The Date of Course Enrollment as a Predictor of Success and Persistence

By

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ABSTRACT

A recurring issue among community colleges is the perceived high rate of attrition of their students. Summers (2000) conducted a study at a Midwest comprehensive community college to examine the relationship between student enrollment behaviors and various outcomes. He found that students who persisted enrolled earlier than those who did not. He also found that for each additional course dropped the likelihood of enrolling the following spring decreased by 50%. Based in part on this study some community colleges have begun to limit full matriculation after a given date at the beginning of the fall semester allowing late-start students to enroll part-time in "late-start" classes. The purpose of this study is the replicate Summer's findings using a similar cohort but at a different community college and then to apply the same techniques, if possible, to "late start" classes. Phase One of this study had similar findings to that reported by Summer. However, significant problems were encountered when similar techniques were applied to "late-start" classes. A brief review of relevant literature is included along with recommendations for further research.

INTRODUCTION

Almost from their inception community colleges have been faced with the problem of how to help their students meet a variety of educational goals and objectives (Cohen & Brawer, 2002; Rouche & Rouche, 1994; Tinto, 1987, 1993). A recurring issue has been a perceived high attrition rate among community college students. Summers (2003, spring) argues that “A more in-depth understanding of the process and those participating in it is necessary to develop initiatives that can reduce further student attrition (64).”

A midwestern community college which shall be called Other College for the purpose of this study is not immune to the problem of student attrition. According to data provided by the Office of Institutional Research and Evaluation (OIRE, 2005a), only 64% of the students who were enrolled as full-time students in Fall 2003 were enrolled at the College in Fall 2004. In other words, approximately one in three of students who enroll as full-time, degree-seeking students are still enrolled at the College one year later. Among all credit-seeking students the return rate is even smaller. Fewer than half of the credit-seeking students who enrolled in Spring 2004 returned to take classes in Fall 2004 (OIRE, 2005b).

The purpose of this research is to explore some of the factors that might contribute to the attrition of students. Specifically, this study will explore the role of late registration for courses and the impact of that late registration on the successful completion of those courses.

SELECTED REVIEW OF THE LITERATURE

Research has been conducted for nearly a half century on community college attrition rates. Early research by Clark (1960a) found that more than 40% of community college freshmen either did not complete their educational objectives or did not return for their second year. In another study Clark alluded to structural factors for this attrition using street slang to describe how community colleges “conned” students into accepting high drop-out/flunk-out rates for the benefit of all higher education.

Various theoretical models have been developed to identify and analyze some of the variables that might have an impact on students’ decisions to either remain in college or to drop out. Tinto (1975) developed a model for student attrition that Summers (2003, spring) argues “continues to be the most widely recognized and tested model (67).” In summary, Tinto believed that students had a tendency to stay in college depending upon how fully integrated they were into the social and academic life of a college.

Bean and Metzner (1985) built on Tinto’s model of student attrition by considering how the nontraditional student might differ from those considered in earlier models. They argued that a student’s decision to drop out was based on academic performance as measured by grade point average, an intent to leave, various background variables such as high school performance and educational goals, as well as other environmental variables.

There has been extensive research on various characteristics of community college students and how these relate to attrition. A commonly described variable is age (Lanni, 1997; Mohammadi, 1994), gender (Mohammadi, 1994), ethnicity (Zhao, 1999), and socio-economic status (Adelman, 1999). Another variable that has been studied includes full- and part-time work (Lanni, 1997). Academic factors have long been studied as a predictor of student attrition. In general, students who were unprepared for community college coursework were less likely to persist. Adelman (1999) suggests that such students have fewer “tools in their toolbox”.

Less well studied variables include issues around registration and schedule changes (Belcher and Patterson, 1990; Deikoff ,1992; Peterson, 1986; Street, Smith, and Olivarez, 2001; Summers, 2000, 2003). Some of these variables will serve as the basis for this research.

Peterson (1986) focused on GPA and attrition rates among late registrants at Honolulu Community College. Her analysis indicated that the completion rate among late registrants was unusually high (214 courses attempted with 152 completed). Peterson concluded that late registrants dropped one or two courses but did not drop entirely out of college. She also found that success rates rose when students enrolled in vocational courses as compared to liberal arts courses.

Diekhoff (1992) examined late registrants in his Introduction to Psychology course at a four-year liberal arts university. His study also examined the impact of a restrictive attendance policy. In general, Deikhoff found there was no significant differences between late and timely registrants with respect to scores on course exams. He did find that late registrants were more than twice as likely to drop (or have been dropped) compared with timely registrants in a course with a more restrictive attendance policy.

Belcher and Patterson (1990) examined students attending Miami-Dade Community College to determine who enrolled late and what were their characteristics. According to Summer's summary (2003) of this study the characteristics included (a) not pursing a degree; (b) status as former students; (c) more likely to be part-time, males, Black, non-Hispanics, and older than recent high school graduates.

Street, Smith, and Olivarez (2001) examined new and returning community college students to determine whether students who returned late were less likely to persist. They found that 80% of those who registered during the regular period persisted to the next semester as compared with only 35% of those who registered late.

Summers (2000) conducted a comprehensive study of community college student attrition at a college that is generally accepted as being a cohort to Other College. The purpose of his research was to examine the relationship between community college student enrollment behaviors and various outcomes. His findings included that students who persisted averaged initial enrollment for fall semester classes nearly 29 days earlier than these students who dropped out. He used a logistic regression model to predict student attrition from enrollment and registration behaviors while holding other student characteristics constant. Major findings included the fact that for each additional course dropped, the likelihood of enrolling the following spring decreased by over 50%. On the other side of the equation, the odds of enrolling for the spring semester increased by 1.3% for each additional day earlier the student initially enrolled for the fall semester.

It would appear that Summers (2000) restricted his study primarily to full-time students as well as enrollment in college. At Other College a significant percentage of classes are taken by part-time students. There have also been internal questions raised about actual enrollments in classes rather than initial enrollment in the college although obviously anyone who enrolls late for college will also enroll late for individual classes.

RESEARCH QUESTIONS

The specific research questions are identified for two phases of this study. Phase One involves a replication of the study done by Summers (2000) including a number of the hypotheses he put forward. Phase Two of the study will employ research methodology similar to that used by Summers but restricted to courses specifically identified as late-start courses at Other College. The basic research questions for Phase One are:

- What are the relationships between student characteristic data (age, gender, ethnicity, and financial aid) and academic success as defined by term grade point average (GPA).

Specifically:

- ➢ Are there differences in when a student enrolls based on identified student characteristics?
- ➢ Are there differences in the number of courses dropped based on identified student characteristics?
- ➢ Are there differences in fall Grade Point Average (GPA) based on identified student characteristics?
- ➢ Are there differences in the number of courses dropped based on identified student characteristics?
- ➢ Are there differences in the ratio of courses completed against courses attempted based on identified student characteristics?

- What are the relationships between enrollment patterns of behavior (date of enrollment, number of courses dropped, ratio of courses completed) and academic success and persistence as measured by re-enrollment the following semester. Specifically:

- ➢ Are there differences in persistence/attrition based on identified student characteristics?
- ➢ Is there a relationship between GPA and persistence/attrition?
- ➢ Can persistence/attrition be predicted using enrollment behavior patterns while holding student characteristics constant?

The basic research questions for Phase Two of the study are:

- If the unit of analysis is changed from the student to the individual courses taken, can the same methodologies be used and will the findings be similar to those from Phase One?

- If the findings cannot be replicated from Phase One what factors seem to be effecting the outcomes and what modifications need to be made to better understand the effects of enrollment behavior patterns on academic success and persistence?

METHODOLOGY

This study will consist of an ex post facto analysis of enrollment patterns and grades for students enrolled for credit in courses in Fall 2004 (term 043). The data sets used are from the Office of Institutional Research at Other College. Analysis on those data will be performed using SPSS for Windows, ver.13.0. Each semester OIRE records two major data sets. One data set referred to as the “course data set” records each course taken by each student. A second data set referred to as the “student data set” records demographic information for each student enrolled that semester. A variable in the course data set records the date when the student enrolled in the course.

Phase One:

In Phase One an attempt will be made to replicate the study done by Summers (2000) which will include, where appropriate, independent t-tests, multiple regression analysis, and logistic regression analysis. The population used by Summers was first-time, full-time degree-seeking students enrolled in the fall semester 1995. Summers further restricted his dataset to students who were either Black or White. This study will examine students enrolled for the first-time in higher education and first-time at Other College in Fall 2004 (but will not include students who may be new to Other College but not new to Higher Ed.), full-time (defined as attempting 12 or more credit hours), and degree-seeking (specifically eliminating students who self-identified as taking courses for Personal Interest/Course Enrollee). A more specific description of each population may be found elsewhere in this study.

Phase Two:

In Phase Two an attempt will be made to apply research methodologies similar to that of Phase One except that they will be applied at the course level. One of the implications of Summers' (2000) research was that some colleges have either implemented or considered implementing policies that would restrict full matriculation for students who attempt to enroll "late". However, in order to serve these students they are often allowed to enroll as course enrollees in courses that have been specifically identified as "late-start" courses. This phase of the study will restrict its examination to those students enrolled in those courses specifically identified in the course catalog as "late-start". A more specific description of the population in this phase may be found elsewhere in this study.

DEFINITIONS

Academic Semester

Other College has three “academic semesters” during an academic year. Fall semester runs from mid-August until mid-December. Spring semester runs from mid-January until mid-May. Summer semester has three sub-sets which run during mid-May to mid-August. Summer semester data will not be used for this study. Each semester is coded in the data set by the last two digits of the academic year followed by the month in the academic year in which that semester nominally begins. The academic year runs from July until June. The summer term for academic year 2004-2005 would thus be coded 051. The fall term for that same year would be coded 053, and the spring term 056.

Late Start

Initial analysis of the results revealed that certain courses designed at “Late Start” courses tended to obscure the meaning of the results. These courses were designed to start later in the semester than the typical course; in some cases by several weeks and in other cases by several months. Courses designated as “Late Start” were eliminated from this phase of the analysis.

Success

Only grades of “A”, “AH”, “B”, “C”, “D”, “F” and “W” will be considered. Success will be arbitrarily defined as an earned grade of “A”, “AH”, “B” or “C”. In some programs an earned grade of “C” will not allow the student to advance to the next level while in other programs an earned grade of “D” will allow the student to continue on. In no programs do grades of “F” or “W” allow the student to continue to the next highest level course.

Persistent

Persistence will refer to a student enrolled in the fall semester 2004 who continued to be enrolled in the Spring semester 2005.

Other Restrictions

Only courses that were offered for credit were used for this study. Initial analysis indicated that students enrolled in certain courses tended to obscure the results. Courses clearly designated for non-college ready students (“GED” prefix) were eliminated from the study as were courses designed for students taking English as a Second Language (“ESL” prefix). Course enrollment patterns for students enrolled in online courses also created difficulties with understanding the results and thus they were eliminated.

PHASE ONE:

FINDINGS AND DISCUSSION

Table 1 describes the population for both Summers (2000) study and this study.

Table 1.

Student Characteristics

	Fall Cohorts:			
Characteristics	Summers n	(%)	**Author n**	**(%)**
Age				
Traditional	1,194	(87.5)	**795**	**(91.7)**
Non-Traditional	171	(12.5)	**72**	**(8.3)**
Gender				
Female	777	(56.8)	**401**	**(46.3**)
Male	588	(43.2)	**466**	**(53.7)**
Ethnicity				
Black	108	(8.8)	**175**	**(20.2)**
White	1,114	(91.2)	**692**	**(79.8)**
Financial Aid				
No	788	(57.7)	**289**	**(33.3)**
Yes	577	(42.3)	**578**	**(66.7)**

The data set used by Author was limited to students who were enrolled in the fall semester term (053) for the first-time at Other College and first-time in higher education, full-time (12 or more credit hours), considered only students who had self-identified as either black, non-Hispanic or white, non-Hispanic, degree-seeking (program code not equal to 'Y PICE' which is used to indicate a course enrollee), and who had received some form of financial aid or not. It is possible that the financial aid data recorded dichotomously as either Yes or No, might or might not accurately reflect financial need. The data set records all scholarships including athletic scholarships as a Yes. It should also be noted that Summers' cohort was from academic year 1996-97 while Author's cohort was from academic year 2004-05.

Summers used an enrollment flag called Intent to determine if the students were enrolled in Occupational or transfer programs. The data set used by Author had a similar flag, however, previous experience with this flag in this data set has demonstrated that it may not be a reliable indicator of true intent, and thus was not reported on in this phase of the study. A more accurate method for determining occupation program intent is by actual courses enrolled. This cohort will be reported in another section of this study.

The cohort used by Author was similar to that used by Summers only smaller. Because Other College traditional has a larger enrollment than the college used by Summers it is possible that Summers did not restrict first-time, full-time, degree-seeking in the same way. The cohort used by Author had a much larger portion of students self-identified as Black, non-Hispanic as well as a larger portion identified as having received financial aid.

The first research question examined if there was a relationship between student characteristics and what Summers (2000, p. 80) refers to as "registration behaviors." Summers used data based on the mean number of days prior to the beginning of the semester that students enrolled for courses. Because the data used by Author was based on the date of the last enrollment for a given course rather than the date of actual enrollment the first time in a course dates might differ. Therefore, Author used data based on the mean of the mean number of days enrolled prior to the start of classes. Independent samples t- tests were conducted on the variables. Where Levene's Test ($p<.05$) indicated unequal variance an adjusted t-value was reported.

Table 2 reports the findings of this question with Summers' findings reported above those of Author's whose findings are noted in **bold** print.

Table 2.

When Students Enroll

Group		n	M	SD	t
Age					
	Traditional	1,194	96.99	48.54	8.250***
		795	**44.40**	**35.1**	**3.44*** **
	Non-traditional	171	64.27	48.24	
		72	**29.55**	**35.6**	
Gender					
	Female	777	96.40	47.63	2.966***[A]
		401	**43.28**	**34.03**	**0.084**
	Male	588	88.27	51.59	
		466	**43.08**	**36.47**	
Ethnicity					
	Black	108	63.95	49.62	-5.676***
		175	**21.04**	**32.12**	**-9.764*** **
	White	1,114	92.30	48.87	
		692	**48.77**	**33.92**	
Financial Aid					
	No	788	101.25	46.64	7.294***[A]
		289	**47.50**	**33.97**	**2.062** **
	Yes	557	81.48	51.45	
		578	**41.01**	**35.84**	

Note 1. [A] An adjusted t value is reported based on unequal variances of the subgroups.
Note 2. Author values recorded in **bold** below Summers findings.
**p <.01; ***p <.001.

Summers found that students who were of traditional age initially enrolled on average more than 32 days earlier than students of non-traditional age (p. 82). Author found that on average this cohort enrolled much later (almost two month's difference from that reported by Summers), and that the difference between traditional and non-traditional dates of enrollment was only slightly more than two weeks (14.85 days), and although the t-test was smaller it was still significant at the level reported by Summers. Summers reported a significant difference in date of enrollment between females and males. Author found no significant difference based on gender. Summers found that White students enrolled on average nearly 32 days earlier than

Black students. Author found a slightly smaller difference (27.7 days) but the t test was larger and still significant at the level reported by Summers. Summers found that students not eligible for financial aid enrolled nearly 20 days earlier than those eligible. Author found a much smaller difference (about 6.5 days) and the difference was less significant; however, the tendency was similar.

The second question examines the number of times that the students dropped (or withdrew) from courses in their fall schedule. Summers was able to track all schedule changes. Author was only able to track behavior in those courses in which the student was enrolled at the official census date of the college (10th day). This data set misses a significant number of schedule changes such as drops and re-enrollments made prior to the official census date. In the data set used by Author, drops prior to census date were not recorded. Only courses from which the student was enrolled on census date and then withdrawn (W grade) were considered. Hence only those somewhat similar results will be reported.

Table 3 reports the number of drops (Summers, 2000, p.89) or withdrawals (Author). Where the data had unequal variances based on Levene's Test ($p<.05$), an adjusted t-value was reported. Summers reported no significant difference in the number of drops between traditional and non-traditional students. Author found a small difference (0.32 drops) significant at $p<.05$. Summers found that Blacks had a significantly greater number of drops (.57 drops, $p<.05$) when compared with Whites. Author found a slightly smaller number of drops for Blacks (.52) but at a greater level of significance ($p<.001$). Summers found no significant difference based on eligibility for financial aid. Author found a small difference (.22, $p<.05$). Both Summers and Author found no significant difference based on gender.

Table 3.

Number of Course Drops (or Ws)

Group		n	M	SD	t
Age					
	Traditional	1,194	1.66	1.79	-0.142
		795	**0.75**	**1.25**	**-2.048***
	Non-traditional	171	1.68	1.91	
		72	**1.07**	**1.44**	
Gender					
	Female	777	1.60	1.74	-1.514[A]
		401	**0.75**	**1.23**	**-0.067**
	Male	588	1.75	1.88	
		466	**0.80**	**1.31**	
Ethnicity					
	Black	108	2.07	1.75	2.593*
		175	**1.21**	**1.44**	**5.075*****
	White	1,114	1.50	1.81	
		692	**0.67**	**1.20**	
Financial Aid					
	No	788	1.60	1.78	-1.482
		289	**0.63**	**1.17**	**-2.407***
	Yes	577	1.75	1.83	
		578	**0.85**	**1.31**	

Note 1: [A] An adjusted t value is reported based on unequal variances of the subgroups.

Note 2: Author's findings are reported below Summers and are shown in **bold** print.

*p<.05; ***p<.001.

Findings Related to Academic Outcomes

Descriptive information relating to fall grade point average (GPA), course completion (term hours earned divided by term hour attempted), and attrition (re-enrolled in spring term or did not re-enroll) are presented in the next three tables. Summers' (2000) findings were taken from pps. 96-103). Summers' dataset recorded grades on a 5.0 scale. Other College grades were reported on a 4.0 scale. While something would be lost regardless of the conversion, it seemed simpler to add one point to each Other College term GPA.

Table 4

Fall Semester Grade Point Average

Group		n	M	SD	t
Age					
	Traditional	1,194	3.13	1.37	-0.630[A]
		795	**3.37**	**1.20**	**0.611**
	Non-traditional	171	3.22	1.74	
		72	**3.26**	**1.54**	
Gender					
	Female	777	3.23	1.41	2.548*
		401	**3.51**	**1.23**	**3.304*** **
	Male	588	3.03	1.42	
		465	**3.23**	**1.23**	
Ethnicity					
	Black	108	2.41	1.52	-5.438***[A]
		175	**2.73**	**1.23**	**-7.663*** **
	White	1,114	3.24	1.38	
		692	**3.52**	**1.19**	
Financial Aid					
	No	788	3.31	1.29	4.961***[A]
		289	**3.49**	**1.12**	**2.295***
	Yes	577	2.92	1.55	
		578	**3.30**	**1.28**	

Note 1: [A] An adjusted t value was reported based on unequal variances of the subgroups.
Note 2: Author's results are reported below Summers and are in **bold** print.
*p<.05; ***p<.001

Neither Summers nor Author found significant differences in GPA between traditional and non-traditional age students. Summers found a 0.2 GPA difference between females and males ($p<.05$) while Author found a 0.28 GPA difference ($p<.001$). Summers found a 0.83 GPA difference between Black and White students while Author found a 0.79 GPA difference. Both had a significance of $p<.001$. Summers found that students who were not eligible for financial aid had a 0.39 GPA higher than those who were eligible ($p<.001$). Author found that those who did not receive financial aid had a 0.19 GPA higher than those who did ($p.<.05$).

Table 5 records differences in course completion based on student characteristics. Author calculated a course completion ratio based on semester hours earned divided by semester hours attempted. Summers found no statistically significant differences in course completion for age or gender. Summers did find that Black students completed just over one-third of their courses while White students completed almost two-thirds ($p<.001$). Summers also found a small, but statistically significant difference between students eligible for financial aid and those who were not ($p<.001$). Author found statistically significant differences in age ($p<.05$), ethnicity ($p<.001$) and whether or not the student received financial aid ($p<.001$).

Table 5.

Fall Semester Course Completion

Group	n	M	SD	t
Age				
Traditional	1,194	.623	.356	1.824[A]
	795	**.740**	**.353**	**1.997***
Non-traditional	171	.564	.398	
	72	**.638**	**.420**	
Gender				
Female	777	.628	.360	1.507
	401	**.752**	**.343**	**1.554**
Male	588	.598	.364	
	465	**.714**	**.373**	
Ethnicity				
Black	108	.357	.343	-8.132***
	175	**.568**	**.381**	**-6.909*** **
White	1,114	.646	.353	
	692	**.773**	**.342**	
Financial Aid				
No	788	.670	.335	6.555***[A]
	289	**.786**	**.334**	**3.294*** **
Yes	577	.540	.383	
	578	**.704**	**.369**	

Note 1: A An adjusted t value is reported based on unequal variances of the subgroups.
Note 2: Author's findings are reported below Summers' and are printed in **bold**.
*p<.05; ***p<.001

Table 6 reports the results of attrition (did not re-enroll in the spring semester) and persistence (did re-enroll) by number and percentage along with a chi^2 test for each sub-group. Summers found that there was a statistically significant difference based on age groups ($p<.010$) while Author found a difference that was less statistically significant ($p = .088$). Neither Summers nor Author found statistically significant differences based on gender. Summers found that a significantly larger percentage of White student persisted compared with Black ($p<.002$).

Author found a smaller chi^2 (2.032) and no statistically significant differences based on ethnicity.

Summers found a significantly larger percentage of students who were not eligible for financial aid persisted compared with those who were eligible (p = .000). Author found almost exactly opposite percentages than did Summers. Those differences were not statistically significant. Of all of the findings, this was perhaps where the greatest difference between the two studies was found.

Table 6.
Attrition by Student Characteristic

	Not Enrolled		Enrolled		Chi^2	
Group	n	%	n	%		
Traditional	227	82.8	967	88.6	6.694* *	p<.010
	(112)	**(88.2)**	**(683)**	**(92.3)**	**(2.403)***	**p=.088**
Non-traditional	47	17.2	124	11.4		
	(15)	**(11.8)**	**(57)**	**(7.7)**		
Gender						
Female	148	54.0	629	57.7	1.183	p=.277
	(55)	**(43.3)**	**(346)**	**(46.8)**	**(0.519)**	**p=.267**
Male	126	46.0	462	42.3		
	(72)	**(56.7)**	**(394)**	**(53.2)**		
Ethnicity						
Black	34	13.9	74	7.6	9.829	p<.002
	(32)	**(25.2)**	**(143)**	**(19.3)**	**(2.302)**	**p=.082**
White	210	86.1	904	92.4		
	(95)	**(74.8)**	**(597)**	**(80.7)**		
Financial Aid						
No	129	47.1	659	60.4	15.930	p=.000
	(45)	**(35.4)**	**(244)**	**(33.0)**	**(.295)**	**p=.327**
Yes	145	52.9	432	39.6		
	(82)	**(64.6)**	**(496)**	**(67.0)**		

Note 1: Author's findings are reported below Summers' and are printed in **bold**.
p scores are noted in the results.

To determine the relationship between student GPA and attrition/persistence, independent samples t-tests were conducted on these variables. Data for fall GPA had an unequal variance based on Levene's test ($p<.05$). As a result an adjusted t-value is reported. Table 7 reports the findings. Summers found a statistically significant difference ($p<.001$) in GPA between those who persisted ($M = 3.50$) and those who did not ($M = 1.71$). Author's findings were similar ($p=.000$) except that the GPA difference was even larger ($M = 3.61$ for those who did re-enroll compared with $M = 0.88$ for those who did not.). These findings would suggest that a large number of students who did not re-enroll did not successfully complete a very large percentage of their courses.

Table 7.

Fall Semester Grade Point Average

Group	n	M	SD	t
Did not enroll	184	2.54	1.32	-11.141***[A]
	127	**0.88**	**1.23**	**-14.946*** **
Did enroll	1,044	3.66	0.83	
	740	**3.61**	**1.04**	

Note 1: [A] an adjusted t-value is reported based on unequal variance of the subgroups.
Note 2: Author's findings are reported below Summers' and are printed in **bold**.
***p<.001

Table 8a
Multiple Regression Model Summary for GPA by Enrollment and Registration Behaviors (Summers, n=1,053)

Model	R	R Square	Estimate	F	df	Sig.
1[a]	.433	.188	1.35	242.98	1,1051	.000
2[b]	.593	.351	1.21	284.26	2,1050	.000
3[c]	.605	.367	1.20	202.34	3,1049	.000
4[d]	.613	.376	1.19	157.71	4,1048	.000

[a] Predictors: (Constant), DROPS
[b] Predictors: (Constant), DROPS, ADDS
[c] Predictors: (Constant), DROPS, ADDS, RLY_S_CH
[d] Predictors: (Constant), DROPS, ADDS, RLY_S_CH, DAYS_RG

Table 8b
Multiple Regression Model Summary for GPA by Enrollment and Registration Behaviors (Author, n=897)

Model	R	R Square	Estimate	F	df	Sig.
1A	.619	.383	0.97	536.98	1, 865	.000
2B	.629	.395	0.96	281.69	2, 864	.000

[a] Predictors: (Constant), DROPS
[b] Predictors: (Constant), DROPS, DAYS_RG

Summers found that his Model 4 was best able to predict fall semester GPA from enrollment and registration behaviors. According to his study 37.6% of the variation in students' fall semester GPA could be accounted for by a combination of four variables. Author used only two variables (DROPS and DAYS_RG). Author's Model Two was the better at predicting fall

GPA from enrollment and registration behaviors. A slightly higher percentage (39.5%) of the variation in fall GPA could be accounted for by a combination of two variables.

Table 9a.

Multiple Regression Analysis with GPA as the Outcome Variable (Summers n= 1.053)

Variable	B	SE B	beta	t
(Constant)	3.114	.096		32.278***
DROPS	-0.496	.025	-.587	-19.711***
ADDS	0.382	.035	.362	10.869***
RLY_S_CH	0.447	.108	.108	4.134***
DAYS_RG	0.003	.001	.099	3.931***

***p<.001

Table 9b.

Multiple Regression Analysis with GPA as the Outcome Variable (Author n= 897)

Variable	B	SE B	beta	t
Constant	3.604	.060		60.999***
DROPS	-0.576	.026	-.593	-21.804***
DAYS_RG	0.004	.001	.111	4.083***

***p<001

Summers found that for each increase of one course-drop, fall GPA would be decreased by .496 when other variables are held constant. Author's findings indicate a slightly greater impact of .576. Summers also found that when a student initially enrolled in relation to the beginning of the fall semester increased the fall GPA by .003. Author had similar findings with each day enrolled increasing Fall GPA by .004.

Before running a logistic regression model Summers looked at independent t-tests grouped by whether or not the students re-enrolled the following semester, what Summers referred to as Attrition Subgroups (0 = did not re-enroll, 1 = did re-enroll). These tests were performed on several variables including when the students enrolled and the number of course drops. Summers reported on more variables than those listed in Table 10a.

Table 10a.

Comparison of Enrollment and Registration Behaviors for Attrition Subgroups (Summers).

Behavior	Sub-group	n	M	SD	d	t
When enrolled	0	274	69.86	53.06	-.58	-8.216***[A]
	1	1,091	98.68	47.08		
# of drops	0	274	3.03	2.14	.93	12.401***~~[A]~~
	1	1,091	1.32	1.53		

Note 1: [A] An adjusted t value was reported based on unequal variances of the subgroups.
***p<.001

Table 10b.

Comparison of Enrollment and Registration Behaviors for Attrition Subgroups (Author).

Behavior	Sub-group	n	M	SD	d	t
When enrolled	0	127	93.55	35.73		-4.046***
	1	740	107.17	34.91		
# of drops	0	127	2.05	1.87		8.667***[A]
	1	740	0.56	0.99		

Note 1: [A] An adjusted t value was reported based on unequal variances of the subgroups.
***p<.001

Summers found that students who did re-enroll the following semester initially enrolled approximately 29 days earlier than those who did not based on mean data reported in the independent t-test. Author found only about a 14 day difference in that same test. Summers reported that students who did re-enroll had significantly fewer drops (1.32) than those who did not re-enroll (3.03). Author had similar findings (0.56 for those who re-enrolled compared with 2.05 for those who did not.).

A logistic regression model was used by Summers to determine the ability of enrollment and registration behaviors to predict student attrition in the spring. A forward likelihood-ratio (LR) method was used. Author employed a similar methodology for comparison. For Summers the criterion for the forward LR test inclusion of the predictor variables was based on a significance level of the chi square for a change in the -2 log-likelihood increase of <= .050 and a -2 log-likelihood decrease of >= .100.

Table 11a.

Logistic Regression Analysis with Attrition as the Outcome Variable (Summers, n=1,053)

Variable	B	SE B	Wald	df	Exp (B)
DROPS	-0.708	.056	158.949	1	0.493***
ADDS	0.472	.070	45.62	1	1.693***
DAYS_RG	0.012	.002	55.20	1	1.012***
(Constant)	1.406	.186	57.20	1	4.079***

***p<.001

Table 11b.

Logistic Regression Analysis with Attrition as the Outcome Variable (Author, n=867)

Variable	B	SE B	Wald	df	Exp (B)
DROPS	-0.711	.070	103.951	1	.491***
(Constant)	2.575	.144	318.518	1	13.136***

***p<.001

Summers found that for each course dropped the odds of enrolling the next semester decreased 50.7% (.493 is .501 less than one). Author had similar findings (odds decreased by 50.9%). Summers found that for each additional day earlier the student enrolled, the odds of enrolling in the spring increased by 1.2%. The date of enrollment did not meet the significance test in Author's findings and was not reported.

Table 12a

Logistic Regression Model Summary for Attrition by Enrollment and Registration Behaviors (Summers, n=1,053).

Step	-2 Log Likelihood	Chi-Square	df	Sig.
1[A]	1008.98	138.237	1	.000
2[B]	934.68	74.301	1	.000
3[C]	881.86	52.814	1	.000

Note Initial -2 Log Likelihood: 1147.216
[A] Variable entered on step 1: DROPS
[B] Variable entered on step 2: Days_RG
[C] Variable entered on step 3: ADDS

Table 12b

Logistic Regression Model Summary for Attrition by Enrollment and Registration Behaviors (Author, n=867).

Step	-2 Log Likelihood	Chi-Square	df	Sig.	Cox&Snell R^2	Negelkerke R^2
1	695	116.85	1	.000	.126	.223

Variable entered on step 1: DROPS.

Summers found that the best model was model 3. Author had only one model. Summers did not report a Cox & Snell R^2 or a Negelkerke R^2 .

Tables 13 a & b provides information on the comparison of the model predictions with the actual observed outcomes as indicated by the results. Both Summers' and Author's models were able to predict those students who did enroll the following semester. Neither Summers' nor Author's model was able to predict very accurately those who did not re-enroll. Although Author's model was marginally better at predicting both enrollment and overall, it was somewhat less accurate at predicting those who did not re-enroll in the spring.

Table 13a.
Classification Table for Logistic Regression Model 3 (Summers, n = 1,053)

	Predicted n		Predicted
Observed	Not Enrolled In Spring	Enrolled In Spring	Percentage Correct
Attrition			
Not enrolled = 247	111	136	44.9%
Enrolled = 806	43	763	94.7%
Overall percentage			83.0%

Table 13b.
Classification Table for Logistic Regression Model 3 (Author, n = 867)

	Predicted n		Predicted
Observed	Not Enrolled In Spring	Enrolled In Spring	Percentage Correct
Attrition			
Not enrolled = 127	42	85	33.3%
Enrolled = 740	19	721	97.4%
Overall percentage			88.0%

Table 9.
Logistic Regression Analysis for Attrition With Enrollment, Registration, and Academic Outcomes as Predictors While Holding Student Characteristics Constant

Variable	B	SE B	Wald	df	Exp (B)
Constant	-0.688	.444	2.395	1	0.503
	-.193	**.500**	**0.148**	**1**	**0.825**
SEM_GPA	0.378	.099	14.473	1	1.459***
	0.828	**.148**	**31.274**	**1**	**2.289*** **
DROPS	-0.281	.057	24.247	1	0.755***
	-0.291	**.117**	**6.219**	**1**	**0.747** **

(Summers N = 932; Author N = 341. Students who did not drop and the types of courses were not included in this analysis.)

Summers found that for each additional one-point increase in fall GPA, the odds of enrolling for the spring increased by 45.9%. Summers also found that for each additional course dropped, the odds of enrolling decreased by 24.5% (.755 is .245 less than 1). Author found that for each additional one-point increase in fall GPA, the odds of enrolling for the spring semester increased by 129%. Author also found that for each additional course dropped, the odds of enrolling decreased by 25.3%. However, further analysis indicated that the model correctly predicted returning in the spring only 90% of the time while correctly predicting non-returning about 49% of the time.

CONCLUSIONS - PHASE ONE

Even though this study utilized slightly different definitions and there was almost a ten year difference between when the student groups were sampled, it is worth noting that in many cases very similar findings were reported. In general, there does seem to be a negative effect that results from enrolling later, an effect that is exacerbated by an increasing number of course withdrawals. Had access to the full spectrum of program changes, it is likely that had this study that even more similarities might have been found. In addition, many of the differences were at similar statistically significant levels. Having noted that, it still might not be advisable to change admissions policies on limiting full matriculation of late-enrolling students.

The models developed in this study were very accurate at predicting academic success and persistence based on student characteristics and enrollment patterns of behavior. But just as it is easier to correctly identify apples and oranges than it is to correctly identify non-apples and non-oranges, so too it is difficult to predict non-success and attrition (non-persistence). Correct prediction of non-success and non-persistence routinely fell well outside the acceptable 95% confidence levels. In some cases the models predicted non-success were as low as 30% and non-persistence as low as 8%. Clearly, more research is needed here.

FINDINGS AND DISCUSSION - PHASE TWO

Phase two of this study examines student characteristics and enrollment behavior patterns in those courses specifically identified in the College's Fall Course Schedule as being "Late-Start".

The first indication that this dataset was perhaps different in important ways came with a closer examination of age range of the population. In Phase One none of the students were in the category of under 16. In Phase Two - First Pass, 121 (11.7%) were 16 and under. A second indication came with a quick examination of persistence/attrition. In Phase One the large majority

(25%- Summers, 17% - Author) of that population re-enrolled in the spring semester. In Phase Two - First Pass the majority of students did not re-enroll (57.8%). A closer examination of what courses were in the sample showed that a large number (453 of 1,133) of students were from one class, CIS 101 Introduction to Computers, being taught off-site to a special group of under traditional age students. Little internal study had been done on whether or not this special group persisted in general or if this was a special group that better fit Adelman's (2005) metaphor of visitor. In order to make more realistic comparisons with Phase One, a decision was made to arbitrarily eliminate all students 16 and under from Phase Two.

Table 10 identifies the student characteristics in the population of this sub-sample. The numbers reported in Table 10 are unduplicated headcount. Table 10 shows that the population is somewhat similar to that reported in Phase One. Of course, all ethnicities are reported in this phase instead of only Black/White. This dataset uses a duplicated headcount and is linked to specific courses that were identified as "late start" in the College's Course Timetable.

Table 10.

Student Characteristics Phase Two.

Group		N	%
Age			
	Traditional	860	83.4
	Non-Traditional	171	16.6
Gender			
	Female	406	39.4
	Male	624	60.5
	Not Reported	1	0.1
Ethnic			
	Asian/Pacific Islander	23	2.2
	Native American	6	0.6
	Black, Non-Hispanic	351	34.0
	Hispanic	90	8.7
	White, Non-Hispanic	493	47.8
	Non-Resident Alien	18	1.7
	Not Reported	50	4.8
Financial Aid			
	Yes	289	28.0
	No	742	72.0

Table 11 shows when students enrolled for late-start courses by student characteristics. Students conceivably could have enrolled from Day 1 approximately 132 days before the start of class. It does not appear that many did. Table 11 indicates the mean date of enrollment from the day classes started. Larger numbers represent earlier enrollment while negative numbers represent days after the official start date of the fall semester but which still might be before the official start date of a given class.

The results in Table 11 indicate similar findings to Phase One (Table 2) with traditional age students tending to enroll earlier than non-traditional age students. Or, put another way, non-traditional age students enrolled later. However, unlike the results in Phase One, these differences were not statistically significant.

Table 11

When Late-Start Students Enroll

Variable	n	M	SD	t
Age				
Traditional	766	-2.90	41.66	1.210
Non-traditional	186	-7.20	43.92	
Gender				
Female	425	-3.74	45.17	-0.002
Male	527	-3.74	39.54	
Ethnic				
White	514	-11.30	49.80	-6.333***
Non-White	438	5.13	30.33	
Aid				
No	634	-3.54	36.82	-0.184
Yes	318	-4.13	51.14	

*p<.05; **p<.01; ***p<.001

Table 11 shows no difference in the mean date of enrollment based on Gender. There were differences based on whether or not the student received financial aid, but these differences were not statistically significant. As in Phase One there were statistically significant differences in enrollment dates based on Ethnicity although the mean enrollment dates were less than a week apart.

Table 12 shows Course Grade by student characteristic. It should be noted that at the individual course level Other College records a quality point as well as a letter grade. However, in an attempt to make the dataset similar to that used in Phase One, a five point system was used. Consequently, an A or AH was awarded 5 points, a B four points and so forth. An F was awarded 1 point while a W was awarded 0 points. This assignment of points may under- or over-value the F grade with respect to the W grade. Nevertheless, the number system is somewhat more consistent with that used in Phase One.

Table 12

Course Grade By Student Characteristic

Group	n	M	SD	t
Age				
Traditional	766	3.269	1.922	0.033
Non-traditional	186	3.263	2.043	
Gender				
Female	425	3.04	2.002	-3.026***[A]
Male	527	3.45	1.880	
Ethnic				
White	514	3.40	1.92	2.232*
Non-White	438	3.11	1.96	
Financial Aid				
No	634	3.65	1.79	-8.613***[A]
Yes	318	2.50	2.02	

Note 1: [A] An adjusted t-value is reported based on unequal variances of the subgroups.
Note 2: Other College GPA was converted to a 5-point scale.
*p<.05, ***p<.001

Differences from Phase One began to appear. In Phase Two, unlike Phase One, traditional age students had slightly higher GPA although these differences were not significant. In Phase Two men had significantly higher GPA than women; Whites had a slightly higher GPA than Non-Whites, although those differences were not as significant as in Phase One, while students with no financial aid had significantly higher GPA in both phases.

Course completion ratios were not examined in Phase Two.

Table 13 shows the results of a Logistic Regression analysis. Student Characteristics were held constant. A Forward-Stepwise (Likelihood Ratio - LR) was used.

Table 13.

Logistic Regression Analysis for Attrition with Enrollment Date and Course Grade as Predictors While Holding Student Characteristics Constant.

Variable	B	SE B	Wald	df	Exp (B)
Constant	4.118	.502	67.170	1	61.452
Date	-.007	.002	12.641	1	0.993***
Grade	.114	.041	7.640	1	1.121**

**p<.01; ***p<.001
N = 952

Table 13 shows that for each additional one-point increase (*e.g*. one letter grade), the odds for enrolling in the spring increased by 12%. For each additional day later enrolled, the odds of re-enrolling in the spring decreased by 0.7% (0.993 is .007 less than 1). However, neither the ability to predict persistence or attrition was acceptably high as is shown in Table 14 which shows the predicted versus the observed results.

Table 14.

Predicted versus Observed Results of Re-enrollment

			Predicted		
			Survivor		percentage correct
Observed			Did Not	Did	
Step 1	survivor	Did Not	368	129	74.0
		Did	156	299	65.7
	overall percentage				70.1
Step 2	survivor	Did Not	383	114	77.1
		Did	161	294	64.6
	overall percentage				71.1

a The cut value is .500

Conclusions: Phase Two

While Phase Two produced a useful baseline with which to compare future data, the inability to predict either persistence or attrition suggest that other methodology should perhaps be explored. The large number of under-traditional age students coupled with the relatively low percentage of students who do not persist suggest that other important factors are at work. It seems reasonable to conclude that late-start classes as they are currently utilized by students may well represent specialized needs that are being met (or not) by short-term enrollments. It is also likely that a longer-time reference needs to be examined to ensure students who did not re-enroll in the spring do not re-enroll at some future date. If the students' needs are met in one semester, it is likely these students are best described using Adelmen's model (2005) identifying them as visitors although this author prefers to describe them as tourists. Should these student re-enroll at some future date they still might be tourists, but they might also be "tenants".

If these students are indeed "tourists", then it is logical to ask what it is that attracts them. The term used by Author to describe such courses is Roadside Attractions. Given the broad mission of a comprehensive community college, the term "Roadside Attraction" is not pejorative. Part of the community college's mission is to meet the emerging needs of business and industry. These needs have been known to change over time. Courses which help meet those needs do generate significant revenues for the College. Indeed, there have been numerous studies to examine such "Roadside Attractions" and how community colleges can create more of them. There is, however, a danger that "tourists" might get confused for Home Owners. The needs of the two groups are not necessarily the same. Care needs to be taken to ensure any analysis of the context for "Home Owners" has carefully filtered out the tourists.

OVERALL CONCLUSIONS AND RECOMMENDATIONS

An underlying assumption in both studies is that enrollment patterns are based on more general patterns of behavior that can be changed. Certainly gender and ethnicity cannot be easily changed. Age is a factor that will change but not likely to be of immediate benefit at an individual level. Socio-economic status for which financial aid may be a proxy can be influenced by financial aid, but it may be that earlier effects may be less malleable. In short, changing when a student enrolls may be one of the few variables over which institutions may have any control whatsoever if they wish to influence student success.

An attempt at influencing when students enroll adopted by some community colleges has been to restrict full matriculation of students who enroll after a given cut-off date. Phase One of this study, as well as the earlier study by Summers suggests that there may be merit in such restriction although the models seem to be more accurate at predicting persistence than in predicting attrition. However, faced with a potential loss of revenue if late-enrolling students are restricted, some of these colleges have adopted intentionally late-start classes. Phase Two of this study seems to suggest that among those students who opt for late-start classes, the date of enrollment does not predict either persistence or attrition.

If date of enrollment is a proxy for motivation, which seems reasonable, then more research is needed to determine its cumulative effect on students at community colleges. Both the studies done by Summers and Author initially looked at first-time, full-time students. It seems reasonable that a study that looked at continuing students would find even greater effects of early enrollment: first, because low-motivated (late-enrolling) students are less likely to persist thus adding to a "creaming effect" of the remaining students; secondly, because those students who may have initially enrolled later but were still successful may have "learned their lesson".

An initial hypothesis might suggest that returning students would enroll before new students (and would be more successful) such that the effect would accumulate, whereby students approaching graduation would be the most highly motivated and thus the ones who would be most likely to enroll the earliest. While theoretically all students might have the same access date, students on-campus might actually take advantage of early enrollment dates. It might also be speculated that students in programs in which certain times of day or certain instructors might be preferred would provide additional motivation for early enrollment. Thus courses such as second-year or even second-semester nursing clinical hours would fill up first, leaving less desirable sections to those who enroll later.

Most statistical tests used in these studies relied upon mean dates of enrollment. It is possible that with a larger set of students a broader spectrum of actual enrollment dates would be selected. If this spectrum is not normally distributed then using the mean is somewhat more problematic than using the median enrollment dates. Using the median dates might be found by using more advanced statistical tools similar to survival analysis.

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