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Relationship between High School Math Course Selection and Retention Rates at Otterbein University

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Relationship between High School Math Course Selection and Retention Rates at Otterbein University

20 March 2015

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Abstract

Binary logistic regression was used to study the relationship between high school math course selection and retention rates at Otterbein University. Graduation rates from postsecondary institutions are low in the United States and, more specifically, at Otterbein. This study is important in helping to determine what can raise retention rates, and ultimately, graduation rates. It directs focus toward high school math course selection and what should be changed before entering a post-secondary institution. Otterbein will have a better idea of what type of students to recruit and which students may be good candidates with some extra help. Recruiting is expensive, especially when the main purpose is having a higher retention rate because it leads to more funding and a more attractive appearing school to incoming students (Siekpe & Barksdale, 2013).

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HIGH SCHOOL COURSE SELECTION AND RETENTION RATES

Explaining enrollment, retention, and graduation rates has been a subject on which many researchers (Barron, Elliot, Harackiewicz, & Tauer, 2002; Boone et al., 2012; Shepler & Woosley, 2011; Talbert, 2012) have focused their attention. Although about 70% of North American high school graduates enroll in post-secondary institutions, not all of them graduate with a degree (Boone, et al., 2012). Otterbein's graduation rate is about 58.7% which is a little higher than the national average of about 49% (College Factual, 2014)[1].

There is no one solution to raise retention rates as college students vary tremendously on the individual level. Since there are also many factors that can affect retention rates, it would be impossible to have one solution to control any and all circumstances affecting post-secondary retention rates. It is important to widen the perspective and focus on factors that affect students at all universities: institution-wide level factors.

Academic and social factors are the main predictors of college success (Boone, et al., 2012; Mbuva, 2011). Academic factors include high school GPA, standardized test scores, and other factors of past academic performance (Mbuva, 2011). Academic factors are highly correlated with retention rates at post-secondary institutions (Mbuva, 2011). The top four measures used to predict student retention are all academically related: grades in college preparation courses, strength of curriculum at a student's high school, standardized test scores (ACT or SAT), and a student's GPA in high school (Radunzel & Noble, 2013). Social factors include a student's ethnicity, socioeconomic status and whether they are a first generation student; some social factors classify students as at-risk, meaning they are less likely to retain.

[1] These percentages are based on earning a degree within 150% of the expected time (three years for a two year degree and six years for a four year degree).

Paying attention to the important factors that affect whether or not a student thrives is essential to raising graduation rates from post-secondary institutions. Knowing which factors are important is a challenge by itself. Past research is helpful when determining whether certain factors are powerful and what additional factors could be studied.

Radunzel and Noble (2012) indicate that the combination of ACT composite scores and high school GPA improved prediction accuracy. According to Harackiewicz et al., the two key predictors for student success are standardized test scores and their prior academic performance (2002). These predictors have been shown to be independent of each other, meaning that prior academic performance does not cause or rely on standardized test scores, and to be positive predictors of college success (Harackiewicz, J., et al., 2002). Radunzel and Nobel (2013) indicate that including test scores increase the prediction accuracy over using high school GPA as a predictor alone. Noble (2003) indicated that there is a difference among high schools (i.e. rigor of classes, grading scale), so using a standardized test score would reflect different educational preparation and readiness of the student more accurately than HSGPA alone. It was also shown that students with higher ACT composite scores and high school grade point averages have greater college success rates than those with lower composite scores or high school GPAs (Radunzel & Noble, 2012). There is a lot of research that proves ACT composite scores and HSGPAs as valid measures of early college success (Allen, Robbins, Casillas & Oh, 2008; Harackiewicz, J. et al., 2002; Radunzel & Noble, 2012), which is why these predictors will be included in this research as independent variables.

High school GPA has a higher correlation than standardized test scores in predicting first year GPA (Sawyer, 2013). Test scores when used alone have a correlation of .35, HSGPA has a correlation of .36 and the combination of the two have a correlation of .46 (Sawyer, 2013).

Standardized test scores add incremental predictive validity when predicting first year GPA (Sawyer, 2013). Institutions have different levels of selectivity and therefore have different definitions of college success. Institutions that are highly selective define success with a higher first year GPA (3.0) and would be more likely to use standardized test scores when making predictions about incoming students (Sawyer, 2013). Students with high GPAs and high standardized test scores would be more likely to have long-term success (where long-term success is defined as graduating or retaining until degree completion). While long-term success is important to post-secondary institutions, Otterbein is not a highly selective school so would select applicants that are more likely to succeed in the short term (i.e. retain past first year) (Sawyer, 2013).

Math education in the United States is not comparable to other countries; our curricula are not as rigorous (Abraham et al., 2014). To change this, children should be encouraged in math from a young age. The way in which children are taught math should be changed in a way to help children appreciate and understand the importance of mathematics (Abraham et al., 2014). A higher standard for mathematics education in the United States would allow more opportunities for students to work in careers in STEM fields, which are typically higher paying jobs (Abraham et al., 2014).

Students that are not ready for college level mathematics are more likely to not succeed (Abraham et al., 2014). Introduction to mathematics courses are in almost all of college curricula; they are also among the highest failure rates (Daugherty et al., 2013). High failure rates among introduction courses would lead to a low first year GPA, which is a good predictor of retention (Daugherty et al., 2013). Since mathematics is an important predictor of success, it is included in this study as an independent variable.

There is also a divide in gender expectations in regards to mathematics. Although Otterbein is predominantly female, the math courses and majors are overwhelmingly dominated by male students. Women in America are an underrepresented population, especially in STEM fields (Bailey et al., 2014). Only about 20% of engineering degrees are earned by women (Bailey et al., 2014). Women tend to have lower self-efficacy in hard science fields because of this gender discrimination (Bailey et al., 2014). There may be some interaction between gender and the level of math courses when predicting retention.

Fiscally speaking, universities should also be concerned about raising retention rates. Tuition, dollar aid to students, and faculty salaries are high correlated with freshman retention (Webster & Showers, 2011). Colleges receive more outside funding if they have higher retention rates (Anstine, 2013). High attrition rates reflect poorly on universities and also lead to lost revenue (O'Keefe, 2013). Colleges look more attractive to prospective students and outside funding sources if there are high retention rates.

Enrollment officers at colleges and universities spend a lot of money and time recruiting and enticing students that are more likely to retain and eventually graduate from their respective college or university (Sawyer, 2010). It costs less to retain a current student than to recruit a new one (Webster & Showers, 2011). The two common goals for admission offices are to help enrolled students succeed academically and also to find out which applicants could potentially benefit from learning at the university and enroll as many as possible (Sawyer, 2010). To put it simply, recruiters are interested in success and accuracy. Sawyer (2010) defines academic success as retention through the first year and overall first year GPA; he also says that high school GPA is largely accurate, in fact it is more accurate than admissions test scores, when predicting freshman year GPA (2010). Enrollment officers take all of this research into account when looking at prospective students because high retention rates improve a university's ranking

(Goodstein & Szarek, 2013).

I added to this body of knowledge of factors that affect retention rates by analyzing a certain population of students at Otterbein University using logistic regression. I studied the relationship between high school math course selection and other factors (ACT composite score, high school GPA, gender, academic rank) and retention rates at Otterbein University. There has been past research that taking rigorous college prep mathematics courses is associated with high ACT composite scores (Noble & Schnelker, 2007). Since ACT composite scores are a good predictor of college success, it is logical to make connections between college prep mathematics courses and college success. Using past research to guide my hypothesis, I believe participants that have taken more math courses in high school will have a higher likelihood of retention at Otterbein University.

Method

Participants

Two-hundred-seventy-five first-time freshmen entering Otterbein between fall semester 2011 through fall semester 2013 were used in this data sample retrieved from Otterbein's admission office. These participants had an academic rank, assigned by the admissions office, of 0 or 1. Academic rank is based on the participant's college admission test scores, their high school GPA, and their high school rank percentile. The range for academic rank is from zero to five, with zero being the lowest academic rank. The sample that was used for analyses included the two lowest numbers on the range for academic rank. Students with academic ranks of 0 or 1 were explained to be at an increased risk of underperformance in academics and likely in need of remedial classes. The data included 167 male and 108 female participants. Since the population at Otterbein is mostly white, the sample was divided into 158 white and 117 non-white students (as opposed to classifying every participant by ethnicity or race), so that none of the participants would be identifiable. This analysis was performed on archival data from the admissions office, no recruiting was necessary.

Measures

Before the data was received, Otterbein's IRB approved this study and a confidentiality agreement was signed between the researcher and the admission office. The data was received on a flash drive from Debbie Crouse in Otterbein's admission office. Many variables were available to use, including race (white or non-white), sex, academic rank (0 or 1), and a list of all math courses a participant took in high school. Other factors included were the start term for each participant and whether the participant was here for first, second, and/or their third fall semester. The number of math courses taken in high school was included; this number was obtained from a simple formula in excel that counted the number of math classes listed in another column. The maximum possible number of math courses taken in high school for all participants was six.

The sample had some missing data where participants either took the SAT instead of the ACT or vice versa. A macro was written using a concordance table, obtained from the ACT website (Compare ACT and SAT Scores, 2015) to convert the scores. According to the concordance table, there is no true equivalent for the scores since the tests' material differs in content (Understanding Concordance, 2015). The concordance table is used for approximations. The table is used in this study to fill in all the blank spaces for standardized test scores for all participants; the SAT critical reading and math (SATCRM) and ACT composite (ACTC) scores could then be compared using logistic regression to see if there was a significant difference in predicting power between SATCRM and ACTC scores.

Procedure

Data was analyzed with logistic regression using Minitab 17. Logistic Regression was chosen because of the binomial characteristic of the dependent variable (students were either enrolled during their second fall semester or they were not enrolled). These particular logistic regression equations can be used to predict the odds that a student at Otterbein will be enrolled during their second fall. Odds should not to be confused with the probability of retention. Logistic regression does not output the probability of retaining a certain student, but outputs the odds of being enrolled (a case, 1) versus not being enrolled (a non-case, 0)[2]. Woosley and Shepler indicate that a significant proportion of attrition in post-secondary institutions occurs during students' first year (2011).

Several analyses were performed. The dependent variable for all analyses was whether the participant was enrolled at Otterbein for their second fall semester (0 for not enrolled, 1 for enrolled). The independent variables used were high school grade-point average, ACT Composite score, and the number of math classes a participant took during high school. P-values of 0.15 were used to test statistical significance.

The first analysis was hierarchical stepwise logistic regression using the original set of data. Hierarchical logistic regression is used when data are nested within groups or when the dependent variable may depend on both individual characteristics and group memberships (Noble & Schnelker, 2007). Hierarchical logistic regression in Minitab 17 starts with a model including only the constant and one predictor. The procedure then adds in predictors after each step to make a completed model; predictors with p-values of greater than 0.15 were not included

[2] An example may help illustrate the difference between probability and odds. The probability of getting a tail two times in a row when flipping a coin twice is .25 or 25%. The odds of getting a tail two times in a row when flipping a coin twice are 3:1 (there are four different outcomes when flipping a coin two times in a row, only ONE outcome leaves two tails in a row, so the odds are 3:1).

in the complete model. The second analysis was a comparison between ACTC and SATCRM using the data filled in with the macro. This analysis tested to see if there was a significant difference between using the ACTC or the SATCRM as a predictor for retention. The third analysis tested whether there were significant differences in models between sex (labeled as "GENDER" by the admission office). This was done by splitting the data by sex (male and female) and running two different analyses using the variables discussed above. The fourth analysis was done using hierarchical stepwise logistic regression and included sex as an independent variable. The fifth analysis done tested interactions between the predictors: ACTC, HS_GPA, GENDER, and the number of math courses a participant took in high school. There was a final analysis which tested academic rank as an independent variable to see if there was significant difference between an academic rank of zero versus an academic rank of one.

Results

The mean ACT Score was 19.34 with a standard deviation of 2.12. The mean SAT score was 923.64 with a standard deviation of 85.20. The mean HS_GPA was 2.81 with a standard deviation of .286. The mean number of math courses taken in high school was 3.82 with a standard deviation of .725 (see Table 1 for summary of descriptive statistics).

All predictors in the final step of analysis one had a p-value equal to or less than 0.15 (See Figure 1). ACTC had the lowest p-value at 0.003. MATH_YRS had a p-value 0.105. The hierarchical logistic regression did not include HS_GPA in the final step. Using ACTC as a predictor in analysis two showed that ACTC had a p-value of 0.002 with an odds ratio of 1.23 (See Figure 3). Using the SATCRM score as a predictor in analysis two showed that SATCRM had a p-value of 0.001 with an odds ratio of 1.01 (See Figure 4). Analysis three was thrown out in favor of analysis four. Analysis four used GENDER as an independent variable and was not shown to be statistically significant (See Figure 5&6). HS_GPA was also not statistically significant with a p-value of 0.250. Analysis five included interactions between the predictors (HS_GPA*MATH_YRS, HS_GPA*ACTC, ACTC*MATH_YRS, GENDER*HS_GPA, GENDER*MATH_YRS, GENDER*ACTC). No interaction terms were significant; ACTC had a p-value of 0.001, MATH_YRS had a p-value of 0.086, and GENDER had a p-value of 0.144 (See Figures 7&8).The predictor ACADEMIC_RANK had a p-value of 0.846 in analysis six (See Figures 9&10).

Discussion

While the average ACT Composite score in this study of 19.338 is less than the national average of 20.8 (Noble, 2003), it isn't statistically significant as the difference is less than one standard error (0.121). The range for HS_GPA in this sample is [2.07, 3.58]; High School GPAs of 2.00, 2.50, and 3.00 are slightly better at predicting college success than ACT Composite scores and HS GPAs of 3.25 and 3.50 are poor at predicting college success (Noble & Sawyer, 2002). While the majority (72.4%) of participants had a HS_GPA less than or equal to 3.00, HS_GPA is not seen as a statistically significant predictor. This could because of the lack of representation of predictors as the sample is all academic ranks of 0 or 1.

Analysis one had p-values of less than or equal to 0.15 for all predictors in the final step, which showed the statistical significance of the predictors for this equation. The number of math courses in high school was shown to be a predictor significantly different than zero in this stepwise analysis. The standard error coefficient for the ACTC as a predictor in analysis two was 0.0648 while the standard error coefficient for SATCRM as a predictor was 0.00162. The standard error for ACT composite scores (calculated by dividing the standard deviation by the square root of the sample size) was 0.128; the standard error for SATCRM is 5.14. The standard error coefficients for these predictors are not different by one standard error, so these predictors can be considered equivalent when used in this logistic regression analysis for retention rates. In other words, SATCRM and ACTC scores both have the same predicting power when studying this sample. The only predictors of statistical significance in analysis four were ACTC score and MATH_YRS. The other predictors were all over 0.15. GENDER was shown to be a statistically significant predictor in analysis five with a p-value of 0.147. Academic rank was not statistically significant in analysis six because the p-value of 0.846 is greater than 0.15. Since only academic ranks of 0 or 1 were included in these analyses, it should be noted that it is not possible to predict the role that academic rank would have if the full range were included.

The sample analyzed was a very specific pool of participants at Otterbein University and was not selected randomly. In skipping the randomization process, one must be careful about generalizing results to the greater population of Otterbein students. The sample does not reflect the entire population retention rate at Otterbein of about 76%. It would be beneficial to re-run these regression analyses on the entire population of Otterbein students.

These results seem to be similar to results of previous research, showing statistical significance with ACTC score. ACTC score and MATH_YRS were seen to be statistically significant predictors for academic rank 0 or 1 students at Otterbein University. It should be noted that HS_GPA was not a statistically significant predictor in any of these analyses.

It might be of value for further research to be done indicating which students have taken post-secondary level math classes that also count for college credit and comparing their retention rates look to students that only took high school math. It would also be interesting to look at either the entire population at Otterbein or a random sample of Otterbein students that would accurately reflect the population. I believe that would produce more accurate results in the regression equations that would be more applicable to future students.

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Table One

Descriptive Statistics

PREDICTOR	MEAN	ST DEV	ST. ERROR
ACT COMPOSITE	19.338	2.120	0.121
SAT SCORE	923.636	85.204	5.137
HS GPA	2.809	0.286	0.017
MATH COURSES	3.822	0.726	0.044

Table Two

ACT Composite Histogram

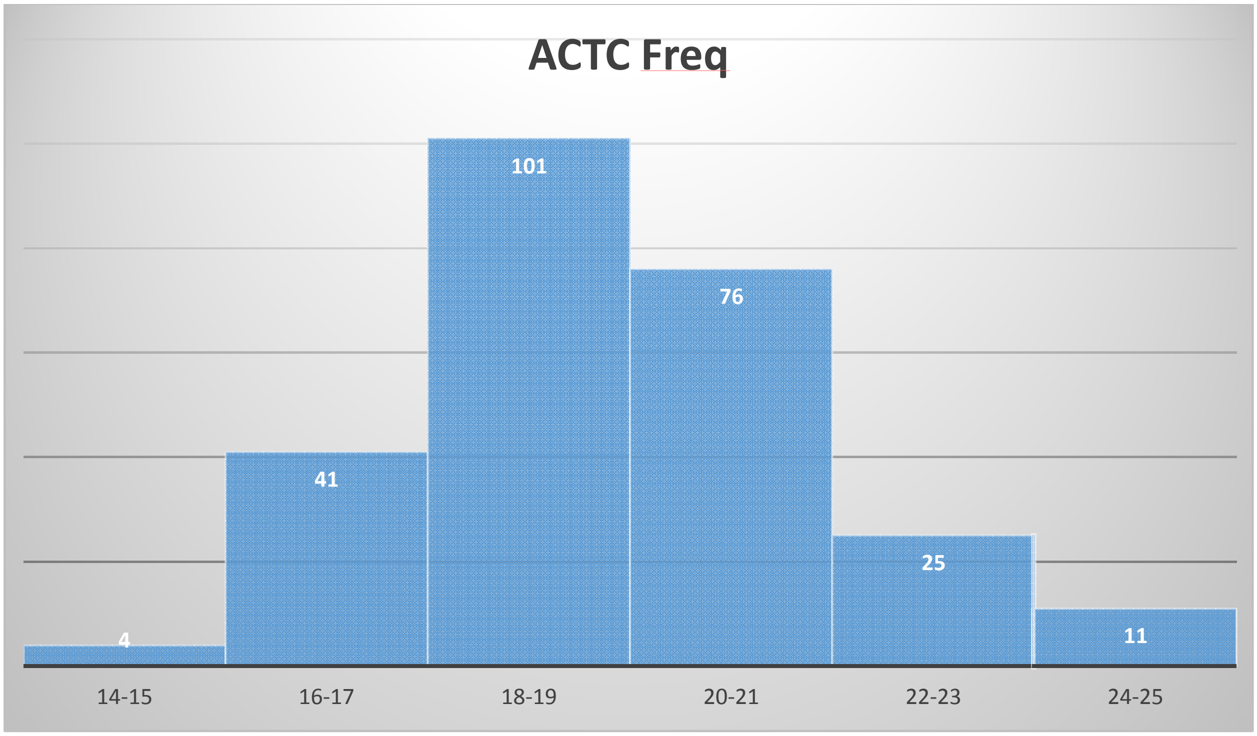

Figure One

Analysis One: Hierarchical Stepwise

Stepwise Selection of Terms

Candidate terms: HS_GPA, ACT_COMP, MATH_YRS

	----Step 1----		----Step 2----	
	Coef	P	Coef	P
Constant	-3.31		-4.22	
ACT_COMP	0.1975	0.002	0.1879	0.003
MATH_YRS			0.290	0.105
Deviance R-Sq		2.88%		3.62%
Deviance R-Sq(adj)		2.60%		3.07%
AIC		357.32		356.63

α to enter = 0.15, α to remove = 0.15

Response Information

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	2	13.159	6.579	13.16	0.001
ACT_COMP	1	9.292	9.292	9.29	0.002
MATH_YRS	1	2.691	2.691	2.69	0.101
Error	271	350.631	1.294		
Total	273	363.789			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
3.62%	3.07%	356.63

Figure 2

Analysis One: Regression Equation

```
Odds Ratios for Continuous Predictors

          Odds Ratio       95% CI
ACT_COMP      1.2067  (1.0654, 1.3667)
MATH_YRS      1.3363  (0.9409, 1.8979)


Regression Equation

P(1)  =  exp(Y')/(1 + exp(Y'))


Y' = -4.22 + 0.1879 ACT_COMP + 0.290 MATH_YRS
```

Figure 3

Analysis Two: ACT Composite Score as Predictor

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

* NOTE * 274 cases were used
* NOTE * 1 cases contained missing values

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-6.26635	2.05330	-3.05	0.002			
HS_GPA	0.614426	0.459089	1.34	0.181	1.85	0.75	4.55
ACT_COMP	0.205331	0.0648289	3.17	0.002	1.23	1.08	1.39
MATH_YRS	0.284613	0.180183	1.58	0.114	1.33	0.93	1.89

Log-Likelihood = -174.408
Test that all slopes are zero: G = 14.973, DF = 3, P-Value = 0.002

Figure 4

Analysis Two: SAT Critical Reading & Writing Score as predictor

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

* NOTE * 274 cases were used
* NOTE * 1 cases contained missing values

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-7.13255	2.23268	-3.19	0.001			
HS_GPA	0.625193	0.459639	1.36	0.174	1.87	0.76	4.60
SAT_CRM+M	0.0052060	0.0016160	3.22	0.001	1.01	1.00	1.01
MATH_YRS	0.284422	0.180251	1.58	0.115	1.33	0.93	1.89

Log-Likelihood = -174.214
Test that all slopes are zero: G = 15.361, DF = 3, P-Value = 0.002

Figure 5

Analysis Four

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	4	16.581	4.145	16.58	0.002
HS_GPA	1	1.290	1.290	1.29	0.256
ACT_COMP	1	11.369	11.369	11.37	0.001
MATH_YRS	1	2.790	2.790	2.79	0.095
GENDER	1	1.608	1.608	1.61	0.205
Error	269	347.209	1.291		
Total	273	363.789			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
4.56%	3.46%	357.21

Figure 6

Analysis Four: Regression Equation

```
Odds Ratios for Categorical Predictors

Level A  Level B  Odds Ratio       95% CI
GENDER
  1      0            1.4078  (0.8274, 2.3953)

Odds ratio for level A relative to level B


Regression Equation

P(1)  =  exp(Y')/(1 + exp(Y'))


GENDER
0       Y' = -6.365 + 0.5262 HS_GPA + 0.2136 ACT_COMP + 0.2994 MATH_YRS

1       Y' = -6.023 + 0.5262 HS_GPA + 0.2136 ACT_COMP + 0.2994 MATH_YRS
```

Figure 7

Analysis Five:

```
Candidate terms: HS_GPA, ACT_COMP, MATH_YRS, GENDER, HS_GPA*ACT_COMP,
HS_GPA*MATH_YRS,
     ACT_COMP*MATH_YRS, HS_GPA*GENDER, ACT_COMP*GENDER,
MATH_YRS*GENDER
```

	----Step 1----		----Step 2----		----Step 3----	
	Coef	P	Coef	P	Coef	P
Constant	-3.31		-4.22		-4.28	
ACT_COMP	0.1975	0.002	0.1879	0.003	0.1999	0.002
MATH_YRS			0.290	0.105	0.306	0.090
GENDER					-0.388	0.147
Deviance R-Sq		2.88%		3.62%		4.20%
Deviance R-Sq(adj)		2.60%		3.07%		3.38%
AIC		357.32		356.63		356.50

α to enter = 0.15, α to remove = 0.15

Response Information

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	3	15.291	5.097	15.29	0.002
ACT_COMP	1	10.308	10.308	10.31	0.001
MATH_YRS	1	2.946	2.946	2.95	0.086
GENDER	1	2.132	2.132	2.13	0.144
Error	270	348.498	1.291		
Total	273	363.789			

Figure 8

Analysis Five: Regression Equation

Odds Ratios for Continuous Predictors

	Odds Ratio	95% CI
ACT_COMP	1.2213	(1.0766, 1.3854)
MATH_YRS	1.3575	(0.9529, 1.9338)

Odds Ratios for Categorical Predictors

Level A	Level B	Odds Ratio	95% CI
GENDER			
M	F	0.6785	(0.4017, 1.1462)

Odds ratio for level A relative to level B

Regression Equation

P(1) = exp(Y')/(1 + exp(Y'))

GENDER

F Y' = -4.277 + 0.1999 ACT_COMP + 0.3057 MATH_YRS

M Y' = -4.665 + 0.1999 ACT_COMP + 0.3057 MATH_YRS

Figure 9

Analysis Six

Response Information

Variable	Value	Count	
REGISTERED_2ND_FALL	1	170	(Event)
	0	104	
	Total	274	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	4	15.011	3.7527	15.01	0.005
HS_GPA	1	1.807	1.8067	1.81	0.179
ACT_COMP	1	10.393	10.3934	10.39	0.001
MATH_YRS	1	2.408	2.4079	2.41	0.121
ACADEMIC_RANK	1	0.038	0.0377	0.04	0.846
Error	269	348.779	1.2966		
Total	273	363.789			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
4.13%	3.03%	358.78

Figure 10

Analysis Six: Regression Equation

```
Regression Equation

P(1)  =  exp(Y')/(1 + exp(Y'))


ACADEMIC_RANK
0              Y' = -6.341 + 0.6419 HS_GPA + 0.2081 ACT_COMP + 0.2793 MATH_YRS

1              Y' = -6.396 + 0.6419 HS_GPA + 0.2081 ACT_COMP + 0.2793 MATH_YRS
```