

# The Relationship between Student Time Allocation Decisions and Outcomes: An Interactive Simulation Model

Nathan Dickmeyer, Ph.D.<sup>1</sup>  
Sam Michalowski, Ph.D.<sup>2</sup>

A Paper Presented at the 52<sup>nd</sup> Annual Forum of the Association for Institutional Research, New Orleans, LA: June 5th, 2012

## Introduction

“If I have to work 30 hours per week, take care of my family five hours a day and only have ten hours per week to study, how many courses should I take? When will I graduate? How likely is it that people like me ever graduate?”

Most student advisors do not have the tools to help students answer these questions. An interactive simulation model presented here allows students and advisors to explore the trade-offs involved in setting up a student's schedule. There is ample evidence that the less time students spend working and caring for families and more time studying, the more likely they are to be successful. Can we, however, get underneath this truism with a model of success that accounts for implied causal relationships? Can we create a set of relationships that have sufficiently dependable mathematical properties across different colleges which when utilized in a game-like model can help all those involved better understand the impact that students' time allocation decisions have on the educational and lifetime financial outcomes?

To pursue these questions we set four goals:

- 1) To frame many of the postulates of the qualitatively derived critical Junctures framework regarding community college students' progress (Michalowski , in submission) as quantitative relationships using available administrative data;
- 2) To develop model parameters that correctly predict the probability of dropping out over twelve semesters for known student achievement profiles;
- 3) To develop an interactive model that can be used as a game to allow practitioners and students to model the impact of students' time allocation decisions on their likelihood of dropping out; and
- 4) To compare model results from an identical cohort of associates degree students at two colleges to explore the interactive simulation's applicability to other student populations and institutional contexts.

---

<sup>1</sup> Director, Office of Institutional Research and Assessment, CUNY LaGuardia Community College

<sup>2</sup> Director, Office of Institutional Research and Assessment, CUNY College of Staten Island

The intentions of interactive modeling differ from those of predictive modeling. Predictive modeling uses techniques like regression to link a set of characteristics to a dependent or outcome variable. In interactive modeling, the results of descriptive and predictive statistics allow users to test the application of their values to relationships (often derived from statistics) constrained by real world outcomes. Interactive financial planning models for universities have been used to test the impact of various scenarios on value formulation in higher education financial decision makers (Dickmeyer, 1983). Users learn about the modeled impact on outcomes of selecting various alternatives. This learning changes the user's views about the desirability of the alternatives.

The relationships in the model described here are consistent with many of the postulates of the critical junctures framework of community college students' progress (Michalowski, in submission). Using a qualitative approach, Michalowski finds that many community college students' enrollment disruptions (i.e., going part-time, stopping out, dropping out) result from crises where their performance of responsibilities and tasks internal and external to their college-going is simultaneously threatened. The resulting "pile up of stressors" (Wells, 2006) causes critical junctures in their progress. Difficulties with family and work responsibilities, personal health, and living arrangements coincided with academic challenges, counter-productive behaviors by instructors and staff and administrative hurdles.

Michalowski (in submission) finds that community college students develop and employ strategies of resilience during critical junctures to remain productively enrolled. These strategies involved interpersonal skills such as time management and accessing social resources such as administrative gatekeepers and informants. In general, deployment of such strategies was more evident among interviewees lacking significant external constraints (e.g., children, full-time employment), and/or were not too shy or proud to seek help from instructors, tutors and family and other social support systems. Older students tended more to the latter behavior. Younger students tended to have fewer constraints, but also weaker problem-solving skills to manage critical junctures. In some cases, attending part-time or stopping-out was actually an adaptive reaction to critical junctures permitting them to temporarily reprioritize their energies.

Incorporating these and other findings, Michalowski (in submission) arrives at a conceptual temporal risk-field model for enrollment disruptions encountered by community college students. This model suggests that the academic and administrative aspects of college-going combine with the challenges of life tasks at specific stages of their college careers to produce differential risks for enrollment disruptions. This model stipulates that the likelihood for enrollment disruptions may be lessened by the protective influence of certain college-side interventions and improvement in students' task-competence over their careers. Due to the permanence of life task challenges, however, Michalowski's study suggests that a certain degree of risk is ever-present in community college students' lives.

## Data Used

Descriptive statistics presented in this paper use a longitudinal dataset of new students (freshmen and transfers) starting in fall 2004 at a community college (College A). The multivariate model compares outcomes at College A to College B, a Carnegie Master's L comprehensive college which also enrolls and graduates a sizable number of associate degree students. During model development, we selected parameters such that the model correctly predicted the probabilities of dropping out by semester, as well as the rates of graduation, for the entering new student cohort of fall 2004. The model was calibrated to get a best fit against credit load, successful course completion rates, stop-out frequencies and time to degree for 1) the average student in the cohort, 2) those students who completed with a 3.0 final cumulative grade point or higher, and 3) students with a final cumulative grade point less than 2.5. Specific parameters are calibrated so as to produce the lowest sum of squared differences between predicted and actual dropout rates for these three groups.

It should be noted that the relationship between hours of study and the probability of passing a course could not be tested with available data. Nevertheless, students revealed in interviews (Michalowski, in submission) that those with the worst grade points were the ones who studied very little. Interviews with successful students indicated a much greater dedication to study and help-seeking behaviors.

This comparison of the results between College A and College B can gauge how well the model estimates graduation and dropout rates from differing college environments, how calibration parameters must be adjusted to accommodate their differing student background profiles, and what those adjustments may mean.

## Applied Value

When presented to students and instructional or counseling practitioners in the field, the model offers a way for individuals to trade-off various immediate responsibilities or desires (e.g., caring for a child, income) against the somewhat uncertain value they assign to getting a degree. Experimenting with their simulated time allocations, working less and studying more, for example, and seeing the impact on time to degree and the likelihood of staying in school may have an impact on how students' real-world time allocation decisions, based on the earlier research on the use of interactive financial models by decision makers (Dickmeyer, 1983).

## Theoretical Framework

Four postulates that relate to how student behaviors lead to successful college completion emerge from the critical junctures framework (Michalowski, in submission). These will later be combined mathematically using one "Law of Time" to create the interactive model. The four postulates concern: The Role of Fate, The Impact of Preparation, The Impact of Intervention, and The Impact of Investment.

## The Role of Fate

Postulate: Life events happen to everyone at about the same rate. To model this, we found that assigning a life event sufficiently dire to push a student out of college about once every five semesters fit best our data. Michalowski (in submission) found that students who dropped out were usually attempting to deal with insufficient income to support a family, a death or illness in the family, or other life problem that made the cost and time of school extremely difficult to handle. Many students found ways to handle these pressures, and not all problems seemed as great as others. Nevertheless, few students with no outside pressure seemed to be dropping out. The description of drop-out pressures suggests that the risk for and cumulative effect of life events is a sort of constant for all students. Therefore, we conclude that fate intervenes such that each student deals with these life events in one way or another at some (or most) points in his or her academic career.

This is not necessarily the only possible postulate of “fate.” A competing theory is that some people are winners, while others are losers. In other words, people’s fates are more predestined than random, and we should be able to tell who is going to succeed at some early stage. In fact, much of our research looking for “high risk” students is based on this way of viewing fate. Nevertheless, those of us who have followed this line of research have been fairly frustrated over the years. Each time we uncover a new “marker” of risk, we find that it correlates closely with all our old markers and the number of those at risk that we identify goes down. Our identification accuracy remains poor.

Let’s look at some of the markers. There is much focus on the differential educational attainment of students by their racial or ethnic backgrounds. Using an ultimate rate of institutional success (transfers + graduates), the following differences are observed among the major race/ethnic categories: Asians (55%), Whites (54%), Blacks (47%) and Hispanics (41%) at College A.

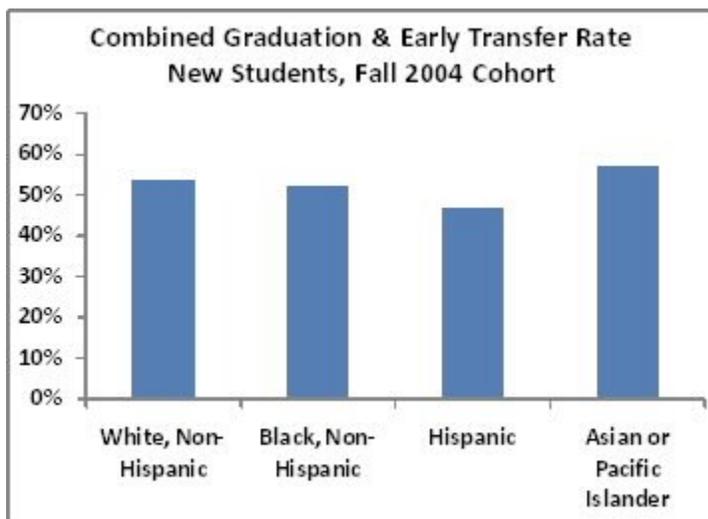


Figure 1

Yet, these relatively similar averages make it difficult to claim that a student from one particular group is more likely to drop out than one from another. All groups cluster around 50%: some higher, some lower. If we are to find “high risk” students, we will need more accurate descriptors than these.

Basic skills could be another way to separate “winners” from “losers.” Unfortunately, developmental skills tests do not, in general, allow us to determine who is highly likely to drop out or graduate with one exception: those who have the lowest scores in math. These students have graduated from high school, yet they are not proficient at arithmetic. We surmise that, among all academic skills, math acts most directly as a proxy for the social problems that threaten students’ progress. While data reflect that most students can be prepared for college work, those who require the lowest levels of remedial math are the least likely to graduate. While it has yet to be tested, the abstract-seeming nature of math coursework may contrast with math-challenged students’ concrete life problems and crises in such a way that they more readily underestimate their likelihood of passing even remedial-level courses.

Figure 2 shows how unlikely it is for a student who needs the lowest level math preparation to graduate, especially if the student has other basic skill needs. Nevertheless, notice how similar the graduation rates for students with low reading and writing scores are when compared to those who need no basic skills remediation.

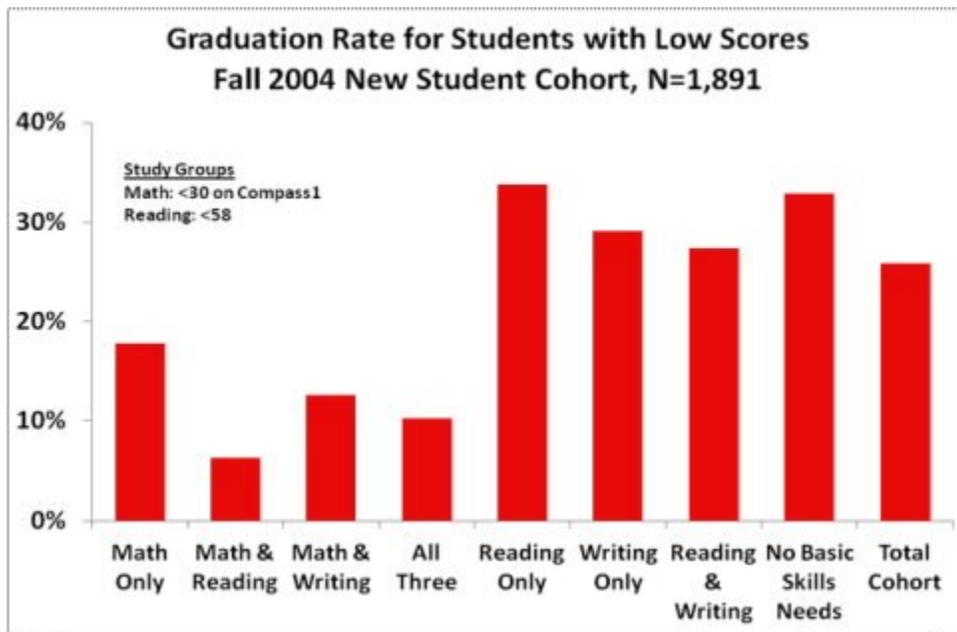


Figure 2

Using such “predestined” correlates of success and failure has not, for the most part, led to a smoking gun. The critical junctures framework (Michalowski, in submission) led us to incorporate fate as random: at least among the less academically prepared associate degree populations, dropping out is not readily predicted using pre-college and initial enrollment

characteristics because these are nearly identical in value. Keeping the probability of an academic career-halting life event constant in the model improves its' ability to predict dropout behavior. The constant background of fate is held constant in the model along with the positive impact of preparation and intervention and the momentum of personal investment.

### The Impact of Preparation

Postulate: A low level of preparation makes it harder to graduate. By combining the first two theories in a model, the model can better fit the data. Although life events may be random, dropping out and graduation rate predictions can be adjusted relative to test scores. The reader should note that students requiring developmental work on their basic skills will take longer to graduate and will be exposed to the random events of life longer, automatically decreasing the probability of graduation.

A competing assumption is that a community college can help any student graduate, regardless of preparation. Figure 3 tells us again that the proposed postulate is more true for math than for English, where the competing assumption appears true. Most students can be brought up to the level required of students who are admitted directly into credit-bearing English courses.

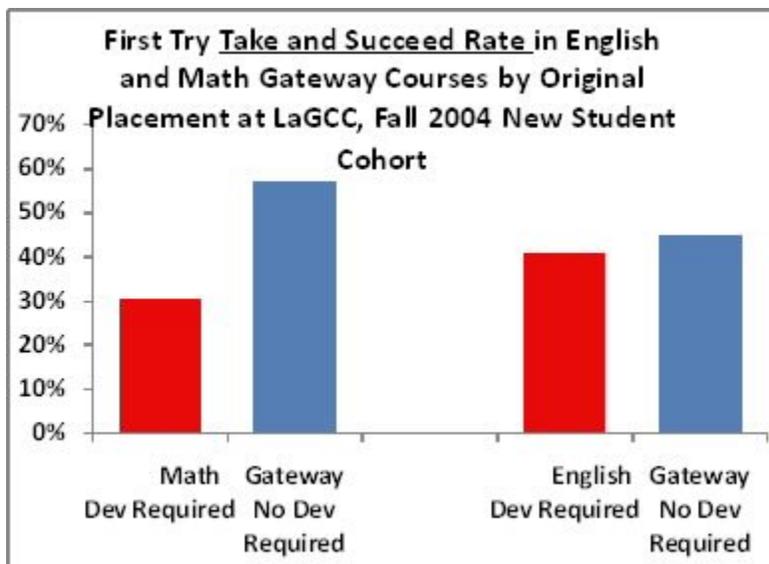


Figure 3

Figure 4, however, shows that those who do manage to get out of developmental math are able to pass the Math 101 Gateway type courses as well as those who initially test out of developmental math. The challenge with math seems to be passing the developmental level courses. This falls in line what others have discovered about remedial-needs students; those who satisfy remedial requirements tend to do as well over the long term as their non-remedial peers (Attewell, Lavin, Domina, & Levey, 2006; Behr, 2008). This is a comforting thought.

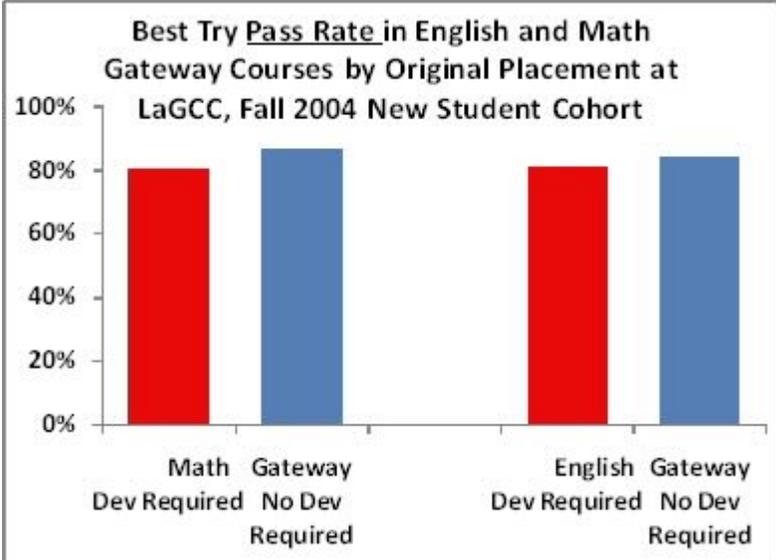


Figure 4

Figures 5 and 6 confirm that the more developmental skill needs a student starts college with (both breadth and depth—placing into lower level courses), the less likely it is that the student will be in a position to take all credit courses and move on to graduation.

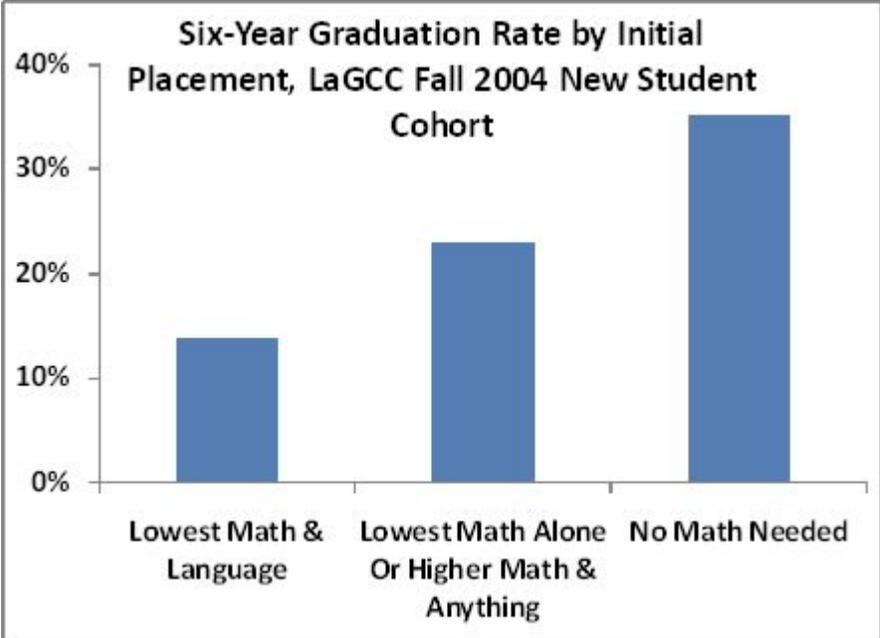


Figure 5

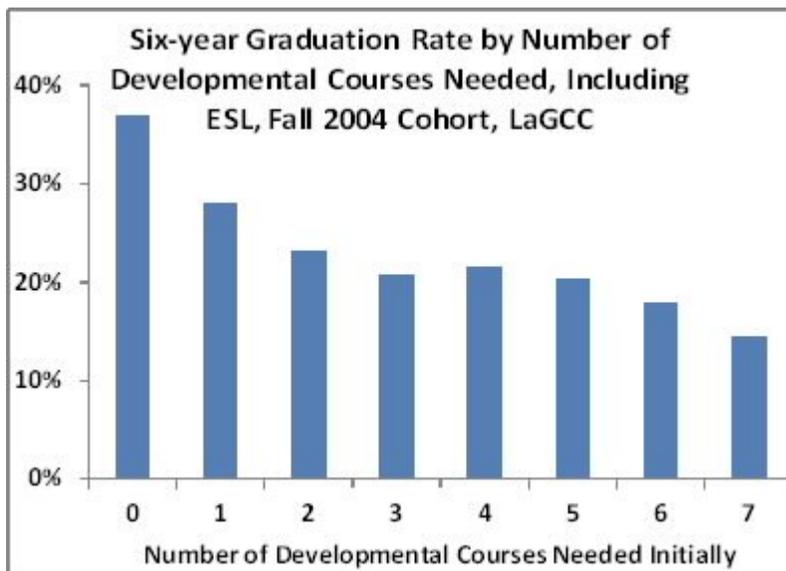


Figure 6

Thus, our model should also account for the fact that the more developmental work that a student is required to take, the greater their risk of dropping out early.

### The Impact of Intervention

Postulate: Students who experience an intervention are more likely to graduate. Many students come to community colleges after some sort of failure experience. Some have left high school and return after earning their GED. Others do not get into a four-year institution because of basic skill needs. Still others have failed out of other colleges and enrolled in community colleges as a last resort. Many do not understand or did not yet learn that college-level course work requires a very different commitment than they needed to get through high school. Many community colleges have designed a large number of experiences and interventions to change perceptions that minimal commitment is all that is required to graduate and to turn around students' expectations of failure.

Nevertheless, a competing assumption says that only students who are more likely to graduate seek out interventions. A growing literature on student engagement among community college students suggests that there is a relationship between academic and social integration and engagement and outcomes, but this relationship is not always straightforward. It is essentially very difficult to develop data supporting the primary theory of intervention. Researchers rarely get a chance to assign students randomly to an intervention but some promising local demonstration studies are underway. Students, randomly assigned to orientations using Value Auctions, had higher retention after the first semester than those from other orientation (see Levy, M.A., Jones V., McGowan L. & Polnariiev, 2011, for a description of the activity). And anecdotal "turn around" stories abound where many eventually successful students adopted successful strategies because of work with a specific faculty member or program counselor.

At best we feel that the number of hours a student dedicates to seeking help, getting advice, participating in campus events, working with student government and other activities should have some small effect on the probability of reaching graduation. This effect is clearly present in the accounts of successful students in Michalowski (in submission). Students who were able to break through their pride and ask for help and were relentless in doing so were able to overcome significant academic hurdles. This largely circumstantial and anecdotal evidence is not convincing enough, however, to make this factor very significant in the model's equations.

### The Impact of Investment

Postulate: The more a student studies, the more likely it is that the student will graduate. If nothing else, the probability of passing courses should increase as a student spends more time studying. The quality of the time can not, unfortunately, be measured. Isn't an hour studying in the library going to be more valuable than an hour on public transit?

The competing assumption holds that some students are smart and some are lucky and that time spent studying isn't important. All we know is that the higher a student's grades are the more likely he or she is to graduate. Hard data needed to calibrate this parameter isn't available. Again, only anecdotes from successful and unsuccessful students exists; those who take the time to study are the ones who graduate.

As a way of approximating the effect of effort on outcomes, Figure 7 shows the cumulative probability of dropping out for the cohort as a whole and for strong students, or those students with higher grade points (986 students graduated, dropped out or transferred out of College A out of the original fall 2004 new student cohort of 3,280 with a cumulative GPA of 3.0 or higher), against weak students, or those with lower grade points (1,656 students left with a cumulative GPA less than 2.5). Note how the probability starts fairly high, climbs quickly in early semesters, then continues growing with each passing semester. Note also that those students who leave with a low cumulative average have the highest initial probability of dropping out, the steepest early increases and the highest continuing probability.

Figure 7 presents the key set of data that ties all the postulates together for College A. Students begin with somewhat differing probabilities of dropping out. Some students, however, appear to pick up some protection from dropping out during their experience at College A as represented as those with higher cumulative grade points. While exposure to life events continues, these students have a growing level of resilience that protects them and causes their probabilities of dropping out to grow much more slowly than those who have lower GPAs.

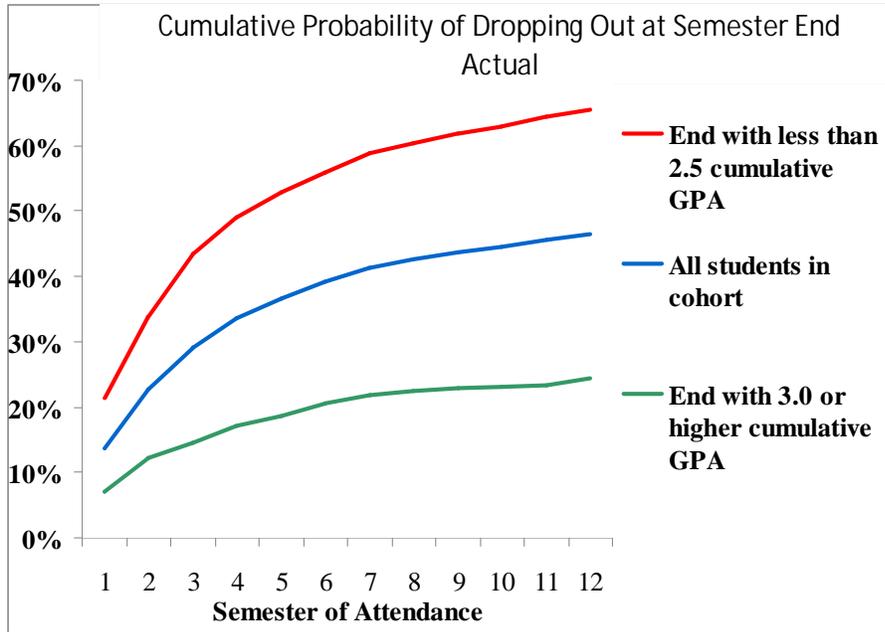


Figure 7

Figure 8 looks at the same cohort, but examines the correlation of a single semester's GPA against eventual probabilities of graduating. Over the first four years, with each passing semester, a high semester GPA becomes more and more predictive of graduation. Also in the first three years, a low GPA in a single semester is very predictive of not graduating. After four years, there are fewer students (those who have not graduated, dropped out completely or transferred) in the cohort and the probabilities are more unstable.

The correlation between hours spent studying and the probability of graduating is still not directly accounted for, but the connection between good grades and graduation is strong. Grades are, therefore, utilized as a proxy, albeit an imperfect proxy, for time spent studying. Figure 9 has a different set of break points to show a more extreme view of the relationship between semester grades and the probability of graduating. Both Figures 8 and 9 show the interaction of persistence, which we model as a gain in investment, and GPA on graduation probability. Nevertheless, Figure 9 demonstrates that even persistence does not improve graduation chances for the lowest GPA students.

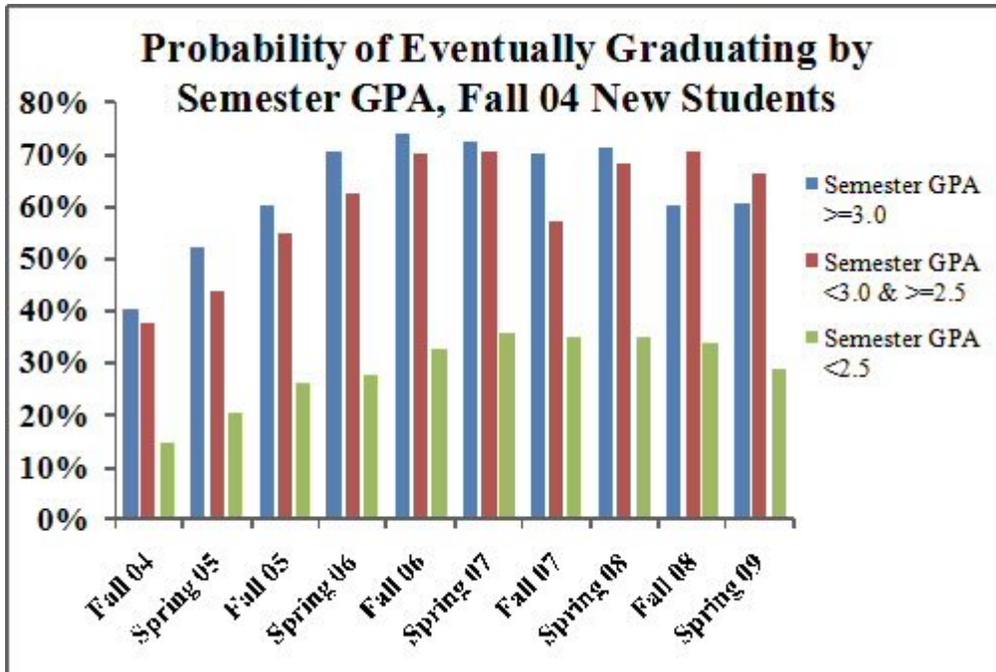


Figure 8

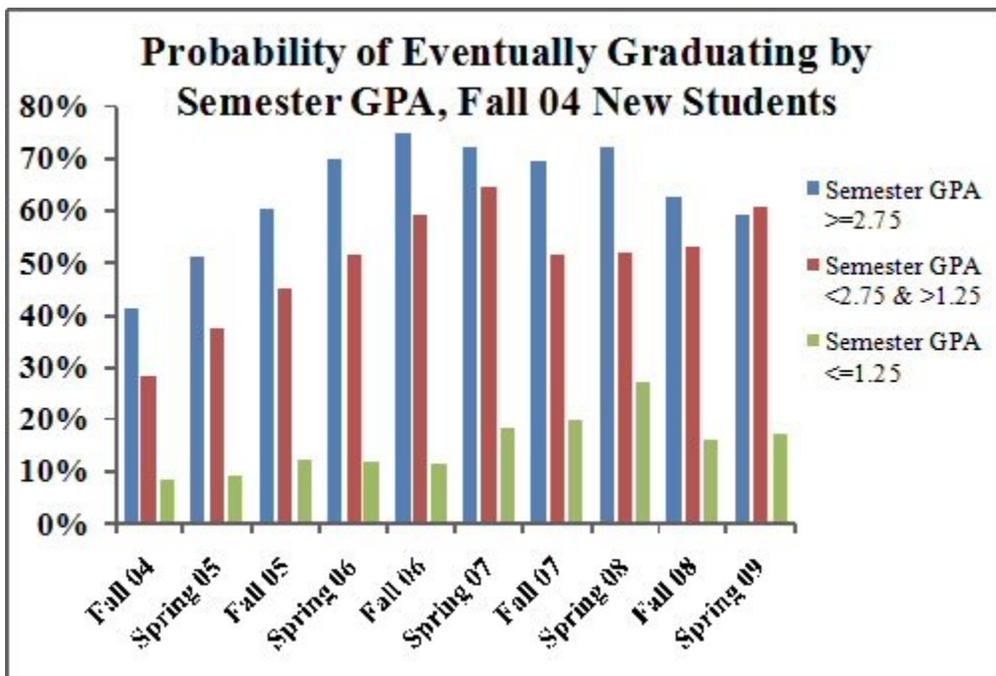


Figure 9

### Law of Time

Law: There are only 168 hours in a week. And, in those 168 hours a person has to accomplish a certain number of tasks or activities, whether mandatory, required or optional.

Mandatory tasks are necessary for life to continue at least to modern standards and include: procuring food and eating, sleeping, maintaining a domicile and procuring money (through all possible means).

Required tasks are those tasks which a person is required to do according to social standards, but are in essence not mandatory. These include self-care (e.g., bathing), taking care of family and children, washing and cleaning, commuting to work or school, attending classes, and accomplishing administrative tasks (e.g., paying bills).

Optional tasks include activities related to enjoyment and self-improvement, like spending time with friends and family, exercising, shopping and consuming entertainment media.

In some instances required tasks overlap with optional activities particularly in the realm of schooling or training. For instance, some students must attend college so that they qualify for financial aid, which they need to support themselves. However, an optional activity can also turn into a required task, but by definition a required task cannot become an optional activity. How students parcel out these 168 hours among mandatory, required or optional tasks and activities is operationalized in our model.

## The Model

The model is thus based on the most likely postulates: 1) Stressful life events happen to everyone at about the same rate; 2) A low level of preparation makes it harder to stay in college and graduate; 3) Students who experience an intervention are more likely to graduate; and 4) The more a student studies, the more likely it is that the student will graduate. To this the law of time is added: there are 168 hours in a week which are spoken for in various ways.

A series of equations model these relationships. Parameters (calibration and standard) are then set to control the equations to align results with known outcomes. These outcomes were primarily those shown in figure 5, survival rates under various conditions (or the inverse: the cumulative probability of dropping out, which is one minus the survival rate).

## Model Modalities

The model runs in two modalities "typical" and "individual." In the typical mode, developmental needs and high school GPA (starting conditions) plus time allocations for taking courses, studying, working and other activities are input. Results are returned as probabilities of dropping out, transferring early, and graduating for each semester. The probabilities represent the proportion of a group of students, with those starting conditions and making those choices, who our model predict will drop out, transfer early or graduate.

In individual mode, meant as the game-like adaptation of the model to be used "in the field", the same input is used to generate individual outcomes, using random numbers to predict the outcome of various probable events, like a stressful life event or passing a course. A single pushbutton is used to re-generate random numbers and outcomes for any number of

individuals. For example, although a set of inputs may result in probable graduation by the sixth semester in the typical modality, in the individual version an individual might graduate in the seventh semester (or drop out in the second semester, etc.) because of the “roll of the dice” on life events and grades.

Table 1 presents the calibration and standard parameters and where applicable the comparative values used to match each of the two colleges’ data.

#### Probability of a Life Event

In the model this parameter is called BadFac. The constant percentage that gave the best fit was 21% at College A and 17% at College B. In other words, each student, every semester had a 21% and 17% chance, respectively, of suffering a life event great enough to knock the student out of school, if no other factors intervened. The slightly lower BadFac for College B may in part be due to the protective features of the higher average socioeconomic status of that college’s student population.

#### Application of the Protection Probability

In the model a factor was applied to BadFac that effectively decreased the probability that the life event would knock the student out of school. The formula used was:

The probability of dropping out any semester =  $(1 - \text{ProProb}) \times \text{BadFac}$

With any set of parameters, the model calculates the minimum and maximum number of protection points that a student might accumulate. The minimum number is one protection point (Minprot), while the maximum (Maxprot) ranged between two and four thousand.

In pursuit of a curve that mimicked the data shown in Figure 7, we sought a simple equation that would transform protection points into our protection probability. We settled on a fractional exponential using the one-fourth root as best approximating the curve. This limited the number of arbitrary factors, although the  $\frac{1}{4}$  exponential (Profac) has no unique behavioral basis. It is simply the simplest fraction to give a good fit.

The full formula is:

Protection probability (Proprob)=  
 $(1 - ((\text{Minprot} + (\text{Maxprot} - \text{Protection Points})) / \text{Maxprot}))^{1/4} \times \text{Profac}$

The initial section of the formula normalizes the number of protection points to be a proportion of the distance away from maximum protection. The  $\frac{1}{4}$  factor causes early protection points to be much more “protective” as far as a gain in protection from life events than points gained closer to the maximum. This allows the curves to fit better with the reality of our data.

Calibration Parameters, Selected Standard Parameters and Probability Equations Used in the Interactive Simulation Model

Name	Description/formula	College A	College B
<b>Calibration Parameters</b>			
Probability of a Life Event	BadFac	The chance that a student will suffer a life event great enough to knock them out of school net of other factors	0.21 0.17
Support activities factor	SupFac	The weight for each weekly hour engaged in support activities	0.8 20
Credit earned factor	CredFac	The weight for each credit earned in the last semester	1 8
Grades additional multiplier	GrdFac	The weight for each weekly hour of studying for each credit taken up to a maximum of three hours per credit	9 0.4
Developmental course penalty	DevFac	Protection points subtracted for each course below the maximum number of developmental courses a student can be placed into	7 35
High school grades factor	HsgrdFac	The weight per point in high school grade point to give to protection	6 35
<b>Standard Parameters</b>			
Developmental course max	MaxDev	Maximum number of developmental courses a student can be placed into	7 6
Minimum probability of passing a course	MinPass	Corresponds to not studying at all; set to pass rate of weak student group	63 61
Maximum probability of passing a course	MaxPass	Corresponds to maximum number of hours a student could spend studying (three hours per week for each credit of course load); set to pass rate of strongest achieving group	90 97
Sleep achievement factor	SleepFac	The weight for each hour of sleep lost below a six hour minimum	-1
Maximum Study	MaxStudy	Maximum number of hours that study is useful per course credit	3
Transformation of protection points into protection probability	ProFac	Used to create a curve that mimics data; has no unique behavioral basis; simply the simplest fraction to give a good fit	1/4 root
<b>Probability Equations</b>			
Probability of passing courses in a semester	PassProb	The fraction of hours spent studying out of the maximum number of hours allowed for studying (Maxstudy) applied to the distance between the minimum and maximum course passing probabilities; $\text{Minpass} + (\text{Hours of study per credit-week}/\text{Maxstudy}) * (\text{Maxpass} - \text{Minpass})$	
The probability of dropping out any semester	DropProb	A 100% ProProb level would completely protect the student from a life event, while 0% offered no mitigation at all; $(1 - \text{ProProb}) * \text{BadFac}$	
Protection Probability	ProProb	A factor applied to badfac that effectively decreases the probability that the life event would knock the student out of school; $(1 - ((\text{Minprot} + (\text{Maxprot} - \text{Protection Points})) / \text{Maxprot}))^{\text{Profac}}$	

Table 1

## Protection Points

The formula for all semesters after the first was:

Protection points =

- the previous semester's protection points
- + the number of hours studying per hour of credit hours taken (up to a maximum) x Grdfac
- + the number of credits earned in the previous semester x Credfac
- + the number of hours in support activities (up to a maximum) x Supfac
- the number of hours of sleep (below a minimum) x Sleepfac

Thus, protection from dropping out increases each semester by studying, earning credits in the previous semester and engaging in support activities. Protection decreases by sleeping less than a minimum. In general, protection points grow each semester the student is enrolled.

Studying has a double impact in that the probability of passing a course increases with studying, and thus gaining credits is also affected by the number of hours of studying. Thus, studying hits the protection points formula once directly and then again in the following semester when the number of credits gained from the previous semester enters the formula.

In the first semester initial protection points are entirely determined by the high school grade point average and the number of developmental courses required. A student who places in the lowest level of math and reading (each having two levels), for example, will need to pass out of four developmental courses before being allowed in all college-level entry courses.

The formula for determining protection points in the first semester is:

$$\begin{aligned} &= (\text{Maxdev} - \text{the number of required developmental courses}) \times \text{Devfac} \\ &+ \text{high school GPA (0.00 to 4.00)} \times \text{Hsgrdfac} \\ &+ 1 \end{aligned}$$

At College A, a student may test into a maximum of seven developmental courses (MaxDev), including placement into ESL courses. Thus, if the student needs the maximum of seven developmental courses, the student has no added protection points. For each course below the maximum, the student gains protection points equal to DevFac.

The high school grade point factor is HsgrdFac. A student coming with a high school GPA of 4.00 has additional protection points equal to four times HsgrdFac.

## Probability of Passing a Course

In a decision theoretic framework, the probability of passing a course (PassProb) times the number of credits for the course gives the average passing value. In the model when running in "typical" mode, for example, the "average student" taking 12 credits with a 75% chance of passing would gain 9 credits. Running in individual mode, however, an individual student with a 75% chance of passing would, using random numbers, pass each course on 75% of the runs:

sometimes passing and sometimes failing. In individual mode, a student only earns credits when the random number comes up favorably.

In the model the current parameter for the maximum number of hours spent studying per week per credit of course load is three (MaxStudy). The cut-off is abrupt. The gain in probability of passing a course for each increase in time spent is linear, until the maximum is reached when there is no further gain. That is, going from 8 hours of studying to 9 hours per week for a three-credit course produces some increase in the probability of passing a course. Whereas, going from 9 to 10 hours does not.

Also, using data on average pass course rates for low and high GPA students, the minimum probability of passing a course was set to 63% (MinPass) for zero studying and the maximum to 90% (MaxPass) for College A. For College B, these were 61% and 97%, respectively.

### Lifetime Earnings

By adding a calculation of lifetime earnings based on outcomes to the model, the game produces a concrete focal point for students. Lifetime earnings are determined by educational attainment and the probable number of years at each attainment level. Hourly wages while enrolled in college are also added into the lifetime total. Inflation was assumed to equal salary growth. Thus, future earnings were not discounted. The average student age was assumed to allow 43 years of earnings from entry into college.

Average yearly income by educational attainment was taken from U.S. Census Bureau data (2009). Annual income for "some college" is \$46,168, for associate's degree is \$48,534 and for bachelor's degree was \$71,044.

Based on a study of the graduation rates of out-transfer students at College A (Zhu & Gau, 2009), 55% of graduates transfer to another college and 54% of these post-associate's degree transfers earn a baccalaureate degree. On the other hand, 48% of students who transfer before receiving their degree from College A earned a baccalaureate.

These parameters interact with the probabilities of graduation, dropping out and transfer to determine lifetime earnings. The higher the probability of dropping out, the lower will be the probability of earning a degree, as well as a higher degree. This lowers the probable number of years of earning at a higher rate. If a student is able to work more hours without lowering time for studying or seeking advice, then lifetime earnings goes up slightly.

## Model Calibration

The model was calibrated against the drop-out probabilities shown in Figure 7.<sup>3</sup> The goal of the calibration was to duplicate the probabilities for all three groups in Figure 7 using the same set of parameters for all three achievement groups. The parameters also had to produce a probable graduation point in eight semesters, including one semester of stop-out and one change of major in the second semester for the average student. Average students took credit loads similar to average College A students: six three-credit courses in the first two semesters, then a stop-out semester, then two more six-course semesters, followed by a five-course semester, and then continuing with three-course semesters to graduation. The average student needs two developmental courses and has a high school GPA of 2.50. The student does not work during the first two semesters, but begins full-time work during the stop-out semester, drops to 30 hours one semester after returning to school, but then goes back to full-time for the rest of his academic career. This student has time to study one hour per week for each course credit during the first two semesters, but does not study outside of class after that. The student begins with one hour in the first semester, and then increases to in two hours per week of participation in support activities until graduation.

The strong students' simulation was set to match the characteristics of students who left College A with a GPA 3.0 or higher. These students graduated after four semesters, do not change majors, do not stop out and do not work. Strong students have no developmental course needs and have a 3.75 GPA in high school. Simulated strong students take five courses each semester until graduation. They also study the maximum number of hours. Simulated strong students participate in developmental activities at the maximum ten hours per week.

The weak student simulation was set to match the characteristics of students who left college with a GPA below 2.50. These students entered with maximum developmental course requirements and the lowest possible high school GPA. These students worked 30 hours per week in the first two semesters and 40 hours in all following semesters. These students took a low course load and stopped out several times in the following course taking pattern over the twelve semesters: 3, 2, 0, 3, 2, 0, 2, 2, 0, 2, 2, 2. These students did not study outside of class, changed major in the fifth semester, and participated in two hours per week of developmental activities in the first semester, one in the second semester and none in the following semesters. These students, even if they did not drop out or transfer early, did not earn enough credits to graduate in twelve semesters.

Because our data indicated that even students who had earned 45 or more credits had a higher than 10% probability of dropping out, we felt that the rate of a strong negative life event had to be between 15% and 20% per semester.

During final calibration the probability of a bad life event affected the height of the curves, the factors for the initial semester (Devfac and Hsgrdfac) affected the starting point of the curves,

---

<sup>3</sup> Figures presented here are from College A. Appropriate adjustments were made to those for College B according to descriptive statistics collected from that college and are presented in Table 1.

and the exponential in the protection probability equation (Profac) affected the shape of the curves. The factors involved in setting protection points (Supfac, Credfac, Grdfac, and Sleepfac) helped differentiate the three cases, but made only minor differences in the shape of the curves, and, because of the complexity of the grade relationships, sometimes had a counter-intuitive effect on drop-out probabilities.

The match between the actual probabilities and those generated by the model for College A are shown in Figure 10 and those for College B in Figure 11. The model does quite well in matching the drop-out probabilities for all but the better students in their initial semesters. The sum of the squares of the differences of the decimal probabilities between the actual data for the 2004 cohort and the model predictions for all three lines has been under .02 for both colleges. The flaw in the model for the higher GPA students seems to be that differences in high school GPA and number of developmental courses required between high GPA students and the average student are too small to predict the initial actual low probability of dropping out of high GPA students.

This is clearly a flaw in data, rather than a model flaw. Until students actually begin to accumulate credits and college grades, we have little to go on that can help us predict the low probability of dropping out of students who go on to earn high GPAs.

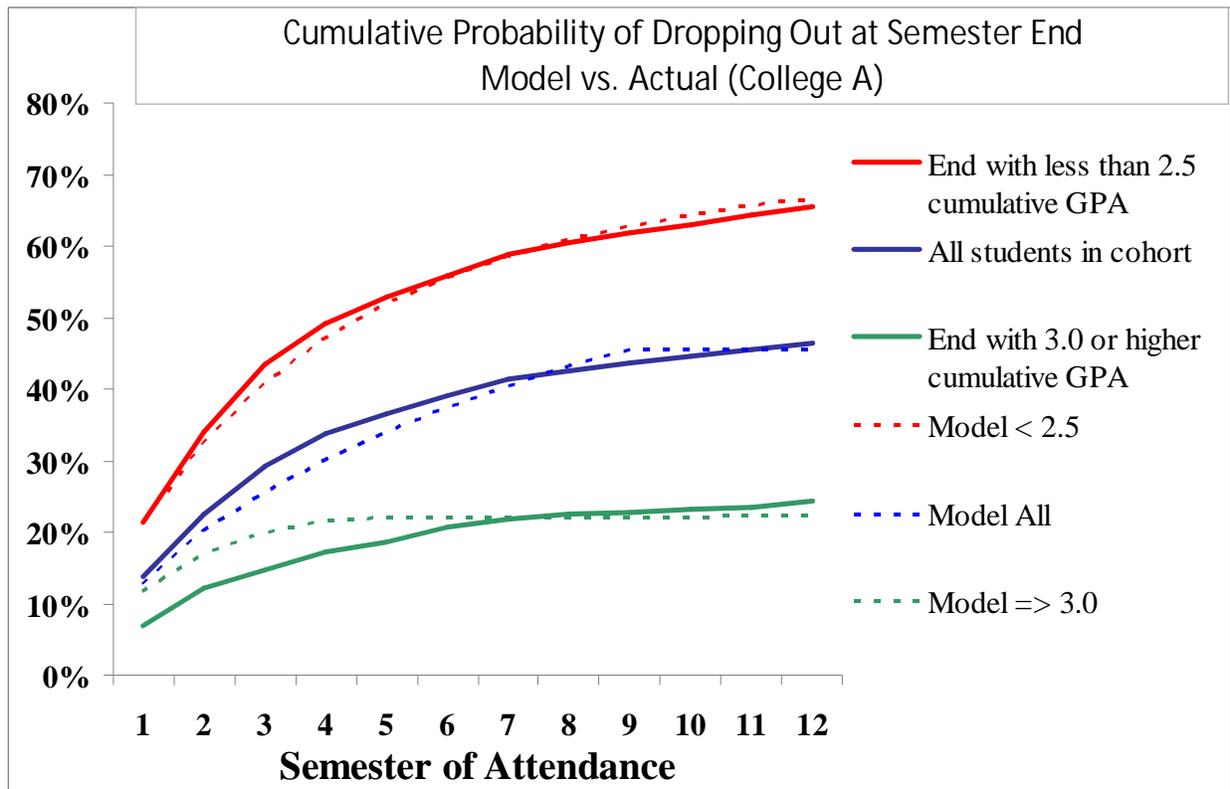


Figure 10

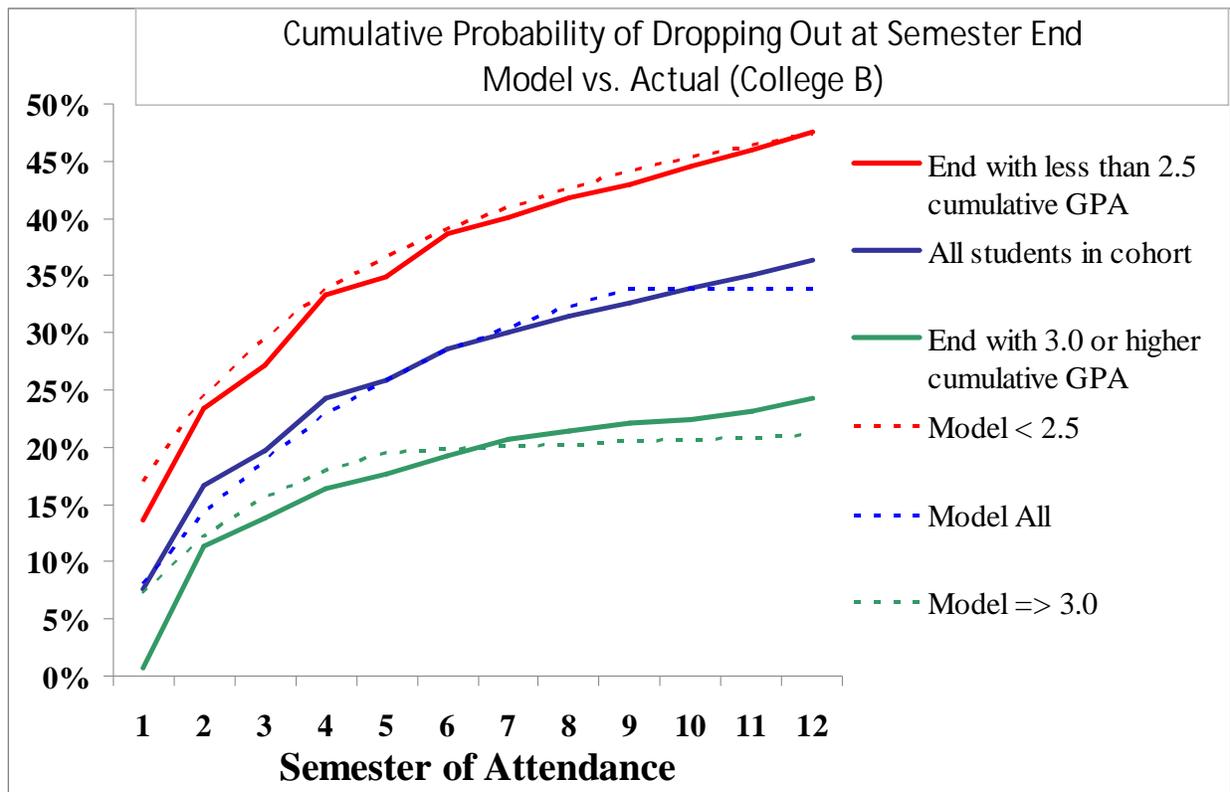


Figure 11

### Discussion

While we have come close to matching the actual drop-out behaviors of separate cohorts of associate degree cohorts at two different colleges with the model, we have not exactly matched. It seems that an exact match would require more information to differentiate high performance students from average students in their first semester.

The next step in this work will be to test whether “playing” with the model will help students make better decisions about allocating their time and, thus, help them stay in school. We are currently in the planning stages for a unit to be piloted among students in academic assistance programs.

## References

- Attewell, P., Lavin, D., Domina, & Levey, T. (2006). New evidence on college remediation. *The Journal of Higher Education*, 77(5), 886-924.
- Behr, P. R. (2008). Does mathematics remediation work?: A comparative analysis of academic attainment among community college students. *Research in Higher Education*, 49(5), 420-450.
- Dickmeyer, N. (1983) Measuring the Effects of a University Planning Decision Aid. *Management Science* 29(6), 673-685.
- Levy, M.A. , Jones V., McGowan L. & Polnariev B.A. (2011) "Purposeful Student Leadership: A Goals Clarification Activity." Program ID-255. NASPA, March [Philadelphia, PA].
- Michalowski, S. (in submission). Critical Junctures in Community College Student Progress.
- U.S. Census Bureau, Current Population Survey. (2009) "Educational Attainment--People 25 Years Old and Over, by Total Money Earnings in 2009, Work Experience in 2009, Age, Race, Hispanic Origin, and Sex." Retrieved from the web at:  
[http://www.census.gov/hhes/www/cpstables/032010/perinc/new03\\_000.htm](http://www.census.gov/hhes/www/cpstables/032010/perinc/new03_000.htm).
- Zhu, J. & Gau, J. (2009) "Differences in Baccalaureate Achievement: Early Transfers and Graduates." Internal LaGuardia Community College document.