of a group of students who voluntarily left Clarion University, 57 percent left to attend another post-secondary institution. Fralick (1993) found that 15 percent of community college students left to pursue study elsewhere. Borglum & Kubala (2000) found that 81% of community college students planned to transfer, and 61% were planning to earn a baccalaureate. This is an important consideration regarding retention research that is often ignored. In many cases, students do not leave academia altogether, they may simply transfer to another college. This may not be favorable to the institution, but it cannot be seen in the same light as dropout. In many of the studies reviewed, there was no consideration for transfer, likely because the information was not available. However, considering that many students enter

community colleges with the intention of transferring without taking a degree, and further that there may be systematic differences between such students and those who plan to obtain a degree from that college, it is important to distinguish between the two types of leaving. Consider, for example, a good student who plans to go to a four year school, but wants to earn a few credits at a community college close to home for financial reasons, whereas an academically poorer student may simply attend the local community college because it was the only school to which he was admitted. The latter case may well leave the community college after a year, whereas the former may remain enrolled. In this case, prediction using such variables as GPA may be confused due to insufficient information in the dependent variable. In this instance, if we only know that the student has left, and have no information as to whether the student has transferred to another institution or simply dropped out of higher education altogether, we may not appreciate the predictive power of GPA because we have combined two very different outcomes into one apparent outcome.

Fortunately, it is currently possible to track whether and where students have enrolled as transfer students. Few studies have attempted to this, but a few including Porter (2000) and Jones-White et al. (2010) have done so.

The Current Study: Use of Institutional Data to Predict Risk of leaving

Research over the past thirty years has sought to determine characteristics of students as well as schools that may lead to dropout. Tinto (1975, 1982, 1988, 1997) has focused on the social integration of students into college life, and has advised colleges to set up programs that encourage socialization. Other researchers have sought to determine how personal attributes such as age, gender, and ethnicity are correlated with persistence, while still others look to family history, academic ability and financial resources. The current study will focus on the aspects of

Tinto's theory as well as that of other researchers that can be measured using institutional data that colleges have available to them. It is hoped that this information could provide college officials such as advisors or professors with understanding of the antecedents of departure. The discussion will begin with how aspects of Tinto's theory may be measured using institutional data. Much of Tinto's theory appears to be focused on the traditional college student who is studying full-time and either lives on campus or in college affiliated housing such as fraternities or sororities, or with other students in off-campus housing. This would argue that for community college students, who are either living with their parents or independently, the model ought to be expanded to include by external circumstances that are not central to Tinto's theory. This is done here under the rubric of "external influences". Following this, rationale behind a focus on community will be discussed and the community college system of New York City will be briefly described. Finally, since few studies have addressed non-graduation transfer, this will be done here.

Tinto's theory (1993) predicts that students will remain in college as a function of the pre-entry attributes that they possess before enrolling, the goals that they have for college, the experience that they have within the college setting, and to a lesser extent, external forces. Tinto's theory, however, places the greatest emphasis on the experiences and integration of the student in the immediate college setting, and much less on personal attributes or external events and circumstances. This places the onus of retention firmly in the hands of the institution. Tinto contends that institutions often emphasize the role of the student and de-emphasize their own role in student retention. The current study seeks to use institutional data to address hypotheses suggested by Tinto's (1993) model as well as others. Clearly, because many of his constructs

involve mental phenomena that cannot be observed directly, not all aspects of his theory can be addressed, but many parts may be observed indirectly or inferred.

Tinto's (1993) theory involves the following constructs arranged longitudinally:

1. Pre-Entry Attributes
2. Goals and Commitments
3. Institutional Experiences
4. Integration
5. Outcome

The model is recursive with respect to 2, 3 and 4. We will first discuss how the current study can address these constructs. We will later discuss external influences that are not explicitly present in Tinto's model.

Pre-Entry Attributes

Students enter with a number of indicators of their academic abilities which should provide some indication of future academic performance. These include high school GPA and test scores such as COMPASS tests, New York State Regents Scores and SAT scores. At entry, these variables exert direct influence over which kind of classes a student may take (discussed below), and are at least nominally indicative of the student's fitness for college-level work.

Goals and Commitments

Although we are not able to directly ask students about their goals, we can infer them to a degree using information that the colleges have on hand. One such indicator includes the type of degree that the student is pursuing; if the student is pursuing an applied degree, then the student expects to learn a skill that he would be unlikely to learn at a four-year college. We would

expect this student to be less likely transfer to a four-year school than a student who is pursuing a liberal arts or science degree.

Another indicator of a student's goals (and likely commitments) is whether or not the student initially applied to the school or was allocated to it. Students who apply to the City University of New York are permitted to list up to 6 colleges. Those who are not accepted into one of the senior colleges are offered admission to a community college. In the case of a student who did not apply to the community college that he is attending, we might infer that the student aspires to bachelor's degree, and is therefore likely to transfer to a senior college later on.

College Performance

Students often enter college unprepared for the work that awaits them. Tinto (1993) suggests that colleges address this issue by offering remedial courses that will teach students the skills that are needed for college-level work. This action addresses the requirement that students learn, but since remedial courses do not represent college level work, they do not carry credit, and therefore do not directly address the student's goal of becoming credentialed. Stated simply, the student who finds himself in college, but lacking the requisite skills to pursue college level work, may find himself performing a great deal of remedial work. From the student's perspective, he is spending time in class, investing money in tuition and fees, but has no tangible evidence that he is getting any closer to his goal of a college degree. Moreover, because he is taking non-credit courses, he may not qualify for certain types of financial aid. Ishitani (2006) notes that remedial work will necessarily delay graduation; Zeidenberg, Jenkins & Calcagno (2007) showed that taking remedial courses is negatively associated with completion. This research will address whether remedial work is associated with an increased risk of leaving the

higher education system, and if so, whether taking for-credit courses alongside remedial courses moderates this risk.

Another aspect of institutional experiences in Tinto's Model is academic performance. Clearly, the indicator for this would be the grades and credits that the student receives for the classes that she takes. For the current study it is proposed that academic performance be accounted for in several different ways:

1. Credits earned – This accounts for the student's progress toward her goals
2. GPA – This accounts for the student's success
3. Failed Credits- This accounts for student's lack of success
4. Withdrawal Credits – These occur when a student is removed from the class roster, usually at his request. In doing this, the student surrenders any tuition that he has paid for the course, and the course grade is not included in his GPA. Officially, a withdrawal is an indication by the student that he misunderstood the nature of the course, the material that would be covered, or his own ability to handle the content. As such, a withdrawal may be viewed as an indication of a lack of preparation, interest or judgment. Functionally, a withdrawal may simply be a means for the student to exit a class that he believes may negatively impact his GPA should he persist any further. In one sense, withdrawing from a course is a lesser form of institutional withdrawal. This research aims to determine whether it also serves as a prelude to it.

It is expected that the relationship between GPA and the probability of leaving will not be strictly monotonic. While we may expect that students with low GPA's, many failed credits or

withdrawals will be more likely to leave, we may also expect that high GPA's, especially in the presence of 4-year aspirations, will be more likely to transfer.

Integration

Tinto's theory (1993) predicts that students who are not sufficiently integrated into the college socially or academically are at higher risk for leaving. In order for integration to occur, meaningful interaction between the student and other students or between the student and faculty or staff must occur. Unfortunately, for many community colleges, part-time study tends to be the norm. One possible problem with part time study is that students may not even have the opportunity to interact because their time on campus is short. Consider for example a student who attends one class per day. Such a schedule might be likely for part time students who are working and wish to avoid the fatigue of multiple classes. This student arrives on campus, attends class, and is likely to depart for home as soon as the class is dismissed. This student has no real reason to remain on the campus and perhaps several very good reasons to depart, and there is no opportunity to make other students' acquaintance. On the other hand, if the student has at least a short break between two classes, there is at least some free time on campus in which to develop some sort of relationship with other students or faculty there. The current study looks at student's schedules to see if there is any relationship between interclass time on campus and retention.

Another issue addressed by Tinto (1993) regarding student integration is class size. Clearly, the larger a class is, the less time any individual has to participate in an active manner. If professors are to cover material, they must resort increasingly to lecture over class discussion with larger class sizes. This necessarily puts a limit on faculty-student interaction and well as student-student interaction. Further, it is likely that many meaningful discussions that take place

outside of the classroom actually originated in the classroom. If they cannot begin in class in the first place, it might be a long time before they begin, if ever. This study addresses the question of whether there is a relationship between class size and retention.

External Variables and Support

Other variables that will be examined fall somewhat outside of Tinto's model, because they encompass the external environment outside of the institution. These include the time that a student spends traveling to get to the campus and the composition of the financial aid package that the student receives. Tinto (1993) tends to disregard financial aid, arguing that if students really want to go to college, there are means of doing so, including student loans, that the student may utilize. He argues that students who cite financial difficulty as the reason for leaving are using this as a rationalization for a decision that has been made already. Other researchers have demonstrated that financial aid is helpful (Ishitani and DesJardins, 2002). Among other things, it is probably useful to consider relative cost. It is well known that private colleges charge tuition rates that are considerably higher than state colleges, and community colleges are usually seen as low-cost alternatives. This study will address whether financial aid in the form of loans and grants is associated with community college retention.

Original Research Questions

The following questions have not been addressed by the literature thus far, and are examined by the current study:

1. Is the travel time between the student's home and the campus related to a student's likelihood to be retained in the following semester?
2. Is the student's schedule related to retention, specifically in terms of:
 - A. Number of classes taken per week (credit load)

- B. Number of days per week that the student is scheduled to attend classes (more days meaning a more arduous commuting schedule, and more time spent in transit per credit hour)
- C. Number of hours on campus between classes (this might speak to social integration on campus as addressed by Tinto (1975) or simply to an availability of free time on campus for study or research)
- D. Is the student-faculty ratio, as experienced by the student, related to her decision to depart? This addresses the question concerning whether students have enough opportunity to interact with one another or with faculty.

A list of variable classes and variables is presented in the method section.

Community College Focus

The present study attempts to develop a model for student attrition at the six community colleges of the City University of New York. The reasoning behind focusing on community colleges is as follows:

1. Community colleges are thought to attract a student base that that is less well prepared for college work, and so may better represent the population of interest – individuals who might in former times have been less inclined to pursue higher education.
2. Students may be choosing community colleges due to their lower cost, and thus are likely to come from economically disadvantaged families.
3. Students who decide to attend community colleges are likely making the decision to attend based on the school's proximity to home rather than on the a particular course of study.

4. One-year retention rates for students in associate programs is considerably lower (66.9% in 2005) than in baccalaureate programs (83.3% in 2005) (City University of New York, 2007).

Community Colleges in New York City and Student Proximity

Every borough of New York City except Staten Island has at least one community college; Staten Island (the least populous) has a comprehensive college that offers both associate and baccalaureate degrees. Within the four boroughs of New York City that have community colleges, a student would be able to find a school that is within nine miles of his home, and no student residing in New York City is more than 25 miles away from any CUNY community college. This proximity would appear to make getting to class a simple matter, except when one considers that New York City has an uncommonly congested road system and limited parking options, and that many residents do not own an automobile. Ameliorating this problem somewhat is New York City's excellent public transit system, including a subway system that is relatively inexpensive, but not all of the colleges are located in close proximity to a subway station, and for those colleges, a student who does not own a car and does not live within walking distance of the school would need to make use of the bus system. Further, some students in Queens and Brooklyn do not live within walking distance of a subway station, and there are no subway lines in Staten Island.

Transfer

Finally, for community college students, non-graduation transfer may be seen as an acceptable outcome. As of 2008, a survey by the City University of New York indicated that about one-third of community college students planned to transfer to another college (City University of New York, 2008). This study will address the question of non-graduation transfer

to CUNY colleges using the CUNY data and external transfer using data obtained from the National Student Loan Clearinghouse (NSLC).

Chapter Three: Method

Subjects

The original dataset consisted of 23,846 students who matriculated as first-time freshmen in fall 2004 and fall 2005 at one of the six community colleges of the City University of New York. A little less than ten percent needed to be excluded for methodological reasons, missing data or practical concerns. These reasons are presented in Table 1.

Table 1. Original Sample and Exclusions

	2004		Cohort 2005		Total	
	N	%	N	%	N	%
Original Cohort Size	11,978	100	11,868	100	23,846	100
Cumulative Exclusions					0	
Not pursuing an Associate Degree*	231	1.9	259	2.2	490	2.1
Missing Transit Travel Time Outside of New York City and Adjacent Suburbs**	342	2.9	291	2.5	633	2.7
Missing Class Schedule	103	0.9	105	0.9	208	0.9
Age not between 17 and 50	318	2.7	287	2.4	605	2.5
Matriculated at more than One College	92	0.8	92	0.8	184	0.8
Total Exclusions	0	0.0	2†	0.0	2	0.0
Usable Cases	1,086	9.1	1,036	8.7	2,122	8.9
	10,892	90.9	10,832	91.3	21,724	91.1

*Nondegree; or pursuing a certificate or combined Associate/Baccalaureate.

**Adjacent suburbs include Westchester and Nassau Counties, New York

†One student represented twice

About two percent of the students in each of the cohorts were not pursuing an associate degree. These students were variously enrolled in a certificate program, registered as non-degree students, or enrolled in a baccalaureate program than included an en route associate degree. Of those who were pursuing an associate degree, an additional 2.7 percent had addresses that could

not be located. Of those remaining, about one percent of the incoming class gave addresses that were located outside of New York City and its adjacent suburban counties. Since community colleges are primarily intended to serve the local area, students who did not live in one of the five boroughs of New York City or the adjacent suburbs of Westchester county or Nassau county were excluded. An additional 2.5 percent of students had at least one class whose schedule was missing while they were enrolled. Since the number of days per week that the student is required to be on campus is an important predictor in this study, these students were excluded as well. Students whose birthdate indicated an age of less than 17 years or more than 50 were excluded as well; these comprised less than one percent of the remaining cases. Finally, one student was found to be simultaneously enrolled as a first-time freshman in two separate schools (counted as two students); this student's records were removed.

Data: Source

Data for this study consisted of archival information from student's college and precollege record at CUNY. The bulk of the data are maintained by the CUNY Central Office of Institutional Research and Assessment. These data consisted of information from the College Application System (CAS) which includes high school GPA, SAT verbal and math scores, and whether the student is a high school graduate or holds a GED. Also included in this file are the other colleges in the CUNY system to which the student applied. College record data such as courses taken and grades received in a semester are maintained in the Central Office Institutional Research Database (IRDB). The student's age, demographic information and place of residence is maintained in this database as well. Financial aid application and award data are also maintained by the Central Office. The time and location of courses were gathered from the CUNY Administrative Data Warehouse (ADW). Subsequent enrollment (transfer) data for

students who enroll elsewhere in the CUNY system were similarly drawn from the IRDB; for students who enroll elsewhere, data were gathered via a student tracker request to the National Student Loan Clearinghouse (NSLC). Data on travel time between the student's home and college was calculated using an application developed by the author which utilized HopStop.com, a website that gives directions and travel time using public transportation. The application entered location information regarding the student's home and college or colleges attended (many students attended classes at multiple CUNY colleges). The website allows a user to consider all public transportation options including subways, buses and light rail.

Dependent Variable

The current study models 5 types of leaving:

1. (GRADUATE) the student leaves the institution having obtained a degree. The student is registered for all semesters from entry to graduation.
2. (IMMEDIATE TRANSFER) The student leaves this institution but is registered at another institution within the scope of the next semester following departure. For fall terms, this means that the student is registered the following spring semester at another CUNY college or at college outside of CUNY between January and June. For spring terms, this means that the student that the student is enrolled at another CUNY college the following fall, or at an outside college between July and December.
3. (DELAYED TRANSFER). The student leaves the college for another institution, but does not appear at the new school until one semester has passed. For example, a student last attends in fall 2006, skips spring 2007, and is registered at another institution in fall 2007.

4. (STOPOUT). The student is absent from the college for one semester without attending anywhere else, and then reappears at the original college one year later.
5. (DROPOUT) The student is not enrolled in any college for two or more semesters.

The reference category is continued enrollment in the immediately following semester.

Predictor Variables

The study made use of the data that the college collects and maintains for all students, and did not require any additional information from the student. The model seeks to identify which students are at highest risk for dropping out, as well as the variables that place them at risk. The purpose of this research is to identify, estimate and test these parameters. Based on prior research, it is hypothesized that the following variables and variable types may be useful in predicting retention:

Time-Related

1. Academic Year or Semester
2. Spring (reference category is fall)
3. Winter Term registration
4. Summer term registration
5. Age

Demographics

6. Gender
7. Race/Ethnicity
8. International Student (reference category is resident)
9. Financial Independence
10. Marital Status

Precollege Record

11. SAT Score
12. High School GPA
13. Regents Score
14. High School Type
15. Applied to Community College
16. Senior College Rank Choice
17. Pursuing Applied Degree

College Performance

18. Attempted Credits
19. Earned Credits
20. Cumulative Earned Credits
21. Intersession Credits
22. Remedial Hours
23. Compensatory Hours
24. Course Withdrawals
25. Course failures
26. Semester GPA
27. Cumulative GPA
28. Math proficient
29. Writing Proficient

Environment and Support

30. Total hours in class per week

31. Total hours on campus per week
32. Individual student/faculty ratio (an explanation and formula for this is presented in Appendix B)
33. Student has a financial aid record
34. Grant Amount
35. Loan Amount
36. Weekly Travel Time (a detailed explanation of how this was obtained is provided in Appendix C)

Re-entry Models

37. Missed Semesters
38. Number of re-entries since matriculation

Based on prior research, it was further hypothesized that the predictive value of these variables may be modulated depending upon time. This basic premise of the model is to utilize as many of the variables as are available at a given point in a student's career. There are a number of variables that might be useful, but are not available for all students. Examples of such variables would be student's commitment to higher education, parent's educational achievement, and student attachment to the college. The utility of this approach lies in using the data that do exist to address aspects of the theoretical model. In this way, we can gain a sense of the extent to which the observed data address college leaving, and how much of the variance it left unaccounted for. Also, it is hoped that that this could lead to policy implications for improving retention.

The ultimate goal is to be able to develop a “risk score” for each student that will probabilistically define the likelihood of dropout for a student at a given point in time, as well as individual scores on each variable that place the student at risk. Eventually, such scores could be used to identify a subset of students who are at high risk for dropping out. Although not part of the current study, one of the practical uses of this research would be that students who are at risk could be contacted and preventive measures could be taken. As an example, if it were determined that a lack of financial aid placed a student at risk, then the financial aid department might be able to contact the student and help him or her identify and apply for other sources of funding. The utility of this method would be that university would be able to proactively contact students who are at risk, without the burden of contacting, and possibly inconveniencing students who are not at risk. This would carry financial benefits for the university in the form of additional tuition dollars and prestige benefits from higher retention rate, and ultimately, a higher graduation rate.

Statistical Model

The current study employs Event History Modeling, known also as Survival Analysis, the name deriving from its development in the medical field, where it was used to predict how long a participant in a medical study would survive following a the procedure that was being developed. The dependent variable in Event History Analysis may be measured continuously or discretely. Since college attendance falls neatly into semesters, measuring the dependent variable discretely makes intuitive sense. This analysis requires the construction of a person-period dataset, with each observation consisting of a student in a semester. In this analysis, students will be tracked for as long as they remain continuously enrolled in the regular fall and spring semesters.

A given probability that a student will leave is referred to as hazard. Probabilities can be troublesome due to the bounded nature of the statistic: they must fall between 0 and 1. Since models may provide estimates that fall outside of this interval, probabilities can be transformed into an odds, which re-expresses a probability as the ratio between a probability that an event will occur and the probability that it will not:

$$\text{ODDS} = p/(1-p)$$

As Singer & Willet (2003) note, odds are bounded by 0 and infinity. By taking the natural logarithm of the odds, the statistic may take on any real value and thus avoid problematic values:

$$\ln(\text{ODDS}) = \text{logit } h(t_{ij})$$

This transformed logit hazard, $\text{logit } h(t_{ij})$ is defined as the logit hazard that a student i will leave in semester j .

In the case of more than two outcomes, the odds is ratio of the probability of the outcome of interest ($p_1 \dots p_k$) to the reference category (p_0).

The fact that students may leave an institution in more than one way gives rise to the term “competing risks” (Singer & Willet, 2003), that is that the various means of leaving compete with one another to end a student’s career (at a given college, at least). Multinomial logistic regression deals with this by modeling the odds of a particular outcome versus some reference category; in this case, the reference category would be continued enrollment. This occasions the need for an equation for each alternate outcome: For example, if we are trying to differentiate between remaining continuously enrolled versus leaving altogether or transferring we need two equations, one to model leaving versus continuous enrollment, and another to model transferring versus continued enrollment.

The following equation takes into account the various forms of leaving by including the k subscript:

$$\ln(\text{ODDS}) = \text{logit } h(t_{ijk})$$

This transformed logit hazard, $\text{logit } h(t_{ijk})$ is defined as the logit hazard that a student i will leave in semester j in manner k (i.e. graduate, transfer, stopout, etc.).

The first model to be defined uses only time as a predictor:

$$\text{logit } h(t_{ijk}) = \alpha_{k1}S_1 + \alpha_{k2}S_2 + \alpha_{k3}D_3 + \dots + \alpha_{kj}S_j$$

Where S_1 is a dummy variable for the first semester, S_2 is a dummy variable for the second semester, and so on.

The following model also uses time as a predictor, but rather than associating each time period with a particular hazard of leaving, the model predicts that the hazard of leaving will change as an increasing or decreasing function of time:

$$\text{logit } h(t_{ijk}) = \alpha_{k0} + \alpha_{k1}(\text{SEM}-C)$$

SEM here refers to the semester; α_{k0} refers to the value of (SEM-C) at 0. α_{k1} is the linear growth coefficient; C is a centering constant. It is needed to give meaning to the α_0 term, which is defined as the logit hazard rate in semester 0. Because there is no semester 0, α_{k0} would have no meaning. By setting C to 1, the first semester becomes the zeroth semester, and α_{k0} can be interpreted as the log odds corresponding to the probability of leaving after the first semester. This model will never provide a better fit than the general model, but it is simpler and makes a more general statement about the pattern of leaving.

Intuitively, we can see that the model with a linear function of time is simpler because it involves using fewer variables. Note however, that all of the information that is present in the general model is present in the linear model as well and vice versa: There is sufficient

information in both datasets to create one from the other. The setup of the data is merely a means of arranging the data so that SPSS will be able to perform the appropriate analysis. Again, the linear model will never provide a better fit than the general model, but it may be possible to adequately and more parsimoniously fit the data with the simple linear model. Methods for addressing how well each model accounts for the data will be discussed below.

It is also possible that the hazard of leaving will initially grow and then decline (or decline and then grow). Such a pattern may be modeled by adding a quadratic term to the linear model:

$$\text{logit } h(t_{ijk}) = \alpha_{k0} + \alpha_{k1}(\text{SEM-C}) + \alpha_{k2}(\text{SEM-C})^2$$

The added quadratic term allows us to determine whether and where the inflection point (the bend) in the hazard function occurs. The quadratic model will always fit better than the linear model, but it is more complex. A statistical test will need to be performed to test whether the additional term improves the fit enough to justify the loss of parsimony associated with the simpler model.

It is also possible that a the hazard of leaving will have two inflection points; in order to model this relationship, we add a cubic term, $\alpha_3(\text{SEM-C})^3$:

$$\text{logit } h(t_{ijk}) = \alpha_{k0} + \alpha_{k1}(\text{SEM-C}) + \alpha_{k2}(\text{SEM-C})^2 + \alpha_{k3}(\text{SEM-C})^3$$

The addition of the cubic term allows us to test whether a second bend in the function occurs, and to determine its placement. In fact, we may add as many higher order terms to the model, up until the number of semesters less 2 (the total number of bends that are possible). The models may be written succinctly as:

$$\text{logit } h(t_{ijk}) = \sum_{m=0}^M \alpha_{km}(\text{SEM-C})^m$$

Where M is the total number of possible higher order terms.

At this point, only time-related variables have been included in the model. The model will now be expanded to include other predictors as well. Predictors may be either time-variant, meaning that the value of the variable is subject to change, or time-invariant, meaning that the variable is not subject to change. An example of a time-variant variable is the student's semester GPA, which will fluctuate from term to term. An example of a time-invariant variable is the student's High School GPA, which is established before the student matriculates in college and does not change throughout the student's college career. Variables may either be discrete or continuous. An example of a discrete variable is gender; GPA would be an example of a continuous variable.

Following the notation of Singer and Willett (2003), we use the β coefficient for predictors that do not relate to time. Variables, whether time-variant or time-invariant, may be introduced to the model as a single vector. One predictor that is investigated in the current study is high school grade point average, which would be represented as follows:

$$\text{logit } h(t_{ijk}) = \underline{\alpha}_k + \beta_{k1}\text{HS}$$

In the interest of space, and to avoid distraction, all of the alpha terms have been replaced by $\underline{\alpha}_k$. Here, HS represents the student's high school grade point average and β_{k1} is the corresponding regression coefficient. In this example, $\underline{\alpha}_k$ represents the general model for time. High school GPA is time-invariant; its value does not change over time for a given student. One

reasonable hypothesis might be that high school GPA is a good index of academic aptitude, and that students with low high school GPAs may find college work overly challenging and be at greater risk for leaving. Expressing the model in this manner makes a very important assumption: That the relationship between the predictor and the criterion is also time-invariant. One very compelling reason to call this assumption into question is that this relationship may in fact vary with time. It is not difficult to imagine that a student's high school GPA may be predictive of retention in the early semesters, but may be less so in later semesters. The model as stated above cannot test this assumption because there is no interaction with time. The assumption is that a student with a low high school GPA is at the same level of risk for leaving in the third semester (holding all other predictors constant) as he is in the first semester. One means of testing whether a predictor has a differential relationship (interaction) with time is to model the predictor in each separate time period:

$$\text{logit } h(t_{ijk}) = \underline{\alpha}_k + \beta_{k1}\text{HS}(S_1) + \beta_{k2}\text{HS}(S_2) + \beta_{k3}\text{HS}(S_3) + \dots + \beta_{kj}\text{HS}(S_j)$$

Here, the high school GPA is modeled for each semester separately, and each semester has its own associated beta weight. This is a general model for time and high school GPA. The model presented above clearly resembles the general model for time. Like that model, we can test simpler models that test for more general relationships, like the linear model:

$$\text{logit } h(t_{ijk}) = \underline{\alpha}_k + \beta_{k0} + \beta_{k1}\text{HS}(\text{SEM})$$

As in the model for time, quadratic, cubic, quintic and other higher-order relationships may be modeled as well. These can be succinctly expressed using the following equation:

$$\text{logit } h(t_{ijk}) = \underline{\alpha}_k + \sum_{m=0}^M \beta_{km}(\text{SEM})^m$$

Where M is the desired higher-order value.

Time-variant variables are treated in the same manner as time-invariant variables, the only difference being that these variables are subject to change from semester to semester. They may be modeled as single predictors, but as such their relationship with the criterion is assumed to be invariant relative to time.

Assessing Model Fit

The research has two phases, model identification and model testing. In Phase 1, model identification, variables for a single cohort of students would be entered into a multinomial logistic regression model and tested for fit. The final model would consist of the variables that are useful in predicting attrition and their associated beta weights. In Phase 2, model testing, the beta weights derived in Phase 1 would be used to predict which students in another cohort would leave (in the three ways discussed above) given the values for those students on the identified variables. This would allow for an assessment of the model's predictive utility.

Demaris (1992) and Singer & Willet (2003) present a number of statistical tests for assessing model fit. These make use of the log-likelihood statistic (LL) that is available from SPSS. A model's fit can be assessed by comparing its LL to a nested model's LL. For example, a model that contains a predictor such as high school GPA and semester may be compared with a model that contains only semester (time) as a predictor. The Deviance statistic given by

$$-2(LL_{\text{model1}} - LL_{\text{model2}})$$

Has a χ^2 distribution with $(I-1)(D-1)$ degrees of freedom where

I is the number of independent variables

And D is the number of levels of the dependent variable (including the reference category).

Non-nested models, in which the independent variables in the model do not form a subset of the other, the preceding statistic may not be used. In the case of non-nested models, the above test is not tenable, and the AIC (Akaike Information Criterion) or the BIC (Bayesian Information Criterion), which are penalized versions of the $-2LL$, may be used to compare models. As an example, a model that uses only high school GPA as a predictor may not be compared with a model that uses only SAT as a predictor using the $-2LL$ deviance statistic because these models are disjoint. These models could be compared using the AIC or BIC.

The forgoing tests constitute an overall test of model fit, and indicate that at least one of the predictor variables is significant. In this respect, it is analogous to the F-test in linear regression. Following an omnibus test, each predictor of variable in the model may be assessed as well.

Since the beta weights are expressed as log odds, a positive value would indicate an increased risk for a particular form of leaving relative to remaining enrolled; a negative beta weight is associated with a decreased risk for remaining enrolled. The log odds may be exponentiated to transform them into the more intuitive odds ratio, in which case values greater than unity express an increased likelihood of the alternative outcome (leaving) and values less than unity express a decreased likelihood of leaving given larger values of the predictor.

Analysis Plan

Three models of leaving were explored in two phases. Phase I involves using all of the data to generate an overall analysis of model fit and to generate parameter estimates for all of the predictors. Phase II generated model parameters using only data from the 2004 cohort and then applied those parameters to the data from the 2005 cohort to assess the predictive validity of the model. The three models will be explained below:

Model I: Long and Short Term Outcomes: Graduation, Transfer, Stopout and Dropout

Since data collection covered the period from fall 2004 through spring 2011 and involved analysis of semester-level predictors for ten semesters, it is possible to specify an outcome model that includes semester outcomes that will cover two terms. This makes it possible to test whether the model will be useful in differentiating 1-term stopout and 1-term delayed transfer from longer-term absence. This is because the 2005 cohort's last observed semester (the tenth) is spring 2010. For students who are continuously enrolled through spring 2010, it is possible to observe which students are absent in fall 2010 but re-enroll in spring 2011 (the last term in which registration data are available). This model allows the prediction of five different outcomes for a student at the conclusion of a semester:

1. Graduating (Graduate)
2. Transferring to another college within two years of the last enrollment (Transfer)
3. Stopping out for semester and then returning (Stopout)
4. Transferring after a one-semester absence (Delay Transfer)
5. Dropping out (being absent for more than two consecutive semesters) (Dropout)

The reference category would be re-enrollment in the semester that follows. It is not possible to predict absences of more than one semester without decreasing the number of semesters that are observed. For example, if one wanted to differentiate between 1-semester absence, 2-semester absence and longer-term absence, the number of semesters observed would need to be decreased to nine.

The outcomes may be expressed as probabilities:

$$p_1 = P(\text{Graduate})$$

$$p_2 = P(\text{Transfer})$$

$$p_3 = P(\text{Stopout})$$

$$p_4 = P(\text{Delay Transfer})$$

$$p_5 = P(\text{Dropout})$$

$$p_0 = P(\text{Retain})$$

Model II: Institution Leaving: Transfer vs. Stopout

For any particular institution, predicting long-term leaving would present something of an administrative dilemma: Does the institution regard potential dropouts as the “sicker patients” who need increased attention, or does it attend to the potential stopouts whose prognosis is arguably better and instead focus its attention on them? Further, students who do not return may do so not due to experiences that they have after leaving college and not while they are enrolled. Arguably, these two alternatives might be combined into a single outcome of semester absence. Also, since both graduation and continuation are successful outcomes, and since graduation is not possible until several semesters are completed and may present difficulties assessing model fit, these two outcomes will be combined as well. As such, Model II has the following outcomes:

1. Transferring to another college in the next semester (Transfer)
2. Being absent from any college during the next semester (Absent)

The reference category would be continuing or graduating. The associated probabilities would be:

$$p_1 = P(\text{Transfer})$$

$$p_2 = P(\text{Absent})$$

$$p_0 = P(\text{Retain or Graduate})$$

These three outcomes would allow the institution to focus its retention efforts on students who are at risk for being absent the following semester and obviate the need to choose between students who are risk for long-term versus short-term absence.

Model III: System Leaving: Leaving Higher Education

Many community colleges are constituted as means for a student to improve his skills and abilities to the point at which he is able to pursue a baccalaureate. In such cases, transfer to another college without completing an associate degree need not be viewed as an unfavorable outcome. In the CUNY system, this is implicit in the process by which students who apply senior colleges are offered admission to community colleges. In this scenario, retention, graduation and seamless transfer may all be gathered together as a successful outcome, and absence as an unsuccessful outcome with the following probabilities:

$$p_1 = P(\text{Absence})$$

$$p_0 = P(\text{Retention, Transfer or Graduation})$$

Since there are only two outcomes, this scenario may be expressed as a simple logistic model. One attractive aspect of this model is that the classification cutoff may be altered in an uncomplicated manner and the sensitivity and specificity of the predictions can be adjusted to

reflect the economic resources of the college that will be required to apply interventions with students at risk for leaving.

Predictor Variable Transformations

Several of the predictor variables needed to be transformed for practicality or meaning; the following is a list of these variables along with the rationale for the transformations:

1. Age is centered on 18, the traditional college-going age for students graduating from high school in the United States. Without this transformation, the intercept of the age variable would be that of a newborn child.
2. High School GPA was transformed from a 100-point scale to the traditional 4-point scale and then mean-centered on a score of 1.81. Because many students who did not have a high school GPA, these were assigned a score of zero, and an indicator variable was computed to identify them as not having an available high school GPA.
3. Regents scores across the various subject areas were averaged for each student and mean-centered around a score of 66.95.
4. The SAT score for the analysis was generated by summing the SAT Verbal and Math scores and mean-centering the total around 795.21. A missing indicator was computed for students who lacked an SAT score.
5. Semester and cumulative grade point averages (GPA) were centered on 2, which is equivalent to a score of C (satisfactory). In cases where the student did not have a GPA, the student was assigned a score of 0 and a missing GPA indicator was set to unity.
6. Cumulative credits are centered on the semester mean.
7. Individual Student/Faculty Ratio is mean-centered around 23.33.

Chapter Four: Results

Description of the Sample

Table A-1 provides a breakdown of the sample by gender, ethnicity, residency, marital status, dependency and age. Hispanics comprised the largest group in the study, with more than one-third of both cohorts. About one-third of the students were African-American or black, a little less than one-fifth were white, and about 12 percent were Asian. Less than one percent of the students were Native Americans. About 58 percent of the students were women. Generally, these proportions were similar across cohorts; the one exception to this is Nonresident Aliens, who comprised less than 9 percent of the 2004 cohort but 12.7 percent of the 2005 cohort. Dependency status was determined from the financial aid record, by marital status, or by the student being 23 years of age or older. Overall, about 59 percent of the freshmen entered as dependents, a little less than one quarter were independent, and around 17-18 percent had a dependency status that was not available.

Both cohorts have a mean age of 21 in the first semester of enrollment, and more than three-quarters of the students are in the traditional college-going age range of 17-22. However, considering that these ages are for the first year of study, it is clear that this sample is somewhat older than the traditional college freshman.

In general, proportional representation by race and gender does change very much with the passage of time. International student representation does appear to grow with time; there are also a greater proportion of nonresident aliens in the 2005 cohort than in the 2004 cohort. Table A-2 provides survival rates by gender and ethnicity.

More than one-third of the students did not have a high school GPA. About half of the students were graduates of the New York City public school system, and about 5.5 percent were

from private or parochial schools in New York City. About 5.5 percent attended a US high school located outside of New York City; a little less than ten percent of the students attended high school outside of the US. Almost fifteen percent of the students did not have a high school record; the proportion of such students was much higher in the 2005 cohort than in the 2004 cohort. 14.6 percent of the students passed the General Educational Development (GED) examination in lieu of obtaining a traditional high school diploma; the proportion of these students was considerably higher in the 2004 cohort. Of some interest is that more than half of the students who had a GED did have a grade point average. This may be due to those students having attended a GED preparatory program that issues a GPA. High School Record Statistics are presented in Table A-3.

The overall mean high school GPA of entering freshmen was 1.84, equivalent to a letter grade of C/C-. The table shows that nearly half of students entered with a GPA in the D+ to F range. Table A-4 presents a breakdown of high school Grade Point Average (GPA) for all students who have an available GPA.

Applicants may elect to take the Scholastic Aptitude Test (SAT), and have their scores sent to the CUNY admissions office for consideration in placement among the colleges that they have selected on their applications. Individual CUNY Colleges use this information as part of their decision whether to admit the applicant. This information is also used to evaluate whether a student is in need of remedial instruction in reading, writing or mathematics. As Table A-5 shows, a minority of students took this test. About seventeen percent of the 2004 cohort and just over one-fourth of the 2005 cohort took the test. This difference somewhat reflects the differences observed between the number who have a high school GPA. The means on the SAT

for are considerably lower than the generally recognized population means of 500 for the verbal test, 500 for the math test and 1000 total score.

Students who attend high school in New York State are required to sit for a series of Regents examinations. These achievement tests are designed to test students' knowledge in a variety of subject areas. These exams are graded on a 100-point scale, with 65 being a passing score. Performance on these exams may be used in admission and placement in colleges, especially for public colleges in New York. Among the strengths of these exams is that they are standardized for all students who take them and are thus comparable in ways that other scores such as high school GPA may not be. Unfortunately, these scores are not available for all students. Students who do not have a high school diploma, students who did not graduate recently, or students who went to high school outside of New York State are unlikely to have these test scores. Additionally, not all students who went to New York high schools have sat for all exams. Table A-6 provides performance statistics the 2004 and 2005 cohorts on the Math and English Regents exams. As the table shows, a minority of first year students have taken any one of these exams. The most commonly taken exam is the standard English regents. Students in the sample took as many as twelve Regents exams. As Table A-7 shows, more than half of the entrants in the 2004 Cohort and nearly half of the entrants in the 2005 cohort did not have scores for any Regents exam. In general, average scores were higher when more exams were taken.

CUNY undergraduate applicants are permitted to list as many as six colleges to which they would like to apply. The applicant is asked to select schools in the order of greatest to least preference. The applications may be to one or more of the seven senior colleges that grant baccalaureate degrees, one or more of the four comprehensive colleges that grant both associate

and baccalaureate degrees, or to one or more of the six community colleges that grant associate degrees. If an applicant is not accepted to one of the senior colleges that he or she has selected, the student is offered enrollment in one of the community colleges. Table A-8 presents a cross-tabulation of whether the student applied to a community college (columns) by the number of her highest senior college choice (rows), if any. A little less than 90 percent of students selected a community college. Among students who did not apply to community college, more than three quarters had a senior college as a first choice, suggesting that these students want to pursue a baccalaureate rather than an associate (students who applied to neither a community nor a senior college likely applied to a comprehensive college). Alternatively, just less than two-thirds of the students who indicated a community college indicated no senior college among their choices. This suggests that these students, if interested in pursuing a baccalaureate, consider it a more distal goal.

Students may pursue an Associate of Arts (AA), an Associate of Science (AS), or an Associate of Applied Science (AAS). Generally students who choose the AAS degree have less of a need to achieve a bachelor's degree than do students who pursue the AA or the AS. Slightly less than forty-three percent of the students were pursuing an applied degree. Table A-9 presents the type of degree that students were pursuing as of their first semester.

Many students attending community college qualify for the Federal Pell award as well as a grant from the New York State Tuition Assistance Program (TAP). These and other scholarships are aid that does not need to be repaid. The average grant award has a tendency to decline over time: In the first semester the average grant package was more than \$1,600; by the tenth semester, it had declined to under \$800. Statistics on Financial Aid grant awards are presented in Tables A-10 and A-11. The average grant aid that is provided in all semesters is

around \$1,500, which was slightly less than the tuition and fees paid for in-state full-time study at the time (see Table A-12).

As time passes, an increasing proportion of remaining students fail to receive any grant aid at all. A little less than 60 percent of students receive grant aid in the first semester of study, but by the tenth semester, only about half are still receiving aid. Overall, about one-third of the students do not receive any grant aid in a given semester. Table A-11 presents distribution statistics on grant awards for surviving students by semester.

The Pell grant is federal program that provides scholarships to needy students. It is frequently used as a poverty indicator; around two thirds of the entering cohort qualified for Pell at some point in their careers and thus can be described as having been needy at some point. Table A-13 presents the proportion of students in each semester who received a Pell Grant either prior to or during the semester.

Although some students borrow several thousand dollars per term, in the average semester fewer than six percent of students at CUNY take out a loan. Table A-14 presents mean loan amounts borrowed by students during each semester. The average loan amount is quite small, but grows larger with the passage of time. As Table A-15 shows, this is reflective of the fact that very few students take out loans; no more than 10 percent of students take out a loan at any time.

About one-fifth of the students take 12 credits or more in the first semester. This proportion rises in semesters 2-4, peaking in semesters 4 and five, and then declines. A similar pattern hold for the mean number of credits attempted. Table A-17 presents the number of credits that students attempted in each semester in which they were enrolled in the first spell.

Some students did not attempt any credits, often because they were engaged solely in remedial work; in the first semester this is the case for 10-11 percent of the students, as Table A-17 shows.

In general, the average number of credits earned increases from semester 1 to semester 5 and then declines in succeeding semesters. Tables A-18 and A-19 present summary information on the number of credits that the students earned during the semester. Tables A-20 and A-21 summarize the number of cumulative credits that surviving students have.

Students who are not deemed to be proficient in reading, writing or math skills are required to take courses that are designed to improve their proficiency to the college level. Such courses are called remedial, developmental or compensatory. Remedial courses deal with material that is not deemed to be college-level and do not carry college credit. About one-fifth of students take twelve or more remedial hours in the first semester, and less than one quarter of all students take none, indicating that in the first semester, remedial education is a major activity. Remedial education declines in succeeding terms, but at no point are fewer than 10 percent of student taking remedial classes students. Tables A-22 and A-23 summarize the number of hours that students spent in remedial courses before leaving college for the first time.

Developmental courses are similar to remedial courses, except that some of the work is deemed to be college level and carries some credit, albeit not as much as a regular course with the same number of contact hours. Developmental courses were taken fairly infrequently, as Tables A-24 and A-25 show.

Compensatory courses, like developmental courses, have a credit and non-credit component. Unlike developmental and remedial courses, students who take compensatory courses have met the college's skill-proficiency requirements. The portion of the course that does not carry credit includes skills below the college level that address the specific needs of the

course. Compensatory courses are rarely taken, although not as rarely as developmental courses, as Tables A-26 and A-27 show.

On average across terms in the first spell, nearly 20 percent of students in any given semester receive a failing mark. Additionally, failures become more common in the second and third semesters when nearly one-quarter of the students receive at least one failing mark. Table A-28 presents summary information on the number of courses that students failed during their first spell. Withdrawing from a course is more prevalent than failing a course, especially in the second and third semesters, when the share of students withdrawing from at least one course is around one-third. Summary statistics on withdrawals are presented in Table A-29. Table A-30 considers both withdrawal and failure for all students regardless of spell. Looking across all semesters, more than 40 percent of students do not complete a semester without failing or withdrawing from a class.

The overall semester average is a 2.4, which translates to a letter grade of C+. Table A-31 provides summary information on the semester GPA achieved by students in semesters before they left the college for the first time. Students who did not complete any credit-bearing courses in a semester do not have a GPA and are represented in the 'None' column.

Average cumulative GPA starts out at about 2.4 in the first term and then rises to 2.6, where it remains. The cumulative GPA is summarized in Table A-32. Some students may have had a few credits from earlier study; the first semester cumulative GPA is slightly different than the semester GPA as a result.

Students are required to demonstrate proficiency in the skill areas of reading, writing, and mathematics. Only slightly more than one-third of all students are fully skills proficient by the end of the first semester. About three-quarters of all students are reading proficient, slightly

fewer than that are math proficient. Writing is the area where the most students are deficient upon entry. Table A-33 shows the changes in proficiency status with passing semesters.

On average, students attend class 4 days per week. The average number of days per week on campus declines with each succeeding semester. A very small percentage (usually less than 1%) of students is not on campus for any classes. This may happen when students attend classes online, are engaged solely in internships, or are registered on record without taking any classes. A very small number of students attend classes seven days per week. Table A-34 summarizes the number of days per week that students are on campus.

The daily time on campus consisted of the time from the beginning of the first class to the end of the last class on a given day. The weekly time on campus consisted of the sum of the daily time on campus over the course of one week. The average time on campus for the first semester was 16.4 hours; this number tended to decline in following semesters. The average amount of time that the student was scheduled to be in class per week was about 11.8 hours in the first semester, and had a tendency to decline somewhat in later semesters. These trends are summarized on Table A-35.

It was estimated that the average transit commute time for students in the first semester was 7.8 hours per week; average weekly travel time tended to decline with succeeding semesters. Table A-36 summarizes trends in estimated travel time.

Between 11 and 16 percent of surviving students attended during summer session; a much smaller number participated in winter sessions. In general, a much greater share of students in the spring register for summer semesters than students in the fall register in the winter. For the 2004 cohort, a winter term following the first fall did not exist. Students who completed no credits but registered for the intersession either withdrew from all classes, failed all

classes, or took only non-credit courses. Table A-37 summarizes registration and credit taking in the winter and summer intersessions.

Online courses were first offered fall 2006, and so were not available for the first four semesters of the fall 2004 cohort and the first two semesters of the 2005 cohort. Nonetheless, they were taken by a significant proportion of students and the proportion has a tendency to rise with the passage of time. Courses could be fully online, in which the students did not need to travel to the campus for weekly meetings, or they could be partially online. Online course taking patterns are summarized in Table A-38.

On average, classes are of moderate size, with about 28 students. The overall counts are slightly lower than the number of students in each term because some students do not take classes. Table A-39 presents the mean of mean class size for students within a semester.

The student/faculty ratio is a statistic that is often used to rate a college, but cannot be applied to individual students within a college. From the student's perspective, the student/faculty ratio would correspond somewhat to class size. Since classes meet for varying period of time, some for as few as thirty minutes per week and some for several hours, class size is a less than desirable approximation of how much attention any individual student can expect in class. For this reason, a calculated measure was developed that would reflect the student/faculty ratio from the student's perspective. This measure, the Individual Student Faculty Ratio (ISFR) takes into account the number of students in the class section and weights it by the number of hours in which the class meets in a week. Descriptive statistics on the ISFR are presented in Table A-40. The overall class size, adjusted for hours in the classroom, is just under 23, but as the Table shows, this number varies greatly from student to student, with some students in classes that average 4 students and others with more than 200.

Generalizability of the Sample

The six CUNY community colleges participate in Title IV federal financial aid programs, are under public control, and offer associate degrees, but not baccalaureates. As sub-baccalaureate granting institutions, they are part of the larger universe of institutions that collectively comprised 17% percent of American institutions and served 34% of post-secondary students in 2005. Table 2 provides a breakdown of the fall 2005 post-secondary population which is derived from the National Center of Educational Statistics' Integrated Postsecondary Education data System (IPEDS). Each category presented is a subset of the category above.

Table 2. U.S. Postsecondary Enrollment: Fall 2005.

	Institutions		Enrollment			
	N	%	N	Mean	SD	%
Total Enrollment	6,689	100%	18,262,102	2,730	5,747	100%
Participates in Title IV federal financial aid programs	6,596	99%	18,176,729	2,756	5,771	100%
Public Control	2,044	31%	13,188,011	6,452	8,110	72%
Offers Associate but not Baccalaureate	1,149	17%	6,246,558	5,437	6,099	34%

Source: IPEDS.

Table 3 provides a further breakdown of these institutions by the size of the municipality in which they are located, and presents summary statistics by enrollment size. As the table shows, community colleges in large cities comprise nearly 10 percent of associate-granting institutions, and serve more than 20 percent of the students; CUNY community colleges belong to this group.

Table 3. Enrollment in Public Colleges Offering an Associate but not a Baccalaureate, by Locale: Fall 2005.

Locale	Institutions	Enrollment			Tuition and Required Fees		
	N*	N	Mean	SD	N*	Mean	SD
City Large	114	1,282,073	11,246	9,190	107	\$2,597	\$1,614
City Midsize	81	763,570	9,427	7,211	78	\$2,103	\$1,270
City Small	137	809,130	5,906	5,076	130	\$2,599	\$1,304
Suburb Large	153	1,350,823	8,829	7,121	141	\$2,940	\$1,749
Suburb Midsize	35	200,568	5,731	4,810	35	\$2,075	\$1,245
Suburb Small	24	132,800	5,533	7,567	24	\$2,835	\$1,591
Town Fringe	34	99,356	2,922	1,964	34	\$2,549	\$1,345
Town Distant	103	278,605	2,705	2,583	93	\$2,435	\$1,485
Town Remote	136	278,533	2,048	1,715	126	\$2,379	\$1,157
Rural Fringe	240	859,588	3,582	3,389	227	\$2,445	\$1,376
Rural Distant	58	151,261	2,608	2,344	55	\$2,555	\$1,464
Rural Remote	32	35,831	1,120	1,216	30	\$2,382	\$860
Not available	2	4,420	2,210	892	2	\$1,445	\$544
Total	1,149	6,246,558	5,437	6,100	1,082	\$2,512	\$1,430

*N for enrollment in table A-45 differs due to missing data.

Source: IPEDS.

Table 4 presents total enrollment for each of the six CUNY community colleges in fall 2005 from IPEDS. The six CUNY colleges range greatly in size, with Hostos having an enrollment of less than 4,500 and Borough of Manhattan Community College with more than 18,000. In this regard, the colleges are more representative of the larger community colleges in the nation, as Table 5 demonstrates.

Table 4. Overall Enrollment in CUNY Community Colleges: Fall 2005

College	N
CUNY Borough of Manhattan Community College	18,776
CUNY Bronx Community College	8,470
CUNY Hostos Community College	4,477
CUNY Kingsborough Community College	15,265
CUNY La Guardia Community College	13,489
CUNY Queensborough Community College	12,838
Total	73,315
Mean	12,219
Standard Deviation	4,624

Source: IPEDS.

Table 5. Public Colleges offering an Associate but not a Baccalaureate, by Enrollment size: Fall 2005.

Enrollment	N	%	Cum%	CUNY Community Colleges In Interval
20-3,999	631	54.9	54.9	
4,000-7,999	281	24.5	79.4	Hostos
8,000-11,999	105	9.1	88.5	Bronx
12,000-15,999	53	4.6	93.1	QBCC, LaGuardia, KBCC
16,000-19,999	30	2.6	95.7	BMCC
20,000-23,999	25	2.2	97.9	
24,000-27,999	11	1.0	98.9	
28,000-31,999	7	0.6	99.5	
32,000-35,999	2	0.2	99.7	
36,000+	4	0.3	100.0	
Total	1149	100.0		

Source: IPEDS

The tuition and fees at CUNY community colleges are very similar, as Table 6 demonstrates. The CUNY schools cost somewhat more on average than community colleges in large cities, as shown in Table 7.

Table 6. CUNY Community College in-state Tuition and Fees: Fall 2005.

CUNY Community College	Tuition and Fees
Borough of Manhattan Community College	\$3,068
Bronx Community College	\$3,104
Hostos Community College	\$3,105
Kingsborough Community College	\$3,100
La Guardia Community College	\$3,092
Queensborough Community College	\$3,086
Mean	\$3,093
Standard Deviation	\$13

Source: IPEDS

Table 7. Community College Tuition and Fees: Fall 2005.

Locale	Tuition and Required Fees		
	N*	Mean	SD
City Large	61	\$2,809	\$1,621
City Midsize	51	\$2,271	\$1,329
City Small	79	\$2,782	\$1,221
Suburb Large	88	\$3,454	\$1,745
Suburb Midsize	19	\$2,101	\$1,152
Suburb Small	16	\$3,082	\$1,417
Town Fringe	23	\$2,940	\$1,346
Town Distant	63	\$2,744	\$1,563
Town Remote	83	\$2,265	\$951
Rural Fringe	141	\$2,696	\$1,335
Rural Distant	33	\$2,656	\$1,448
Rural Remote	23	\$2,282	\$774
Not available	1	\$1,060	-
Total	681	\$2,717	\$1,419

*N in table A-42 differs due to missing data.

Source: IPEDS

One particular concern with this study is the locale in which the colleges are located. New York City, with more than 8 million inhabitants, is by far the largest city in the United States; in fact it is more than twice as large as any other U.S. city. As a consequence, it also has a large number of colleges. All CUNY community colleges have at least 16 publicly administered baccalaureate-granting colleges in close proximity (less than 25 miles). This situation may serve to encourage transfer because there are many alternatives, more than in other cities. To put this in perspective, data from the IPEDS system were utilized. The fall 2009 data set for colleges provide geographical data for all institutions, and it is possible to find out the number of institutions that lie in close proximity to others. Using the 2009 IPEDS data, the number of publicly administered in-state baccalaureate-granting that lie within 25 miles of each associate granting institution were calculated and are presented in Table 8. As the table demonstrates, more than 41 percent of associate-granting institutions do not have a public senior college in close proximity; nearly half have only one to three. In fact, there is only one other community college that has as many public alternatives as the CUNY community colleges. All CUNY community colleges have at least 16 public senior colleges nearby. Alternatively, all CUNY community colleges have a public senior college that is less than four miles away. As Table 9 demonstrates, only about 23 percent of US community colleges have a public senior college that is less than 5 miles away.

Table 8. Colleges offering an associate but not a baccalaureate, number of public 4-year colleges within 25 miles: Fall 2009.

Public Senior Colleges Nearby	N	%	Cum %
0	421	41.6	41.6
1	283	28.0	69.6
2	127	12.6	82.2
3	81	8.0	90.2
4	31	3.1	93.3
5	28	2.8	96.0
6	14	1.4	97.4
7	9	0.9	98.3
8	5	0.5	98.8
9	4	0.4	99.2
10	1	0.1	99.3
11	0	0.0	99.3
12	0	0.0	99.3
13	0	0.0	99.3
14	0	0.0	99.3
15	0	0.0	99.3
16*	2	0.2	99.5
17*	4	0.4	99.9
18*	1	0.1	100.0
Total	1,011	100.0	100.0

*All CUNY Community colleges are found in these intervals; only one non-CUNY college is found here.

Table 9. Colleges offering an associate but not a baccalaureate: Distance from closest in-state senior college (in miles): Fall 2009.

Distance	N	%	Cum %
0 - 5	233	23.0	23.0
5 - 10	151	14.9	37.9
10 - 15	86	8.5	46.4
15 - 20	58	5.7	52.1
20 - 25	62	6.1	58.2
25 - 30	52	5.1	63.3
30 - 35	64	6.3	69.6
35 - 40	60	5.9	75.5
40 - 45	38	3.8	79.3
45 - 50	28	2.8	82.1
50 - 55	30	3.0	85.1
55 - 60	28	2.8	87.9
60 - 65	22	2.2	90.1
65 - 70	12	1.2	91.3
70 - 75	18	1.8	93.1
75 - 80	10	1.0	94.1
80 - 85	12	1.2	95.3
85 - 90	8	0.8	96.1
90 - 95	2	0.2	96.3
95 - 100	8	0.8	97.1
100 +	29	2.9	100.0
Total	1,011	100.0	100.0

The CUNY system, in addition to its six community colleges, has an additional 11 colleges that offer the baccalaureate degree. The governance structure of the CUNY system is also highly centralized, and there are clear articulation agreements that allow students to transfer credits from one institution to another. In general, it is important to recognize that there may be many more opportunities to transfer in CUNY community colleges than at other community colleges.

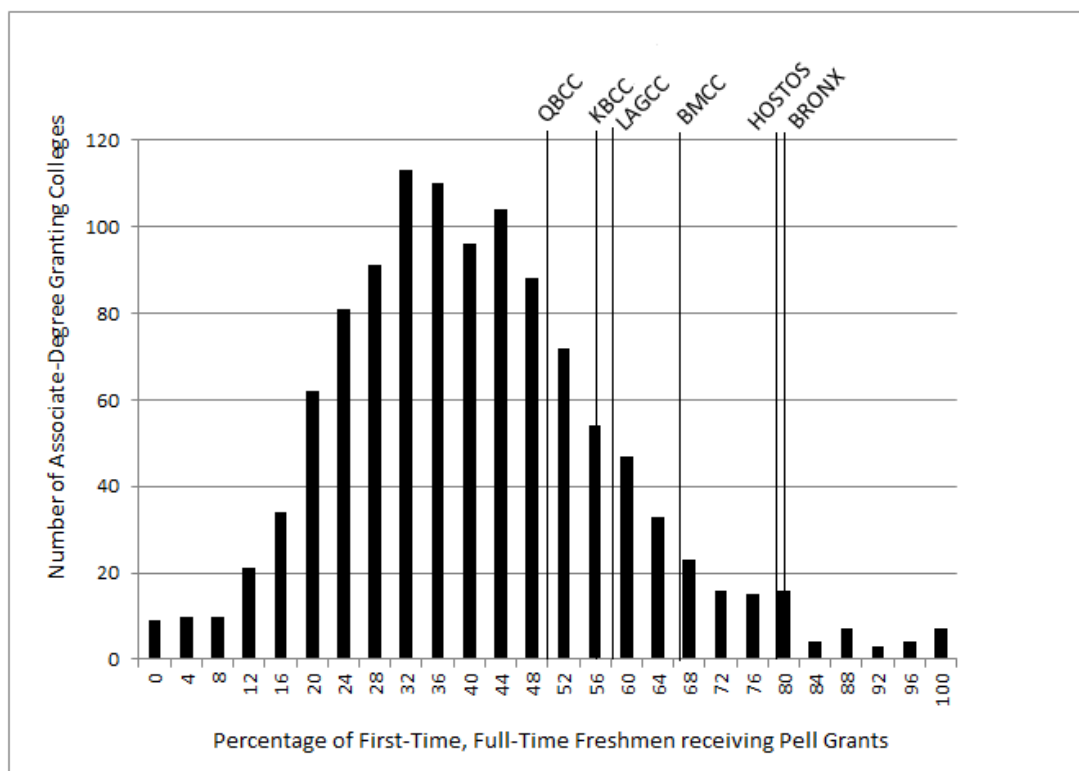
Another consideration is level to which CUNY community colleges represent are serving a needy population. As noted above, about two-thirds of CUNY community college students

receive Pell grants at some point in their college careers, which is generally seen as an indicator of need. Table 10 presents the percentages of full-time-first-time degree-seeking freshmen in the fall 2004 and fall 2005 samples used in this study, as well as the fall 2007 cohort using IPEDS data. The percentages across years are fairly close. Queensborough Community College has the smallest proportion of students with Pell Grants and Bronx Community College has the most. To contextualize this, Figure 1 presents the distribution of percentages for all publicly-administered associate-only granting institutions that appear in the 2007 IPEDS dataset. As the figure shows, CUNY community colleges have proportions of needy students that fall in the upper reaches of the distribution.

Table 10. Percentage of CUNY Community college first-time, full time freshmen receiving Pell Grants, fall 2004 and fall 2005 samples, and fall 2007 IPEDS (full cohort).

	Sampled Cohort		IPEDS
	2004 %	2005 %	2007 %
CUNY Borough of Manhattan Community College	66	67	67
CUNY Bronx Community College	78	75	80
CUNY Hostos Community College	80	77	79
CUNY Kingsborough Community College	60	58	56
CUNY LaGuardia Community College	54	55	58
CUNY Queensborough Community College	57	52	50
Total	63	62	63

Figure 1. Distribution of Percentage of Full-time First-time Degree-seeking Freshmen receiving Pell Grants: Fall 2005.



Source: IPEDS.

In general, the six community colleges of the City University of New York can be said to be larger in size, serve a needier population and present more opportunities for transfer than many in the larger universe of community colleges. If all these variables are considered simultaneously, CUNY community colleges could be said to exist in a class of their own. On the other hand, CUNY community colleges as a group present a degree of diversity among themselves. It would probably be prudent to consider any findings as suggestive and subject to further study rather than definitive regarding community colleges in general.

Outcomes: The First Spell

Table 11 represents leaving type for students after the first spell (period from initial matriculation through the semester immediately preceding the first absence). The leftmost panel presents the outcome to the extent that the observation period allows. It is important to note that the category “dropout” is provisional; if the observation period could be extended, some “dropouts” could fall into stopout and transfer categories should they re-enter college. The second, third, and fourth panels demonstrate how outcomes are combined into the categories specified under Models I, II and III.

At the end of 5-1/2 academic years (6 fall and 5 spring terms), slightly less than one percent of the students had remained enrolled without interruption; these are represented by the “Continue” row. The remaining rows represent different forms of leaving arranged from most to least favorable. Sixteen percent of the students persisted without absence from initial matriculation to graduation. Since continuation and graduation both represent students who did not miss any semesters and who did not change colleges, they are combined in Model II. The next row, “Immediate Transfer”, represents the group of students who left without earning a degree, but who were found to be enrolled in another college or university in the following semester. About 14 percent of the students left the college and transferred to another institution without interruption. Continuation, graduation and transfer can be considered to be “successful” semester outcomes in that their educations have not been interrupted; these outcomes are combined in Model III.

One-term stopouts are students who left for one semester and then reenrolled the following regular (fall or spring) semester at the same school; these comprised about 14 percent of the initial leaves from the first spell. Since these students re-enrolled at a later time, these

students will be examined as part of the second spell, provided that they returned by the tenth semester. One-term transfers, the next row, are students who were absent from the higher education system for one regular term, followed by matriculation at a different school. About four percent of the students took one semester off and then registered at another college.

Functionally, these students are similar to stopouts (both missed at one semester), but since they do not return to the original school, they will not be examined as part of the second spell.

Students whose initial leave consisted of only one missed semester are modelled separately in Model I.

The remaining four categories consist of students who missed at least two consecutive semesters and are treated as a single category under Model I. About 8.5 percent of the students took two or more semesters off but returned to the original college in a fall or spring term before the end of the observation period. These students are also examined as part of the second spell if they returned by the tenth semester. Nearly 11 percent took more than one term off and then registered at another college. A very small number of students left for more than one term and returned to the original college, although not in a regular (spring or fall) term. These students who returned for intersessions only will not be examined as part of the second spell. The final slice, "Dropout", represents students who left the college without returning to it or any other school for the duration of the observation period. Dropouts comprised just less than 31 percent of the initial leaves. Leaves that consist of more than one semester are combined in Model I. Leaves that involve any absence are combined in Models II and III.

Semester by leaving type is detailed in Table 12. Overall, a little more than 80 percent of students/semesters had a successful outcome, that is, the students continued, graduated or transferred in the next term.

Table 11. First Spell Leave Type for the 2004 and 2005 Freshman Cohorts.

Outcome			Model I			Model II			Model III		
	N	%		N	%		N	%		N	%
Continue	204	0.9%	Continue	204	0.9%	Continue/ Graduate	3,743	17.2%	Success	6,835	31.5%
Graduate	3,539	16.3%	Graduate	3,539	16.3%						
Immediate Transfer	3,092	14.2%	Immediate Transfer	3,092	14.2%	Immediate Transfer	3,092	14.2%			
Stopout, One term	3,066	14.1%	Stopout, One term	3,066	14.1%	Absence	14,889	68.5%	Absence	14,889	68.5%
Transfer After One Term	914	4.2%	Transfer After One Term	914	4.2%						
Stopout > One Term	1,841	8.5%	Absence, > One Term	10,909	50.2%						
Transfer > One Term	2,355	10.8%									
Stopout, Intersession Return	48	0.2%									
Dropout	6,665	30.7%									
Total	21,724	100.0%	Total	21,724	100.0%	Total	21,724	100.0%	Total	21,724	100.0%

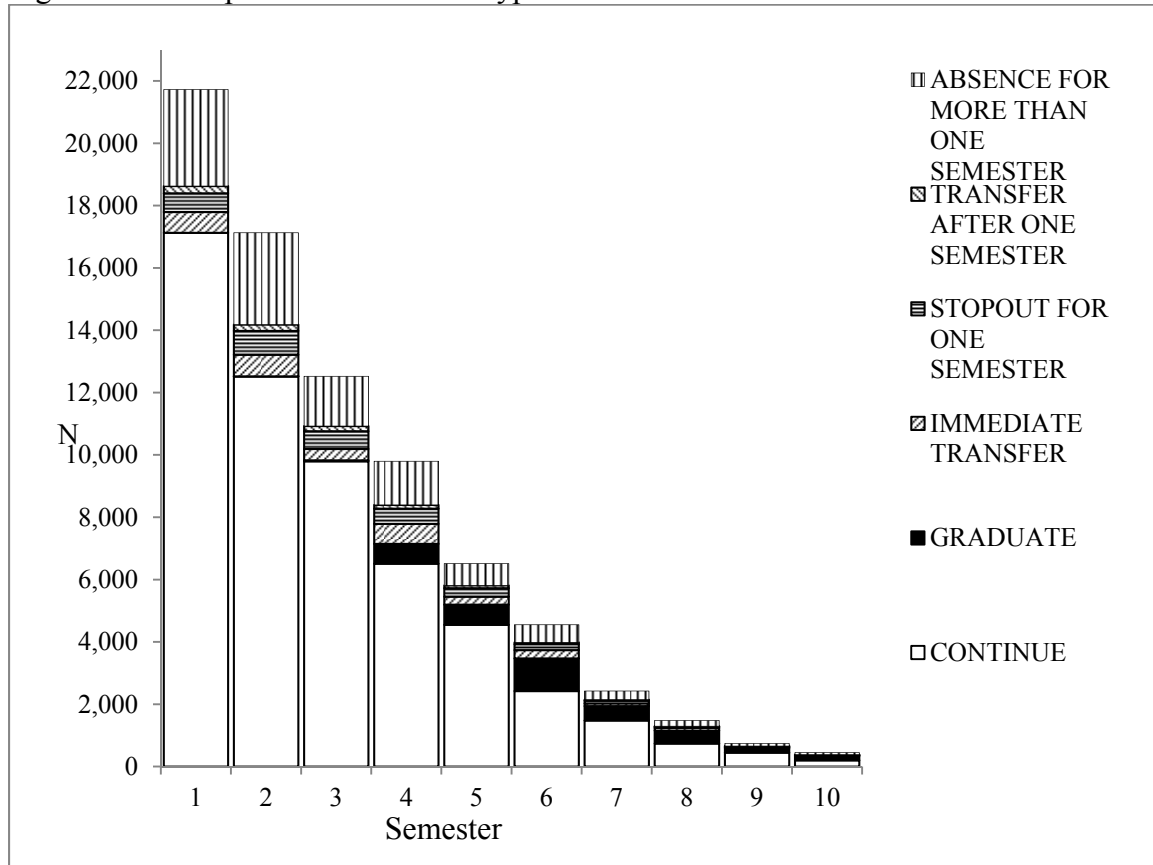
Table 12. First Spell Semester Outcomes.

Term	Total	Continue	Graduate	Transfer, Immediate	Successful	Stopout	Transfer, 1-Term Delay	Transfer, > 1-Term Delay	Stopout, >1 Term	Stopout, Inter- session Return	Dropout	Not Successful
	N	N	N	N	N	N	N	N	N	N	N	N
1	21,724	17,126	0	669	17,795	602	228	590	531	12	1,966	3,929
2	17,126	12,523	1	692	13,216	766	199	550	641	6	1,748	3,910
3	12,523	9,798	30	362	10,190	573	164	277	364	9	946	2,333
4	9,798	6,512	638	640	7,790	486	121	205	385	3	808	2,008
5	6,512	4,548	650	255	5,453	274	88	101	180	7	409	1,059
6	4,548	2,423	1,048	269	3,740	188	55	74	137	4	350	808
7	2,423	1,478	466	83	2,027	88	33	26	55	3	191	396
8	1,478	741	418	84	1,243	40	14	11	36	2	132	235
9	741	447	152	23	622	29	8	5	14	2	61	119
10	447	204	136	15	355	20	4	2	12	0	54	92
Total	77,320	55,800	3,539	3,092	62,431	3,066	914	1,841	2,355	48	6,665	14,889
	%	%	%	%	%	%	%	%	%	%	%	%
1	100	78.8	0.0	3.1	81.9	2.8	1.0	2.7	2.4	0.1	9.0	18.1
2	100	73.1	0.0	4.0	77.2	4.5	1.2	3.2	3.7	0.0	10.2	22.8
3	100	78.2	0.2	2.9	81.4	4.6	1.3	2.2	2.9	0.1	7.6	18.6
4	100	66.5	6.5	6.5	79.5	5.0	1.2	2.1	3.9	0.0	8.2	20.5
5	100	69.8	10.0	3.9	83.7	4.2	1.4	1.6	2.8	0.1	6.3	16.3
6	100	53.3	23.0	5.9	82.2	4.1	1.2	1.6	3.0	0.1	7.7	17.8
7	100	61.0	19.2	3.4	83.7	3.6	1.4	1.1	2.3	0.1	7.9	16.3
8	100	50.1	28.3	5.7	84.1	2.7	0.9	0.7	2.4	0.1	8.9	15.9
9	100	60.3	20.5	3.1	83.9	3.9	1.1	0.7	1.9	0.3	8.2	16.1
10	100	45.6	30.4	3.4	79.4	4.5	0.9	0.4	2.7	0.0	12.1	20.6
Total	100	72.2	4.6	4.0	80.7	4.0	1.2	2.4	3.0	0.1	8.6	19.3

First Spell, Model I.

Model I categories by semester are presented in Figure 2. The unfilled portion of the bars represent students who remained enrolled the following term.

Figure 2. First Spell Model I Leave Type for the 2004 and 2005 Freshman Cohorts.



The first model to be examined differentiates risks for students of graduating, transferring to another college in the following term, stopping out (leaving for one semester), transfer to another college after a one term absence, and finally, being absent from higher education for two or more semesters (referred to in this section as “dropout”). The initial analysis utilized the 2004 cohort; this cohort was used to choose the final variable list. The final model was compared with a time-only model that used

binary semester indicator variables. Bayesian Information Criteria indicated that the final model was a much better fit. The comparison is summarized in Table 13.

Table 13. Spell I Comparison of a Time-Only Model I with Final Model I.

	Model	
	Time Only	Final
Log-Likelihood	-34678.05	-27,482.55
-2LL	69,356.10	54,965.10
N	38,814	38,814
Predictors	9	28
Outcome Categories	6	6
Model Parameters	45	140
BIC	69,831.59	56,444.42
χ^2		13,387.18
df		95
p		0.000

A test for collinearity was performed by converting the dependent variable into a series of binary indicators and performing a linear regression analysis with the same set of predictors. No serious threats were detected, the highest Variance Inflation Factor being 4.445, which is well below the generally accepted value of 10. In addition to this, Pearson and Deviance Goodness-of-fit statistics are not significant, which indicates that the model is a good fit; these statistics are summarized in Table 14.

Table 14. Pearson and Deviance Goodness-of-Fit Statistic for Spell I, Model I.

	χ^2	df	p
Pearson	188,249.457	193,925	1.000
Deviance	54,965.107	193,925	1.000

Odds ratios for Spell I Model I outcomes are presented in Table 15. Parameters for the combined cohorts are presented below parameters for the 2004 Cohort separately.

Table 15. First Spell, Model I: Odds Ratios for Leaving versus Continuation, 2004 and 2005 Cohorts.

Category	Predictor	Cohort	Odds of Leaving				
			Graduate	Transfer	Transfer1	Stopout	Dropout
Time							
	Academic Year	2004	1.557****	1.045	1.006	1.040	0.930**
		Both	1.405****	1.072*	0.993	1.055	0.897****
	Spring Semester	2004	2.901****	1.614****	1.063	1.395****	1.326****
		Both	2.664****	1.679****	1.098	1.396****	1.359****
	Age Centered on 18	2004	0.976***	0.944****	0.944****	0.996	1.013****
		Both	0.978****	0.952****	0.955****	0.996	1.016****
Demographics							
	Latin	2004	1.128	0.717****	0.857	1.144*	1.105**
		Both	1.143*	0.725****	0.976	1.182****	1.107****
	International Student	2004	0.752*	0.586****	0.447***	0.931	0.904
		Both	0.738***	0.578****	0.576****	0.889	0.874***
	Has PELL Now or Previously	2004	0.676*	1.319**	0.795	1.098	1.041
		Both	0.848	1.343****	0.880	1.062	0.999
Pre-College Characteristics							
	Missing SAT Score	2004	1.195*	1.047	1.024	1.315***	3.025****
		Both	1.172**	0.996	1.100	1.285****	2.206****
	Missing High School GPA	2004	0.944	0.920	0.951	1.097	1.275****
		Both	0.979	0.916	0.878	1.126**	1.185****
	Applied to this College	2004	0.871	0.457****	0.706*	1.007	1.074
		Both	0.796**	0.499****	0.708***	0.965	1.011
	Pursuing an Applied Degree	2004	0.581****	0.630****	0.844	1.008	0.931*
		Both	0.649****	0.640****	0.854*	0.939	0.951*

Category	Predictor	Cohort	Odds of Leaving				
			Graduate	Transfer	Transfer1	Stopout	Dropout
College Performance							
	Earned Credits in Semester	2004	1.018	0.973*	0.911****	0.966**	0.905****
		Both	1.032****	0.966****	0.929****	0.956****	0.904****
	Cumulative Credits Earned	2004	1.040****	1.019****	0.988	0.976****	0.990****
		Both	1.032****	1.023****	0.993	0.982****	0.988****
	Earned at Least 60 Credits	2004	104.615**	2.684****	3.120****	1.405	2.634****
		Both	130.668**	2.416****	4.031****	1.358*	2.717****
	At least 60 credits; GPA is less than 2.0	2004	0.074****	0.953	1.031	0.556	1.466
		Both	0.074****	0.553	0.826	1.429	1.731*
	Remedial Hours	2004	0.797****	0.961****	0.903****	0.954****	0.944****
		Both	0.784****	0.961****	0.924****	0.949****	0.942****
	Compensatory Hours	2004	0.871****	0.954***	0.938*	0.989	0.945****
		Both	0.874****	0.950****	0.945**	0.983	0.948****
	Prior Developmental Hours	2004	0.949****	0.951***	0.982	1.004	1.005
		Both	0.949****	0.957****	0.984	1.002	1.002
	Withdrawals	2004	0.584****	1.200****	1.306****	1.185****	1.382****
		Both	0.676****	1.170****	1.304****	1.201****	1.393****
	Semester GPA	2004	1.224****	1.060	0.917	0.756****	0.718****
		Both	1.200****	1.037	0.808****	0.751****	0.713****
	Prior Cumulative GPA	2004	1.213*	1.223****	0.804**	0.770****	0.756****
		Both	1.336****	1.257****	0.694****	0.771****	0.780****
	Missing Semester GPA	2004	1.408	1.637****	1.267	1.282*	1.724****
		Both	1.434	1.656****	1.525****	1.345****	1.724****
	Writing Proficient	2004	1.639****	1.298****	0.939	0.891	0.796****
		Both	1.499****	1.382****	0.998	0.966	0.795****

Category	Predictor	Cohort	Odds of Leaving				
			Graduate	Transfer	Transfer1	Stopout	Dropout
Environment and Support							
	Days on Campus	2004	0.851***	0.808****	0.886	0.942	0.980
		Both	0.837****	0.835****	0.794****	0.952*	0.969*
	Total Hours in Class per Week	2004	0.942****	0.978**	0.996	1.001	0.991
		Both	0.946****	0.979****	1.005	0.995	0.990***
	Individual Student/Faculty Ratio	2004	1.022****	1.027****	0.981*	1.009	1.006*
		Both	1.026****	1.030****	1.001	1.011***	1.005*
	Grant (Thousands)	2004	1.077	0.836****	0.933	0.856****	0.825****
		Both	1.005	0.839****	0.899*	0.876****	0.832****
	Grant Loss (Thousands)	2004	1.236***	0.974	1.377****	1.153*	1.270****
		Both	1.195***	1.004	1.284****	1.188****	1.282****
	Weekly Transit Travel Time	2004	1.031**	1.062****	1.062****	1.013	1.006
		Both	1.024***	1.060****	1.065****	1.008	1.007

The table shows that the passage of time in years is positively and significantly related to graduating and immediate transfer, and negatively related to dropout. Further, all forms of leaving except delayed transfer are significantly more likely following the spring semester than the fall. Students who are older are significantly less likely to graduate or transfer (immediate and delayed) and significantly more likely to be absent from higher education for more than a year.

The only two demographic indicators indicated in the model are Latino and International students: Gender, black, Asian and Native American are not significant. Latino students are less likely than non-Latino students to transfer, and more likely to stop out or drop out. When considering the combined cohorts, Latinos are more likely to graduate. International students are less likely than American citizens or resident aliens to graduate or transfer (both forms). They are also more likely to drop out. Students who had a Pell Grant in the current any prior semester were more likely to transfer and less likely to graduate.

There are several precollege characteristics that were found to be associated with leaving. Students who lacked an SAT score had a particularly high risk for dropping out and an elevated risk for stopping out. They also had had a higher likelihood of graduating. Students who did not have a high school GPA had a higher risk of dropping out and a somewhat elevated risk for stopping out (but for stopping out the risk is only significant for the combined cohort). Students who applied to the college (as opposed to being assigned to it) were significantly less likely to transfer (immediate and with delay) but also less likely to graduate. Students who pursue an applied degree were significantly less likely to graduate or transfer (both types), and less likely to drop out.

College performance indicators are presented in the third panel. The number of earned credits in a semester was negatively associated with transfer (immediate and delayed), stopout and dropout; there was also a slightly higher likelihood of graduating. In general, students with more accumulated credits are more likely to graduate or transfer and less likely to stop out or drop out.

Students who had earned at least 60 credits were much more likely to graduate but also to transfer (immediately or delayed), stop out or drop out. For students who had accumulated 60 credits, but whose GPA was less than 2.0, the likelihood of graduating was extremely low and the odds of dropping out are higher. The number of remedial hours that the student is taking is negatively and significantly associated with all forms of leaving; it can thus be inferred that students taking remedial classes are more likely to stay. Compensatory hours show a similar pattern, although the risk for stopping out is not significant. Prior developmental hours (hours accumulated in previous terms) are associated with a lowered likelihood to graduate or transfer immediately. Withdrawing from classes presents a lowered likelihood of graduating, an increased likelihood of transfer (immediate and delay), and an increased likelihood of stopping out and dropping out.

Semester GPA is positively associated with graduating, and presents a reduced hazard for delayed transfer, stopping out and dropping out. Prior Cumulative GPA shows a similar pattern, except that it is also positively associated with immediate transfer, while semester GPA is not. Students who did not have a GPA in the semester were more likely to transfer (immediate and delay), stop out or leave for more than one term. Being writing-proficient is positively associated with graduation and immediate transfer and negatively associated with dropout.

Environmental and support is summarized in the fifth panel. The number of days that a student is scheduled to be present per week on campus is associated with a decreased likelihood with graduating, transfer (immediate and delay) as well as with stopout and dropout. The number of hours that a student spends in class is associated

with a decreased risk for graduation, immediate transfer and drop out. Individual student/faculty ratio is associated with an increased risk for all types of leaving.

Scholarship grants are negatively related to transfer (immediate as well as delayed), stopping out and dropping out.

Students who experience a loss in grant support relative to the level that they had been receiving are more likely to leave in all manners except immediate transfer, but this needs to be interpreted with caution. It may simply be a timing issue, with students who have only a few more credits to go raising the needed funds and students who have a longer road ahead giving up.

Weekly transit travel time shows a significant positive association with graduation and transfer (both immediate and delayed).

The next three tables demonstrate how well the model performed in predicting whether and how students left in a given semester versus the actual outcome of the semester. Table 16 shows predicted versus actual outcomes for the 2004 cohort with correct predictions in boldface type. As the table shows, about 94 percent of the students who would continue to the following semester were correctly identified. More than 80 percent of graduates were also correctly identified. The model performed poorly in predicting transfer and stopout, but correctly identified almost 35 percent of dropouts. One possible reason for the model's failure to discriminate stopouts is that the coefficients associated with the predictors are generally in the same direction for both stopouts and dropouts.

Table 16. First Spell: Model I Confusion Matrix for the 2004 Cohort.

		Predicted							
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence	Total	
Observed	Continue	N	26,396	578	0	0	0	1,044	28,018
		Row %	94.2%	2.1%	0.0%	0.0%	0.0%	3.7%	100.0%
		Col %	79.9%	25.2%	0.0%	--	--	30.0%	72.2%
	Graduate	N	347	1,445	0	0	0	7	1,799
		Row %	19.3%	80.3%	0.0%	0.0%	0.0%	0.4%	100.0%
		Col %	1.1%	63.0%	0.0%	--	--	0.2%	4.6%
	Immediate Transfer	N	1,268	137	7	0	0	118	1,530
		Row %	82.9%	9.0%	0.5%	0.0%	0.0%	7.7%	100.0%
		Col %	3.8%	6.0%	70.0%	--	--	3.4%	3.9%
	Stopout	N	1,209	15	1	0	0	248	1,473
		Row %	82.1%	1.0%	0.1%	0.0%	0.0%	16.8%	100.0%
		Col %	3.7%	0.7%	10.0%	--	--	7.1%	3.8%
	Delayed Transfer	N	308	20	0	0	0	106	434
		Row %	71.0%	4.6%	0.0%	0.0%	0.0%	24.4%	100.0%
		Col %	0.9%	0.9%	0.0%	--	--	3.0%	1.1%
	Absence	N	3,501	100	2	0	0	1,957	5,560
		Row %	63.0%	1.8%	0.0%	0.0%	0.0%	35.2%	100.0%
		Col %	10.6%	4.4%	20.0%	--	--	56.2%	14.3%
Total	N	33,029	2,295	10	0	0	3,480	38,814	
	Row %	85.1%	5.9%	0.0%	0.0%	0.0%	9.0%	100.0%	
	Col %	100.0%	100.0%	100.0%	--	--	100.0%	100.0%	

A similar pattern is demonstrated when both cohorts are included in the analysis, as demonstrated in Table 17. In this analysis, more than 34 percent of dropouts are correctly identified:

Table 17. First Spell: Model I Confusion Matrix for the 2004 and 2005 Cohorts.

		Predicted							
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence	Total	
Observed	Continue	N	52,644	1,160	3	0	0	1,993	55,800
		Row %	94.3%	2.1%	0.0%	0.0%	0.0%	3.6%	100.0%
		Col %	79.8%	25.3%	21.4%	--	--	29.6%	72.2%
	Graduate	N	657	2,863	0	0	0	19	3,539
		Row %	18.6%	80.9%	0.0%	0.0%	0.0%	0.5%	100.0%
		Col %	1.0%	62.4%	0.0%	--	--	0.3%	4.6%
	Immediate Transfer	N	2,553	289	6	0	0	244	3,092
		Row %	82.6%	9.3%	0.2%	0.0%	0.0%	7.9%	100.0%
		Col %	3.9%	6.3%	42.9%	--	--	3.6%	4.0%
	Stopout	N	2,507	40	2	0	0	517	3,066
		Row %	81.8%	1.3%	0.1%	0.0%	0.0%	16.9%	100.0%
		Col %	3.8%	0.9%	14.3%	--	--	7.7%	4.0%
	Delayed Transfer	N	656	46	0	0	0	212	914
		Row %	71.8%	5.0%	0.0%	0.0%	0.0%	23.2%	100.0%
		Col %	1.0%	1.0%	0.0%	--	--	3.1%	1.2%
	Absence	N	6,962	190	3	0	0	3,754	10,909
		Row %	63.8%	1.7%	0.0%	0.0%	0.0%	34.4%	100.0%
		Col %	10.6%	4.1%	21.4%	--	--	55.7%	14.1%
Total	N	65,979	4,588	14	0	0	6,739	77,320	
	Row %	85.3%	5.9%	0.0%	0.0%	0.0%	8.7%	100.0%	
	Col %	100.0%	100.0%	100.0%	--	--	100.0%	100.0%	

Table 18 is a classification matrix of outcomes in the 2005 cohort using parameters extracted from the 2004 cohort. Similar patterns are observed for continuation and graduation; more than 95 percent of students who continue and 79 percent of students who graduate are correctly identified. The number of dropouts correctly identified is somewhat lower, with a little more than 3 in ten dropouts correctly identified. The number of immediate transfers identified is low, and no stopouts or longer-term transfers are correctly identified.

Table 18. First Spell: Model I Confusion Matrix for 2005 Cohort Using Parameters

Obtained from 2004 Cohort.

		Predicted							
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence	Total	
Observed	Continue	N	26,387	567	4	0	0	824	27,782
		Row %	95.0%	2.0%	0.0%	0.0%	0.0%	3.0%	100.0%
		Col %	79.1%	25.4%	57.1%	--	--	28.3%	72.1%
	Graduate	N	348	1,380	0	0	0	12	1,740
		Row %	20.0%	79.3%	0.0%	0.0%	0.0%	0.7%	100.0%
		Col %	1.0%	61.8%	0.0%	--	--	0.4%	4.5%
	Immediate Transfer	N	1,314	145	0	0	0	103	1,562
		Row %	84.1%	9.3%	0.0%	0.0%	0.0%	6.6%	100.0%
		Col %	3.9%	6.5%	0.0%	--	--	3.5%	4.1%
	Stopout	N	1,327	26	1	0	0	239	1,593
Row %		83.3%	1.6%	0.1%	0.0%	0.0%	15.0%	100.0%	
Col %		4.0%	1.2%	14.3%	--	--	8.2%	4.1%	
Delayed Transfer	N	364	24	0	0	0	92	480	
	Row %	75.8%	5.0%	0.0%	0.0%	0.0%	19.2%	100.0%	
	Col %	1.1%	1.1%	0.0%	--	--	3.2%	1.2%	
Absence	N	3,611	91	2	0	0	1,645	5,349	
	Row %	67.5%	1.7%	0.0%	0.0%	0.0%	30.8%	100.0%	
	Col %	10.8%	4.1%	28.6%	--	--	56.4%	13.9%	
Total	N	33,351	2,233	7	0	0	2,915	38,506	
	Row %	86.6%	5.8%	0.0%	0.0%	0.0%	7.6%	100.0%	
	Col %	100.0%	100.0%	100.0%	--	--	100.0%	100.0%	

Since stopping out, delayed transfer and longer term absence all involve leaving higher education for at least one semester, and since continuing, immediate transferring and graduation can all be considered successful forms of leaving, the probabilities of each out can be combined to form two outcomes similar to those that will be tested in the third model. If this is done, a sensitivity/specificity schedule can be generated; Table 19 presents such a schedule. In Table 19, if the summed probabilities of stopping out,

delayed transfer and longer-term absence for a student exceed the cutoff criterion in the left column, the outcome is predicted to be a leave. Some of these predicted leaves are correct (the student is absent) and others are false positives (the student actually graduates, immediately transfers, or continues).

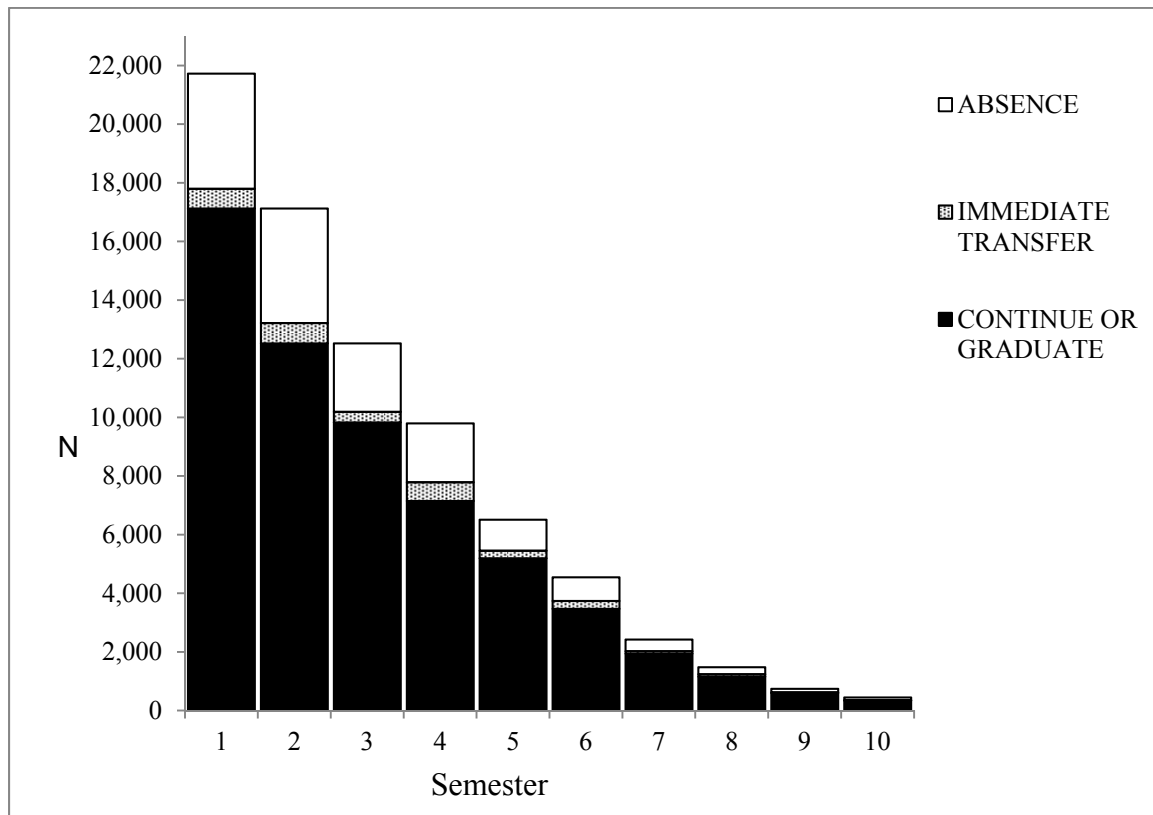
Table 19. Sensitivity/Specificity Schedule for First Spell, Model I.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1 Term Total N = 7,467				Missed Semester ≥ 1 Term Total N = 7,422			
	Correct	False	Correct	False	Correct	False	Correct	False
	Detections	Positives	Detections	Positives	Detections	Positives	Detections	Positives
	N	N	%	%	N	N	%	%
.05	7,200	23,571	96.4	76.6	7,110	22,407	95.8	75.9
.10	6,518	14,858	87.3	69.5	6,377	13,760	85.9	68.3
.15	5,851	9,977	78.4	63.0	5,674	9,315	76.4	62.1
.20	5,222	7,129	69.9	57.7	5,078	6,621	68.4	56.6
.25	4,725	5,294	63.3	52.8	4,609	4,937	62.1	51.7
.30	4,256	4,057	57.0	48.8	4,135	3,686	55.7	47.1
.35	3,842	3,052	51.5	44.3	3,681	2,735	49.6	42.6
.40	3,462	2,371	46.4	40.6	3,209	2,083	43.2	39.4
.45	3,045	1,815	40.8	37.3	2,780	1,570	37.5	36.1
.50	2,604	1,387	34.9	34.8	2,291	1,158	30.9	33.6
.55	2,156	1,035	28.9	32.4	1,843	842	24.8	31.4
.60	1,685	745	22.6	30.7	1,401	590	18.9	29.6
.65	1,256	504	16.8	28.6	1,030	388	13.9	27.4
.70	867	275	11.6	24.1	701	214	9.4	23.4
.75	524	127	7.0	19.5	422	109	5.7	20.5
.80	263	58	3.5	18.1	201	52	2.7	20.6
.85	85	21	1.1	19.8	81	18	1.1	18.2
.90	15	1	0.2	6.3	13	0	0.2	0.0
.95	0	0	0.0	--	0	0	0.0	--

First Spell, Model II.

Model II categories are presented in Figure 3.

Figure 3. First Spell Model II Leave Type for the 2004 and 2005 Freshman Cohorts.



Model II combines all forms of leaving that include at least one missed semester into a single category; these outcomes include dropping out, stopping out and delayed transfer. Immediate transfer, in which the student is enrolled in another college during the next semester, is treated as separate category. Graduation and continuation are combined and treated as the reference category.

The 2004 cohort was used to develop the model. A test for collinearity among the predictors was performed using a linear regression procedure; the highest variance inflation factor was 4.649, which is lower than the generally accepted tolerance level of

10. The final Model II was compared to a time-only model, and BIC comparison demonstrated Model II to be a better fit. The comparison is summarized in Table 20.

Table 20. Comparison of a Time-Only Model II with Final Model II.

	Model	
	Time Only	Final
Log-Likelihood	-25,006	-20,486
-2LL	50,012.00	40,971.62
N	38,814	38,814
Predictors	9	24
Outcome Categories	3	3
Model Parameters	18	48
BIC	50,202.20	41,478.81
χ^2		8,723.38
df		30
p		0.000

Another indicator of good fit is the Pearson and Deviance Goodness-of-Fit Statistics, both of which are non-significant. These statistics are presented in Table 21.

Table 21. Pearson and Deviance Goodness-of-Fit statistic for Spell I, Model II.

	χ^2	df	p
Pearson	78,164.155	77,540	.057
Deviance	40,953.569	77,540	1.000

The odds ratios associated with each predictor and form of leaving for the 2004 cohort as well as the combined 2004 and 2005 cohorts are presented in Table 22:

Table 22. First Spell, Model II: Odds Ratios for Immediate Transfer and Absence versus Graduation or Continuation.

Category	Predictor	Transfer		Absence	
		2004	Both	2004	Both
Time					
	Spring semester	1.584****	1.601****	1.415****	1.439****
	Winter term following fall	0.567	0.254****	0.238***	0.233****
	Summer term following spring	0.586****	0.637****	0.355****	0.359****
Demographics					
	Asian	1.174*	1.189***	0.804****	0.809****
	Latin	0.717****	0.729****	1.030	1.047*
Pre-College Characteristics					
	Missing SAT Score	0.862*	0.839****	2.162****	1.858****
	Applied to this College	0.445****	0.490****	0.996	0.950
	Pursuing an Applied Degree	0.636****	0.639****	0.978	0.973
College Performance					
	Earned Credits in Semester	0.999	0.990	0.937****	0.937****
	Cumulative Credits Earned	1.016****	1.017****	0.984****	0.985****
	At least 60 credits; GPA is less than 2.0	2.590*	1.409	2.774****	3.358****
	Remedial Hours	0.978*	0.975***	0.958****	0.959****
	Withdrawals	1.280****	1.238****	1.377****	1.395****
	Failed Courses, current term	1.126	1.133*	1.142****	1.185****
	Semester GPA	1.008	0.998	0.770****	0.768****
	Prior Cumulative GPA	1.118*	1.173****	0.769****	0.777****
	Missing Semester GPA	1.749****	1.761****	1.759****	1.805****
	Writing Proficient	1.286****	1.390****	0.779****	0.803****
Environment and Support					
	Days on Campus	0.814****	0.835****	0.959*	0.948****
	Total Hours in Class per Week	0.973***	0.975****	0.988**	0.984****
	Individual Student/Faculty Ratio	1.028****	1.029****	1.005	1.005**
	Grant (Thousands)	0.924****	0.936****	0.852****	0.854****
	Grant Loss (Thousands)	1.090	1.144****	1.253****	1.250****
	Weekly Transit Travel Time	1.069****	1.067****	1.009	1.010***

* p<.05

** p<.01

*** p<.005

**** p<.001

The first panel presents time-related predictors. The progression of time is not a significant predictor of any kind of leaving in this model and is not included. There is an increased likelihood to leave or transfer following the spring semester (as opposed to the

fall. A student who enrolls in a winter or summer session is significantly less likely to leave or to transfer.

Asian students were more likely to transfer and less likely to leave. Latino students generally show a decreased likelihood to transfer. Latinos also show a decreased risk for transfers and an increased risk for leaving, although the leaving risk is significant only for the combined cohorts. The indicators for Black and Native American are not significant predictors of leaving in this model

With regard to precollege indicators, students who did not have an SAT score were at a significantly increased risk for leaving and a significantly decreased risk for transfer. Students who had applied to the college (vis-à-vis having been allocated to it) were at a significantly less likely to transfer. Students who were pursuing an applied degree were significantly less likely to transfer as well.

Under Model II, each credit earned in a semester was significantly associated with a decrease in the risk for leaving. The number of cumulative credits earned was associated with an increased likelihood to transfer and a decreased risk of leaving. Students who had accumulated 60 credits but had a GPA less than 2.0 were more likely to leave and more likely to transfer, although the increased likelihood to transfer was only significant for 2004. In order to graduate, a student needs to have a GPA of 2.0, and it is likely that this played a role in the student's failure to graduate.

The number of remedial hours that a student took was associated with a significantly decreased risk for both transfer and leaving.

The number of classes from which the student withdrew in the current semester was associated with an increased risk for both transfer and leaving. The number of

classes that a student failed in the current term was positively associated with both transfer and dropout, but for transfer, this is significant only in the combined cohorts.

A higher semester GPA is associated with a decreased risk for leaving; a higher cumulative beginning of term GPA is associated with a higher likelihood to transfer as well as a decreased likelihood to leave. Not having a semester GPA (this can occur because the student has taken no credit-bearing courses or has withdrawn from all of her courses) is positively and significantly associated with both transfer and leaving. Writing proficiency is significantly associated with an increased likelihood to transfer and a decreased likelihood to leave.

The number of days that the student is scheduled to be on campus as well as the number of hours that the student is scheduled to be in class are both associated with a decreased risk for transfer and a decreased risk for leaving.

A higher individual student faculty ratio is associated with an increased risk for both transfer and leaving.

Scholarship dollars in the form of grants was associated with a decreased risk for both transfer and leaving. A decrease in grants relative to the average amount that the student had received in previous semesters presents an increased risk for both transfer and leaving.

More weekly transit travel time was associated with an increased risk for both transfer and leaving.

The following three tables demonstrate how the prediction of the three outcomes compared with actual outcomes. Table 23 cross tabulates the predicted versus the actual outcome for the 2004 cohort. More than 95 percent of continuations/graduations are

correctly identified, and those that were misidentified were misidentified as leavers. Less than one percent of transfers were correctly identified; just fewer than 90 percent of those who transferred were misidentified as continue/graduate. This model correctly identified 37 percent of leavers. The model does not accurately predict transfers, however. This is probably because the model does not include data that would indicate a likelihood transfer. Also, it is reasonable to conclude that students who transfer immediately have much in common with those who graduate or continue. Possible variables to include would be a student application for transfer, or perhaps to simply ask the student whether he is considering transferring to another college.

Table 23. First Spell: Model II Confusion matrix for 2004 Cohort.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	28,461	0	1,356	29,817
		Row %	95.5%	0.0%	4.5%	100.0%
		Col %	82.4%	0.0%	31.7%	76.8%
	Immediate Transfer	N	1,370	6	154	1,530
		Row %	89.5%	0.4%	10.1%	100.0%
		Col %	4.0%	75.0%	3.6%	3.9%
	Absence	N	4,697	2	2,768	7,467
		Row %	62.9%	0.0%	37.1%	100.0%
		Col %	13.6%	25.0%	64.7%	19.2%
	Total	N	34,528	8	4,278	38,814
		Row %	89.0%	0.0%	11.0%	100.0%
		Col %	100.0%	100.0%	100.0%	100.0%

Table 24 cross tabulates the predicted versus actual outcome for the combined 2004 and 2005 cohorts. The distribution is quite similar to that of the 2004 cohort.

Table 24. First Spell: Model II Confusion Matrix for Both Cohorts.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	56,590	2	2,747	59,339
		Row %	95.4%	0.0%	4.6%	100.0%
		Col %	82.4%	20.0%	31.9%	76.7%
	Immediate Transfer	N	2,764	6	322	3,092
		Row %	89.4%	0.2%	10.4%	100.0%
		Col %	4.0%	60.0%	3.7%	4.0%
	Absence	N	9,358	2	5,529	14,889
		Row %	62.9%	0.0%	37.1%	100.0%
		Col %	13.6%	20.0%	64.3%	19.3%
	Total	N	68,712	10	8,598	77,320
		Row %	88.9%	0.0%	11.1%	100.0%
		Col %	100.0%	100.0%	100.0%	100.0%

Table 25 provides a cross tabulation of predicted versus actual semester outcomes for the 2005 Cohort using parameters extracted from the 2004 cohort. Again, transfer is not accurately identified, but more than one-third of leavers are properly identified.

Table 25. First Spell: Model II Confusion Matrix for 2005 Cohort using Parameters Obtained from 2004 Cohort.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	28,298	4	1,220	29,522
		Row %	95.9%	0.0%	4.1%	100.0%
		Col %	81.8%	80.0%	31.1%	76.7%
	Immediate Transfer	N	1,422	0	140	1,562
		Row %	91.0%	0.0%	9.0%	100.0%
		Col %	4.1%	0.0%	3.6%	4.1%
	Absence	N	4,855	1	2,566	7,422
		Row %	65.4%	0.0%	34.6%	100.0%
		Col %	14.0%	20.0%	65.4%	19.3%
	Total	N	34,575	5	3,926	38,506
		Row %	89.8%	0.0%	10.2%	100.0%
		Col %	100.0%	100.0%	100.0%	100.0%

Table 26 presents a specificity/sensitivity analysis for various cutoff levels using parameters obtained from the 2004 cohort and applied separately to the 2004 and 2005 Cohorts. For this analysis, the probability of continue/graduate is added to the probability of immediate transfer. If the probability of leaving is greater than or equal to the cutoff criterion, then the case is classed as a leave. The schedule for 2005, which applies parameters obtained from one dataset and applied to a naïve dataset, is presented in the rightmost panel. This schedule shows that by adjusting the cutoff criterion, a larger

number of leavers may be identified depending on the tolerance for false positives. For example, if one is willing accept a false positive rate of about 50 percent, then about 60 percent of all leavers can be correctly identified by setting the cutoff criterion somewhere between .25 and .30.

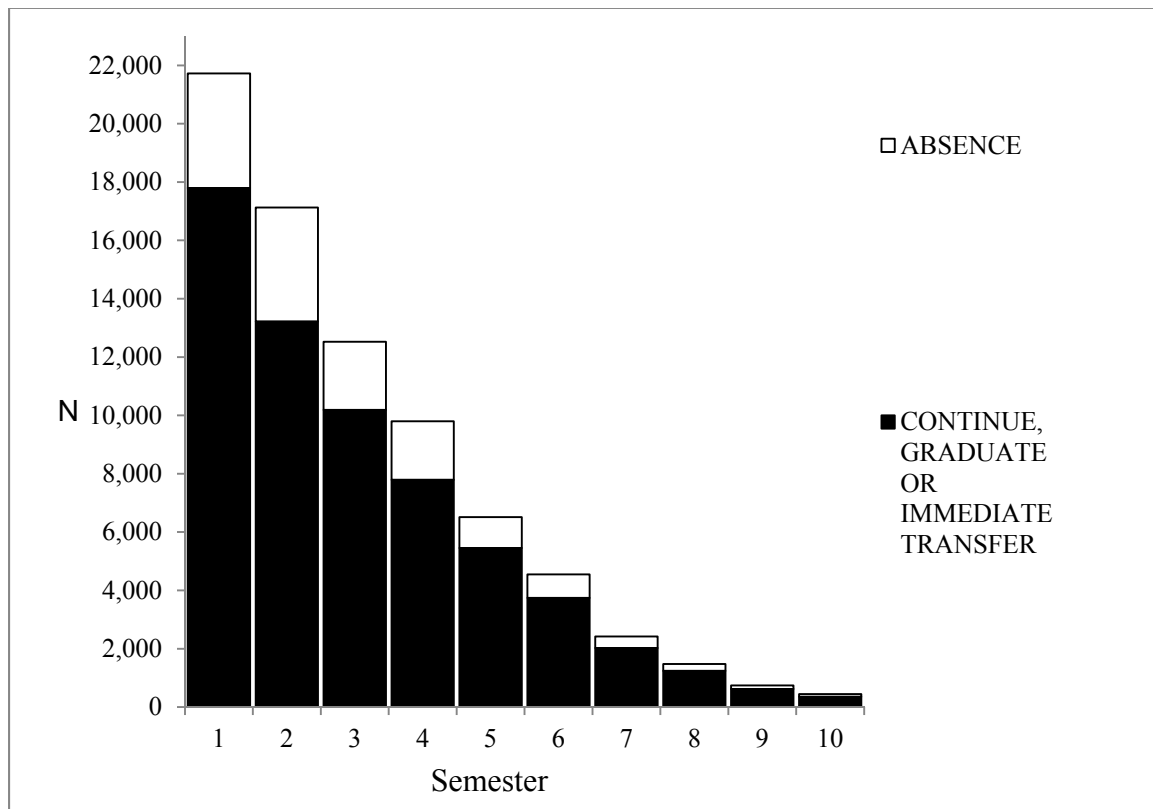
Table 26. Sensitivity/Specificity Schedule for Spell 1, Model II.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1 Term Total N = 7,467				Missed Semester ≥ 1 Term Total N = 7,422			
	Correct	False	Correct	False	Correct	False	Correct	False
	Detections	Positives	Detections	Positives	Detections	Positives	Detections	Positives
	N	N	%	%	N	N	%	%
.05	7,190	23,364	96.3	76.5	7,097	22,253	95.6	75.8
.10	6,551	14,915	87.7	69.5	6,391	13,895	86.1	68.5
.15	5,868	10,034	78.6	63.1	5,713	9,343	77.0	62.1
.20	5,239	7,120	70.2	57.6	5,138	6,733	69.2	56.7
.25	4,747	5,337	63.6	52.9	4,665	5,012	62.9	51.8
.30	4,287	4,084	57.4	48.8	4,212	3,738	56.8	47.0
.35	3,874	3,052	51.9	44.1	3,779	2,817	50.9	42.7
.40	3,485	2,366	46.7	40.4	3,303	2,135	44.5	39.3
.45	3,048	1,812	40.8	37.3	2,847	1,594	38.4	35.9
.50	2,601	1,359	34.8	34.3	2,360	1,193	31.8	33.6
.55	2,186	1,025	29.3	31.9	1,902	863	25.6	31.2
.60	1,702	724	22.8	29.8	1,465	598	19.7	29.0
.65	1,281	492	17.2	27.7	1,043	388	14.1	27.1
.70	850	290	11.4	25.4	710	227	9.6	24.2
.75	490	140	6.6	22.2	414	110	5.6	21.0
.80	250	54	3.3	17.8	206	44	2.8	17.6
.85	68	9	0.9	11.7	62	12	0.8	16.2
.90	10	1	0.1	9.1	8	1	0.1	11.1
.95	0	0	0.0	--	0	0	0.0	--

First Spell, Model III.

Model III combines all “successful” (continuing, graduating and immediate transfer) into a one category and all “unsuccessful” outcomes (delayed transfer, stopout and dropout) into another. The unsuccessful outcomes thus involve at least a one-semester interruption in the student’s career while the successful outcomes do not. This model involves a single question, namely, “will the student be enrolled in college next semester”? In this regard, Model III is the same as Model II except that it does not treat transfer as a separate form of leaving and does not attempt to model it. Model III categories are presented in Figure 4.

Figure 4. First Spell Model III Leave Type for the 2004 and 2005 Freshman Cohorts.



A test for collinearity was performed using a linear regression procedure; there were no serious threats, the highest variance inflation factor being 3.665. A comparison of the final model with a time-only model demonstrated that the final model was a superior fit; the results of this comparison are presented in Table 27.

Table 27. Spell I: Comparison of a Time-Only Model III with Final Model III.

	Model	
	Time Only	Final
Log-Likelihood	-18,949.59	-14,780.25
-2LL	37,899.18	29,560.50
N	38,814	38,814
Predictors	9	31
Outcome Categories	2	2
Model Parameters	9	31
BIC	37,994.28	29,814.10
χ^2		8,180.18
df		22
p		0.000

For this model, the Pearson Goodness-of-Fit statistic was significant, which cast some doubt on the model's fit. Pearson and Deviance statistics are presented in Table 28.

Table 28. Pearson and Deviance Goodness-of-Fit Statistics for Spell I, Model III.

	χ^2	df	p
Pearson	40,210.600	38,786	.000
Deviance	29,552.176	38,786	1.000

Table 29 presents the odds ratios of leaving (delayed transfer, stopout or dropout) associated with each predictor utilized in the model. Parameters associated with the combined 2004 and 2005 Cohort as well as the 2004 alone are presented in the table.

Table 29. First Spell, Model III: Odds Ratios for Unsuccessful Leaving (Stopout, Dropout or Delayed Transfer).

Category	Predictor	2004 Cohort	Both Cohorts
Time			
	Spring Semester	1.422****	1.451****
	Summer term following spring	0.522****	0.522****
	Age Centered on 18	1.013****	1.015****
Demographics			
	Asian	0.796****	0.791****
Pre-College Characteristics			
	Missing SAT Score	2.110****	1.802****
	Missing High School GPA	1.241****	1.188****
College Performance			
	Earned Credits in Semester	0.904****	0.902****
	Earned at Least 60 Credits	0.580****	0.593****
	At least 60 credits; GPA is less than 2.0	3.003****	3.767****
	Intersession Credits	0.850****	0.854****
	Credits taken at another CUNY College	0.805****	0.841****
	Remedial Hours	0.949****	0.947****
	Withdrawals	1.270****	1.275****
	Prior Withdrawals	1.042****	1.049****
	Failed Courses, Prior Term	1.174****	1.174****
	Failed Courses, 2 Terms ago	1.167****	1.148****
	Semester GPA	0.860****	0.859****
	Cumulative GPA	0.744****	0.734****
	Missing Semester GPA	1.377****	1.398****
	Missing Cumulative GPA	1.465****	1.490****
	Writing Proficient	0.791****	0.812****
Environment and Support			
	Grant (Thousands)	0.852****	0.854****
	Grant Loss (Thousands)	1.251****	1.241****
	Loan (Thousands)	0.857****	0.841****

* p<.05

** p<.01

*** p<.005

**** p<.001

Time-related variables are presented in the first panel. The odds ratios indicate that students are at greater risk for leaving in the spring than in the fall. Also, a student who attends a summer session is significantly less likely to leave. Older students are at a greater risk for leaving.

Asian students are at significantly lower risk for leaving relative to non-Asians.

Students who lack an SAT Score or a high school GPA were at a significantly greater risk for leaving.

With regard to college record variables, a higher number of earned credits in a semester as well as a higher number of cumulative credits were significantly associated with a decreased risk of leaving. Students who had earned at least 60 credits had a decreased hazard for leaving unsuccessfully; students who had earned at least 60 credits but who had a GPA of less than 2.0 had a higher risk of leaving, however. Hours in remedial courses were both associated with a significantly decreased risk for leaving.

The number of courses from which a student withdrew was significantly related to an increased risk for leaving, as was then number of courses that a student had withdrawn from in prior semesters. Courses failed in the previous semester and two terms prior were also significantly related to leaving; it is notable that number of failed courses in the current term was not significant. This might be due to the student's not having learned of a course failure until after registration for the next semester. Also, current failures will be captured to a certain extent in the semester GPA, which is significantly and negatively related to leaving as is the cumulative GPA.

The lack of a semester or cumulative GPA due to withdrawing from all courses, or taking only non-credit courses is positively and significantly related to leaving. Students who were writing proficient had a significantly lower risk for leaving.

Financial support in the form of both grants and loans carried a significant reduction in the risk for leaving. Grant loss was a significant hazard for leaving.

Table 30 presents the confusion matrix for the 2004 cohort. 95.7 percent of successful outcomes and 35.1 percent of leavers were accurately predicted using the model.

Table 30. First Spell: Model III Confusion Matrix for 2004 Cohort Only.

		Predicted			
		Graduate Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate Continue Or Immediate Transfer	N	29,987	1,360	31,347
		Row %	95.7%	4.3%	100.0%
		Col %	86.1%	34.2%	80.8%
	Absence	N	4,848	2,619	7,467
		Row %	64.9%	35.1%	100.0%
		Col %	13.9%	65.8%	19.2%
	Total	N	34,835	3,979	38,814
		Row %	89.7%	10.3%	100.0%
		Col %	100.0%	100.0%	100.0%

Table 31 presents the same classification table for the combined 2004 and 2005 cohorts. The proportion of successful outcomes correctly detected is slightly lower than the combined cohort; the percentage of correctly detected leavers was slightly higher.

Table 31. First Spell: Model III Confusion Matrix for 2004 and 2005 Cohorts.

		Predicted			
		Graduate Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate Continue Or Immediate Transfer	N	59,685	2,746	62,431
		Row %	95.6%	4.4%	100.0%
		Col %	86.1%	34.3%	80.7%
	Absence	N	9,619	5,270	14,889
		Row %	64.6%	35.4%	100.0%
		Col %	13.9%	65.7%	19.3%
	Total	N	69,304	8,016	77,320
		Row %	89.6%	10.4%	100.0%
		Col %	100.0%	100.0%	100.0%

Table 32 presents the classification of outcomes in the 2005 cohort using parameters obtained from the 2004 cohort. There is only a slightly lower correct identification rate for unsuccessful outcomes, and the identification rate for successful outcomes is higher.

Table 32. First Spell: Model III Confusion Matrix for 2005 Cohort using Parameters

Obtained from 2005 Cohort.

		Predicted			
		Graduate, Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate, Continue Or Immediate Transfer	N	29,957	1,127	31,084
		Row %	96.4%	3.6%	100.0%
		Col %	85.6%	32.1%	80.7%
	Absence	N	5,040	2,382	7,422
		Row %	67.9%	32.1%	100.0%
		Col %	14.4%	67.9%	19.3%
	Total	N	34,997	3,509	38,506
		Row %	90.9%	9.1%	100.0%
		Col %	100.0%	100.0%	100.0%

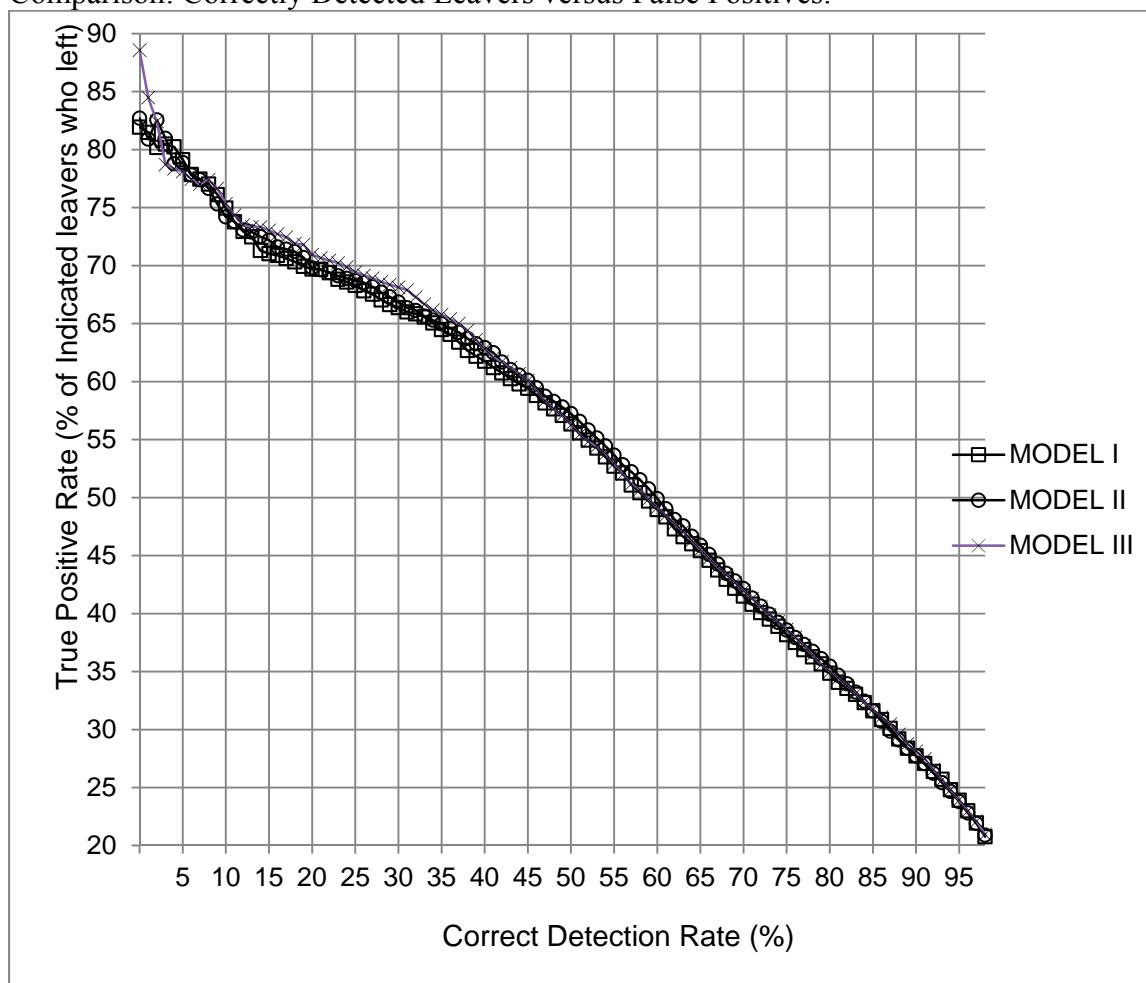
A sensitivity/specificity schedule for the 2004 and 2005 cohorts based on parameters obtained from the 2004 cohort is presented in Table 33. This table shows the number of leavers that will be identified when the cutoff criterion is adjusted as well as the percentage of identified leavers that are actually false positives.

Table 33. Sensitivity/Specificity Schedule for Spell 1, Model III.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1 Term Total N = 7,467				Missed Semester ≥ 1 Term Total N = 7,422			
	Correct	False	Correct	False	Correct	False	Correct	False
	Detections	Positives	Detections	Positives	Detections	Positives	Detections	Positives
	N	N	%	%	N	N	%	%
.05	7,183	23,216	96.2	76.4	7,081	21,846	95.4	75.5
.10	6,548	14,735	87.7	69.2	6,384	13,739	86.0	68.3
.15	5,880	10,055	78.7	63.1	5,702	9,272	76.8	61.9
.20	5,257	7,260	70.4	58.0	5,125	6,706	69.1	56.7
.25	4,778	5,452	64.0	53.3	4,647	5,025	62.6	52.0
.30	4,340	4,180	58.1	49.1	4,200	3,808	56.6	47.6
.35	3,895	3,209	52.2	45.2	3,743	2,840	50.4	43.1
.40	3,505	2,442	46.9	41.1	3,309	2,126	44.6	39.1
.45	3,085	1,829	41.3	37.2	2,859	1,553	38.5	35.2
.50	2,619	1,360	35.1	34.2	2,382	1,127	32.1	32.1
.55	2,136	949	28.6	30.8	1,855	800	25.0	30.1
.60	1,673	671	22.4	28.6	1,403	548	18.9	28.1
.65	1,239	440	16.6	26.2	979	357	13.2	26.7
.70	813	268	10.9	24.8	668	195	9.0	22.6
.75	476	142	6.4	23.0	366	101	4.9	21.6
.80	236	61	3.2	20.5	195	43	2.6	18.1
.85	81	23	1.1	22.1	63	8	0.8	11.3
.90	9	2	0.1	18.2	12	0	0.2	0.0
.95	0	0	0.0	--	0	0	0.0	--

The question of which model is most useful in identifying students who are risk is addressed by Figure 4, which plots the percentage of leavers accurately identified as well as the false positive rate for each model. The figure presents correct detections and false positives in the test data set (2005 cohort) using parameters obtained from the training data set (2004 cohort). With regard to correct detections, the performance of all of the models is quite similar. Model III does have a lower false positive rate, however.

Figure 5. First Leave Sensitivity/Specificity Schedule Predictive Outcome Model Comparison: Correctly Detected Leavers versus False Positives.



First Spell High-Risk Person Profile

Arguably, Model II is the most useful for effectively identifying students who are at risk for unsuccessfully leaving college after the first spell; this is due to both the high correct detection rate and the relatively low false positive rate for non-transfer leavers (37.15% and 35.7% respectively for the combined cohorts). One question that may be asked is which of the indicators are most useful to the model, and of these, whether any can be used to develop a practical profile for students who are at risk for leaving. In order to do this, Model II was re-run multiple times using one less predictor (the one

whose -2LL was lowest) on each run until the model was depleted of indicators. Two variables, the number of credits completed in the semester and the number of classes withdrawn, were needed to differentiate any leavers from those who remained or graduated. It was discovered that a model nearly as useful as the final Model II in differentiating leavers needed only 10 predictors. Of these, six had distributions that were especially striking if they are limited to students whose predicted outcome matched their actual outcome. These distributions demonstrate not only a statistical risk, but are sufficiently pronounced to a degree that they could constitute warning signs that college personnel might be well advised to watch for since students who demonstrate them present an elevated risk for dropping out. These distributions are presented in Figure 6.

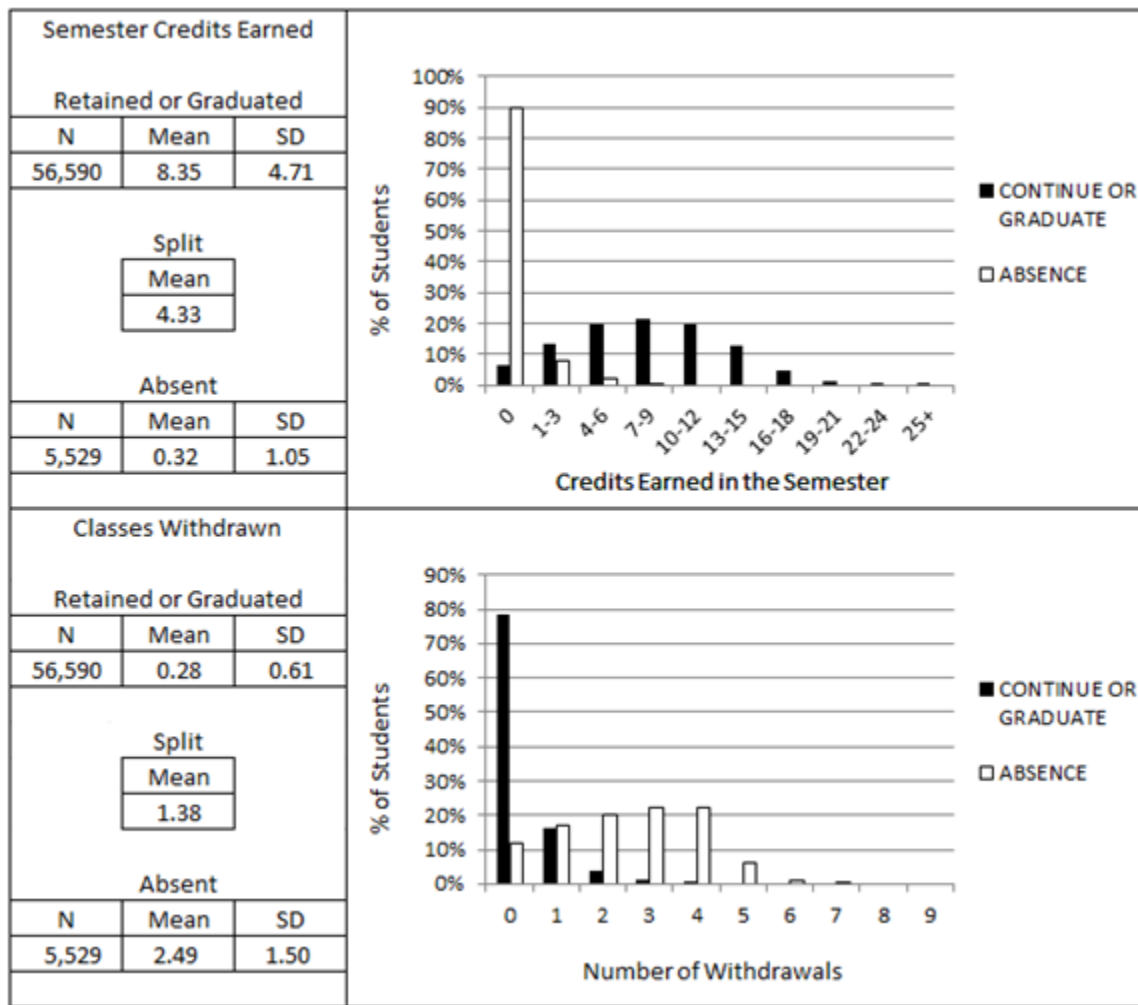
The panels present means and standard deviations as well as a frequency distribution for each indicator for correctly identified retained or graduated students versus leavers. Additionally, a 'split' (the unweighted mean of the means for each group) is presented.

The first panel depicts credits earned during the term. As the graph makes clear, about ninety percent of correctly identified leavers were students who earned no credit, whereas the distribution for those who were correctly identified as retained or graduated has a bell shape and a mean of 8.35. The data indicate that students who earn four credits or less may be at considerable risk.

The second panel depicts class withdrawals. In contrast to leavers, of those who stay or graduate, nearly 8 in 10 did not withdraw from any classes. The data suggest that students who withdraw from two or more classes are at particularly high risk.

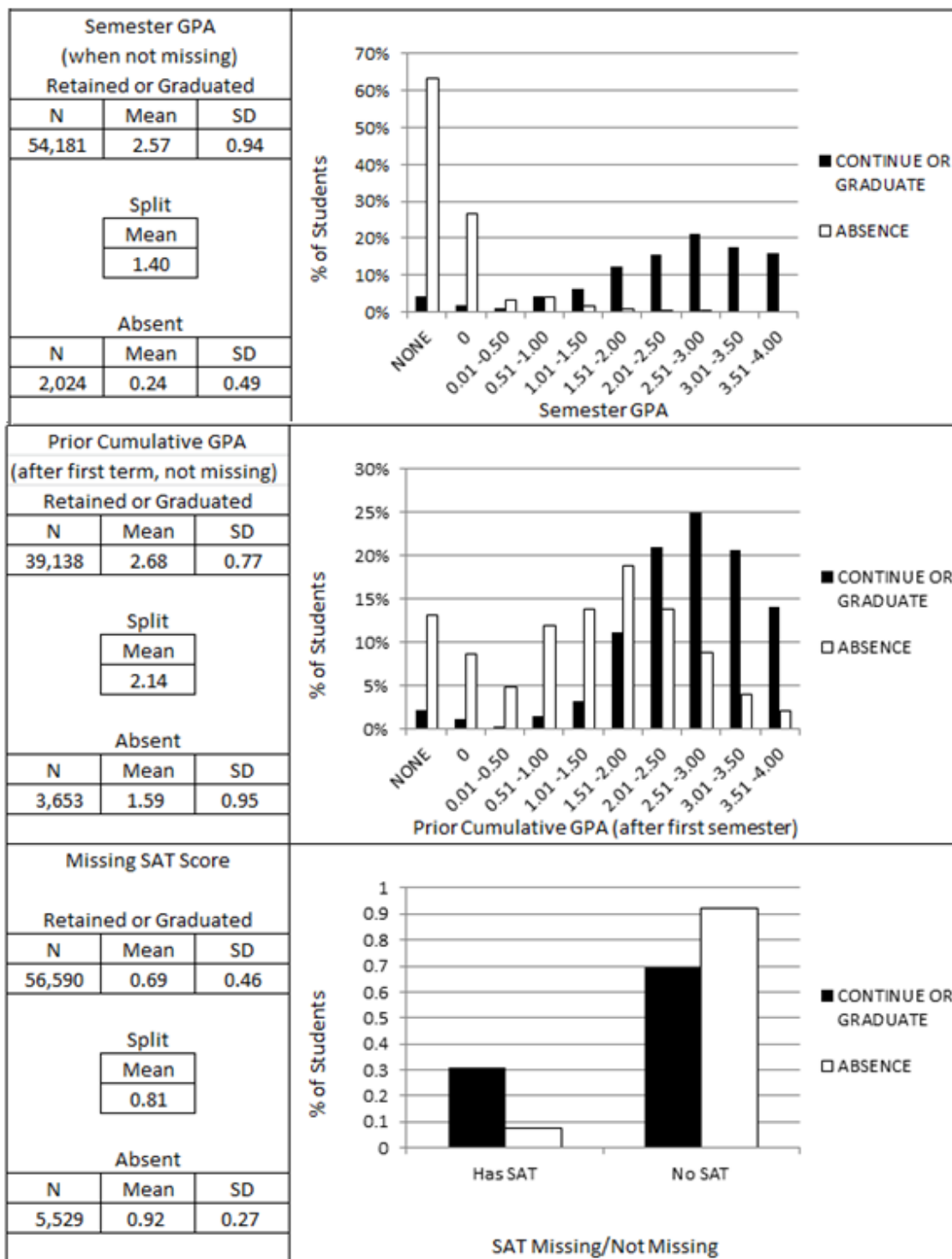
The third panel combines semester GPA and those who had no GPA, both of which are included in the reduced Model II. Nearly 90 percent of correctly identified

Figure 6. Spell I Profile for at-risk students.



(continued on next page)

Figure 6 (Continued).



leavers have no GPA or a GPA of zero, the latter case meaning that the students failed all of the courses that they took.

The fourth panel depicts prior cumulative GPA from the second semester forward (the first semester is not included since virtually no students have a cumulative GPA in that term). The distribution shows a clear separation between leavers and retained or graduated students, but is not quite as striking as the aforementioned indicators.

The fifth panel depicts whether or not students have an SAT score. While many students with no SAT score have satisfactory semester outcomes, it is clear that students who took the SAT are much lower risk.

Taken together, these indicators are quite salient and might prove to be useful to college personnel in identifying students at risk for leaving.

Outcomes: The Second Spell

Students who were absent for one or more semesters but returned to the original college without transferring to another are referred to as “stopouts”. A total of 5,421 students fell into this category, and 5,346 of these did so by the eighth semester. Of these, 4,922 returned before data cessation in the tenth semester (data collection continued for twelve semesters, but the last two semesters are only used to determine if the student registered, which allows for a differentiation between stopouts and longer-term leavers). The period of time between when they returned and when they left for the second time is referred to as the second spell. Table 34 details when students stopped out of the first spell and when they began the second spell:

Table 34. Spell I Stopouts: First Spell Last Term and Second Spell Return.

First Spell Exit Term	Second Spell Return Term										
	3	4	5	6	7	8	9	10	Total by 10	After 10	Total
1	602	151	111	61	53	30	31	30	1,069	64	1,133
2		766	271	106	76	45	38	24	1,326	81	1,407
3			573	139	84	43	39	16	894	43	937
4				486	156	66	63	33	804	67	871
5					274	71	37	19	401	53	454
6						188	63	26	277	48	325
7							88	23	111	32	143
8								40	40	36	76
Total	605	921	960	798	650	451	368	221	4,922	424	5,346

As Table 35 demonstrates, a little more than one-quarter of these students had a “successful” final outcome, i.e. they were still enrolled in the tenth semester (10 percent)

graduated (11.7 percent) or seamlessly transferred to another college (5.7 percent). A little more than one-third of these students experienced a second interruption of their studies in the form of a stopout or delayed transfer, and almost 38 percent did not return for the remainder of the observation period

Table 35. Second Spell Leave Type for the 2004 and 2005 Freshman Cohorts.

Outcome			Model I			Model II			Model III		
	N	%		N	%		N	%		N	%
Continue	493	10.0%	Continue	493	10.0%	Continue/ Graduate	1,067	21.7%	Success	1,348	27.4%
Graduate	574	11.7%	Graduate	574	11.7%						
Immediate Transfer	281	5.7%	Immediate Transfer	281	5.7%	Immediate Transfer	281	5.7%			
Stopout, One term	602	12.2%	Stopout, One term	602	12.2%	Absence	3,574	72.6%	Absence	3,574	72.6%
Transfer After One Term	167	3.4%	Transfer After One Term	167	3.4%						
Stopout > One Term	335	6.8%	Absence, > One Term	2,805	57.0%						
Transfer > One Term	584	11.9%									
Stopout, Intersession Return	21	0.4%									
Dropout	1,865	37.9%									
Total	4,922	100.0%	Total	4,922	100.0%	Total	4,922	100.0%	Total	4,922	100.0%

Second Spell, Model I.

As with the first spell, Model I differentiates risks for students of graduating, transferring to another college in the following term, stopping out (leaving for one semester), transfer to another college after a one term absence, and finally, being absent from higher education for two or more semesters (again, referred to in this section as “dropout”). The final model was compared with a time-only model that used binary semester indicator variables. Bayesian Information Criteria indicated that the final model was a much better fit. The comparison is summarized in Table 36.

Table 36. Comparison of a Time-only Model I with Final Model I for the Second Spell.

	Model	
	Time Only	Final
Log-Likelihood	-5,756.81	-4,646.50
-2LL	11,513.62	9,293.00
N	5,174	5,174
Predictors	7	8
Outcome Categories	6	6
Model Parameters	35	40
BIC	11,812.92	9,635.06
χ^2		2,177.86
df		5
p		0.000

As with the first spell, a collinearity analysis was performed using a linear regression procedure. The highest Variance Inflation Index among the predictor variables was 1.824, which does not indicate any serious threats. Also, the Pearson and Deviance Goodness-of-Fit statistics are non-significant, which is further evidence of adequate fit. The Pearson and deviance statistics are presented in Table 37. Odds ratios for Model I outcome are presented in Table 38.

Table 37. Pearson and Deviance Goodness-of-fit Statistics for Spell II, Model I, 2004 Cohort.

	χ^2	df	p
Pearson	23,773.763	24,950	1.000
Deviance	9,036.090	24,950	1.000

Most of the predictors are academic. The only precollege indicator that remains in the model is the binary variable that indicates that the student had not submitted SAT scores. Students who did not take the SAT were less likely to graduate or transfer (but for both of these, the parameter is only significant for the combined cohorts) and were more likely to stop out or drop out.

Among college performance indicators, students who earned more credits in the semester were less likely to transfer (both immediate and delay) or to stop out or drop out. Students who achieved 60 cumulative credits were more likely to graduate, transfer, stop out, or drop out. The number of credits taken during an intersession (summer or winter) was positively associated with graduation and negatively associated with dropping out. Remedial hours reduced the hazard of dropout and stopout, but also reduced the likelihood that a student would graduate or transfer (immediate). Withdrawals reduced the likelihood of graduating, but increased the hazard of transfer (both forms), stopout, and dropout. A higher semester GPA increased the likelihood of graduating and decreased the hazard of all other forms of departure. Cumulative GPA was similar, but a higher cumulative GPA increased the likelihood of immediate transfer.

Table 38. Second Spell, Model I: Odds Ratios for Leaving versus Continuation, 2004 and 2005 Cohorts.

Category	Predictor	Cohort	Odds of Leaving				
			Graduate	Transfer	Stopout	Transfer1	Dropout
Precollege Record							
	Missing SAT Score	2004	0.676	0.687	1.745***	0.694	2.573****
		Both	0.739*	0.683****	1.348**	0.815	1.787****
College Performance							
	Earned Credits in Semester	2004	0.985	0.958	0.936****	0.915*	0.860****
		Both	1.006	0.961*	0.922****	0.921***	0.852****
	Earned at Least 60 Credits	2004	196.148**	3.159****	1.167	3.034*	1.832***
		Both	154.603**	2.925****	1.162	2.717***	1.605****
	Intersession Credits	2004	1.321****	0.952	0.965	1.116	0.698****
		Both	1.289****	0.859	0.949	1.013	0.701****
	Remedial Hours	2004	0.829***	0.942	0.936***	0.994	0.969**
		Both	0.782****	0.929***	0.941****	0.967	0.950****
	Withdrawals	2004	0.630*	1.189	1.139*	1.395***	1.359****
		Both	0.577***	1.189*	1.136**	1.427****	1.318****
	Semester GPA	2004	1.361*	0.815	0.835*	0.696**	0.815****
		Both	1.195	0.744****	0.832***	0.794*	0.771****
	Cumulative GPA	2004	1.644*	1.276	0.769**	0.664*	0.668****
		Both	1.471**	1.394****	0.880	0.580****	0.674****

*p<.05

**p<.01

***p<.005

**** p<.001

Using the 2004 cohort, Model I is effective in self-identifying students who continue and graduate, and identifies a little more than half of the students who dropped out. The model is unable, however, to discriminate any transfers or stopouts. As with the first spell, the hazards or stopping out generally run in the same direction as dropping out. The classification matrix for the 2004 cohort is presented in Table 39.

Table 39. Second Spell: Model I Confusion Matrix for the 2004 Cohort.

		Predicted						Total	
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence		
Observed	Continue	N	2,611	117	0	0	0	298	3,026
		Row %	86.3%	3.9%	0.0%	0.0%	0.0%	9.8%	100.0%
		Col %	71.8%	29.8%	--	--	--	26.0%	58.5%
	Graduate	N	43	225	0	0	0	4	272
		Row %	15.8%	82.7%	0.0%	0.0%	0.0%	1.5%	100.0%
		Col %	1.2%	57.3%	--	--	--	0.3%	5.3%
	Immediate Transfer	N	98	15	0	0	0	28	141
		Row %	69.5%	10.6%	0.0%	0.0%	0.0%	19.9%	100.0%
Col %		2.7%	3.8%	--	--	--	2.4%	2.7%	
Stopout	N	214	7	0	0	0	74	295	
	Row %	72.5%	2.4%	0.0%	0.0%	0.0%	25.1%	100.0%	
	Col %	5.9%	1.8%	--	--	--	6.5%	5.7%	
Delayed Transfer	N	44	5	0	0	0	29	78	
	Row %	56.4%	6.4%	0.0%	0.0%	0.0%	37.2%	100.0%	
	Col %	1.2%	1.3%	--	--	--	2.5%	1.5%	
Absence	N	625	24	0	0	0	713	1,362	
	Row %	45.9%	1.8%	0.0%	0.0%	0.0%	52.3%	100.0%	
	Col %	17.2%	6.1%	--	--	--	62.2%	26.3%	
Total	N	3,635	393	0	0	0	1,146	5,174	
	Row %	70.3%	7.6%	0.0%	0.0%	0.0%	22.1%	100.0%	
	Col %	100.0%	100.0%	--	--	--	100.0%	100.0%	

The same analysis performed on the combined 2004 and 2005 cohorts results in a similar pattern, shown in Table 40.

Table 40. Second Spell: Model I Confusion Matrix for Both Cohorts.

		Predicted							
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence	Total	
Observed	Continue	N	5,221	266	0	0	0	652	6,139
		Row %	85.0%	4.3%	0.0%	0.0%	0.0%	10.6%	100.0%
		Col %	71.7%	30.9%	--	--	--	26.9%	58.1%
	Graduate	N	88	481	0	0	0	5	574
		Row %	15.3%	83.8%	0.0%	0.0%	0.0%	0.9%	100.0%
		Col %	1.2%	55.9%	--	--	--	0.2%	5.4%
	Immediate Transfer	N	201	27	0	0	0	53	281
		Row %	71.5%	9.6%	0.0%	0.0%	0.0%	18.9%	100.0%
		Col %	2.8%	3.1%	--	--	--	2.2%	2.7%
	Stopout	N	424	18	0	0	0	160	602
Row %		70.4%	3.0%	0.0%	0.0%	0.0%	26.6%	100.0%	
Col %		5.8%	2.1%	--	--	--	6.6%	5.7%	
Delayed Transfer	N	92	9	0	0	0	66	167	
	Row %	55.1%	5.4%	0.0%	0.0%	0.0%	39.5%	100.0%	
	Col %	1.3%	1.0%	--	--	--	2.7%	1.6%	
Absence	N	1,255	59	0	0	0	1,491	2,805	
	Row %	44.7%	2.1%	0.0%	0.0%	0.0%	53.2%	100.0%	
	Col %	17.2%	6.9%	--	--	--	61.4%	26.5%	
Total	N	7,281	860	0	0	0	2,427	10,568	
	Row %	68.9%	8.1%	0.0%	0.0%	0.0%	23.0%	100.0%	
	Col %	100.0%	100.0%	--	--	--	100.0%	100.0%	

Using parameters obtained from the 2004 cohort and applied to the data from 2005 produced similar classification rates for student who continued (86.6 percent correctly identified), graduated (81.1 percent correctly identified). Just over 47 percent of dropouts were correctly detected. Table 41 presents the classification matrix:

Table 41. Second Spell: Model I Confusion Matrix for the 2005 Cohort Using

Parameters Obtained from the 2005 Cohort.

		Predicted							
		Continue	Graduate	Immediate Transfer	Stopout	Delayed Transfer	Absence	Total	
Observed	Continue	N	2,697	138	0	0	1	278	3,114
		Row %	86.6%	4.4%	0.0%	0.0%	0.0%	8.9%	100.0%
		Col %	69.9%	31.1%	--	--	100.0%	25.5%	57.7%
	Graduate	N	53	245	0	0	0	4	302
		Row %	17.5%	81.1%	0.0%	0.0%	0.0%	1.3%	100.0%
		Col %	1.4%	55.2%	--	--	0.0%	0.4%	5.6%
	Immediate Transfer	N	103	13	0	0	0	24	140
		Row %	73.6%	9.3%	0.0%	0.0%	0.0%	17.1%	100.0%
		Col %	2.7%	2.9%	--	--	0.0%	2.2%	2.6%
	Stopout	N	227	11	0	0	0	69	307
Row %		73.9%	3.6%	0.0%	0.0%	0.0%	22.5%	100.0%	
Col %		5.9%	2.5%	--	--	0.0%	6.3%	5.7%	
Delayed Transfer	N	54	5	0	0	0	30	89	
	Row %	60.7%	5.6%	0.0%	0.0%	0.0%	33.7%	100.0%	
	Col %	1.4%	1.1%	--	--	0.0%	2.8%	1.6%	
Absence	N	727	32	0	0	0	684	1,443	
	Row %	50.4%	2.2%	0.0%	0.0%	0.0%	47.4%	100.0%	
	Col %	18.8%	7.2%	--	--	0.0%	62.8%	26.7%	
Total	N	3,861	444	0	0	1	1,089	5,395	
	Row %	71.6%	8.2%	0.0%	0.0%	0.0%	20.2%	100.0%	
	Col %	100.0%	100.0%	--	--	100.0%	100.0%	100.0%	

Table 42 is a sensitivity/specificity schedule for the second leave for Model I.

Probabilities for absence (stopout and dropout are summed. If the total summed

probability is greater than the cutoff criterion, the case is classified as a leave, this results in a correct detection or a false positive. The percentage of correct detections is the number of identified leavers that actually left. The percentage of false positives is percentage of identified leavers that did not actually leave.

Table 42. Sensitivity/Specificity Schedule for Spell II, Model I.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1		Total N = 1,735		Missed Semester ≥ 1		Term N = 1,839	
	Correct Detections	False Positives	Correct Detections	False Positives	Correct Detections	False Positives	Correct Detections	False Positives
	N	N	%	%	N	N	%	%
.05	1,726	3,264	99.5	65.4	1,826	3,315	99.3	64.5
.10	1,679	2,808	96.8	62.6	1,768	2,758	96.1	60.9
.15	1,603	2,257	92.4	58.5	1,675	2,219	91.1	57.0
.20	1,507	1,778	86.9	54.1	1,581	1,714	86.0	52.0
.25	1,397	1,392	80.5	49.9	1,453	1,348	79.0	48.1
.30	1,287	1,092	74.2	45.9	1,319	1,025	71.7	43.7
.35	1,182	848	68.1	41.8	1,181	786	64.2	40.0
.40	1,084	656	62.5	37.7	1,073	595	58.3	35.7
.45	979	514	56.4	34.4	974	470	53.0	32.5
.50	880	392	50.7	30.8	852	357	46.3	29.5
.55	780	293	45.0	27.3	747	271	40.6	26.6
.60	676	228	39.0	25.2	635	207	34.5	24.6
.65	538	166	31.0	23.6	502	138	27.3	21.6
.70	409	116	23.6	22.1	390	93	21.2	19.3
.75	271	72	15.6	21.0	261	55	14.2	17.4
.80	145	36	8.4	19.9	143	24	7.8	14.4
.85	43	9	2.5	17.3	57	10	3.1	14.9
.90	2	0	0.1	0.0	4	0	0.2	0.0
.95	0	0	0.0	--	0	0	0.0	--

Second Spell, Model II.

Under Model II, students who were still enrolled in the tenth semester are combined with graduates, students who seamlessly transferred are included separately, and students who left for one or more terms are classified as leavers. A test for covariance was conducted using a linear regression procedure; no serious threats were detected, the highest Variance Inflation Index being 2.824. A comparison with a time-only model demonstrated that the final model was a superior fit, the BIC test is summarized in Table 43.

Table 43. Comparison of Spell II, Model II for the Final Model versus a Time-only Model.

	Model	
	Time Only	Final
Log-Likelihood	-2,477.40	-2,302.14
-2LL	4,954.80	4,604.28
N	5,174	5,174
Predictors	7	12
Outcome Categories	3	3
Model Parameters	14	24
BIC	5,074.52	4,809.51
χ^2		265.01
Df		10
P		0.000

The final model had the added advantage of having non-significant Pearson and deviance goodness-of-fit statistics, which are summarized in Table 44.

Table 44. Pearson and Deviance Goodness-of-fit Statistics for Spell II, Model II, 2004 Cohort.

	χ^2	df	p
Pearson	10,419.664	10,264	.139
Deviance	6,371.063	10,264	1.000

Table 45 presents odds ratios associated with predictors of the second leave with Model II outcome types.

Table 45. Second Spell, Model II: Odds Ratios for Immediate Transfer and Absence versus Graduation or Continuation.

Category	Predictor	Transfer		Absence	
		2004	Both	2004	Both
Time					
	Semesters missed (centered on 1)	1.047	0.967	1.104****	1.075****
	Spring semester	2.488****	2.130****	1.386****	1.367****
	Summer term following spring	0.570	0.526*	0.381****	0.369****
Pre-College Characteristics					
	Missing SAT Score	0.694	0.732*	2.058****	1.511****
College Performance					
	Earned Credits in Semester	1.018	1.015	0.955***	0.940****
	Withdrawals	1.182	1.216*	1.407****	1.384****
	Semester GPA	0.826	0.801***	0.609****	0.602****
	Missing Semester GPA	1.712	1.478	2.019****	1.879****
	Missing Cumulative GPA	2.349	1.004	1.902*	1.307
	Writing Proficient	1.678*	1.587**	0.814**	0.842***
Environment and Support					
	Total Hours in Class per Week	0.966	0.963*	0.951****	0.954****
	Grant Loss (Thousands)	1.134	1.099	1.205****	1.188****

* p<.05

** p<.01

*** p<.005

**** p<.001

The number of semesters that a student missed between the first and second spells is associated with a significantly higher likelihood of leaving. Students were also more likely to transfer or leave following the spring semester than after the fall, but being registered for a summer session was associated with a significantly decreased likelihood to leave as well as to transfer (although for transfer, this is significant only for the combined cohorts). Students who lack an SAT score are significantly more likely to leave and less likely to transfer.

There is a decreased risk of leaving associated with number of credits earned in a semester.

Course withdrawals present an increased risk of both transfer and leaving; notably, course failure does not appear to be a risk for Model II outcomes in the second spell. Higher semester GPA presents a reduced hazard for both transfer and leaving. Not having a semester GPA presents a significant risk for both transfer and for leaving. Missing a cumulative GPA presents an increased risk for leaving but a reduced risk for transfer. Students who are writing proficient have a lowered risk for leaving. As with Model 1, course failure does not appear in the model.

The number of hours that the student is scheduled to spend in class per week presents a decreased risk for both leaving and transfer. A decrease in the amount of grant aid relative to the average grant aid that the student received in prior semesters also presented a risk for leaving.

Table 46 presents a classification table for observed versus detected outcomes in the combined 2004 cohort. Cells that are accurate classifications are presented in bold outline. Under model II, more than half of all non-transfer leaves were correctly detected. The model did not detect any transfers, misclassifying 75 percent of them as continue or graduate.

Table 46. Second Spell: Model II Confusion Matrix for the 2004 Cohort.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	2,887	0	411	3,298
		Row %	87.5%	0.0%	12.5%	100.0%
		Col %	76.1%	--	29.8%	63.7%
	Immediate Transfer	N	105	0	36	141
		Row %	74.5%	0.0%	25.5%	100.0%
		Col %	2.8%	--	2.6%	2.7%
	Absence	N	803	0	932	1,735
		Row %	46.3%	0.0%	53.7%	100.0%
		Col %	21.2%	--	67.6%	33.5%
	Total	N	3,795	0	1,379	5,174
		Row %	73.3%	0.0%	26.7%	100.0%
		Col %	100.0%	--	100.0%	100.0%

Table 47 presents a classification table for observed versus detected outcomes in the combined 2004 and 2005 cohorts. Cells that are accurate classifications are presented in bold outline. Under model II, more than half of all non-transfer leaves were correctly detected.

Table 47. Second Spell: Model II Confusion Matrix for 2004 and 2005 Cohorts.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	5,845	0	868	6,713
		Row %	87.1%	0.0%	12.9%	100.0%
		Col %	75.8%	--	30.3%	63.5%
	Immediate Transfer	N	213	0	68	281
		Row %	75.8%	0.0%	24.2%	100.0%
		Col %	2.8%	--	2.4%	2.7%
	Absence	N	1,649	0	1,925	3,574
		Row %	46.1%	0.0%	53.9%	100.0%
		Col %	21.4%	--	67.3%	33.8%
	Total	N	7,707	0	2,861	10,568
		Row %	72.9%	0.0%	27.1%	100.0%
		Col %	100.0%	--	100.0%	100.0%

Table 48 presents a classification table for observed versus detected outcomes in the 2005 cohort using parameters obtained from the 2004 cohort. Cells that are accurate classifications are presented in bold outline. Under Model II, 49.6 of all non-transfer leaves were correctly detected.

Table 48. Second Spell: Model II Confusion matrix for 2005 Cohort Using Parameters

Obtained from the 2005 Cohort.

		Predicted				
		Continue Or Graduate	Immediate Transfer	Absence	Total	
Observed	Continue Or Graduate	N	3,035	0	380	3,415
		Row %	88.9%	0.0%	11.1%	100.0%
		Col %	74.5%	--	28.8%	63.3%
	Immediate Transfer	N	114	0	26	140
		Row %	81.4%	0.0%	18.6%	100.0%
		Col %	2.8%	--	2.0%	2.6%
	Absence	N	926	0	913	1,839
		Row %	50.4%	0.0%	49.6%	100.0%
		Col %	22.7%	--	69.2%	34.1%
	Total	N	4,075	0	1,319	5,394
		Row %	75.5%	0.0%	24.5%	100.0%
		Col %	100.0%	--	100.0%	100.0%

Table 49 is a selectivity/sensitivity schedule for the second leave for Model II. Probabilities for remaining enrolled (graduate/continue and immediate transfer) are summed. If the total summed probability is greater than the cutoff criterion, the case is classified as a leave, this results in a correct detection or a false positive. The percentage of correct detections is the number of identified leavers that actually left. The percentage of false positives is percentage of identified leavers that did not actually leave.

Table 49. Sensitivity/Specificity Schedule for Spell II, Model II.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1 Term Total N = 1,735				Missed Semester ≥ 1 Term Total N = 1,839			
	Correct	False	Correct	False	Correct	False	Correct	False
	Detections	Positives	Detections	Positives	Detections	Positives	Detections	Positives
	N	N	%	%	N	N	%	%
.05	1,729	3,283	99.7	65.5	1,827	3,331	99.3	64.6
.10	1,681	2,799	96.9	62.5	1,756	2,740	95.5	60.9
.15	1,598	2,179	92.1	57.7	1,658	2,149	90.2	56.4
.20	1,482	1,688	85.4	53.2	1,542	1,638	83.8	51.5
.25	1,377	1,290	79.4	48.4	1,420	1,242	77.2	46.7
.30	1,273	990	73.4	43.7	1,291	946	70.2	42.3
.35	1,175	777	67.7	39.8	1,172	714	63.7	37.9
.40	1,079	617	62.2	36.4	1,071	568	58.2	34.7
.45	989	489	57.0	33.1	985	463	53.6	32.0
.50	897	398	51.7	30.7	883	376	48.0	29.9
.55	822	310	47.4	27.4	783	289	42.6	27.0
.60	715	240	41.2	25.1	682	228	37.1	25.1
.65	600	176	34.6	22.7	574	164	31.2	22.2
.70	493	125	28.4	20.2	457	110	24.9	19.4
.75	372	78	21.4	17.3	336	56	18.3	14.3
.80	243	35	14.0	12.6	207	30	11.3	12.7
.85	107	13	6.2	10.8	94	9	5.1	8.7
.90	12	1	0.7	7.7	13	0	0.7	0.0
.95	0	0	0.0	--	0	0	0.0	--

Second Spell, Model III.

Under Model III, students who were still enrolled as of the eleventh semester, students who graduated and students who seamlessly transferred are grouped together because their enrollment has not been interrupted. All other students are grouped into the second category because their enrollment in college was interrupted for a second time. A little more than one-quarter of students had a favorable outcome.

The final model was compared to a time-only model, and the final model showed a distinct improvement. A comparison of the two models using Bayesian Information Criteria is summarized in Table 50.

Table 50. Comparison of Spell II, Model III for the Final Model versus a Time-only Model.

	Model	
	Time Only	Final
Log-Likelihood	-3,271.88	-2,606.08
-2LL	4,954.80	4,604.28
N	5,174	5,174
Predictors	7	17
Outcome Categories	2	2
Model Parameters	7	17
BIC	5,014.66	4,749.65
χ^2		265.01
Df		10
P		0.000

A test for covariance was performed using a linear regression procedure; no serious threats were detected, the highest Variance Inflation Factor being 2.844. The Pearson and deviance Goodness-of-fit statistics were also non-significant, which also indicate that the model is a good fit. These statistics are presented in Table 51.

Table 51. Pearson and Deviance Goodness-of-fit Statistics for Spell II, Model III, 2004 Cohort.

	χ^2	df	p
Pearson	5,270.559	5,156	.130
Deviance	5,212.163	5,156	0.289

Odds ratios for leaving versus being enrolled in college or graduating associated with each predictor are presented in Table 52:

Table 52. Second Spell, Model III: Odds Ratios for Unsuccessful Leaving (Stopout, Dropout or Delayed Transfer).

Category	Predictor	2004 Cohort	Both Cohorts
Time			
	Semesters missed (centered on 1)	1.086***	1.060***
	Spring Semester	1.330****	1.320****
	Winter term following fall	0.308*	0.261****
	Summer term following spring	0.377****	0.370****
	Age Centered on 18	1.016*	1.012*
Pre-College Characteristics			
	Missing SAT Score	2.020****	1.562****
	Regents Mean	1.011*	1.010**
College Performance			
	Earned Credits in Semester	0.960***	0.946****
	Earned at Least 60 Credits	0.614***	0.600****
	At least 60 credits; GPA is less than 2.0	3.454***	2.088*
	Withdrawals	1.341****	1.313****
	Semester GPA	0.716****	0.698****
	Cumulative GPA	0.677****	0.701****
	Missing Semester GPA	1.907****	1.797****
	Missing Cumulative GPA	2.158***	1.596***
Environment and Support			
	Total Hours in Class per Week	0.959****	0.961****
	Grant Loss (Thousands)	1.191****	1.190****

* p<.05

** p<.01

*** p<.005 **** p<.001

There is an increased risk of leaving associated with the number of semesters missed between the first and the second spells. Students are also at greater risk of leaving following the spring semester than they are following the fall. Registering for the winter or summer term is associated with a decreased risk for leaving.

Students who do not have an SAT score have a significantly higher risk of leaving than do students who have an SAT score, and students with a higher regents average are at a somewhat higher risk for leaving after the second spell. This relationship is surprising.

With regard to college performance, students who earn more credits have an associated decrease in the risk for leaving; this is also true for students who have earned at least 60 credits. However for students who have earned 60 credits but have a GPA that is less than 2.0, the risk of leaving is greatly increased. Course withdrawal is associated with an increase in the risk for leaving; course failure does not appear as a risk factor (it was not indicated in the forward stepwise procedure used to test the complete variable list). Higher semester and cumulative GPA is associated with a decrease in the risk for leaving. Not having a cumulative or semester GPA is associated with a higher risk for leaving.

The number of hours that the students is scheduled to be in class is associated with a decrease in the risk for leaving. Grant loss relative to average grants in prior terms is associated with an increase in the risk for leaving.

Table 53 presents a classification table for observed versus detected outcomes in the 2004 cohort. Cells that are accurate classifications are presented in bold outline.

Under Model III, slightly more than half of all non-transfer leaves were correctly detected; this is as not as good as Model II.

Table 53. Second Spell: Model III Confusion Matrix for the 2004 Cohort.

		Predicted			
		Graduate Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate Continue Or Immediate Transfer	N	3,042	397	3,439
		Row %	88.5%	11.5%	100.0%
		Col %	78.9%	30.1%	66.5%
	Absence	N	813	922	1,735
		Row %	46.9%	53.1%	100.0%
		Col %	21.1%	69.9%	33.5%
	Total	N	3,855	1,319	5,174
		Row %	74.5%	25.5%	100.0%
		Col %	100.0%	100.0%	100.0%

Table 54 presents a classification table for observed versus detected outcomes in the combined 2004 and 2005 cohorts. There is a slightly higher detection rate for both successful and unsuccessful outcomes.

Table 54. Second Spell: Model III Confusion Matrix for the 2004 and 2005 Cohorts.

		Predicted			
		Graduate Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate Continue Or Immediate Transfer	N	6,149	845	6,994
		Row %	87.9%	12.1%	100.0%
		Col %	78.4%	31.0%	66.2%
	Absence	N	1,693	1,881	3,574
		Row %	47.4%	52.6%	100.0%
		Col %	21.6%	69.0%	33.8%
	Total	N	7,842	2,726	10,568
		Row %	74.2%	25.8%	100.0%
		Col %	100.0%	100.0%	100.0%

Table 55 presents a classification table for observed versus detected outcomes in the 2005 cohort using parameters obtained from the 2004 cohort. Cells that are accurate classifications are presented in bold outline. Under Model II, 49.6 of all non-transfer leaves were correctly detected; so this is not an improvement over Model II.

Table 55. Second Spell: Model III Confusion Matrix for the 2005 Cohort Using Parameters Obtained from the 2005 Cohort.

		Predicted			
		Graduate, Continue Or Immediate Transfer	Absence	Total	
Observed	Graduate, Continue Or Immediate Transfer	N	3,178	377	3,555
		Row %	89.4%	10.6%	100.0%
		Col %	77.0%	29.8%	65.9%
	Absence	N	950	889	1,839
		Row %	51.7%	48.3%	100.0%
		Col %	23.0%	70.2%	34.1%
	Total	N	4,128	1,266	5,394
		Row %	76.5%	23.5%	100.0%
		Col %	100.0%	100.0%	100.0%

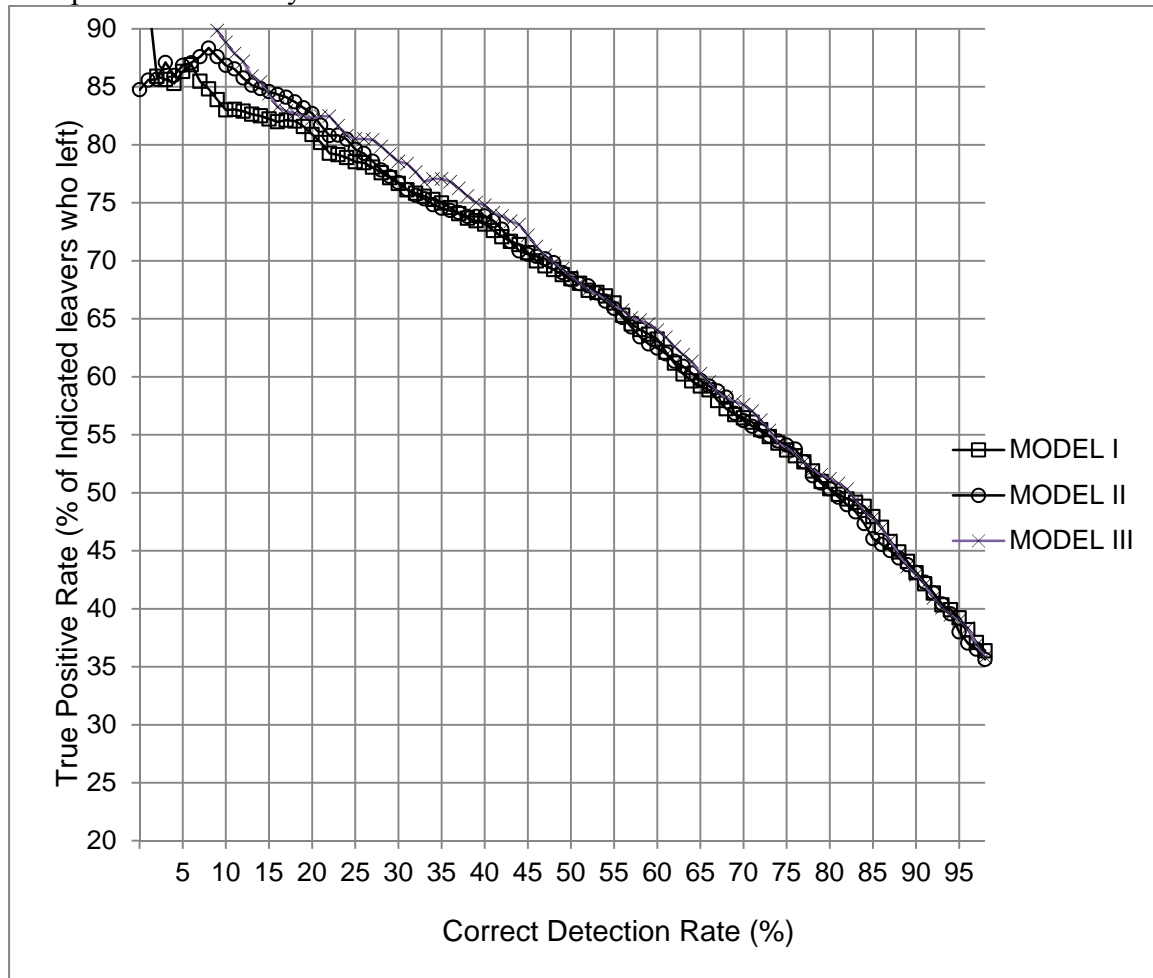
Table 56 is a sensitivity/specificity schedule for the second leave for Model III.

Table 56. Sensitivity/Specificity Schedule for Spell II, Model III.

Cutoff Criterion	2004 Cohort (Training Data Set)				2005 Cohort (Test Data Set)			
	Missed Semester ≥ 1 Term Total N = 1,735				Missed Semester ≥ 1 Term Total N = 1,839			
	Correct	False	Correct	False	Correct	False	Correct	False
	Detections	Positives	Detections	Positives	Detections	Positives	Detections	Positives
	N	N	%	%	N	N	%	%
.05	1,725	3,240	99.4	65.3	1,825	3,294	99.2	64.3
.10	1,676	2,739	96.6	62.0	1,756	2,720	95.5	60.8
.15	1,598	2,153	92.1	57.4	1,661	2,172	90.3	56.7
.20	1,479	1,697	85.2	53.4	1,563	1,666	85.0	51.6
.25	1,389	1,306	80.1	48.5	1,435	1,291	78.0	47.4
.30	1,280	988	73.8	43.6	1,313	971	71.4	42.5
.35	1,178	776	67.9	39.7	1,192	745	64.8	38.5
.40	1,092	626	62.9	36.4	1,095	595	59.5	35.2
.45	997	502	57.5	33.5	981	477	53.3	32.7
.50	922	397	53.1	30.1	889	377	48.3	29.8
.55	821	316	47.3	27.8	809	293	44.0	26.6
.60	726	238	41.8	24.7	715	230	38.9	24.3
.65	599	172	34.5	22.3	598	166	32.5	21.7
.70	506	117	29.2	18.8	466	113	25.3	19.5
.75	372	70	21.4	15.8	330	68	17.9	17.1
.80	240	36	13.8	13.0	214	29	11.6	11.9
.85	100	10	5.8	9.1	103	8	5.6	7.2
.90	12	2	0.7	14.3	11	1	0.6	8.3
.95	0	0	0.0	--	1	0	0.1	0.0

Figure 7 provides a comparison of Models I, II and III for the second leave. Models III can be seen as superior to Models I and II regarding false positive rates.

Figure 7. Second Spell Sensitivity/Specificity Schedule Predictive Outcome Model Comparison: Correctly Detected Leavers versus False Positives.



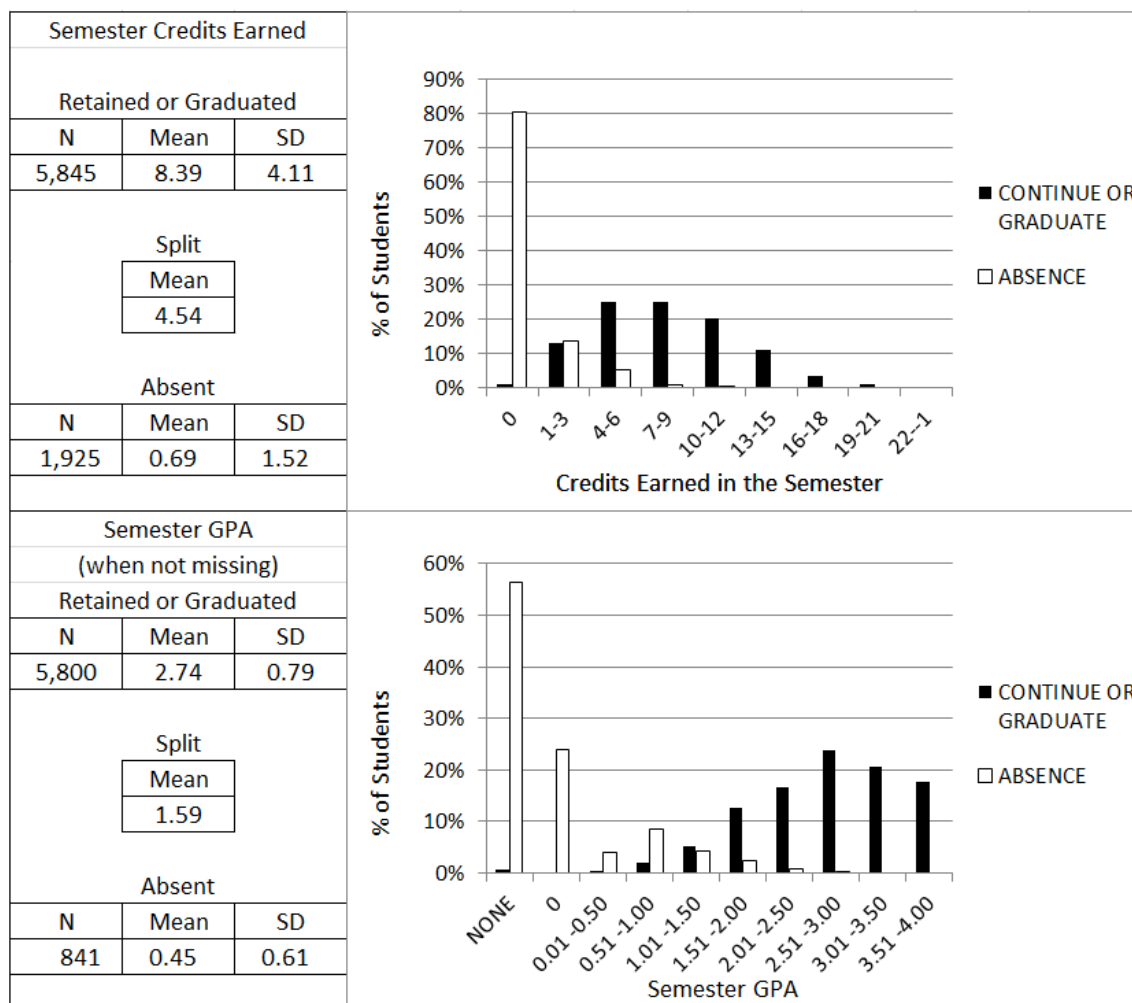
Second Spell High-Risk Person Profile

Since Model II does have the best prediction rate for absences in the second spell, a profile for an at-risk student will be developed using predictors from that model in conjunction with the combined 2004 and 2005 cohorts. As with the first spell, only students who were classified correctly will be used to build the profile. As was done with the first spell, the predictors from the final model were initially entered and then removed one by one until the model was depleted. The most important variables in the model

using this method were the semester GPA and the number of credits earned. In fact, this model identified 55.5 percent of leavers, which is actually higher than the final Model II presented above (53.9), although the false positive rate was higher (34.9% versus 32.7%).

A high risk profile for the second spell is presented in Figure 8.

Figure 8. Spell II Profile for At-risk Students.



As the figure demonstrates, 80 percent of students successfully identified as leavers earn no credits and have a zero or missing GPA. Generally speaking, second spell students with fewer than 4 credits earned and a semester GPA in the F to D range can be regarded as being at risk.

Chapter Five: Discussion

There are several reasons to prefer the simpler Models II and III over Model I of college leaving. This is indicated by the relatively better performance of these models, which do not attempt to make predictions beyond the next semester. Further, it is quite plausible that the decision to return after an absence is controlled by events and circumstances that occur after the student has left. For example, a student may have found gainful or necessary employment that precludes college study. Additionally, models that take next-semester attrition into account can be calibrated and re-assessed only a few months after the beginning of the next semester when re-enrollment or transfer data are available. Models that seek to predict re-enrollment must wait several months or years, and then a status of dropping out is only provisional, contingent on data that may be obtained later. Finally, distinguishing between stopout and dropout presupposes that an institution would be interested in making this distinction, which is by no means settled or clear. For example, would a college choose to address potential dropouts as the more dire cases, or would the institution choose the potential stopout because there may be a greater chance of success? It is important that colleges develop models to assess the attrition risks for students who re-enter after an absence, as has been done here.

Another consideration in choosing among models when using multinomial logistic regression is the assumption of Independence of Irrelevant Alternatives (IIA). This assumption states that an individual's evaluation of two alternatives should not change when a third, irrelevant, alternative is introduced (Kropko, 2008). The IIA assumption does not affect Model III, since there are only two alternative choices, but should be considered for Models I and II in which there are six and three alternatives

respectively. There are several statistical tests that have been proposed to detect situations in which the IIA assumption has been violated and several of these were evaluated by Chen & Long (2007). These authors concluded that tests for violation of IIA are unsatisfactory for empirical research, and recommended that multinomial models be used only when alternative choices can be seen as distinct to the person making the decision. For Model II, which includes the alternatives of continued enrollment (or graduation), immediate transfer, or leaving, the choices are clearly distinct and non-trivial. For Model I, the assumption of irrelevancy among choices is not so clearly tenable. For example, it could be argued that for all of the choices that involve absence, the only choice that was made was not to re-enroll for the first missed semester, and the choice whether or not to return to the institution or to another college was made subsequently. In this light, all choices that involve absence are irrelevant alternatives. This, coupled with the finding that Model I is clearly inferior to Models II and III in terms of making accurate predictions, provides further argument for not using it. It has been argued that research of this nature utilize multinomial probit models, which do not require the IIA assumption, be used in favor of the multinomial logistic model, but Kropko (2008) demonstrates that multinomial logistic models may perform better than multinomial probit models, even when the IIA assumption is violated. He does recommend, however, that alternate models may perform better than either of these; future research should investigate and develop these methods.

This research demonstrates that it is extremely important that colleges take transfer into account. Community colleges are often implicitly and sometimes explicitly constituted as a first step on an educational path that often leads to higher level study at a

baccalaureate-granting institution. As this research demonstrates, many predictors of continuation and graduation are also predictors of transfer. If transfer is not taken into account, many students who go on to pursue higher-level study may be mistaken as having left. It should be borne in mind, however, that the colleges in this study are located in the largest city in the U.S. and that there are many other colleges in close proximity; transfer might not be as practicable or common in other settings. More research is needed in other settings to see whether the relationship between the various predictors holds or if indeed transfer is as common there as it is in CUNY community colleges.

One question regarding transfer that was addressed by this study was whether it should be modeled separately from a successful outcome at the original (Model II) college or as part of a successful outcome (Model III). Given the data available, Model II seems most appropriate to successfully identify leavers in the first spell. This conclusion is supported by the observation that Model II identifies the most leavers and tends to have a lower false positive rate when applied to a naïve dataset. Additionally, Pearson and Deviance goodness-of-fit statistics support the conclusion that Model II is a good Fit, while this is not the case with Model III. The main problem with Model II for the first spell is that it does a poor job of identifying transfers, but since transfer can be considered a successful outcome and since most transfers are misidentified as continue/graduate, the practical concerns of using the model are unaffected. For the second spell, Model II and Model III perform similarly, but while Model II has a better detection rate, it does appear that Model III generally has a lower false positive rate.

The models presented in this research offer some promise in identifying students who are at risk for leaving community college before they actually depart. Still, many difficulties remain. First, while many important risk factors such as class withdrawal are available and known during the semester, other predictors are performance indicators that are not available until the end of the semester; examples of this include class failure, credit accumulation and GPA. If it is necessary to wait until the very end of the semester to determine if a student is at risk for not returning, there may be insufficient time to intervene. One means of dealing with this might be to estimate these predictors using available information. Examples of this might be to estimate the final expected class grade using data from homework, midterms, quizzes and other constituents of a student's final course grade.

Even so, there remains some question as to whether it will be possible to convince a student to re-enroll once his condition reaches that point. Many of the predictors identified in this model are interdependent or serially dependent. For example, students who have not met proficiency requirements are not permitted to take credit courses. Therefore, not being skill proficient will delay the accumulation of credits, which is also a risk factor. Further, students who repeatedly take remedial courses may deplete their grant dollars doing so, thereby placing themselves at risk on that count. This may indeed be happening, since it is observed that grant loss, or a reduction of grant dollars relative to the amount that students had been receiving, presents a hazard for departure. In this scenario, it is clear that at least some students may be identified as being at risk at a time when it is too late to do anything about it. This suggests that colleges may be well-

advised to consider operational changes that may mitigate the risk of leaving early on. Some recommendations will be discussed below.

Time-Related Factors

Spring semesters present a risk for leaving in both the first and second spells. This may be due to the long hiatus (3 months) that exists between the spring and fall semesters; there is only a one-month hiatus following the fall semester. One possible reason for this may be that students develop other pursuits during the summer (employment, for example) that preclude continued enrollment during the fall. It is noteworthy that students who enroll in intersessions (winter and summer) are at significantly reduced risk for leaving, and evidence exists for this in both the first and second spell. There is a question as to whether the reduced risk associated with winter summer sessions is causal or merely related to a third variable. Causal explanations could be that that intersession enrollment helps to “maintain momentum” and precludes attractive alternatives such as gainful employment that compete with education; the fact that the summer break is longer than the winter break supports this. A merely relational explanation is that stronger, more motivated or more ambitious students are both more likely to enroll during intersessions and to stay enrolled until they graduate. Whether this relationship is causal or merely relational has practical policy implications such as whether the semesters should be lengthened or perhaps whether a trimester system might be superior to a semester system. Future research should address these questions.

Age is another time-related variable. In the first spell under Model I age is related to longer-term leaving and but it is associated with a reduced likelihood of transfer. It may be that students who are older have more obligations such as family and work and

are less likely to undertake steps to attend another institution. Age is related to increased risk for leaving in the second spell under Model III.

Demographic Predictors

Demographic predictors that were significant included race and international status; these only appeared as significant predictors in the first spell. In the final models, Asians generally seemed more likely to transfer and less likely to leave, while Latino students were more likely to leave and less likely to transfer. International students were less likely graduate, transfer, or leave long term, but this only appeared in Model I.

Pre-College Indicators

Pre-College indicators, including SAT scores and high school GPA, seem to predict more by their presence or absence than through their values. In all models in which SAT is an indicator, if the student submitted a score, he was less likely to leave. This relationship appeared in both the first and second spells. It may speak to a student's motivation: Given the time and expense of doing so, it is likely that student who took the SAT were more interested in going to college than students who did not. A similar relationship is observed with high school GPA; students who had a high school GPA were less likely to leave.

Skills Proficiency and Remedial Courses

Not being skill-proficient has been identified as a risk for leaving. There are three areas of skill proficiency; these include reading, writing and mathematics. Of these, writing has been shown to be a risk factor for non-transfer leaving, and it appears in all models. Writing is particularly difficult because fewer than half of all students are writing-proficient when they arrive. Also, writing is a risk factor for both the first and

second leaves, which suggests that it especially persistent. Additionally, students who cannot write well will be unable to take most college level courses and thus to acquire credits, the lack of which is a risk factor for leaving. The colleges have a policy of requiring students to take remedial courses until they pass the skills tests. A contingent risk that is created by this circumstance is that students may use up grant money in taking remedial courses and run through the funds before finishing the degree.

Remedial courses have not been demonstrated by this research carry a risk for leaving, on the contrary, the models above have shown that taking remedial hours is associated with a decreased risk. One consideration, however, is the efficacy with which remedial courses are leading to skills proficiency. Given the risk that accompanies a lack of skills proficiency, it should be important to identify the features of remedial courses that lead to proficiency as well as the features of remedial courses that do not. Future research should examine these courses and their requirements. A number of factors, such as class size, length of meeting time, and student productivity (in the case of writing this might include the quality and quantity of writing that is generated by the student) may play a role. Changes could be made that might make students more likely to achieve skill proficiency. For example, it is probably necessary that students simply write a lot in order to improve their skills. If the writing course has too many students, instructors will probably be reluctant to require as much of students because of amount of correcting that will result. More research is needed to determine how much writing (and correcting on the part of an instructor) would be required to improve a student's proficiency to the college level, given a student's level of preparation. This information could in turn be used to inform class size, staffing required, and ultimately, cost.

College Performance

Not surprisingly, college performance is predictive of leaving. Students with higher GPAs and greater credit accumulation both on a semester and cumulative basis are less likely to leave. Students who fail or withdraw from classes are more likely to leave. It is surprising however, that withdrawal is a more potent predictor of leaving, as can be seen by the higher odds ratios that are consistently associated with it, as well as by the observation that withdrawal is retained in models of the second leave while failure is not.

Course withdrawal deserves some further consideration, first because it is strongly related to attrition, and second because it is alarmingly prevalent. There are, as previously noted, at least two reasons that a student might choose to withdraw from a class. The first, the official reason, is that the student has misunderstood the nature or content of the course and does not wish to continue. The second, a more practical reason, is that the student feels he cannot pass the course and has made a strategic decision to avoid a failing grade and a detriment to his GPA as well. In many ways, a decision to avoid a failing mark in this manner is an intelligent one, but it does beg the question as to why withdrawal is associated with a greater risk subsequent leaving. It is possible that a student who withdraws is more aware that he is failing a class than the student who ultimately fails. One possible reason is causal: the student, by withdrawing from a course, becomes more comfortable with the idea of leaving, and later is more prone to leave the college itself. Another reason is merely correlational: The student has already begun to disassociate himself from the college and course withdrawal is merely an early warning sign that this process has begun.

Financial Indicators

Financial Aid in the form of grants has been shown to be a predictor of retention. Much of the student's grant aid consists of need-based government grants including the Federal Pell grant and the New York State Tuition Assistance Program (TAP). While it is unlikely that an increase in this aid is possible, one problem may be that students are using too much of their aid taking courses for which they do not earn credit. Such courses would include remedial courses that do not carry credit, failed courses, and courses from which students withdraw. As mentioned previously, colleges might do well to investigate the features of non-credit courses that quickly lead to remediation. Also, it may be possible to encourage students to take courses for which they are adequately prepared, and to offer assistance in the form of tutoring when they are performing poorly.

Loan aid is associated with a decrease in attrition risk under Model III, but it has also been demonstrated that students are sometimes unwilling to take out loans. Given the recent problems regarding credit, this is quite understandable. Moreover, students who take out educational loans are borrowing to finance a product that is in many ways intangible and in other ways uncertain. Unlike a home or a car, for example, a student does not immediately possess that which he is purchasing. Given this, future research might be needed to assess the reasons why students are unwilling to take out loans.

Travel Time

This research suggests that travel time does play a role in leaving college. Students who spend more hours traveling to and from the campus are more likely to transfer. There also exists some evidence (Spell 1, Model II) that they are more likely to leave. It may be that students who travel many hours transferred to a college that was

closer (or enrolled in a residential college) simply because a long commute was difficult. Another explanation is that student who needed to travel may have missed more classes and had lower grades as a result. Future research that looks at attendance patterns may help to resolve whether this is happening.

The model used in this research used transit travel time; this was done because many students do not own a car and for at least one of the colleges, parking is not available. Several of the colleges do have student parking, however, and a number of students do drive to campus. Data were collected on driving time, and the correlation between driving time and transit time was quite strong ($r = .80$). There is was no centrally available data source on which students were using cars to get to campus, but determining which students were might help to better understand a relationship between travel time and retention. Having these data in central databases would likely be useful.

Time on Campus and Class Size

Scheduled time on campus, especially time spent in class, seems to be related to retention. Naturally, a student who spends more time on campus is more integrated into it; this would seem to lend support Tinto (1975). Of course, this variable does not represent the total time on campus because not all students attend every class. One way of furthering these findings would be to an include daily class attendance in the model; this would require that instructors collect attendance data, or that an electronic means such as daily card swipe data used to gain entry to the buildings be used.

There is some evidence that class size is a risk factor for leaving and for transfer.

Policy Implications

As stated above, writing proficiency is important to retention, and more research is needed to determine whether a student simply needs more opportunity to write, or whether other interventions are needed. Since writing proficiency exists along a continuum, with some students needing only a little attention and others needing more, it might be worthwhile to develop remedial writing courses that are varied to the needs of the student. It might be well to assign students with severe impairments to smaller, more intensive courses and students who are merely marginal to standard courses.

Both course failure and course withdrawal present acute risks and colleges would be well advised to take steps to address and ameliorate these problems. There are at several reasons that a student might fail to complete a course. One is that external forces (e.g., a job offer) have drawn the student away from the college and he is simply withdrawing from a course part and parcel of leaving college. In this case, there is little that the college can do. Another explanation is that the student did not put forth the effort to master the material or that the material presented was too difficult to master given the student's lack of prerequisite skills. In the former case, there is little that can be done, but in the latter, the institution might take steps to identify students who are unfit to take a given course and advise them to avoid it until they have mastered the prerequisites. Take, for example a student who does not understand the order of operations in algebra attempting to take a course in statistics. This student would be well-advised to take a college algebra course and perhaps a series of other courses before attempting statistics. Of course, there are prerequisite courses that are required for higher level courses, but these do not always include a performance level for the prerequisite.

Colleges currently have some indicators that might serve as predictors of course readiness; these include the high school record, which in the case of students who graduated from New York City's public school system includes area proficiencies (such as math, science, social studies, and other areas). Other sources of information include the New York State Regents examination, the college boards, and performance in courses already taken. Additionally, it might be possible to develop domain-specific tests that would help pre-screen students whose fitness for a course is in doubt; these could be developed with the input of faculty, who are likely very acquainted with the skills that are needed to master the material in any given course. All of the foregoing would require the development of technology that would assess a student's fitness for a course and present that information to advisement personnel when the student is registering for classes. One way to manage this would be to have software that predicts whether or not the student will complete (i.e. not withdraw from) a course he is considering, and what the expected grade will be, possibly with a confidence band. In this way, advisement personnel would be able to advise students not to take courses that are outside their zone of proximal development. If the student insists on taking a course for which he may not be prepared, this information might be useful in informing staffing levels (i.e. teaching assistants or tutors) that will be needed for given course sections.

When a student finds herself enrolled in course in which she is performing poorly, an early warning system that alerts advisement personnel who can then intervene and refer the student to tutoring services would be useful. Such a system could make use of an online grade-book that would track interim grades that are received on homework assignments, quizzes, tests, and term papers. The online grade book could also be used to

track and report class absences, which might also be a predictor of poor course performance. Of course, more research is needed to identify whether these variables are good predictors of poor course performance, failure or withdrawal.

Another finding of this research is that students who accumulate 60 credits but have a lower than satisfactory GPA are at acute risk for leaving vis-à-vis students who have accumulated 60 credits but have a satisfactory GPA. This suggests that students who completed enough credits to graduate may be somewhat disinclined to take steps to rehabilitate their record and simply give up. It is also possible that some students may not understand that credit accumulation alone is not sufficient to merit a diploma.

Among the steps that advisement personnel could take in this situation would be to make sure that students understand this, especially if they are accumulating credits with an unsatisfactory passing grade. Developing and utilizing a user-friendly onscreen application that is regularly consulted during the registration process might aid in ensuring that the student is making progress in meeting general education core requirements, major requirements, and minimum GPA requirements.

One final area that has policy implications is financial aid. This research has demonstrated that the loss financial aid in the form of grants is a risk factor for leaving. It is therefore advisable that a system be developed that tracks how much grant aid a student is eligible for, how much the student has used, and how much remains. It is important to recognize that financial aid grants are an exhaustible resource that must be carefully managed and wisely utilized.

Alternate Models

In this study, students were not considered in the context of the individual colleges that they attended; it is possible that the accuracy of the study could be improved by including this information in the model. One simple means of doing this would be to include indicator variables that identify the schools. In this study, this would involve having 5 indicators (there were six colleges; one would serve as the base). The advantage of doing this lies in its simplicity: OR coefficients greater than 1 would indicate that a student is more likely to have a given outcome than the base school and OR coefficients less than one would indicate that the student is less likely to have a given outcome. The problem with this approach is that it does not clarify what characteristic or set of characteristics held by the college are associated with this difference. We only learn whether or not there is a difference between colleges, but no light is shed on why that difference exists.

Another approach would be to include the school identifier as a factor. With this approach, separate coefficients are presented separately for each college, and it is possible to discern whether a given variable is a useful predictor for a given college. This would address the question of whether all of the predictors apply to all of the colleges. One downside of this approach vis-à-vis this study is that there are already a large number of predictors, and approaching the problem would generate six times as many coefficients, making interpretation a challenge.

A third approach to this would be to employ a hierarchical model that would include characteristics of the college on the school level. For example, it has been demonstrated in this study that the separate colleges have differing numbers of needy

students and differing overall enrollments. Also, the colleges are located in somewhat differing neighborhoods (for example, Queensborough is located in a primarily residential area and BMCC is located in the urban core. These and other characteristics could be modeled either alone or as interactions with other variables in a hierarchical model. Examples of questions that could be addresses might include: is the proportion of the overall population receiving Pell Grants associated with retention? Or, does the distance to the nearest subway station interact with transit travel time in explaining retention or transfer?

Event history analysis is a very useful tool for predicting attrition, and this study it has been demonstrated that colleges have a great deal of data at their disposal and can make some reasonably accurate predictions about who will leave and when they will leave. This may not be enough, however. As stated previously, given the nature of the predictors, by the time a potential leaver is identified, it may be too late to do much about it. Additionally, it has been shown that many of the predictors are interrelated. For example, remedial courses, failed courses and course withdrawal necessarily lead to fewer credits accumulated; failed courses lead to lower GPAs, and eventually, unearned credit hours use up grant funds. A possible complement to this event history model could be a structural model that addresses the extent which these and other factors are interrelated. This, in turn could be developed into a feasibility model that could assess the extent to which corrections and improvements for these issues could be implemented given available financial resources.

The Role of a Student Advisor

The findings presented above suggest that much college leaving depends on academic performance as indicated by proficiency in writing, course performance and course completion. In order to bring about more successful outcomes it is suggested that more attention is needed at registration time, when students are choosing courses, and during the semester as the students attend classes. Since this happens on the student level, that natural liaison would be the student's advisor.

During registration, one area that advisors should focus on is whether students will be able to benefit from the courses that they want to take. For remedial courses, this means that students who apply themselves will become proficient in the remedial area and pass subsequent skills tests. Having indicators of the student's level of proficiency might allow advisors to place students in remedial courses that are tailored to the student's need. For example, students with very low proficiency might need to be placed in smaller classes so that instructors would be able to provide extensive feedback. Students who are only marginally skills non-proficient could be placed in larger courses.

In terms of choosing credit-bearing courses, advisors should have access to an application that will indicate whether a student is likely to complete a proposed course, and if so, what grade he is likely to receive. Such an application would make use of information such as prior performance in the subject area, standardized test scores, and other indicators of proficiency. If there exists a fairly high probability that the student would withdraw from the course or receive an unsatisfactory grade (less than a 'C'), the advisor would suggest that the student reconsider taking the proposed course, and further suggest intermediary courses that would prepare the student to take the proposed course

in the future. If the student persists in taking the course, the advisor might ask the student to take a pretest prepared by the faculty that would indicate whether and which prerequisite skills are lacking. Finally, in the event that an student enrolls in a course for which he is not prepared, this information could be used to inform staffing decisions at the section level (number of teaching assistants, graduate assistants or tutors assigned to the section). Finally, software should be available for advisors to document how they advised the students and why and how course selection was determined (for example, why a student persisted in taking a course for which he appeared to be unprepared).

Since cumulative GPA has been implicated in retention, another consideration is that the proposed set of courses would serve to improve a marginal cumulative GPA. Other considerations would be that the student is making sufficient progress in core and major requirements.

Another consideration in developing a course schedule are external risks. Among the external risks identified in this study are travel time and being financially independent. Although data on working and family obligations are not currently available, these are likely part of the reason that financial independence presents a risk. An advisor could discuss outside obligations and develop a course schedule that would lead to the fewest number of conflicts. Further, an advisor could collect useful data in this area.

During the course of the semester, the advisor's role would switch to monitoring for risks. Since poor course performance is indicated in retention, students whose course performance is low (based on homework performance, quizzes, tests, term papers and attendance) should be contacted by advisors could then coordinate tutoring services or

possibly make arrangements between students and faculty for additional attention or for more time to meet course requirements. This suggestion presupposes that information on interim grades would be available, and it is suggested that colleges begin to construct systems that would be able to gather these data, especially for courses with high failure and withdrawal rates.

Withdrawing from classes has been identified a major risk factor in this study. Advisors should be part of the process of withdrawal. Among other things, an advisor should be acquainted with the risks of withdrawing from classes, especially if it is likely to affect a student's future financial aid.

Another role for advisors is planning for transfer. Since many students leave early to pursue a four year degree, an advisor might be able to take a role in identifying students who plan to transfer (perhaps by simply asking them if they are considering doing so). If it is determined that a student is indeed planning to transfer, and advisor might play a role in helping the student identify a transfer college, and advise the students on the courses that will be of greatest use there.

The traditional model usually has a student assigned to a faculty advisor, usually from his or her major. The primary roles of a professor are, of course, to teach and to pursue research, and indeed a professor's remuneration is based on these two roles. In this light, the role as an advisor is an adjunctive one. Further, it is clear that students are having many difficulties in academic performance. Statistics from this study indicate that in any given semester, around forty percent of students either fail or withdraw from at least one course. It could be argued that watching for warning signs of impending failure might be too much to ask of an individual for whom advisement is not even a primary

task. Additionally, there is no guarantee that students will be acquainted with their advisor; indeed a student may never even take a class with him or her. For many students, his faculty advisor may not have any contact with him except at registration time. Also, in the community college setting, students typically have a shorter or more sporadic career and so there may not be enough time to establish a rapport that may more naturally develop at a four-year college.

The foregoing, coupled with the preceding indicators of leaving argue for a role of a professional whose sole responsibility would be to coordinate and disseminate the information presented above. If professors retain the responsibility of advising students, then the administrator's role would be to guide and instruct the professors on the use of advisement software, as well as to its interpretation. A further role of such an administrator would be develop "risk lists" during the course of the term and alert advisors to that a student is performing poorly.

Another role, possibly at very large institutions, would be that of a professional advisor whose role would be to advise students from the beginning to the end of their college careers. Such an individual would have access to all of the indicators described above, and, prior to registration, would be able to assist the student in developing a schedule that would maximize the student's likelihood of success. Also, the advisor would be able to look out for signs of trouble during the semester and to direct the student to available help.

Summary and Conclusion

In conclusion, it is clear that many of the risks for attrition are present in a community college's databases, and that many of them are academic and performance-based. In-

depth research is needed on remedial course effectiveness and whether and how this may be improved. It is clear that Transfer be included as an acceptable outcome, at least at community colleges that are near to baccalaureate-granting institutions, as are the colleges included in this study. This research should be repeated at institutions in less urban settings to see if the relationship holds there as well.

More research also is needed to identify the risks for course withdrawal and failure, and it is likely that this includes evaluative course data during the semester such as homework grades, quizzes and other evaluations. Attendance patterns during the semester may also help. If risks for attrition can be identified early enough, and corrective action can be applied, colleges may be able to retain students longer so that higher graduation and seamless transfer become more common.

Finally, it needs to be noted that many of the determinants of college leaving have yet to be explained. Other variables that have not been examined here may be available, but many are not. The models presented above take many indicators of academic performance into account. Since the primary goal of college is to improve minds, it seems that improving academic aspects of college life should be a primary focus.

Appendix A. Supplementary Descriptive Statistics

Table A-1. Demographics.

	2004		Cohort 2005		Total	
	N	%	N	%	N	%
Gender						
Female	6,416	58.9	6,099	56.3	12,515	57.6
Male	4,476	41.1	4,733	43.7	9,209	42.4
Ethnicity						
Native American	21	0.2	26	0.2	47	0.2
Asian	1,242	11.4	1,356	12.5	2,598	12
Black	3,733	34.3	3,522	32.5	7,255	33.4
Hispanic	3,875	35.6	3,907	36.1	7,782	35.8
White	2,021	18.6	2,021	18.7	4,042	18.6
Non-Resident Alien	968	8.9	1,378	12.7	2,346	10.8
Marital Status						
Single	7,736	71.0	7,926	73.2	15,662	72.1
Married	465	4.3	380	3.5	845	3.9
Separated	161	1.5	121	1.1	282	1.3
Unknown	2,530	23.2	2,405	22.2	4,935	22.7
Dependency						
Dependent	6,250	57.4	6,545	60.4	12,795	58.9
Independent	2,728	25	2,400	22.2	5,128	23.6
Unknown	1,914	17.6	1,887	17.4	3,801	17.5
Age	Mean	SD	Mean	SD	Mean	SD
	21.4	5.47	21	5.05	21.2	5.27
	N	%	N	%	N	%
17-22	8,301	76.2	8,568	79.1	16,869	77.7
22-27	1,368	12.6	1,242	11.5	2,610	12
27-32	505	4.6	454	4.2	959	4.4
32-37	317	2.9	261	2.4	578	2.7
37-42	226	2.1	162	1.5	388	1.8
42-47	135	1.2	109	1	244	1.1
47-50	40	0.4	36	0.3	76	0.3
Total	10,892	100	10,832	100	21,724	100

Table A-2. Gender, ethnicity and residency survival (First Spell) by semester.

Cohort	Term	Gender		Nat. Am %	Ethnicity		
		Female %	Male %		Asian %	Black %	Hisp. %
2004	1	58.9	41.1	0.2	11.4	34.3	35.6
	2	60.3	39.7	0.2	12.0	33.8	35.2
	3	61.0	39.0	0.2	13.0	33.0	34.2
	4	61.5	38.5	0.2	13.4	31.8	34.5
	5	62.1	37.9	0.2	13.6	31.7	35.2
	6	62.2	37.8	0.1	13.9	31.3	36.3
	7	61.0	39.0	0.2	14.9	31.9	34.6
	8	60.0	40.0	0.3	13.9	33.5	34.7
	9	62.7	37.3	0.5	12.5	31.9	36.8
	10	64.2	35.8	0.0	14.6	33.5	34.0
Total		60.5	39.5	0.2	12.6	33.1	35.1
2005	1	56.3	43.7	0.2	12.5	32.5	36.1
	2	57.5	42.5	0.3	13.5	31.6	35.6
	3	59.0	41.0	0.3	14.9	30.1	34.3
	4	59.7	40.3	0.3	15.5	29.7	33.6
	5	59.3	40.7	0.4	16.0	29.6	34.5
	6	59.9	40.1	0.5	16.4	30.0	35.1
	7	61.1	38.9	0.6	16.2	30.3	36.0
	8	60.9	39.1	0.5	16.6	29.9	36.1
	9	61.8	38.2	1.1	15.5	28.1	40.4
	10	58.3	41.7	0.9	14.0	29.4	39.1
Total		58.2	41.8	0.3	14.3	31.0	35.2
Total	1	57.6	42.4	0.2	12.0	33.4	35.8
	2	58.9	41.1	0.2	12.7	32.7	35.4
	3	60.0	40.0	0.3	14.0	31.5	34.2
	4	60.6	39.4	0.3	14.4	30.7	34.1
	5	60.7	39.3	0.3	14.8	30.7	34.8
	6	61.1	38.9	0.3	15.2	30.7	35.7
	7	61.0	39.0	0.4	15.6	31.1	35.3
	8	60.4	39.6	0.4	15.2	31.7	35.4
	9	62.2	37.8	0.8	14.0	30.0	38.6
	10	61.1	38.9	0.4	14.3	31.3	36.7
Grand Total		59.4	40.6	0.3	13.4	32.1	35.2

Table A-3. High school record.

	Cohort					
	2004		2005		Total	
	N	%	N	%	N	%
With HS GPA	7,030	64.5	7,954	73.4	14,984	69
Missing HS GPA	3,862	35.5	2,878	26.6	6,740	31
Have GED	1,901	17.5	1,281	11.8	3,182	14.6
GED with GPA	1,095	10.1	1,056	9.7	2,151	9.9
High School Type						
NYC Public	5,821	53.4	5,072	46.8	10,893	50.1
NYC Private/Parochial	585	5.4	582	5.4	1,167	5.4
New York State	233	2.1	228	2.1	461	2.1
Other US High School	419	3.8	303	2.8	722	3.3
Foreign	1,106	10.2	1,014	9.4	2,120	9.8
GED	1,901	17.5	1,281	11.8	3,182	14.6
Unknown	827	7.6	2,352	21.7	3,179	14.6
Grand Total	10,892		10,832		21,725	

Table A-4. High school Grade Point Average distribution.

	2004		Cohort 2005		Total	
	N	%	N	%	N	%
A	29	0.4	35	0.4	64	0.4
A-	52	0.7	68	0.9	120	0.8
Subtotal A	81	1.2	103	1.3	184	1.2
B+	149	2.1	147	1.8	296	2
B	302	4.3	343	4.3	645	4.3
B-	325	4.6	411	5.2	736	4.9
Subtotal B	776	11	901	11.3	1,677	11.2
C+	594	8.4	649	8.2	1,243	8.3
C	1,088	15.5	1,258	15.8	2,346	15.7
C-	975	13.9	1,145	14.4	2,120	14.1
Subtotal C	2,657	37.8	3,052	38.4	5,709	38.1
D+	2,157	30.7	2,406	30.2	4,563	30.5
D	935	13.3	1,005	12.6	1,940	12.9
D-	333	4.7	377	4.7	710	4.7
Subtotal D	3,425	48.7	3,788	47.6	7,213	48.1
F	91	1.3	110	1.4	201	1.3
Total with GPA	7,030	100	7,954	100	14,984	100
	Mean	SD	Mean	SD	Mean	SD
GED HS GPA	1.68	0.39	1.69	0.42	1.68	0.4
Non-GED HS GPA	1.87	0.62	1.87	0.68	1.87	0.69
Overall HS GPA	1.84	0.68	1.85	0.66	1.84	0.66

Table A-5. Performance on the Scholastic Aptitude Test (SAT).

Cohort		Verbal	Math	Total
2004	Mean	389	405	794
	SD	84.1	85.5	145
	Minimum	200	200	400
	Maximum	800	720	1350
	N	1,857	1,857	1,857
	% Have SAT	17.0	17.0	17.0
	Cohort N	10,892	10,892	10,892
2005	Mean	389	407	796
	SD	83.4	83.9	142.5
	Minimum	200	200	400
	Maximum	730	780	1430
	N	3,090	3,090	3,090
	% Have SAT	28.5	28.5	28.5
	Cohort N	10,832	10,832	10,832
Total	Mean	389	406	795
	SD	83.6	84.5	143.4
	Minimum	200	200	400
	Maximum	800	780	1430
	N	4,947	4,947	4,947
	% Have SAT	22.8	22.8	22.8
	Total N	21,724	21,724	21,724

Table A-7. Performance and taking means for all New York State Regents

examinations.

Cohort	Regents	Score		N	%
	Taken	Mean	SD		
9/1/2004	0	--	--	6,029	55.4
	1	68.9	17	211	1.9
	2	64.5	14.9	228	2.1
	3	63.7	10.6	344	3.2
	4	64.3	10.8	668	6.1
	5	63.7	9.5	870	8
	6	64.9	8.6	974	8.9
	7	66.6	8.2	662	6.1
	8	68	7.8	473	4.3
	9	69.9	7.7	254	2.3
	10	71.7	8.1	161	1.5
	11	71.6	5.1	17	0.2
	12	88.4	--	1	0
	Any	65.7	10.1	4,863	44.6
Mean	5.6	--	--	--	--
Total	--	--	--	10,892	100
9/1/2005	0	--	--	5,295	48.9
	1	67.8	17.5	157	1.4
	2	63.5	14.2	164	1.5
	3	62.9	13.2	244	2.3
	4	64.7	10.9	519	4.8
	5	64.9	10	1,042	9.6
	6	66.4	8.4	1,431	13.2
	7	68.3	7.9	1,122	10.4
	8	70.2	6.7	538	5
	9	71.7	6.6	206	1.9
	10	72.7	8.4	89	0.8
	11	75.8	6.3	23	0.2
	12	70.1	5.1	2	0
	Any	66.9	9.8	5,537	51.1
Mean	5.8	--	--	--	--
Total	--	--	--	10,832	100

Table A-8. Senior college preference on application by community college application.

Cohort	Senior Choice	Applied to Community College					
		No		Yes		Total	
		N	%	N	%	N	%
2004	First	902	76.6	2,178	22.4	3,080	28.3
	Second	73	6.2	670	6.9	743	6.8
	Third	26	2.2	378	3.9	404	3.7
	Fourth	3	0.3	200	2.1	203	1.9
	Fifth	4	0.3	90	0.9	94	0.9
	Sixth	0	0.0	59	0.6	59	0.5
	None	170	14.4	6,139	63.2	6,309	57.9
	Total		1,178	10.82	9,714	89.18	10,892
2005	First	930	76.4	2,390	24.9	3,320	30.6
	Second	63	5.2	683	7.1	746	6.9
	Third	32	2.6	370	3.8	402	3.7
	Fourth	11	0.9	216	2.2	227	2.1
	Fifth	4	0.3	101	1.1	105	1.0
	Sixth	1	0.1	54	0.6	55	0.5
	None	177	14.5	5,800	60.3	5,977	55.2
	Total		1,218	11.24	9,614	88.76	10,832
Total	First	1,832	76.5	4,568	23.6	6,400	29.5
	Second	136	5.7	1,353	7.0	1,489	6.9
	Third	58	2.4	748	3.9	806	3.7
	Fourth	14	0.6	416	2.2	430	2.0
	Fifth	8	0.3	191	1.0	199	0.9
	Sixth	1	0.0	113	0.6	114	0.5
	None	347	14.5	11,939	61.8	12,286	56.6
			2,396	11.03	19,328	88.97	21,724

Table A-9. Degree pursued in first semester.

Degree	Cohort					
	2004		2005		Total	
	N	%	N	%	N	%
Associate of Arts	4,312	39.6	4,320	39.9	8,632	39.7
Associate of Science	1,841	16.9	1,924	17.8	3,765	17.3
Associate of Applied Science	4,739	43.5	4,588	42.4	9,327	42.9
Total	10,892	100.0	10,832	100.0	21,725	100.0

Table A-10. Financial aid total grant award by semester (First Spell).

Cohort	Semester	Mean	SD	Minimum	Maximum	N
2004	1	\$1,616	\$1,450	\$0	\$4,514	10,892
	2	\$1,684	\$1,439	\$0	\$4,865	8,600
	3	\$1,521	\$1,453	\$0	\$5,142	6,291
	4	\$1,519	\$1,425	\$0	\$4,507	4,891
	5	\$1,328	\$1,395	\$0	\$4,250	3,290
	6	\$1,232	\$1,301	\$0	\$4,600	2,281
	7	\$1,005	\$1,230	\$0	\$4,245	1,240
	8	\$864	\$1,034	\$0	\$4,175	750
	9	\$634	\$924	\$0	\$4,389	367
	10	\$693	\$1,014	\$0	\$3,916	212
	Total	\$1,508	\$1,427	\$0	\$5,142	
2005	1	\$1,558	\$1,439	\$0	\$4,514	10,832
	2	\$1,579	\$1,418	\$0	\$4,400	8,526
	3	\$1,467	\$1,454	\$0	\$4,900	6,232
	4	\$1,453	\$1,419	\$0	\$4,684	4,907
	5	\$1,313	\$1,414	\$0	\$5,005	3,222
	6	\$1,239	\$1,350	\$0	\$7,655	2,267
	7	\$972	\$1,249	\$0	\$4,366	1,183
	8	\$878	\$1,120	\$0	\$4,316	728
	9	\$869	\$1,270	\$0	\$4,470	374
	10	\$778	\$1,172	\$0	\$4,768	235
	Total	\$1,453	\$1,424	\$0	\$7,655	
Total	1	\$1,587	\$1,445	\$0	\$4,514	21,724
	2	\$1,632	\$1,430	\$0	\$4,865	17,126
	3	\$1,494	\$1,453	\$0	\$5,142	12,523
	4	\$1,486	\$1,422	\$0	\$4,684	9,798
	5	\$1,321	\$1,404	\$0	\$5,005	6,512
	6	\$1,236	\$1,326	\$0	\$7,655	4,548
	7	\$989	\$1,239	\$0	\$4,366	2,423
	8	\$871	\$1,077	\$0	\$4,316	1,478
	9	\$753	\$1,118	\$0	\$4,470	741
	10	\$738	\$1,099	\$0	\$4,768	447
	Total	\$1,481	\$1,426	\$0	\$7,655	

Table A-11. Financial aid total grant award by semester (First Spell).

Cohort	Term	\$0		\$1-\$999		\$1000-\$1,999		\$2000-\$2,999		\$3000-\$3,999		\$4000+		Total N
		N	%	N	%	N	%	N	%	N	%	N	%	
2004	1	3,429	31.5	1,172	10.8	1,419	13	1,803	16.6	2,986	27.4	83	0.8	10,892
	2	2,464	28.7	957	11.1	1,203	14	1,471	17.1	2,448	28.5	57	0.7	8,600
	3	2,146	34.1	744	11.8	848	13.5	934	14.8	1,589	25.3	30	0.5	6,291
	4	1,580	32.3	627	12.8	692	14.1	800	16.4	1,165	23.8	27	0.6	4,891
	5	1,291	39.2	375	11.4	476	14.5	496	15.1	636	19.3	16	0.5	3,290
	6	844	37	324	14.2	421	18.5	334	14.6	354	15.5	4	0.2	2,281
	7	567	45.7	174	14	206	16.6	164	13.2	121	9.8	8	0.6	1,240
	8	331	44.1	129	17.2	167	22.3	91	12.1	31	4.1	1	0.1	750
	9	198	54	64	17.4	63	17.2	36	9.8	5	1.4	1	0.3	367
	10	108	50.9	45	21.2	34	16	13	6.1	12	5.7	0	0	212
		12,958	33.4	4,611	11.9	5,529	14.2	6,142	15.8	9,347	24.1	227	0.6	38,814
2005	1	3,538	32.7	1,241	11.5	1,382	12.8	1,789	16.5	2,778	25.6	104	1	10,832
	2	2,582	30.3	1,047	12.3	1,225	14.4	1,439	16.9	2,186	25.6	47	0.6	8,526
	3	2,270	36.4	712	11.4	800	12.8	911	14.6	1,476	23.7	63	1	6,232
	4	1,708	34.8	589	12	726	14.8	745	15.2	1,100	22.4	39	0.8	4,907
	5	1,320	41	350	10.9	430	13.3	512	15.9	579	18	31	1	3,222
	6	892	39.3	311	13.7	367	16.2	342	15.1	335	14.8	20	0.9	2,267
	7	579	48.9	149	12.6	184	15.6	162	13.7	103	8.7	6	0.5	1,183
	8	350	48.1	112	15.4	126	17.3	99	13.6	38	5.2	3	0.4	728
	9	210	56.1	45	12	40	10.7	50	13.4	10	2.7	19	5.1	374
	10	135	57.4	28	11.9	33	14	26	11.1	3	1.3	10	4.3	235
		13,584	35.3	4,584	11.9	5,313	13.8	6,075	15.8	8,608	22.4	342	0.9	38,506

Table A-12. Full-time in-state tuition and fees by semester.

Cohort	Semester	Tuition	Fees	Total
2004	1	\$1,400	\$120	\$1,520
	2	\$1,400	\$120	\$1,520
	3	\$1,400	\$120	\$1,520
	4	\$1,400	\$120	\$1,520
	5	\$1,400	\$120	\$1,520
	6	\$1,400	\$120	\$1,520
	7	\$1,400	\$120	\$1,520
	8	\$1,400	\$120	\$1,520
	9	\$1,400	\$120	\$1,520
	10	\$1,400	\$120	\$1,520
	Mean	\$1,400	\$120	\$1,520
2005	1	\$1,400	\$120	\$1,520
	2	\$1,400	\$120	\$1,520
	3	\$1,400	\$120	\$1,520
	4	\$1,400	\$120	\$1,520
	5	\$1,400	\$120	\$1,520
	6	\$1,400	\$120	\$1,520
	7	\$1,400	\$120	\$1,520
	8	\$1,400	\$120	\$1,520
	9	\$1,575	\$159	\$1,734
	10	\$1,575	\$159	\$1,734
	Mean	\$1,435	\$128	\$1,563
Total	1	\$1,400	\$120	\$1,520
	2	\$1,400	\$120	\$1,520
	3	\$1,400	\$120	\$1,520
	4	\$1,400	\$120	\$1,520
	5	\$1,400	\$120	\$1,520
	6	\$1,400	\$120	\$1,520
	7	\$1,400	\$120	\$1,520
	8	\$1,400	\$120	\$1,520
	9	\$1,488	\$140	\$1,627
	10	\$1,488	\$140	\$1,627
	Mean	\$1,418	\$124	\$1,541

Table A-13. Percentage of students who received a Pell Grant during or prior to the current term (First Spell).

Cohort	Semester	% Pell	N
2004	1	59.9	10,892
	2	63.9	8,600
	3	66.0	6,291
	4	66.2	4,891
	5	66.0	3,290
	6	66.6	2,281
	7	67.2	1,240
	8	66.7	750
	9	62.9	367
	10	64.2	212
	Total	63.9	38,814
2005	1	58.5	10,832
	2	62.5	8,526
	3	63.8	6,232
	4	64.2	4,907
	5	64.4	3,222
	6	64.8	2,267
	7	63.7	1,183
	8	63.6	728
	9	61.8	374
	10	60.9	235
	Total	62.1	38,506
Total	1	59.2	21,724
	2	63.2	17,126
	3	64.9	12,523
	4	65.2	9,798
	5	65.2	6,512
	6	65.7	4,548
	7	65.5	2,423
	8	65.2	1,478
	9	62.3	741
	10	62.4	447
	Total	63.0	77,320

Table A-14. Financial aid total loan amount by semester (First Spell).

Cohort	Semester	Mean	SD	Minimum	Maximum	N
2004	1	\$54	\$299	\$0	\$3,265	10,892
	2	\$78	\$393	\$0	\$6,527	8,600
	3	\$78	\$390	\$0	\$4,926	6,291
	4	\$102	\$452	\$0	\$5,149	4,891
	5	\$113	\$514	\$0	\$6,606	3,290
	6	\$142	\$559	\$0	\$4,433	2,281
	7	\$151	\$653	\$0	\$6,727	1,240
	8	\$215	\$812	\$0	\$6,188	750
	9	\$242	\$1,018	\$0	\$7,210	367
	10	\$224	\$946	\$0	\$5,805	212
	Total	\$88	\$439	\$0	\$7,210	38,814
2005	1	\$61	\$325	\$0	\$6,429	10,832
	2	\$81	\$402	\$0	\$6,529	8,526
	3	\$82	\$424	\$0	\$6,699	6,232
	4	\$100	\$469	\$0	\$7,388	4,907
	5	\$131	\$620	\$0	\$8,416	3,222
	6	\$135	\$600	\$0	\$6,940	2,267
	7	\$197	\$871	\$0	\$8,172	1,183
	8	\$195	\$854	\$0	\$7,464	728
	9	\$295	\$1,200	\$0	\$9,752	374
	10	\$224	\$899	\$0	\$6,219	235
	Total	\$94	\$483	\$0	\$9,752	38,506
Total	1	\$57	\$312	\$0	\$6,429	21,724
	2	\$80	\$398	\$0	\$6,529	17,126
	3	\$80	\$407	\$0	\$6,699	12,523
	4	\$101	\$460	\$0	\$7,388	9,798
	5	\$122	\$569	\$0	\$8,416	6,512
	6	\$138	\$580	\$0	\$6,940	4,548
	7	\$174	\$767	\$0	\$8,172	2,423
	8	\$205	\$833	\$0	\$7,464	1,478
	9	\$269	\$1,113	\$0	\$9,752	741
	10	\$224	\$921	\$0	\$6,219	447
	Total	\$91	\$462	\$0	\$9,752	77,320

Table A-15. Financial aid total loan amount by semester (First Spell).

Cohort	Term	\$0		\$1- \$999		\$1000- \$1,999		\$2000- \$2,999		\$3000- \$3,999		\$4000+		Total
		N	%	N	%	N	%	N	%	N	%	N	%	N
2004	1	10,485	96.3	70	0.6	291	2.7	13	0.1	33	0.3	0	0	10,892
	2	8,176	95.1	75	0.9	271	3.2	33	0.4	38	0.4	7	0.1	8,600
	3	5,982	95.1	48	0.8	205	3.3	13	0.2	41	0.7	2	0	6,291
	4	4,599	94	32	0.7	189	3.9	34	0.7	35	0.7	2	0	4,891
	5	3,065	93.2	73	2.2	102	3.1	10	0.3	33	1	7	0.2	3,290
	6	2,093	91.8	54	2.4	83	3.6	18	0.8	30	1.3	3	0.1	2,281
	7	1,150	92.7	25	2	28	2.3	16	1.3	8	0.6	13	1	1,240
	8	680	90.7	20	2.7	19	2.5	5	0.7	10	1.3	16	2.1	750
	9	342	93.2	3	0.8	5	1.4	1	0.3	3	0.8	13	3.5	367
	10	197	92.9	3	1.4	3	1.4	1	0.5	0	0	8	3.8	212
		36,769	94.7	403	1	1,196	3.1	144	0.4	231	0.6	71	0.2	38,814
2005	1	10,374	95.8	74	0.7	325	3	24	0.2	33	0.3	2	0	10,832
	2	8,092	94.9	58	0.7	296	3.5	36	0.4	36	0.4	8	0.1	8,526
	3	5,933	95.2	43	0.7	187	3	20	0.3	42	0.7	7	0.1	6,232
	4	4,627	94.3	37	0.8	169	3.4	27	0.6	43	0.9	4	0.1	4,907
	5	3,027	93.9	43	1.3	69	2.1	41	1.3	20	0.6	22	0.7	3,222
	6	2,120	93.5	30	1.3	58	2.6	32	1.4	15	0.7	12	0.5	2,267
	7	1,100	93	19	1.6	19	1.6	14	1.2	6	0.5	25	2.1	1,183
	8	675	92.7	11	1.5	16	2.2	10	1.4	2	0.3	14	1.9	728
	9	342	91.4	7	1.9	5	1.3	5	1.3	2	0.5	13	3.5	374
	10	216	91.9	5	2.1	2	0.9	6	2.6	0	0	6	2.6	235
		36,506	94.8	327	0.8	1,146	3	215	0.6	199	0.5	113	0.3	38,506

Table A-16. Credits attempted per semester
(First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	7.0	4.6	0.0	26.0	10,892
	2	8.8	4.5	0.0	27.0	8,600
	3	9.7	4.8	0.0	29.0	6,291
	4	9.7	4.5	0.0	26.0	4,891
	5	9.8	4.5	0.0	25.0	3,290
	6	9.0	4.4	0.0	27.0	2,281
	7	7.9	4.2	0.0	25.0	1,240
	8	7.4	4.1	0.0	20.0	750
	9	6.4	3.6	0.0	20.0	367
	10	5.9	4.1	0.0	18.0	212
	Total	8.5	4.7	0.0	29.0	38,814
2005	1	7.0	4.6	0.0	24.0	10,832
	2	8.4	4.4	0.0	26.0	8,526
	3	9.7	4.8	0.0	28.0	6,232
	4	10.0	4.7	0.0	25.0	4,907
	5	9.8	4.5	0.0	26.0	3,222
	6	9.1	4.6	0.0	25.0	2,267
	7	7.9	4.3	0.0	22.0	1,183
	8	7.5	4.4	0.0	24.0	728
	9	7.0	4.0	0.0	22.0	374
	10	6.3	4.1	0.0	17.5	235
	Total	8.5	4.7	0.0	28.0	38,506
Total	1	7.0	4.6	0.0	26.0	21,724
	2	8.6	4.5	0.0	27.0	17,126
	3	9.7	4.8	0.0	29.0	12,523
	4	9.8	4.6	0.0	26.0	9,798
	5	9.8	4.5	0.0	26.0	6,512
	6	9.0	4.5	0.0	27.0	4,548
	7	7.9	4.3	0.0	25.0	2,423
	8	7.4	4.2	0.0	24.0	1,478
	9	6.7	3.8	0.0	22.0	741
	10	6.1	4.1	0.0	18.0	447
	Total	8.5	4.7	0.0	29.0	77,320

Table A-17. Credits attempted per semester (First Spell).

Cohort	Semester	0 %	1-3 %	5-8 %	9-11 %	12-15 %	16+ %	Total N
2004	1	10.8	24.0	27.2	18.1	15.6	4.3	10,892
	2	6.3	11.6	28.2	21.4	26.2	6.2	8,600
	3	5.1	10.5	23.5	21.1	28.6	11.3	6,291
	4	4.4	10.4	22.3	22.8	31.7	8.5	4,891
	5	3.9	10.3	21.3	22.2	33.4	8.8	3,290
	6	4.4	14.0	26.0	21.9	27.5	6.3	2,281
	7	5.2	19.9	29.4	21.9	20.1	3.5	1,240
	8	6.7	21.6	31.9	21.3	15.9	2.7	750
	9	6.3	28.6	39.5	16.6	6.8	2.2	367
	10	14.6	30.2	28.8	14.2	11.8	0.5	212
	Total	6.8	15.5	25.9	20.6	24.4	6.8	38,814
2005	1	11.2	23.3	27.3	18.1	16.0	4.1	10,832
	2	7.0	12.8	27.4	23.0	25.1	4.7	8,526
	3	5.2	10.8	22.9	20.2	30.1	10.8	6,232
	4	4.4	10.5	20.1	20.5	34.0	10.5	4,907
	5	3.8	11.0	21.6	20.3	34.5	8.9	3,222
	6	4.9	14.5	23.4	21.9	28.5	6.8	2,267
	7	6.8	19.5	27.6	22.1	20.8	3.1	1,183
	8	6.9	24.5	27.3	21.6	16.3	3.4	728
	9	7.8	24.1	31.0	21.9	13.4	1.9	374
	10	11.5	28.9	30.2	14.9	12.3	2.1	235
	Total	7.2	15.7	25.1	20.5	25.0	6.6	38,506
Total	1	11.0	23.6	27.2	18.1	15.8	4.2	21,724
	2	6.7	12.2	27.8	22.2	25.7	5.5	17,126
	3	5.2	10.6	23.2	20.6	29.3	11.0	12,523
	4	4.4	10.4	21.2	21.6	32.9	9.5	9,798
	5	3.8	10.6	21.5	21.3	33.9	8.8	6,512
	6	4.6	14.2	24.7	21.9	28.0	6.6	4,548
	7	6.0	19.7	28.6	22.0	20.4	3.3	2,423
	8	6.8	23.0	29.6	21.4	16.1	3.0	1,478
	9	7.0	26.3	35.2	19.3	10.1	2.0	741
	10	13.0	29.5	29.5	14.5	12.1	1.3	447
	Total	7.0	15.6	25.5	20.5	24.7	6.7	77,320

Table A-18. Credits earned per semester (First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	5.7	4.8	0.0	26.0	10,892
	2	7.0	5.1	0.0	27.0	8,600
	3	8.0	5.4	0.0	29.0	6,291
	4	8.3	5.0	0.0	26.0	4,891
	5	8.6	4.9	0.0	25.0	3,290
	6	8.0	4.7	0.0	25.0	2,281
	7	7.0	4.5	0.0	25.0	1,240
	8	6.7	4.3	0.0	20.0	750
	9	5.7	3.7	0.0	20.0	367
	10	5.3	4.1	0.0	18.0	212
	Total	7.1	5.1	0.0	29.0	38,814
2005	1	5.6	4.8	0.0	24.0	10,832
	2	6.7	4.9	0.0	26.0	8,526
	3	8.1	5.4	0.0	28.0	6,232
	4	8.6	5.3	0.0	25.0	4,907
	5	8.7	4.9	0.0	26.0	3,222
	6	8.1	4.9	0.0	25.0	2,267
	7	7.0	4.4	0.0	22.0	1,183
	8	6.6	4.5	0.0	24.0	728
	9	6.3	4.1	0.0	21.0	374
	10	5.4	4.1	0.0	17.5	235
	Total	7.1	5.1	0.0	28.0	38,506
Total	1	5.6	4.8	0.0	26.0	21,724
	2	6.8	5.0	0.0	27.0	17,126
	3	8.0	5.4	0.0	29.0	12,523
	4	8.5	5.1	0.0	26.0	9,798
	5	8.6	4.9	0.0	26.0	6,512
	6	8.0	4.8	0.0	25.0	4,548
	7	7.0	4.4	0.0	25.0	2,423
	8	6.7	4.4	0.0	24.0	1,478
	9	6.0	3.9	0.0	21.0	741
	10	5.4	4.1	0.0	18.0	447
	Total	7.1	5.1	0.0	29.0	77,320

Table A-19. Credits earned per semester, with 0 credits attempted versus earned differential (First Spell).

Cohort	Semester	0 %	1-4 %	5-8 %	9-11 %	12-15 %	16+ %	Total N	Zero Earn-Attempt	
									Att. 0 %	Attempt
2004	1	23.0	25.1	22.9	13.8	12.0	3.3	10,892	10.8	12.2
	2	18.8	15.2	25.5	17.4	18.3	4.7	8,600	6.3	12.5
	3	15.1	14.5	21.8	18.5	21.4	8.7	6,291	5.1	10.1
	4	12.1	13.6	22.7	19.8	24.8	7.0	4,891	4.4	7.7
	5	9.9	12.8	23.6	20.2	26.7	7.0	3,290	3.9	6.0
	6	10.0	17.1	25.9	19.4	22.9	4.7	2,281	4.4	5.5
	7	11.0	23.1	27.4	19.5	16.1	2.8	1,240	5.2	5.8
	8	11.3	24.9	29.5	18.8	13.3	2.1	750	6.7	4.7
	9	12.5	30.2	36.2	13.6	5.4	1.9	367	6.3	6.3
	10	21.2	27.8	28.8	13.2	8.5	0.5	212	14.6	6.6
	Total	16.8	18.2	23.9	17.3	18.5	5.3	38,814	6.8	10.0
2005	1	24.4	23.9	22.7	14.0	11.9	3.0	10,832	11.2	13.3
	2	19.3	17.2	24.6	17.5	17.7	3.7	8,526	7.0	12.3
	3	14.3	14.7	22.2	18.0	22.3	8.5	6,232	5.2	9.1
	4	11.8	13.5	21.1	17.4	27.2	9.0	4,907	4.4	7.4
	5	9.6	14.4	22.1	18.6	28.0	7.4	3,222	3.8	5.9
	6	10.3	16.7	23.1	21.0	23.0	6.0	2,267	4.9	5.4
	7	11.4	23.0	27.4	19.4	16.5	2.4	1,183	6.8	4.6
	8	12.6	27.9	23.9	19.2	13.3	3.0	728	6.9	5.8
	9	14.2	24.3	28.9	19.5	12.0	1.1	374	7.8	6.4
	10	18.7	31.1	26.0	13.6	9.4	1.3	235	11.5	7.2
	Total	17.2	18.5	23.0	17.0	19.0	5.3	38,506	7.2	10.0
Total	1	23.7	24.5	22.8	13.9	11.9	3.2	21,724	11.0	12.7
	2	19.1	16.2	25.1	17.4	18.0	4.2	17,126	6.7	12.4
	3	14.7	14.6	22.0	18.2	21.8	8.6	12,523	5.2	9.6
	4	11.9	13.5	21.9	18.6	26.0	8.0	9,798	4.4	7.5
	5	9.8	13.6	22.9	19.4	27.3	7.2	6,512	3.8	5.9
	6	10.1	16.9	24.5	20.2	23.0	5.3	4,548	4.6	5.5
	7	11.2	23.0	27.4	19.4	16.3	2.6	2,423	6.0	5.2
	8	12.0	26.4	26.7	19.0	13.3	2.6	1,478	6.8	5.2
	9	13.4	27.3	32.5	16.6	8.8	1.5	741	7.0	6.3
	10	19.9	29.5	27.3	13.4	8.9	0.9	447	13.0	6.9
	Total	17.0	18.3	23.5	17.1	18.7	5.3	77,320	7.0	10.0

Table A-20. Cumulative credits earned per semester (First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	5.9	5.2	0	46	10,892
	2	13.8	9.0	0	57	8,600
	3	23.8	12.7	0	69	6,291
	4	34.7	15.7	0	89	4,891
	5	43.8	16.0	0	90	3,290
	6	51.5	15.7	0	100	2,281
	7	54.9	15.6	0	116	1,240
	8	59.5	15.9	0	129	750
	9	60.3	15.2	9	119	367
	10	63.2	15.7	6	105	212
	Total	23.5	20.4	0	129	38,814
2005	1	5.8	5.1	0	42	10,832
	2	13.8	9.0	0	62	8,526
	3	23.8	12.6	0	69	6,232
	4	34.5	15.7	0	83	4,907
	5	43.4	16.1	0	91	3,222
	6	51.1	16.5	0	116	2,267
	7	54.7	16.1	0	104	1,183
	8	58.8	17.2	0	116	728
	9	61.3	15.5	18	112	374
	10	64.6	17.4	18	119	235
	Total	23.4	20.4	0	119	38,506
Total	1	5.8	5.2	0	46	21,724
	2	13.8	9.0	0	62	17,126
	3	23.8	12.7	0	69	12,523
	4	34.6	15.7	0	89	9,798
	5	43.6	16.0	0	91	6,512
	6	51.3	16.1	0	116	4,548
	7	54.8	15.8	0	116	2,423
	8	59.2	16.6	0	129	1,478
	9	60.8	15.3	9	119	741
	10	63.9	16.6	6	119	447
	Total	23.4	20.4	0	129	77,320

Table A-21. Cumulative credits earned per semester (First Spell).

Cohort	Semester	1-						Total N
		0 %	19 %	20-39 %	40-59 %	60-79 %	80+ %	
2004	1	22.7	76.0	1.3	0.0	0.0	0.0	10,892
	2	7.2	66.8	25.4	0.6	0.0	0.0	8,600
	3	2.4	37.1	48.9	11.0	0.6	0.0	6,291
	4	0.7	17.0	45.1	28.9	8.0	0.2	4,891
	5	0.4	7.2	31.7	40.7	19.4	0.7	3,290
	6	0.1	2.4	20.6	40.6	33.8	2.5	2,281
	7	0.2	1.5	14.3	42.0	37.4	4.6	1,240
	8	0.1	0.9	9.3	33.9	47.1	8.7	750
	9	0.0	0.8	8.2	33.5	49.0	8.4	367
	10	0.0	0.9	6.6	30.2	47.2	15.1	212
	Total	8.5	45.1	24.3	13.9	7.6	0.7	38,814
2005	1	24.0	74.8	1.2	0.0	0.0	0.0	10,832
	2	7.4	66.1	25.9	0.6	0.0	0.0	8,526
	3	2.2	36.7	49.3	11.3	0.4	0.0	6,232
	4	0.7	17.5	44.5	28.9	8.3	0.0	4,907
	5	0.4	8.0	30.9	41.7	18.5	0.4	3,222
	6	0.4	3.6	20.3	39.2	33.8	2.8	2,267
	7	0.2	1.9	15.7	38.7	38.4	5.1	1,183
	8	1.0	1.2	8.7	37.5	40.8	10.9	728
	9	0.0	0.8	7.2	36.1	43.9	12.0	374
	10	0.0	0.9	5.1	30.6	46.0	17.4	235
	Total	8.9	44.8	24.2	13.9	7.3	0.8	38,506
Total	1	23.3	75.4	1.2	0.0	0.0	0.0	21,724
	2	7.3	66.4	25.7	0.6	0.0	0.0	17,126
	3	2.3	36.9	49.1	11.2	0.5	0.0	12,523
	4	0.7	17.3	44.8	28.9	8.2	0.1	9,798
	5	0.4	7.6	31.3	41.2	18.9	0.6	6,512
	6	0.2	3.0	20.4	39.9	33.8	2.7	4,548
	7	0.2	1.7	15.0	40.4	37.9	4.8	2,423
	8	0.5	1.1	9.0	35.7	44.0	9.7	1,478
	9	0.0	0.8	7.7	34.8	46.4	10.3	741
	10	0.0	0.9	5.8	30.4	46.5	16.3	447
	Total	8.7	45.0	24.3	13.9	7.4	0.7	77,320

Table A-22. Remedial hours taken per semester (First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	6.2	5.5	0.0	30.0	10,892
	2	3.4	4.3	0.0	26.0	8,600
	3	2.1	3.5	0.0	21.0	6,291
	4	1.3	2.6	0.0	16.0	4,891
	5	0.9	2.3	0.0	25.0	3,290
	6	0.8	2.2	0.0	20.0	2,281
	7	0.7	2.0	0.0	16.0	1,240
	8	0.5	1.8	0.0	16.0	750
	9	0.7	1.9	0.0	10.0	367
	10	0.5	1.6	0.0	10.0	212
	Total	3.2	4.5	0.0	30.0	38,814
2005	1	6.0	5.4	0.0	30.0	10,832
	2	3.1	4.0	0.0	18.0	8,526
	3	2.1	3.5	0.0	23.0	6,232
	4	1.3	2.8	0.0	24.0	4,907
	5	1.0	2.4	0.0	20.0	3,222
	6	0.8	2.0	0.0	16.0	2,267
	7	0.9	2.2	0.0	20.0	1,183
	8	0.8	2.1	0.0	20.0	728
	9	0.6	1.8	0.0	12.0	374
	10	0.6	1.8	0.0	12.0	235
	Total	3.1	4.4	0.0	30.0	38,506
Total	1	6.1	5.4	0.0	30.0	21,724
	2	3.2	4.1	0.0	26.0	17,126
	3	2.1	3.5	0.0	23.0	12,523
	4	1.3	2.7	0.0	24.0	9,798
	5	1.0	2.4	0.0	25.0	6,512
	6	0.8	2.1	0.0	20.0	4,548
	7	0.8	2.1	0.0	20.0	2,423
	8	0.7	2.0	0.0	20.0	1,478
	9	0.7	1.8	0.0	12.0	741
	10	0.6	1.7	0.0	12.0	447
	Total	3.1	4.5	0.0	30.0	77,320

Table 23. Remedial Hours Per Semester
(First Spell).

Cohort	Semester	0 %	1-4 %	5-8 %	9-11 %	12-15 %	16+ %	Total N
2004	1	23.1	21.1	24.0	11.9	13.7	6.2	10,892
	2	50.9	15.9	19.2	7.7	4.6	1.6	8,600
	3	65.6	13.3	14.2	3.8	2.4	0.7	6,291
	4	76.4	10.7	10.1	1.8	0.9	0.1	4,891
	5	82.6	8.3	7.4	0.8	0.7	0.2	3,290
	6	85.2	7.1	6.4	0.7	0.4	0.2	2,281
	7	85.6	7.4	6.0	0.4	0.5	0.1	1,240
	8	89.2	6.3	3.7	0.1	0.4	0.3	750
	9	86.1	6.8	6.5	0.5	0.0	0.0	367
	10	89.2	5.7	4.7	0.5	0.0	0.0	212
	Total	55.8	14.5	15.9	6.0	5.5	2.2	38,814
2005	1	25.1	20.5	24.0	12.4	12.0	6.0	10,832
	2	52.1	16.0	19.4	8.1	3.6	0.8	8,526
	3	66.0	12.9	14.7	3.0	2.6	0.7	6,232
	4	77.0	9.7	10.1	1.4	1.6	0.3	4,907
	5	82.0	8.2	7.9	0.8	0.9	0.2	3,222
	6	84.0	8.1	6.9	0.4	0.5	0.0	2,267
	7	83.1	8.4	7.4	0.5	0.5	0.2	1,183
	8	85.3	6.9	7.1	0.1	0.4	0.1	728
	9	86.6	8.0	4.8	0.3	0.3	0.0	374
	10	86.0	9.4	3.8	0.4	0.4	0.0	235
	Total	56.4	14.3	16.2	6.1	4.9	2.0	38,506
Total	1	24.1	20.8	24.0	12.2	12.8	6.1	21,724
	2	51.5	15.9	19.3	7.9	4.1	1.2	17,126
	3	65.8	13.1	14.5	3.4	2.5	0.7	12,523
	4	76.7	10.2	10.1	1.6	1.3	0.2	9,798
	5	82.3	8.2	7.7	0.8	0.8	0.2	6,512
	6	84.6	7.6	6.6	0.5	0.5	0.1	4,548
	7	84.4	7.9	6.6	0.5	0.5	0.1	2,423
	8	87.3	6.6	5.4	0.1	0.4	0.2	1,478
	9	86.4	7.4	5.7	0.4	0.1	0.0	741
	10	87.5	7.6	4.3	0.4	0.2	0.0	447
	Total	56.1	14.4	16.1	6.1	5.2	2.1	77,320

Table A-24. Developmental hours taken per semester (First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	0.6	2.2	0	16.5	10,892
	2	0.2	1.4	0	16.5	8,600
	3	0.1	1	0	13.5	6,291
	4	0.1	0.7	0	9	4,891
	5	0.1	0.6	0	10.5	3,290
	6	0	0.4	0	9	2,281
	7	0	0.5	0	6	1,240
	8	0	0.3	0	6	750
	9	0	0	0	0	367
	10	0	0.4	0	6	212
	Total		0.3	1.5	0	16.5
2005	1	0.5	2.1	0	16.5	10,832
	2	0.2	1.4	0	16.5	8,526
	3	0.1	1	0	13.5	6,232
	4	0.1	0.7	0	13.5	4,907
	5	0	0.5	0	9	3,222
	6	0	0.6	0	13.5	2,267
	7	0	0.4	0	6	1,183
	8	0	0.5	0	6	728
	9	0	0.5	0	8	374
	10	0	0	0	0	235
	Total		0.2	1.4	0	16.5
Total	1	0.5	2.2	0	16.5	21,724
	2	0.2	1.4	0	16.5	17,126
	3	0.1	1	0	13.5	12,523
	4	0.1	0.7	0	13.5	9,798
	5	0.1	0.6	0	10.5	6,512
	6	0	0.5	0	13.5	4,548
	7	0	0.5	0	6	2,423
	8	0	0.4	0	6	1,478
	9	0	0.3	0	8	741
	10	0	0.3	0	6	447
	Total		0.2	1.4	0	16.5

Table A-25. Developmental hours per semester (First Spell).

Cohort	Semester	0 %	1-4 %	5-8 %	9-11 %	12-15 %	16+ %	Total N
2004	1	92.8	0.1	3.9	2.0	1.0	0.2	10,892
	2	97.2	0.1	1.4	1.0	0.3	0.0	8,600
	3	98.1	0.0	1.1	0.7	0.1	0.0	6,291
	4	98.8	0.1	1.0	0.2	0.0	0.0	4,891
	5	99.0	0.1	0.8	0.1	0.0	0.0	3,290
	6	99.5	0.0	0.4	0.0	0.0	0.0	2,281
	7	99.2	0.0	0.8	0.0	0.0	0.0	1,240
	8	99.7	0.0	0.3	0.0	0.0	0.0	750
	9	100.0	0.0	0.0	0.0	0.0	0.0	367
	10	99.5	0.0	0.5	0.0	0.0	0.0	212
	Total	96.8	0.1	1.8	0.9	0.4	0.1	38,814
2005	1	93.9	0.2	3.2	1.5	1.0	0.2	10,832
	2	97.3	0.1	1.3	1.0	0.3	0.0	8,526
	3	98.1	0.0	1.2	0.6	0.1	0.0	6,232
	4	98.7	0.1	1.0	0.2	0.0	0.0	4,907
	5	99.3	0.0	0.7	0.1	0.0	0.0	3,222
	6	99.3	0.0	0.6	0.0	0.0	0.0	2,267
	7	99.4	0.0	0.6	0.0	0.0	0.0	1,183
	8	99.3	0.0	0.7	0.0	0.0	0.0	728
	9	99.5	0.0	0.5	0.0	0.0	0.0	374
	10	100.0	0.0	0.0	0.0	0.0	0.0	235
	Total	97.1	0.1	1.6	0.8	0.4	0.1	38,506
Total	1	93.4	0.1	3.5	1.8	1.0	0.2	21,724
	2	97.2	0.1	1.4	1.0	0.3	0.0	17,126
	3	98.1	0.0	1.2	0.6	0.1	0.0	12,523
	4	98.7	0.1	1.0	0.2	0.0	0.0	9,798
	5	99.1	0.0	0.7	0.1	0.0	0.0	6,512
	6	99.4	0.0	0.5	0.0	0.0	0.0	4,548
	7	99.3	0.0	0.7	0.0	0.0	0.0	2,423
	8	99.5	0.0	0.5	0.0	0.0	0.0	1,478
	9	99.7	0.0	0.3	0.0	0.0	0.0	741
	10	99.8	0.0	0.2	0.0	0.0	0.0	447
	Total	96.9	0.1	1.7	0.8	0.4	0.1	77,320

Table A-26. Compensatory hours taken per semester
(First Spell).

Cohort	Semester	Mean	SD	Min	Max	N
2004	1	0.7	1.8	0.0	19.5	10,892
	2	1.0	2.1	0.0	19.5	8,600
	3	0.8	1.8	0.0	19.5	6,291
	4	0.7	1.8	0.0	13.0	4,891
	5	0.5	1.6	0.0	12.0	3,290
	6	0.4	1.4	0.0	12.0	2,281
	7	0.4	1.4	0.0	12.0	1,240
	8	0.4	1.5	0.0	12.5	750
	9	0.3	1.2	0.0	9.0	367
	10	0.4	1.2	0.0	9.0	212
	Total		0.7	1.8	0.0	19.5
2005	1	0.7	1.9	0.0	19.5	10,832
	2	1.0	2.2	0.0	19.5	8,526
	3	0.8	1.9	0.0	19.5	6,232
	4	0.6	1.7	0.0	16.0	4,907
	5	0.5	1.6	0.0	16.0	3,222
	6	0.4	1.4	0.0	16.0	2,267
	7	0.5	1.5	0.0	16.0	1,183
	8	0.5	1.6	0.0	12.5	728
	9	0.5	1.6	0.0	12.0	374
	10	0.5	1.5	0.0	8.0	235
	Total		0.7	1.9	0.0	19.5
Total	1	0.7	1.9	0.0	19.5	21,724
	2	1.0	2.1	0.0	19.5	17,126
	3	0.8	1.8	0.0	19.5	12,523
	4	0.7	1.7	0.0	16.0	9,798
	5	0.5	1.6	0.0	16.0	6,512
	6	0.4	1.4	0.0	16.0	4,548
	7	0.4	1.5	0.0	16.0	2,423
	8	0.5	1.5	0.0	12.5	1,478
	9	0.4	1.4	0.0	12.0	741
	10	0.4	1.4	0.0	9.0	447
	Total		0.7	1.8	0.0	19.5

Table A-27. Compensatory hours per semester
(First Spell).

Cohort	Semester	0 %	1-4 %	5-8 %	9-11 %	12-15 %	16+ %	Total N
2004	1	85.4	9.0	4.3	1.2	0.1	0.0	10,892
	2	80.2	13.1	4.8	1.7	0.2	0.1	8,600
	3	83.6	10.7	4.4	1.2	0.0	0.0	6,291
	4	86.0	8.4	4.5	1.0	0.1	0.0	4,891
	5	88.7	6.3	4.4	0.6	0.0	0.0	3,290
	6	90.4	5.4	3.8	0.4	0.0	0.0	2,281
	7	91.0	5.2	3.3	0.2	0.2	0.0	1,240
	8	92.3	3.6	3.5	0.4	0.3	0.0	750
	9	93.7	3.8	2.2	0.3	0.0	0.0	367
	10	92.0	6.1	1.4	0.5	0.0	0.0	212
	Total	85.0	9.4	4.3	1.1	0.1	0.0	38,814
2005	1	85.2	9.2	4.2	1.1	0.1	0.1	10,832
	2	79.9	13.4	4.6	1.8	0.2	0.1	8,526
	3	83.9	10.7	4.2	1.2	0.1	0.0	6,232
	4	86.3	8.9	3.9	0.8	0.1	0.0	4,907
	5	88.8	7.2	3.2	0.6	0.2	0.0	3,222
	6	90.8	5.8	3.0	0.3	0.1	0.1	2,267
	7	90.6	5.4	3.6	0.1	0.2	0.1	1,183
	8	88.9	6.2	4.4	0.3	0.3	0.0	728
	9	91.2	5.1	2.7	0.8	0.3	0.0	374
	10	89.4	5.5	5.1	0.0	0.0	0.0	235
	Total	84.9	9.7	4.1	1.1	0.1	0.1	38,506
Total	1	85.3	9.1	4.2	1.2	0.1	0.0	21,724
	2	80.0	13.2	4.7	1.7	0.2	0.1	17,126
	3	83.8	10.7	4.3	1.2	0.1	0.0	12,523
	4	86.2	8.6	4.2	0.9	0.1	0.0	9,798
	5	88.7	6.8	3.8	0.6	0.1	0.0	6,512
	6	90.6	5.6	3.4	0.3	0.1	0.0	4,548
	7	90.8	5.3	3.5	0.2	0.2	0.0	2,423
	8	90.6	4.9	3.9	0.3	0.3	0.0	1,478
	9	92.4	4.5	2.4	0.5	0.1	0.0	741
	10	90.6	5.8	3.4	0.2	0.0	0.0	447
	Total	85.0	9.6	4.2	1.1	0.1	0.0	77,320

Table A-28. Courses failed per semester (First Spell).

Cohort	Semester	Mean	SD	Max	Courses Failed (%)				N
					0	1	2	3+	
2004	1	0.2	0.5	5.0	82.6	13.7	3.0	0.8	10,892
	2	0.3	0.6	5.0	76.6	17.9	4.4	1.1	8,600
	3	0.3	0.6	7.0	76.6	17.9	4.2	1.2	6,291
	4	0.3	0.6	5.0	79.5	16.4	3.3	0.7	4,891
	5	0.2	0.6	5.0	80.6	15.3	3.3	0.7	3,290
	6	0.2	0.5	4.0	83.8	13.0	2.7	0.5	2,281
	7	0.2	0.5	3.0	85.3	12.0	2.3	0.4	1,240
	8	0.1	0.4	3.0	87.3	10.9	1.5	0.3	750
	9	0.2	0.4	2.0	85.8	12.0	2.2	0.0	367
	10	0.1	0.4	2.0	91.5	6.6	1.9	0.0	212
	Total	0.3	0.6	7.0	80.1	15.6	3.5	0.9	38,814
2005	1	0.3	0.6	5.0	80.5	15.1	3.3	1.1	10,832
	2	0.3	0.6	4.0	77.6	17.4	4.0	1.0	8,526
	3	0.3	0.6	4.0	78.3	16.5	3.8	1.4	6,232
	4	0.2	0.5	4.0	81.3	14.7	3.2	0.8	4,907
	5	0.2	0.5	4.0	81.9	14.5	2.9	0.7	3,222
	6	0.2	0.5	5.0	84.0	13.7	1.9	0.4	2,267
	7	0.2	0.5	3.0	83.2	13.7	2.5	0.7	1,183
	8	0.2	0.5	3.0	86.4	11.1	2.1	0.4	728
	9	0.1	0.4	4.0	87.4	11.5	0.8	0.3	374
	10	0.2	0.5	2.0	80.9	16.6	2.6	0.0	235
	Total	0.3	0.6	5.0	80.2	15.5	3.3	0.9	38,506
Total	1	0.2	0.6	5.0	81.6	14.4	3.2	0.9	21,724
	2	0.3	0.6	5.0	77.1	17.6	4.2	1.0	17,126
	3	0.3	0.6	7.0	77.4	17.2	4.0	1.3	12,523
	4	0.2	0.6	5.0	80.4	15.5	3.3	0.7	9,798
	5	0.2	0.5	5.0	81.3	14.9	3.1	0.7	6,512
	6	0.2	0.5	5.0	83.9	13.4	2.3	0.4	4,548
	7	0.2	0.5	3.0	84.3	12.8	2.4	0.5	2,423
	8	0.2	0.4	3.0	86.9	11.0	1.8	0.3	1,478
	9	0.2	0.4	4.0	86.6	11.7	1.5	0.1	741
	10	0.2	0.4	2.0	85.9	11.9	2.2	0.0	447
	Total	0.3	0.6	7.0	80.1	15.5	3.4	0.9	77,320

Table A-29. Courses withdrawn per semester
(First Spell).

Cohort	Semester	Mean	SD	Max	Courses Withdrawn (%)				N
					0	1	2	3+	
2004	1	0.6	1.1	7.0	71.1	14.7	5.8	8.5	10,892
	2	0.7	1.1	6.0	64.9	19.2	7.0	8.9	8,600
	3	0.6	1.1	8.0	67.2	18.8	6.6	7.4	6,291
	4	0.5	0.9	6.0	69.8	19.1	5.4	5.7	4,891
	5	0.4	0.9	7.0	72.7	18.1	5.1	4.2	3,290
	6	0.4	0.9	8.0	73.7	17.4	4.7	4.2	2,281
	7	0.4	0.8	5.0	76.0	16.0	5.0	3.0	1,240
	8	0.3	0.7	6.0	78.4	15.2	4.4	2.0	750
	9	0.3	0.7	5.0	83.1	11.7	3.3	1.9	367
	10	0.4	0.8	5.0	76.9	14.2	5.2	3.8	212
	Total	0.5	1.0	8.0	69.6	17.4	5.9	7.0	38,814
2005	1	0.6	1.1	9.0	69.6	15.8	6.2	8.4	10,832
	2	0.7	1.2	7.0	64.9	18.2	7.3	9.6	8,526
	3	0.6	1.0	7.0	66.7	19.7	7.0	6.7	6,232
	4	0.5	1.0	6.0	69.3	17.8	7.3	5.6	4,907
	5	0.4	0.8	6.0	72.4	18.2	5.7	3.6	3,222
	6	0.4	0.8	7.0	75.7	16.5	4.4	3.4	2,267
	7	0.4	0.7	5.0	75.3	17.1	5.2	2.4	1,183
	8	0.4	0.8	7.0	77.1	15.9	4.1	2.9	728
	9	0.4	0.8	5.0	74.6	16.6	5.6	3.2	374
	10	0.3	0.7	4.0	79.6	13.6	4.7	2.1	235
	Total	0.6	1.0	9.0	69.1	17.5	6.5	7.0	38,506
Total	1	0.6	1.1	9.0	70.3	15.2	6.0	8.5	21,724
	2	0.7	1.1	7.0	64.9	18.7	7.2	9.2	17,126
	3	0.6	1.1	8.0	66.9	19.2	6.8	7.0	12,523
	4	0.5	1.0	6.0	69.6	18.4	6.4	5.6	9,798
	5	0.4	0.9	7.0	72.6	18.2	5.4	3.9	6,512
	6	0.4	0.8	8.0	74.7	16.9	4.5	3.8	4,548
	7	0.4	0.8	5.0	75.7	16.5	5.1	2.7	2,423
	8	0.3	0.8	7.0	77.7	15.6	4.3	2.4	1,478
	9	0.3	0.7	5.0	78.8	14.2	4.5	2.6	741
	10	0.3	0.8	5.0	78.3	13.9	4.9	2.9	447
	Total	0.6	1.0	9.0	69.4	17.4	6.2	7.0	77,320

Table A-30. Course Withdrawal and Failure, 2004 and 2005 Cohorts, All Spells.

Term	Number of Courses Failed or Withdrawn						Total
	0	1	2	3	4	5+	
	N	N	N	N	N	N	N
1	12,988	4,172	1,937	1,198	1,024	407	21,726
2	8,823	4,027	1,934	1,166	916	261	17,127
3	6,894	3,218	1,444	820	585	179	13,140
4	6,232	2,599	1,172	593	422	98	11,116
5	4,797	1,975	832	348	247	72	8,271
6	3,990	1,567	588	241	190	57	6,633
7	2,744	1,006	418	170	78	34	4,450
8	2,215	781	293	108	66	25	3,488
9	1,550	554	212	86	32	16	2,450
10	1,279	423	180	69	34	10	1,995
Total	51,512	20,322	9,010	4,799	3,594	1,159	90,396
	%	%	%	%	%	%	%
1	59.8	19.2	8.9	5.5	4.7	1.9	100.0
2	51.5	23.5	11.3	6.8	5.3	1.5	100.0
3	52.5	24.5	11.0	6.2	4.5	1.4	100.0
4	56.1	23.4	10.5	5.3	3.8	0.9	100.0
5	58.0	23.9	10.1	4.2	3.0	0.9	100.0
6	60.2	23.6	8.9	3.6	2.9	0.9	100.0
7	61.7	22.6	9.4	3.8	1.8	0.8	100.0
8	63.5	22.4	8.4	3.1	1.9	0.7	100.0
9	63.3	22.6	8.7	3.5	1.3	0.7	100.0
10	64.1	21.2	9.0	3.5	1.7	0.5	100.0
Total	57.0	22.5	10.0	5.3	4.0	1.3	100.0

Table A-31. Semester GPA (First Spell).

Cohort	Semester	Mean	SD	Max	Semester GPA					N
					None	0	0-1	1-2	3+	
2004	1	2.4	1.1	4.0	16.8	6.2	6.1	43.6	27.4	10,892
	2	2.3	1.1	4.0	12.4	6.4	7.7	48.6	24.8	8,600
	3	2.3	1.1	4.0	9.7	5.5	6.9	51.1	26.9	6,291
	4	2.4	1.0	4.0	7.5	4.6	5.8	52.2	29.9	4,891
	5	2.5	1.0	4.0	6.5	3.4	5.0	54.7	30.4	3,290
	6	2.5	1.0	4.0	6.8	3.2	5.4	53.3	31.3	2,281
	7	2.5	1.0	4.0	7.8	3.2	5.6	50.9	32.5	1,240
	8	2.6	1.0	4.0	7.9	3.5	6.0	48.8	33.9	750
	9	2.5	1.0	4.0	8.4	4.1	4.9	53.1	29.4	367
	10	2.6	1.0	4.0	17.9	3.8	5.2	43.4	29.7	212
	Total	2.4	1.1	4.0	11.5	5.3	6.4	48.9	27.9	38,814
2005	1	2.4	1.2	4.0	17.3	7.1	6.6	42.5	26.4	10,832
	2	2.3	1.1	4.0	13.4	5.9	7.8	47.9	24.9	8,526
	3	2.4	1.1	4.0	9.3	5.0	6.6	51.2	27.9	6,232
	4	2.5	1.0	4.0	7.8	4.0	5.6	51.2	31.4	4,907
	5	2.5	1.0	4.0	6.3	3.4	5.3	53.7	31.3	3,222
	6	2.6	1.0	4.0	7.2	3.1	4.6	51.6	33.4	2,267
	7	2.5	1.0	4.0	8.6	2.8	5.7	54.3	28.6	1,183
	8	2.5	1.0	4.0	10.2	2.5	5.2	54.5	27.6	728
	9	2.5	1.0	4.0	9.6	4.5	5.6	48.7	31.6	374
	10	2.4	1.1	4.0	12.8	6.0	6.0	50.2	25.1	235
	Total	2.4	1.1	4.0	11.9	5.3	6.5	48.4	27.9	38,506
Total	1	2.4	1.1	4.0	17.1	6.7	6.3	43.0	26.9	21,724
	2	2.3	1.1	4.0	12.9	6.2	7.8	48.3	24.9	17,126
	3	2.4	1.1	4.0	9.5	5.3	6.7	51.1	27.4	12,523
	4	2.5	1.0	4.0	7.6	4.3	5.7	51.7	30.6	9,798
	5	2.5	1.0	4.0	6.4	3.4	5.2	54.2	30.9	6,512
	6	2.6	1.0	4.0	7.0	3.2	5.0	52.4	32.4	4,548
	7	2.5	1.0	4.0	8.2	3.0	5.7	52.5	30.6	2,423
	8	2.5	1.0	4.0	9.0	3.0	5.6	51.6	30.8	1,478
	9	2.5	1.0	4.0	9.0	4.3	5.3	50.9	30.5	741
	10	2.5	1.1	4.0	15.2	4.9	5.6	47.0	27.3	447
	Total	2.4	1.1	4.0	11.7	5.3	6.4	48.7	27.9	77,320

Table A-32. Cumulative GPA
(First Spell).

Cohort	Semester	Mean	SD	Max	Cumulative GPA					N
					None	0	0-1	1-2	3+	
2004	1	2.4	1.1	4.0	16.8	6.1	6.0	43.9	27.2	10,892
	2	2.3	1.0	4.0	2.9	4.2	9.5	57.8	25.6	8,600
	3	2.4	0.9	4.0	0.9	1.2	6.0	64.7	27.1	6,291
	4	2.5	0.8	4.0	0.2	0.2	3.5	66.6	29.5	4,891
	5	2.6	0.7	4.0	0.1	0.1	1.6	69.6	28.6	3,290
	6	2.6	0.6	4.0	0.0	0.1	0.6	71.2	28.1	2,281
	7	2.6	0.6	4.0	0.0	0.1	0.2	73.5	26.1	1,240
	8	2.6	0.5	4.0	0.0	0.0	0.0	74.0	26.0	750
	9	2.6	0.5	3.9	0.0	0.0	0.0	75.2	24.8	367
	10	2.6	0.5	3.9	0.0	0.0	0.5	76.4	23.1	212
	Total	2.4	0.9	4.0	5.6	2.9	5.4	59.0	27.2	38,814
2005	1	2.4	1.2	4.0	17.3	7.1	6.5	42.7	26.4	10,832
	2	2.3	1.0	4.0	2.8	4.4	10.0	56.4	26.4	8,526
	3	2.4	0.9	4.0	0.7	1.3	6.5	64.0	27.4	6,232
	4	2.5	0.8	4.0	0.1	0.5	3.3	66.1	30.0	4,907
	5	2.6	0.7	4.0	0.1	0.1	1.4	68.6	29.8	3,222
	6	2.6	0.6	4.0	0.0	0.0	0.6	70.7	28.7	2,267
	7	2.6	0.6	4.0	0.0	0.0	0.2	75.0	24.9	1,183
	8	2.6	0.5	4.0	0.0	0.0	0.0	77.6	22.4	728
	9	2.6	0.5	3.9	0.0	0.0	0.0	79.4	20.6	374
	10	2.5	0.5	3.9	0.0	0.0	0.0	81.7	18.3	235
	Total	2.4	0.9	4.0	5.6	3.3	5.7	58.2	27.2	38,506
Total	1	2.4	1.1	4.0	17.1	6.6	6.2	43.3	26.8	21,724
	2	2.3	1.0	4.0	2.9	4.3	9.8	57.1	26.0	17,126
	3	2.4	0.9	4.0	0.8	1.3	6.3	64.4	27.3	12,523
	4	2.5	0.8	4.0	0.2	0.3	3.4	66.3	29.7	9,798
	5	2.6	0.7	4.0	0.1	0.1	1.5	69.1	29.2	6,512
	6	2.6	0.6	4.0	0.0	0.1	0.6	70.9	28.4	4,548
	7	2.6	0.6	4.0	0.0	0.0	0.2	74.2	25.5	2,423
	8	2.6	0.5	4.0	0.0	0.0	0.0	75.8	24.2	1,478
	9	2.6	0.5	3.9	0.0	0.0	0.0	77.3	22.7	741
	10	2.6	0.5	3.9	0.0	0.0	0.2	79.2	20.6	447
	Total	2.4	0.9	4.0	5.6	3.1	5.5	58.6	27.2	77,320

Table A-33. Skills proficiency by semester (First Spell).

Cohort	Term	Reading	Writing	Math	Reading and Writing	Reading and Math	Writing and Math	Reading, Writing Math	Total
		%	%	%	%	%	%	%	N
2004	1	74.6	45.0	73.0	41.6	58.6	36.5	34.3	10,892
	2	79.3	57.7	79.2	54.1	66.5	48.9	46.6	8,600
	3	85.6	70.7	85.2	67.6	75.6	62.9	60.9	6,291
	4	87.4	77.6	87.9	74.2	79.1	70.5	68.1	4,891
	5	89.6	83.6	90.2	79.9	82.9	76.9	74.3	3,290
	6	90.8	86.3	91.6	82.6	85.0	80.2	77.6	2,281
	7	90.7	88.1	91.5	83.4	84.8	81.4	77.9	1,240
	8	90.4	88.7	90.7	83.3	84.1	81.3	77.6	750
	9	88.6	88.0	89.6	82.0	82.8	79.6	76.3	367
	10	88.2	87.7	88.7	81.1	81.6	77.8	74.5	212
Total		82.3	64.6	81.9	61.1	71.0	56.8	54.4	38,814
2005	1	75.3	48.1	73.1	44.8	59.1	38.4	36.5	10,832
	2	80.1	61.5	79.1	57.8	67.0	51.6	49.3	8,526
	3	84.4	73.0	84.6	69.2	74.5	64.1	61.7	6,232
	4	86.5	79.3	87.7	75.3	78.7	71.5	69.0	4,907
	5	88.3	83.6	89.7	79.7	81.5	76.4	73.8	3,222
	6	88.8	86.1	90.5	81.9	82.8	79.3	76.5	2,267
	7	88.7	85.9	89.7	81.4	81.9	77.9	75.1	1,183
	8	89.0	86.8	89.4	81.6	82.1	78.3	75.1	728
	9	88.0	85.3	89.6	78.1	81.0	76.2	71.7	374
	10	86.8	84.3	88.9	77.0	80.0	75.3	71.1	235
Total		82.0	66.8	81.6	63.0	70.6	57.8	55.5	38,506
Total	1	75.0	46.5	73.1	43.2	58.8	37.5	35.4	21,724
	2	79.7	59.6	79.1	55.9	66.8	50.3	48.0	17,126
	3	85.0	71.8	84.9	68.4	75.1	63.5	61.3	12,523
	4	87.0	78.5	87.8	74.8	78.9	71.0	68.6	9,798
	5	88.9	83.6	90.0	79.8	82.2	76.6	74.1	6,512
	6	89.8	86.2	91.1	82.3	83.9	79.7	77.1	4,548
	7	89.7	87.0	90.6	82.4	83.4	79.7	76.6	2,423
	8	89.7	87.8	90.1	82.5	83.2	79.8	76.4	1,478
	9	88.3	86.6	89.6	80.0	81.9	77.9	74.0	741
	10	87.5	85.9	88.8	79.0	80.8	76.5	72.7	447
Grand Total		82.2	65.7	81.8	62.0	70.8	57.3	54.9	77,320

Table A-34. Days per week attending class (First Spell).

Cohort	Term	Days Mean	0 %	1 %	2 %	3 %	4 %	5 %	6 %	7 %	Total N
2004	1	4.2	0.4	1.1	4.5	12.2	42.2	36.4	3.1	0.1	10,892
	2	4.1	0.2	0.7	5.5	11.7	47.7	31.4	2.7	0.1	8,600
	3	4.0	0.4	0.8	6.9	12.2	49.0	27.8	2.9	0.1	6,291
	4	3.9	0.4	1.1	8.0	15.1	47.3	25.6	2.4	0.1	4,891
	5	3.9	0.5	1.8	9.9	14.5	46.6	23.6	3.0	0.1	3,290
	6	3.7	0.4	2.5	14.6	17.4	42.0	20.2	2.8	0.2	2,281
	7	3.5	0.5	3.8	17.6	20.5	40.0	15.8	1.8	0.1	1,240
	8	3.3	0.5	5.5	22.3	19.9	36.3	14.7	0.9	0.0	750
	9	3.2	0.5	6.0	24.8	23.4	32.2	11.4	1.6	0.0	367
	10	3.0	1.4	9.9	29.7	19.3	24.5	13.7	1.4	0.0	212
Total		4.0	0.3	1.4	7.7	13.5	45.1	29.1	2.8	0.1	38,814
2005	1	4.2	0.4	1.0	4.3	12.0	44.4	34.9	2.8	0.2	10,832
	2	4.0	0.3	0.8	6.0	14.2	49.7	26.8	2.0	0.1	8,526
	3	4.0	0.2	1.0	6.6	13.4	51.0	25.6	2.1	0.1	6,232
	4	3.9	0.1	1.3	8.2	16.0	47.4	24.7	2.2	0.1	4,907
	5	3.9	0.3	1.6	9.8	15.8	47.2	22.7	2.5	0.1	3,222
	6	3.7	0.6	2.3	13.8	17.9	43.3	19.8	2.2	0.1	2,267
	7	3.6	0.5	3.6	15.6	18.7	42.8	16.9	1.9	0.0	1,183
	8	3.5	1.4	4.8	19.4	16.9	36.5	18.7	2.3	0.0	728
	9	3.4	0.5	2.7	25.4	21.1	31.6	17.4	1.1	0.3	374
	10	3.2	0.0	8.1	27.2	20.0	31.9	11.1	1.7	0.0	235
Total		4.0	0.3	1.3	7.5	14.3	46.8	27.2	2.3	0.1	38,506
Total	1	4.2	0.4	1.0	4.4	12.1	43.3	35.7	2.9	0.2	21,724
	2	4.1	0.2	0.8	5.8	13.0	48.7	29.1	2.4	0.1	17,126
	3	4.0	0.3	0.9	6.7	12.8	50.0	26.7	2.5	0.1	12,523
	4	3.9	0.3	1.2	8.1	15.5	47.3	25.2	2.3	0.1	9,798
	5	3.9	0.4	1.7	9.9	15.1	46.9	23.2	2.8	0.1	6,512
	6	3.7	0.5	2.4	14.2	17.7	42.6	20.0	2.5	0.1	4,548
	7	3.5	0.5	3.7	16.6	19.6	41.4	16.3	1.9	0.0	2,423
	8	3.4	0.9	5.1	20.8	18.4	36.4	16.6	1.6	0.0	1,478
	9	3.3	0.5	4.3	25.1	22.3	31.8	14.4	1.3	0.1	741
	10	3.1	0.7	8.9	28.4	19.7	28.4	12.3	1.6	0.0	447
Grand Total		4.0	0.3	1.4	7.6	13.9	46.0	28.2	2.5	0.1	77,320

Table A-35. Total Hours on Campus and in Class per Week (First Spell).

Cohort	Semester	Hours on Campus			Hours in Class			N
		Mean	SD	Max	Mean	SD	Max	
2004	1	16.4	8.1	76.3	11.7	5.4	51.4	10,892
	2	16.1	7.9	71.2	11.4	5.0	53.0	8,600
	3	16.4	8.2	70.5	11.7	5.3	48.1	6,291
	4	15.7	8.1	62.4	10.8	4.9	43.6	4,891
	5	15.9	8.7	53.8	11.0	5.3	46.5	3,290
	6	14.7	8.8	59.4	10.3	5.5	44.8	2,281
	7	13.1	8.6	51.0	9.4	5.7	46.0	1,240
	8	12.5	9.2	59.5	9.0	6.2	55.5	750
	9	10.9	7.6	49.3	8.5	5.7	39.0	367
	10	10.0	8.3	40.9	7.8	6.0	31.3	212
	Total	15.8	8.3	76.3	11.2	5.3	55.5	38,814
2005	1	16.4	8.1	65.8	11.8	5.6	55.6	10,832
	2	15.3	7.0	58.5	10.8	4.2	44.0	8,526
	3	16.3	8.1	64.7	11.6	5.2	42.1	6,232
	4	16.6	8.6	54.3	11.5	5.3	51.5	4,907
	5	16.1	8.7	62.5	11.2	5.4	46.0	3,222
	6	15.2	9.1	59.5	10.5	5.8	55.5	2,267
	7	13.8	9.2	60.8	10.0	6.4	53.8	1,183
	8	13.1	9.3	52.0	9.3	5.9	37.8	728
	9	12.3	9.5	60.5	8.9	6.9	55.0	374
	10	10.9	8.5	38.5	7.9	5.5	31.8	235
	Total	15.9	8.2	65.8	11.2	5.3	55.6	38,506
Total	1	16.4	8.1	76.3	11.8	5.5	55.6	21,724
	2	15.7	7.5	71.2	11.1	4.6	53.0	17,126
	3	16.3	8.2	70.5	11.6	5.2	48.1	12,523
	4	16.2	8.4	62.4	11.2	5.1	51.5	9,798
	5	16.0	8.7	62.5	11.1	5.4	46.5	6,512
	6	15.0	8.9	59.5	10.4	5.7	55.5	4,548
	7	13.4	8.9	60.8	9.7	6.1	53.8	2,423
	8	12.8	9.3	59.5	9.2	6.0	55.5	1,478
	9	11.6	8.7	60.5	8.7	6.4	55.0	741
	10	10.5	8.4	40.9	7.9	5.7	31.8	447
	Total	15.8	8.2	76.3	11.2	5.3	55.6	77,320

Table A-36. Travel Time per Week
(First Spell).

Cohort	Term	Hours			Hours					Total N
		Mean	SD	Max	0-5 %	5-10 %	10- 15 %	15- 20 %	20+ %	
2004	1	7.7	3.8	43.0	24.0	51.7	19.9	3.7	0.8	10,892
	2	7.6	3.7	35.5	25.3	52.1	18.7	3.3	0.6	8,600
	3	7.4	3.7	35.5	26.4	52.4	17.6	3.0	0.6	6,291
	4	7.2	3.7	43.0	30.0	51.2	15.3	2.8	0.7	4,891
	5	7.0	3.7	31.2	32.4	49.7	14.6	2.9	0.5	3,290
	6	6.6	3.7	30.2	37.5	46.1	13.9	2.0	0.5	2,281
	7	6.1	3.4	21.2	42.6	43.5	12.0	1.9	0.1	1,240
	8	5.8	3.4	19.2	49.9	38.1	10.4	1.6	0.0	750
	9	5.4	3.3	19.2	54.0	36.8	7.6	1.6	0.0	367
	10	5.1	3.3	21.2	59.0	31.6	8.5	0.5	0.5	212
Total		7.3	3.7	43.0	28.5	50.5	17.3	3.1	0.6	38,814
2005	1	7.8	3.8	29.2	24.2	50.8	20.2	4.0	0.8	10,832
	2	7.4	3.7	29.2	26.6	52.3	17.1	3.4	0.6	8,526
	3	7.3	3.6	27.0	27.3	52.2	17.0	3.0	0.6	6,232
	4	7.1	3.6	29.8	30.0	50.8	16.0	2.8	0.5	4,907
	5	7.0	3.6	29.8	30.9	51.4	14.6	2.6	0.5	3,222
	6	6.7	3.6	24.7	36.3	47.0	13.9	2.3	0.5	2,267
	7	6.4	3.6	23.9	39.8	45.1	12.4	2.4	0.3	1,183
	8	6.3	3.9	29.8	43.8	40.8	12.9	1.6	0.8	728
	9	5.7	3.4	17.9	50.5	37.4	10.7	1.3	0.0	374
	10	5.1	3.5	29.8	61.3	30.6	6.8	0.4	0.9	235
Total		7.3	3.7	29.8	28.6	50.6	17.1	3.2	0.6	38,506
Total	1	7.8	3.8	43.0	24.1	51.2	20.0	3.8	0.8	21,724
	2	7.5	3.7	35.5	26.0	52.2	17.9	3.4	0.6	17,126
	3	7.4	3.7	35.5	26.8	52.3	17.3	3.0	0.6	12,523
	4	7.2	3.7	43.0	30.0	51.0	15.7	2.8	0.6	9,798
	5	7.0	3.6	31.2	31.6	50.5	14.6	2.7	0.5	6,512
	6	6.6	3.6	30.2	36.9	46.6	13.9	2.2	0.5	4,548
	7	6.3	3.5	23.9	41.2	44.3	12.2	2.1	0.2	2,423
	8	6.0	3.7	29.8	46.9	39.4	11.6	1.6	0.4	1,478
	9	5.6	3.3	19.2	52.2	37.1	9.2	1.5	0.0	741
	10	5.1	3.4	29.8	60.2	31.1	7.6	0.4	0.7	447
Grand Total		7.3	3.7	43.0	28.5	50.6	17.2	3.1	0.6	77,320

Table A-37. Intersession Registration and Credits
(First Spell).

Cohort	Term	Reg. %	Credits			Credits					Total N
			Mean	SD	Max	0 %	.5 - 3 %	3.5 - 6 %	6.5 - 9 %	9+ %	
2004	1	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	10,892
	2	12.0	0.3	1.2	14.0	92.8	3.8	2.6	0.7	0.2	8,600
	3	1.5	0.0	0.3	9.0	98.6	1.2	0.1	0.0	0.0	6,291
	4	14.6	0.5	1.5	14.0	88.2	5.4	4.8	1.3	0.3	4,891
	5	2.3	0.1	0.4	5.0	98.0	1.6	0.4	0.0	0.0	3,290
	6	14.6	0.5	1.5	12.0	87.1	6.4	5.2	1.1	0.2	2,281
	7	1.9	0.0	0.3	4.5	98.7	1.1	0.2	0.0	0.0	1,240
	8	13.7	0.4	1.2	9.0	88.8	6.3	4.3	0.7	0.0	750
	9	0.8	0.0	0.2	3.0	99.7	0.3	0.0	0.0	0.0	367
	10	16.0	0.5	1.4	9.0	86.8	7.5	4.2	1.4	0.0	212
Total		6.2	0.2	0.9	14.0	95.4	2.4	1.6	0.4	0.1	38,814
2005	1	0.9	0.0	0.3	4.5	99.2	0.8	0.0	0.0	0.0	10,832
	2	11.1	0.3	1.2	14.0	93.2	3.6	2.3	0.7	0.2	8,526
	3	2.6	0.1	0.4	5.5	97.8	1.9	0.3	0.0	0.0	6,232
	4	12.9	0.4	1.5	13.0	89.5	4.8	4.3	1.1	0.3	4,907
	5	2.4	0.1	0.4	5.0	98.1	1.6	0.4	0.0	0.0	3,222
	6	14.3	0.5	1.5	14.0	88.9	4.8	5.1	0.9	0.3	2,267
	7	3.4	0.1	0.4	4.5	98.3	1.4	0.3	0.0	0.0	1,183
	8	15.2	0.4	1.2	7.0	87.8	7.0	4.5	0.7	0.0	728
	9	1.9	0.0	0.3	3.0	98.1	1.9	0.0	0.0	0.0	374
	10	16.6	0.4	1.3	8.0	88.1	6.8	4.7	0.4	0.0	235
Total		6.3	0.2	0.9	14.0	95.4	2.6	1.6	0.4	0.1	38,506
Total	1	0.4	0.0	0.2	4.5	99.6	0.4	0.0	0.0	0.0	21,724
	2	11.6	0.3	1.2	14.0	93.0	3.7	2.4	0.7	0.2	17,126
	3	2.0	0.1	0.4	9.0	98.2	1.6	0.2	0.0	0.0	12,523
	4	13.7	0.5	1.5	14.0	88.8	5.1	4.6	1.2	0.3	9,798
	5	2.3	0.1	0.4	5.0	98.0	1.6	0.4	0.0	0.0	6,512
	6	14.4	0.5	1.5	14.0	88.0	5.6	5.1	1.0	0.3	4,548
	7	2.6	0.0	0.4	4.5	98.5	1.2	0.2	0.0	0.0	2,423
	8	14.5	0.4	1.2	9.0	88.3	6.6	4.4	0.7	0.0	1,478
	9	1.3	0.0	0.2	3.0	98.9	1.1	0.0	0.0	0.0	741
	10	16.3	0.5	1.3	9.0	87.5	7.2	4.5	0.9	0.0	447
Grand Total		6.3	0.2	0.9	14.0	95.4	2.5	1.6	0.4	0.1	77,320

Table A-38. Online Courses and Credits
(First Spell).

Cohort	Term	Some Online Content			All Online Content			Any Online Content			Total N
		%	Non-Zero Credits		%	Non-Zero Credits		%	Non-Zero Credits		
			Mean	SD		Mean	SD		Mean	SD	
2004	1	0.0	--	--	0.0	--	--	0.0	--	--	10,892
	2	0.0	--	--	0.0	--	--	0.0	--	--	8,600
	3	0.0	--	--	0.0	--	--	0.0	--	--	6,291
	4	0.0	--	--	0.0	--	--	0.0	--	--	4,891
	5	6.7	3.6	1.4	2.9	3.8	2.0	9.2	3.8	1.8	3,290
	6	5.4	3.9	1.6	2.5	3.9	2.2	7.8	3.9	1.8	2,281
	7	5.6	3.7	1.8	3.1	3.3	1.5	8.5	3.6	1.7	1,240
	8	6.4	4.9	3.1	2.8	3.1	1.2	8.8	4.5	2.8	750
	9	3.5	4.8	3.0	2.5	2.9	1.5	5.7	4.2	2.7	367
	10	12.3	4.4	2.4	4.7	2.4	1.1	15.1	4.3	2.4	212
Total		1.3	3.9	1.9	0.6	3.6	1.9	1.8	3.9	2.0	38,814
2005	1	0.0	--	--	0.0	--	--	0.0	--	--	10,832
	2	0.0	--	--	0.0	--	--	0.0	--	--	8,526
	3	7.2	3.7	1.4	1.4	3.3	0.9	8.5	3.7	1.4	6,232
	4	7.3	3.9	1.8	1.7	3.5	1.3	8.9	3.9	1.8	4,907
	5	7.5	4.2	2.5	2.5	3.5	1.5	9.7	4.1	2.4	3,222
	6	7.9	4.7	2.5	3.3	3.4	1.4	11.0	4.4	2.4	2,267
	7	7.2	5.1	2.8	3.4	2.8	1.5	9.0	5.1	3.1	1,183
	8	16.2	4.1	2.4	3.4	3.2	1.4	19.0	4.1	2.3	728
	9	10.4	4.8	2.9	3.7	3.1	1.5	13.9	4.4	2.7	374
	10	10.2	3.9	1.7	3.4	3.1	1.9	12.8	3.9	1.7	235
Total		3.9	4.1	2.1	1.1	3.3	1.4	4.8	4.0	2.1	38,506
Total	1	0.0	--	--	0.0	--	--	0.0	--	--	21,724
	2	0.0	--	--	0.0	--	--	0.0	--	--	17,126
	3	3.6	3.7	1.4	0.7	3.3	0.9	4.2	3.7	1.4	12,523
	4	3.7	3.9	1.8	0.8	3.5	1.3	4.4	3.9	1.8	9,798
	5	7.1	3.9	2.1	2.7	3.7	1.8	9.5	4.0	2.1	6,512
	6	6.6	4.4	2.2	2.9	3.6	1.8	9.4	4.2	2.2	4,548
	7	6.4	4.5	2.5	3.2	3.0	1.5	8.8	4.4	2.6	2,423
	8	11.2	4.3	2.6	3.1	3.2	1.3	13.8	4.3	2.5	1,478
	9	7.0	4.8	2.9	3.1	3.0	1.4	9.9	4.4	2.7	741
	10	11.2	4.1	2.1	4.0	2.7	1.5	13.9	4.1	2.1	447
Grand Total		2.6	4.0	2.1	0.8	3.4	1.6	3.3	4.0	2.1	77,320

Table A-39. Mean Section Size by Term (First Spell).

Cohort	Term	Mean	SD	N
2004	1	28.5	4.43	10,854
	2	29.3	4.25	8,586
	3	28.5	4.50	6,269
	4	28.0	4.76	4,875
	5	27.1	5.68	3,282
	6	26.4	5.96	2,281
	7	26.1	6.84	1,239
	8	26.0	6.45	749
	9	24.7	7.48	367
	10	25.2	8.04	212
	Total	28.2	4.96	38,714
2005	1	27.8	4.68	10,788
	2	28.7	4.23	8,504
	3	28.5	4.49	6,221
	4	27.7	4.82	4,903
	5	27.0	5.71	3,217
	6	26.5	5.92	2,260
	7	26.2	6.65	1,180
	8	25.9	6.26	722
	9	25.8	6.75	374
	10	25.9	6.32	235
	Total	27.8	4.96	38,404
Total	1	28.1	4.57	21,642
	2	29.0	4.25	17,090
	3	28.5	4.49	12,490
	4	27.9	4.79	9,778
	5	27.1	5.69	6,499
	6	26.4	5.94	4,541
	7	26.1	6.75	2,419
	8	25.9	6.36	1,471
	9	25.3	7.14	741
	10	25.6	7.19	447
	Total	28.0	4.96	77,118

Table A-40. Individual Student/Faculty Ratio (First Spell).

Cohort	Semester	Individual Student/Faculty Ratio					N
		None (N)	Min	Mean	Max	SD	
2004	1	42	4.1	23.2	210.0	6.6	10,892
	2	18	3.7	23.8	93.3	5.1	8,600
	3	27	1.9	22.9	154.6	5.5	6,291
	4	25	3.2	23.0	77.2	5.4	4,891
	5	19	1.9	22.0	61.7	6.0	3,290
	6	11	3.4	21.5	57.5	6.2	2,281
	7	8	2.2	21.2	68.3	6.9	1,240
	8	5	2.5	21.1	41.6	6.6	750
	9	3	2.6	20.1	39.7	7.3	367
	10	4	3.8	20.4	51.7	7.6	212
	Total	162	1.9	22.9	210.0	6.0	38,814
2005	1	53	1.0	22.4	122.7	5.3	10,832
	2	27	3.4	23.8	135.0	4.8	8,526
	3	16	3.3	23.0	137.5	5.3	6,232
	4	9	1.9	22.7	137.2	5.6	4,907
	5	11	4.1	21.9	65.6	5.9	3,222
	6	17	2.8	21.7	43.9	6.1	2,267
	7	7	2.2	21.2	69.9	7.0	1,183
	8	12	4.0	20.8	51.7	6.5	728
	9	2	4.4	20.4	47.3	6.9	374
	10	3	6.3	20.5	41.9	6.3	235
	Total	157	1.0	22.7	137.5	5.5	38,506
Total	1	95	1.0	22.8	210.0	6.0	21,724
	2	45	3.4	23.8	135.0	5.0	17,126
	3	43	1.9	22.9	154.6	5.4	12,523
	4	34	1.9	22.9	137.2	5.5	9,798
	5	30	1.9	21.9	65.6	6.0	6,512
	6	28	2.8	21.6	57.5	6.2	4,548
	7	15	2.2	21.2	69.9	6.9	2,423
	8	17	2.5	21.0	51.7	6.5	1,478
	9	5	2.6	20.2	47.3	7.1	741
	10	7	3.8	20.4	51.7	6.9	447
	Total	319	1.0	22.8	210.0	5.8	77,320

Appendix B: Individual Student/Faculty Ratio

The Individual Student/Faculty ratio could also be described as a weighted class size. In this study, only traditional classes that meet in classrooms are included. There are three factors that are taken into account:

1. The number of students in the class
2. The number of minutes that that the class meets
3. The total number of minutes that the student is scheduled to be in class per week

For each student/class, the number of total minutes that the class meets is divided by the total number of students. The quotient (number of minutes per student) for each student is then summed for all classes taken by the student. Finally, the total number of minutes that the student is scheduled to be in class per week is divided by summed minutes per student.

Algebraically:

$$ISFR = (\sum_{k=1}^{Ks} cmk / ns) / tms$$

Ks = Number of classes that the student takes

cmk = Number of minutes in the class per week

ns = Number of students in the class

tms = total number of minutes that the student is scheduled to be in class per week

Appendix C: Commuting Time

Commuting time was estimated using the HopStop.com website and address information for each student and college that he or she attended. The address for each student was stripped of all information except street name, street number and zip code. Addresses that utilized post office boxes were not used. Street types (avenue, boulevard, road, street, etc.) were standardized. A Visual Basic program was developed by the author that automatically entered this information into HopStop.com. HopStop.com was instructed to compute the minimum travel time using subway, buses, light rail and walking. The resulting directions included the travel time, which was read from the website using another Visual Basic procedure. The procedure was run on weekdays between 6 a.m. and 9 p.m. A parallel procedure using MapQuest.com was developed and utilized for automobile travel time, but these data were ultimately not used for this study in any of the models.

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