

Economic Analysis on the Graduation Gap between Undergraduate Students and Student-Athletes: A study of the SEC, ACC, Pac 12, Big 10, and Big 12 Conferences

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Professor Murphy

Senior Honors Thesis

28 March 2015

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I would like to thank Professor Robert Murphy of Boston College's Economics Department for his hard work and dedication in advising me on this Economics thesis. I would also like to thank Dean Robert Lay for allowing me to access the U.S. News & World Report Academic Insights data archive.

I. Introduction

Recently, the graduation success rate of student-athletes has become a pressing issue for the NCAA, individual universities, and the public. Although recent studies have found a slight increase in the graduation rates of NCAA athletes, they are typically still below the graduation rates of their non-athlete counterparts. The primary reason behind this issue is that NCAA Division I athletic programs are treated more like a business than a collegiate sport. Colleges are focused on their athletic programs succeeding at the expense of their student-athletes. Many studies have attempted to explain why this educational achievement gap between regular students and student-athletes persists. That said, the results are not uniform and the independent variables used changes from study to study.

This study proposes several causes that may explain why NCAA Division I athletes graduate at a lower rate than regular students. Previous studies have attempted to determine the factors that affect the graduation gap between regular students and student-athletes using predictive academic achievement variables, such as SAT scores. This study builds off of those foundations, but is different because it instead focuses on the characteristics of colleges and their athletic programs, such as revenue generated from athletics, academic rank, acceptance rate, and student/faculty ratio to name a few. It examines how those variables have affected the gap in graduation rates from 2003-2006.

The main tradeoff that we examine in this paper is how the academic quality of a school affects student-athletes' chances of succeeding relative to the rest of the student body. Are student-athletes more likely to succeed at weaker academic institutions because they can compete better in the classroom against the regular students? On the other hand, are top academically ranked institutions more dedicated to the academic success of their student-athletes

because they want to maintain a strong academic ranking relative to other schools? My hypothesis is that the gap in graduation rates between the undergraduate student body and student-athletes will be smaller at weaker academic institutions¹ and larger at top-ranked schools because student-athletes can compete better in the classroom against a weaker academic student body and thus have a higher chance of succeeding relative to their classmates.

College athletic programs are becoming more businesslike, and student-athletes are transforming into just athletes. If so, the gap in graduation rates between regular students and student-athletes should be larger at schools that place an emphasis on producing wins and generating a lot of revenue from their athletic teams. Through this study, we hope to pinpoint the underlying causes of this graduation gap between regular students and student-athletes, hopefully leading us to suggest policies to improve the future academic success of NCAA athletes.

II. Theory and Literature Review

Theoretical Literature

The theoretical framework of this study combines Gary Becker's allocation-of-time model and human capital theory. The idea of exploiting athletes for economic gains in athletics arises from this framework, which is also an important component of this study. Long and Caudill (1994) leveraged Becker's allocation-of-time model to study the effects of athletic participation on graduation rates. Becker's theory suggests that student-athletes can divide their time into three categories: athletics, academics, and leisure. College athletic programs require a large time commitment to activities such as weightlifting, practice, meetings, games, interviews, and travel, which implies that athletes spend a disproportionate amount of time in athletics compared to academics. Becker's time allocation theory suggests that time spent on academic

¹ Weaker academic institutions: higher acceptance rate, lower SAT scores, higher rank, larger student/faculty ratio.

activities, namely attending class, studying, and completing assignments, etc. decreases because of athletes' large time commitment to their respective sports. NCAA Division I athletic programs notoriously place little importance on the acquisition of academic-related human capital, which can negatively affect graduation rates for student-athletes.

The human capital theory builds off of the allocation-of-time theory, as athletes have to decide how much time they will invest in academic-related human capital versus athletics. Athletes at larger schools with big name athletic programs will have a more difficult time devoting their efforts to academics (Long and Caudill, 1991). Another potential problem arises from the recruiting process, as student-athletes are recruited based on their athletic skills and may lack the ability to succeed at a top-rated academic institution (Sack, 1998). Many Division I student-athletes receive athletic scholarships, which pressure them to perform athletically (Sack, 1998; Suggs et al., 2003). While these athletic incentives increase team success and boost revenues for the school's athletic programs, it comes at a cost to the students' academic success rate.

Empirical Literature

The revenue generated by college athletic programs is a function of team success. Amato et al. (1996) found that football team success is inversely related to the players' academic achievement in Division I-A. Although their study was focused on football, it is possible that this relationship holds for other revenue-generating sports. Thus, building off Amato et. Al.'s (1996) framework, I expand the observations to include other revenue-generating sports, such as men's basketball, women's basketball, and baseball.

One of the major studies that this one builds on includes Mallory Heydorn's (2009) "Explaining the Graduation Gap – Athletes vs. Non-Athletes: A study of the Big Ten and

Missouri Valley Conferences.” While Heydorn’s research provides a great framework for analyzing the graduation gap between regular students and student-athletes, there are holes and weaknesses in her study that can be improved upon. First, Heydorn’s analysis used the Federal Graduation Rate over the Graduation Success Rate. The FGR measures the percentage of first-time, full-time freshman, who graduate within six years of entering their original four-year institution (NCAA, 2013). For my study, I use the NCAA’s GSR, which was developed in response to criticism that the FGR understates the academic success of athletes because it fails to account for students transferring to and from an institution (NCAA, 2013). By using the GSR, the resulting graduation gap is more accurate than in Heydorn’s study, thus giving a more precise depiction of the causes.

Another shortcoming to Heydorn’s study includes the fact that she only incorporated one of the main NCAA conferences, the Big 10. This study expands the data to all of the top 5 NCAA conferences, namely the SEC, ACC, Pac 12, Big 10, and Big 12. Furthermore, Heydorn’s study only spans over one year (2001), whereas mine covers from 2003-2006. A larger sample size provides a more accurate picture of the relationship between the graduation gap and the main independent variables, specifically a college’s athletic revenue and academic rank.

The final weakness in Heydorn’s analysis includes the fact that she did not incorporate any predictive characteristics for the colleges that student-athletes attend. To fill this void in her analysis, I add the average incoming math SAT, acceptance rate, and student/faculty ratio of colleges to better explain the causes of the graduation gap.

Bryan Cook and Natalie Pullaro’s (2010) study, “College Graduation Rates: Behind the Numbers,” illustrates Congress’ increased concern for the graduation gap between undergraduate students and student-athletes. Congress enacted the “Student Right-to-Know Act” because the

“increasing revenue from college athletics was so great that the educational mission of the university is too easily forgotten” (Cook & Pullaro, 2010). Cook and Pullaro (2010) describe how the perfect database/model for calculating graduation rates has yet to be created when they say, “Because of the importance of these factors to truly assessing the effectiveness of an institution at graduating its students, using any of the databases mentioned in this report individually may paint an incomplete picture of institutional quality.” While my study does not completely explain the causes of the gap in graduation rates between the entire student body and student-athletes, I believe that the framework established in this paper better explains this persisting issue of institutional accountability for student-athletes’ academic success.

III. Data

The data used in this paper come from the National Collegiate Athletic Association (NCAA) Division I Graduation Success Rate database, the U.S. News & World Report Academic Insights data archive, and the Office of Postsecondary Education Equity in Athletics database to test our hypothesis. The NCAA data break down the graduation rates of Division I student-athletes by their respective sport (Football, Baseball, Men’s Basketball, and Women’s Basketball) and by the school’s athletic conference from 1998 to 2006. Furthermore, the data also consist of the overall average graduation rate of athletes at each school. The NCAA data use freshman cohorts, who entered college during a specific year and graduated within six years.

The U.S. News & World Report Academic Insights data provided us with the undergraduate graduation rate, academic rank, incoming SAT verbal, incoming SAT math, acceptance rate, and student/faculty ratio for the schools we analyzed from 2003 to present. The undergraduate graduation rate – the GSR rate for student-athletes formed the graduation gap.

The Office of Postsecondary Education Equity in Athletics database contains revenue data for the Division I NCAA programs in this study. The revenue data are based on the current year to properly illustrate the effects of these variables on the current graduation gap. This database spans from 2001 to 2013.

The ultimate timeline for my study spans from 2003 to 2006 because those are the years that the multiple datasets that I am using overlap, eliminating any gaps in the data.

IV. Empirical Model

This study examines several factors that impact the graduation rate differential between regular students and student-athletes. The main hypothesis of this study is that the gap in graduation rates between the undergraduate student body and student-athletes will be smaller at weaker academic institutions² and larger at top-ranked schools because student-athletes can compete better in the classroom against a weaker academic student body and thus have a higher chance of succeeding relative to their classmates.

The standard estimating equation that we use in our analysis expresses the difference in graduation rates between the undergraduate student body and student-athletes as a function of various independent variables. We consider graduation rates for the overall student-athlete population as well as the graduation rates for specific sports, including men's basketball, women's basketball, football, and baseball. There are two different types of independent variables considered in this study. The first type is intended to capture the characteristics of the school in terms of academic quality and selectivity of admissions. The second type of variables pertains to the performance of an institution's athletic program as well as the conference that an

² Weaker academic institutions: higher acceptance rate, lower SAT scores, higher rank, larger student/faculty ratio.

institution belongs to. Table 1 provides the definitions of the variables used in this study as well as the predicted sign for each explanatory variable.

Table 1: Variable Definitions and Predicted Signs

Dependent Variables:

Variable	Definition	Predicted Sign
Nonathathoverall	Overall Student Body's Graduation Rate – The Average of the NCAA Sports' Graduation Rate	N/A
Nonathmbball	Overall Student Body's Graduation Rate – The Average Graduation Rate for the School's Men's Basketball Team	N/A
Nonathwbball	Overall Student Body's Graduation Rate – The Average Graduation Rate for the School's Women's Basketball Team	N/A
Nonathfootball	Overall Student Body's Graduation Rate – The Average Graduation Rate for the School's Football Team	N/A
Nonathbaseball	Overall Student Body's Graduation Rate – The Average Graduation Rate for the School's Baseball Team	N/A

Independent Variables:

Variable	Definition	Predicted Sign
Revenuefromsports	Revenue generated by the school's athletic programs.	+
Rank	Academic rank of the school.	–
AvgSATverbal	Average incoming verbal SAT score for the school.	–
AvgSATmath	Average incoming math SAT score for the school.	–

Studentfac	Student/Faculty ratio at the school.	+
Acceptancerate	Acceptance rate of the school.	+
Studentfac	Student/Faculty ratio at the school.	+
Conf	Dummy variable that will isolate the individual effects from each of the top 5 college athletic conferences. Confdum1: ACC Confdum2: Big 10 Confdum3: Big 12 Confdum4: Pac 12 Confdum5: SEC	N/A ³

V. Results

Why Fixed Effects Did Not Work

We had to omit fixed effects because this panel dataset did not have much time variance. The unobservable attributes of a school were highly correlated with the ones we could observe. There was not much time variation in the observable variables, and the addition of fixed effects into the model was capturing the effects of these observable variables, thus causing the variables to lose significance. The fixed effects were washing out the cross-sectional variation, so theoretically there was no variation left to explain. This can be seen in Figure #1, where the P-values for all of the right hand side variables increase when fixed effects is introduced to the regression.

See Figure #1

Why SAT Verbal was Eliminated from the Model

For the regression results with avgsatverbal and avgsatmath, see Figure #2

³ Note: this dummy variable is used to compare the graduation gap across the different conferences.

See Figure #3

Chi-Squared (1) = .18

Prob > Chi-Squared = 0.6697

This chi-squared test was performed to test for collinearity between the avgsatverbal and avgsatmath variables. Based on the results from the test, we could not reject the hypothesis that the coefficients on those terms are equal. There is a 67% chance of getting a chi-squared of .18, which is a high probability, indicating that we cannot reject the equality of the coefficients. Thus, the math score and verbal score's effects are statistically the same. The math variable had a larger coefficient and a smaller p-value. When we left the avgsatmath and avgsatverbal variables in the regression, the effect of the verbal variable was diminished by the math variable due to collinearity. As seen in Figure #3, where both the avgsatverbal and avgsatmath variables were left in the regression, the coefficient for the avgsatverbal variable was negative whereas the avgsatmath variable's coefficient was positive. The variables were seemingly competing against each other, and thus when considered together in the regression, made their effects undistinguishable. Thus, we just proceeded with the avgsatmath variable in the regressions and eliminated the avgsatverbal variable.

Random Effects Linear Model (Xtreg)

See Figure #7

To develop an understanding for why this gap in graduation rates persists between the undergraduate student body and student-athletes, we ran a series of random linear effects models for the overall NCAA athlete population as well as the football, baseball, men's basketball, and women's basketball teams. The regressions for the overall NCAA athlete population, football,

and baseball teams are discussed in this section whereas the men and women's basketball teams are discussed in the following section regarding gender differences. The incoming characteristics of a school that we tested include the student/faculty ratio, the academic rank of the school, the average math SAT score for a specific year's incoming freshman cohort, the acceptance rate of the school in that specific year, and the revenue generated by the school's athletic program that year.

We found that the rank variable, which represents the academic rank of the school⁴ as reported by the U.S. News and World Report, was highly significant for the overall NCAA athlete population (Coefficient = $-.0977459$; p-value = $.000$), the football team (Coefficient = $-.1008932$; p-value = $.017$), and for the baseball team (Coefficient = $-.2958496$; p-value = $.003$). The results from this regression explain that for the academic rank variable, as the rank of the school increases, the gap in graduation rates between undergraduate students and student-athletes decreases, so students would be academically better off attending weaker academic institutions, where they can compete better in the classroom and graduate at the same or a higher rate than the rest of the student body. These results for the rank variable were consistent with my hypothesis that college athletes should attend weaker academic institutions because they can compete better in the classroom with the overall undergraduate student body and thus have a better chance of succeeding relative to their fellow classmates.

The variable, *acceptancerate*, was also highly significant for the overall NCAA athlete population (Coefficient = $-.1097103$; p-value = $.003$) and the football team (Coefficient = $-.1504181$; p-value = $.038$), but not for the baseball team. The negative coefficient for the *acceptancerate* variable indicates that as the acceptance rate at a school increases, the gap in

⁴ #1 would be the highest ranked school, #2 would be the next best, and so on.

graduation rates between the undergraduate student body and student-athletes decreases. This is consistent with the results found for the rank variable, assuming that as the acceptance rate of a school increases, the academic rank of the school would also increase (worsen) because it is a less academically competitive institution.

It is important to mention that although the revenue from an institution's athletic program was the primary focus of this study, it was consistently insignificant at the 5% level and often had the wrong sign⁵. There are several possible explanations for this. First, revenue differs greatly from one athletic program to another based on their popularity, size, and history. The scatter plot for the revenue from sports and nonathletic overall variables shows that there is not a strong relationship between the graduation gap and an institution's revenue from their sports programs. The lack of uniformity and correlation between the two variables explains why there were no significant p-values found for revenue from sports at the 5% level.⁶

Difference Between Males and Females: Analyzing Men's Basketball vs. Women's Basketball

See Figure #8

⁵ Revenue had the right sign for the random linear effects model with women's basketball. It was significant at the 10% level for men's basketball.

⁶ Revenue had the right sign for the random linear effects model with women's basketball. It was significant at the 10% level for men's basketball.

```
. xtreg nonathmbball studentfac rank avgsatmath revenue acceptancerate

Random-effects GLS regression           Number of obs   =       172
Group variable: schl                   Number of groups =        46

R-sq:  within = 0.1242                 Obs per group:  min =         1
      between = 0.1774                   avg =           3.7
      overall = 0.1308                   max =           4

                                           Wald chi2(5)    =       22.57
corr(u_i, X) = 0 (assumed)             Prob > chi2     =       0.0004
```

nonathmbball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	.1384866	.6860668	0.20	0.840	-1.20618	1.483153
rank	-.2632405	.0931467	-2.83	0.005	-.4458047	-.0806764
avgsatmath	-.0263806	.0939613	-0.28	0.779	-.2105414	.1577802
revenuefromsports	-2.65e-07	9.77e-08	-2.72	0.007	-4.57e-07	-7.38e-08
acceptancerate	-.1435199	.1690344	-0.85	0.396	-.4748212	.1877815
_cons	58.20168	68.46996	0.85	0.395	-75.99697	192.4003
sigma_u	15.451301					
sigma_e	11.096398					
rho	.65974216	(fraction of variance due to u_i)				

```
. xtreg nonathwbball studentfac rank avgsatmath revenue acceptancerate

Random-effects GLS regression           Number of obs   =       172
Group variable: schl                   Number of groups =        46

R-sq:  within = 0.0574                 Obs per group:  min =         1
      between = 0.4156                   avg =           3.7
      overall = 0.3871                   max =           4

                                           Wald chi2(5)    =       37.38
corr(u_i, X) = 0 (assumed)             Prob > chi2     =       0.0000
```

nonathwbball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.1940106	.3849228	-0.50	0.614	-.9484454	.5604242
rank	-.1236035	.0618931	-2.00	0.046	-.2449116	-.0022953
avgsatmath	-.0008499	.0587934	-0.01	0.988	-.1160829	.114383
revenuefromsports	1.82e-08	5.47e-08	0.33	0.739	-8.91e-08	1.26e-07
acceptancerate	-.3331145	.0988743	-3.37	0.001	-.5269047	-.1393243
_cons	11.3507	41.67415	0.27	0.785	-70.32912	93.03053
sigma_u	11.986429					
sigma_e	5.6934231					
rho	.81591715	(fraction of variance due to u_i)				

In this paper, we also wanted to test for the gender differences in the graduation gap between the entire undergraduate student body and student-athletes. To do this, we reran the random linear effects model, except this time just for the men's basketball and women's basketball teams. We felt that using basketball would be the best approach because we could

control for any unobservable effects that may not be captured by using two different sports teams, for example football and women's basketball.

When we compared the random linear effects models for men's basketball and women's basketball, the first difference that we noticed was the way in which the student/faculty ratio variable, *studentfac*, affects the gap in graduation rates between undergraduate students and student-athletes. For men's basketball, *studentfac* has a positive coefficient (Coefficient = .138466; p-value = .840), but for women's basketball, the coefficient is negative (Coefficient = -.1940106; p-value = .614). This means that the gap in graduation rates between the undergraduate student body and the men's basketball increases as the school's student/faculty ratio increases. On the other hand, the gap in graduation rates between the undergraduate student body and women's basketball athletes decreases as *studentfac* increases.

The *revenuefromsports* variable presented even more interesting conclusions than the *studentfac* variable did. First, as in the case with the *studentfac* variable, the signs on the coefficients for the *revenuefromsports* variable were negative for the men's basketball team (Coefficient = $-2.65e-07$; p-value = .007) and positive for the women's basketball team (Coefficient = $1.82e-08$; p-value = .739). Based on these results, men's basketball student-athletes would be better off attending big-name schools that earn a lot of revenue from their sports teams whereas women should avoid these large schools because the increasing emphasis on sports teams' success to boost revenue negatively affects their chances to graduate. The case can also be made that if a women's basketball player attends one of these successful college basketball programs, that brings in a lot of revenue for the school and paves the way for a lot of basketball athletes to become successful in the NBA, she has a high chance of going pro and never graduating. This, coupled with the fact that college basketball teams often carry no more

than fifteen players on a roster, illustrates how player departure greatly affects the graduation rate of a school's basketball team versus their football team, which often carries nearly one hundred players on a roster. Regardless, the results from this regression support Long and Caudill's (1991) conclusions that athletes at larger schools with big name athletic programs, due to the emergence of college sports as a business, will have a more difficult time devoting their efforts to academics and experience lower graduation rates relative to the rest of the student body.

We found that the rank variable, which represents the academic rank of the school⁷ as reported by the U.S. News and World Report, was also highly significant for the men (Coefficient = $-.2632405$; p-value = $.005$) and women's basketball teams (Coefficient = $-.1236035$; p-value = $.046$). The results from this regression explain that for the academic rank variable, as the rank of the school increases, the gap in graduation rates between undergraduate students and student-athletes decreases, so students would be academically better off attending weaker academic institutions, where they can compete better in the classroom and graduate at the same or a higher rate than the rest of the student body.

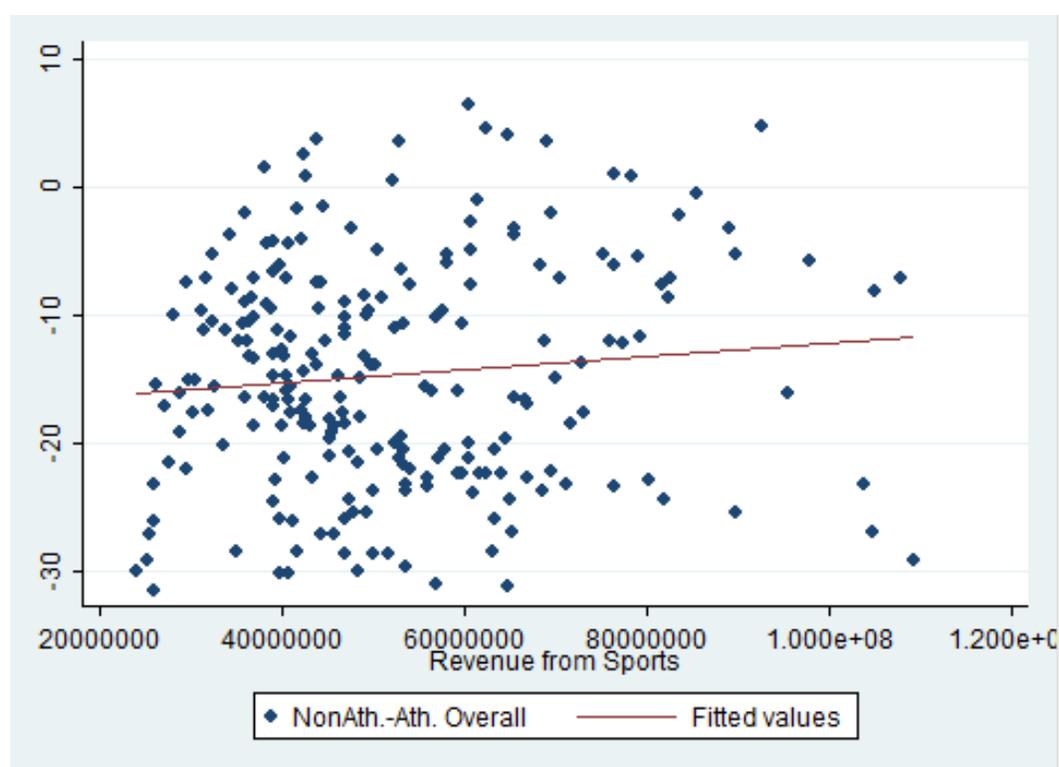
The variable, *acceptancerate*, was also highly significant for the women's basketball team (Coefficient = $-.3331145$; p-value = $.001$), but not for the men. As expressed in the previous section, the negative coefficient for the *acceptancerate* variable indicates that as the acceptance rate at a school increases, the gap in graduation rates between the undergraduate student body and student-athletes decreases. This is consistent with the results found for the rank variable, assuming that as the acceptance rate of a school increases, the academic rank of the school would also increase (worsen) because it is a less academically competitive institution.

⁷ #1 would be the highest ranked school, #2 would be the next best, and so on.

Scatter Plots

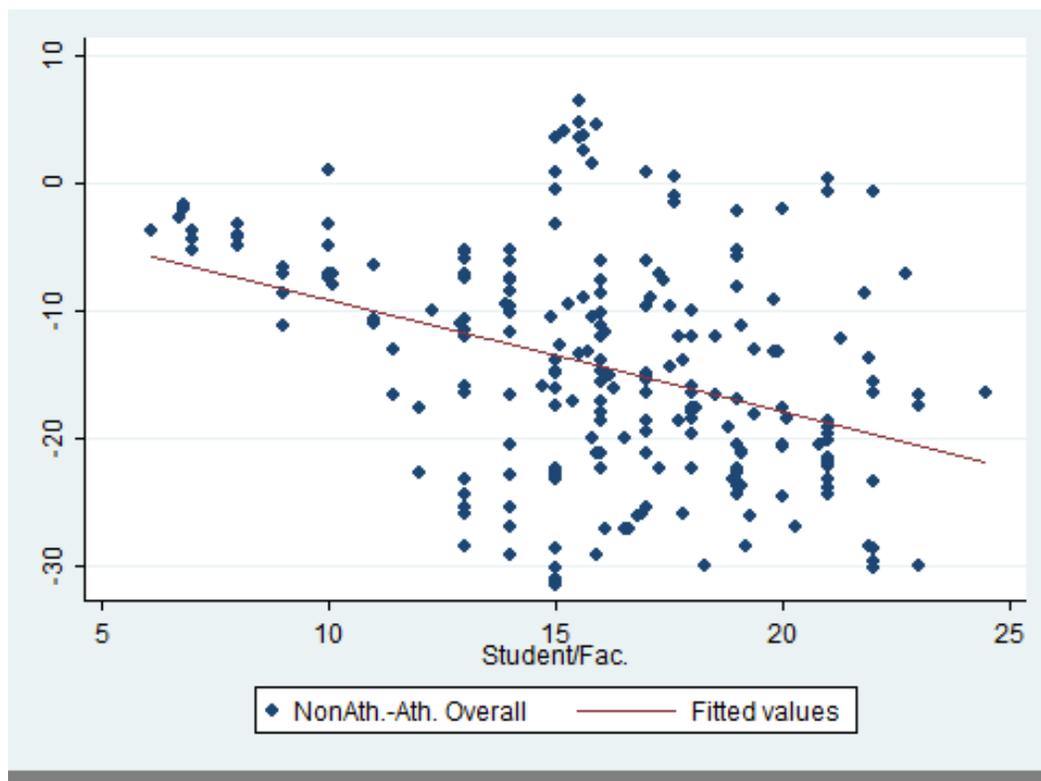
As a way of trying to understand the relationship and pattern of significance between the graduation gap and the independent variables, we estimated the bivariate scatterplots of the independent variables and the graduation gap.

Graph twoway scatter nonathathoverall revenuefromsports || lfit nonathathoverall revenuefromsports



As indicated from this scatter plot, there is hardly any correlation or uniformity to the relationship between the graduation gap and an institution's revenue from their sports programs. The lack of correlation explains why there were no significant p-values found for the variable, *revenuefromsports*, at the 5% level. That said, *revenuefromsports* was significant in the regression (*xtreg*) for men's basketball (*mball*).

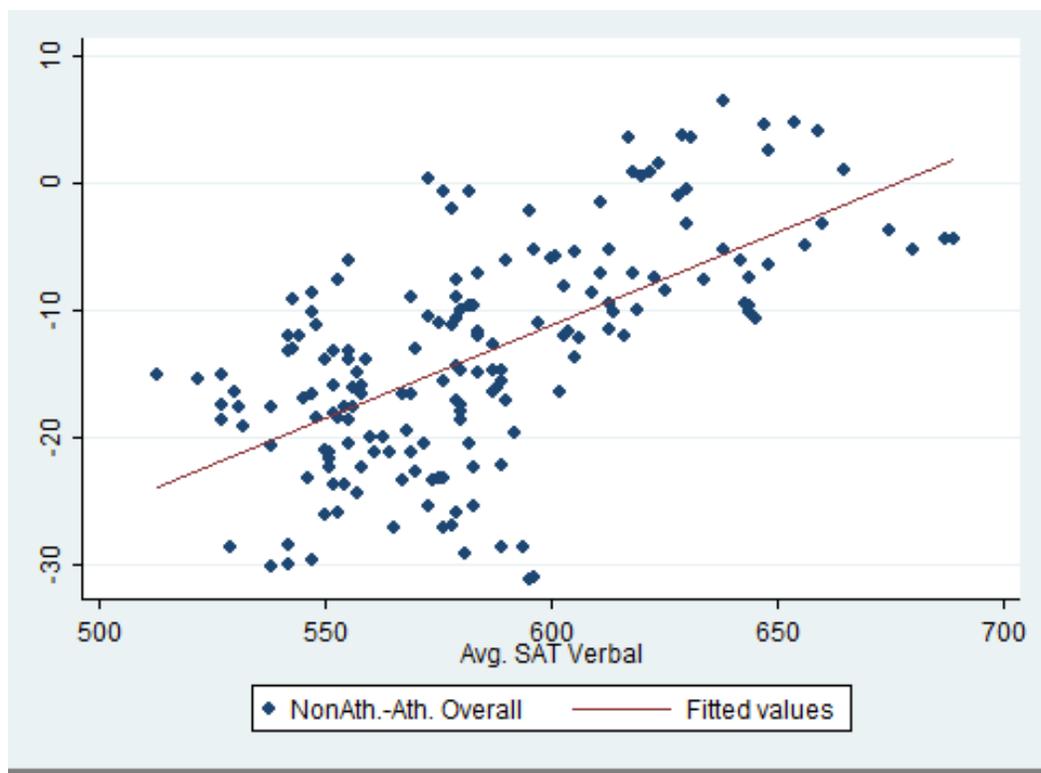
Graph twoway scatter nonathathoverall studentfac || lfit nonathathoverall studentfac



As the student/faculty ratio increases, the gap shrinks and eventually becomes negative, indicating that at schools with high student faculty ratios, the athletes' graduation rate is higher than that of regular students.

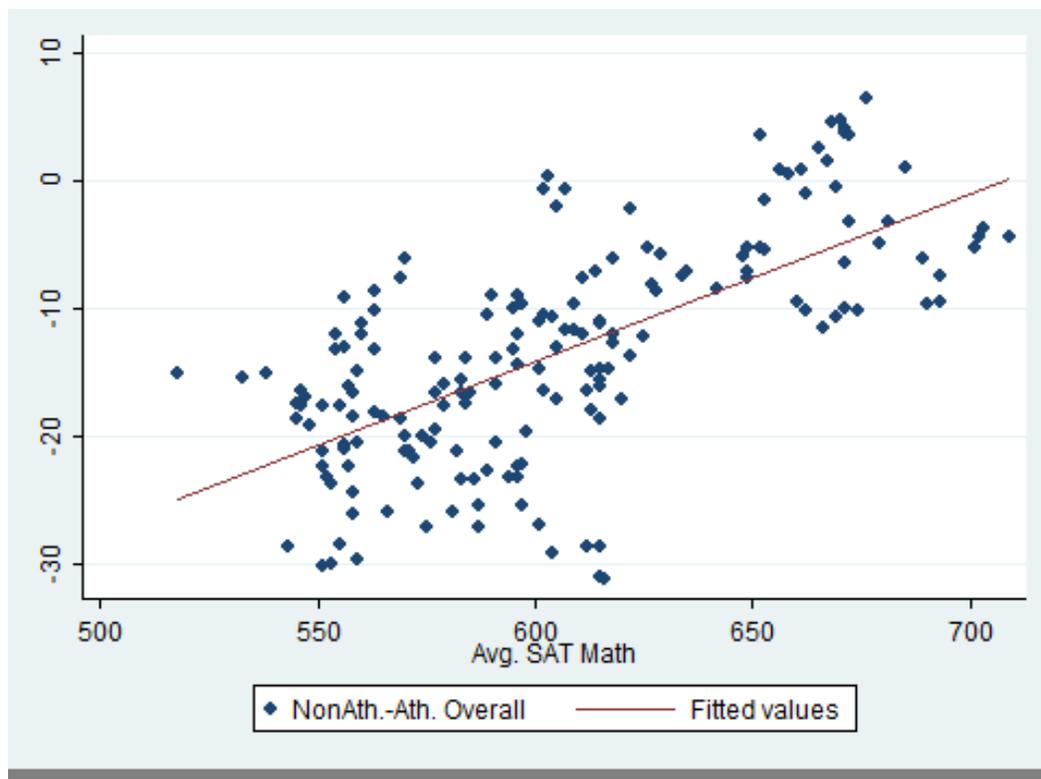
Graph twoway scatter nonathathoverall avgsatverbal || lfit nonathathoverall avgsatverbal⁸

⁸ Note: even though avgsatverbal was omitted from the regression, it was still included to show its relationship with the gap in graduation rates.



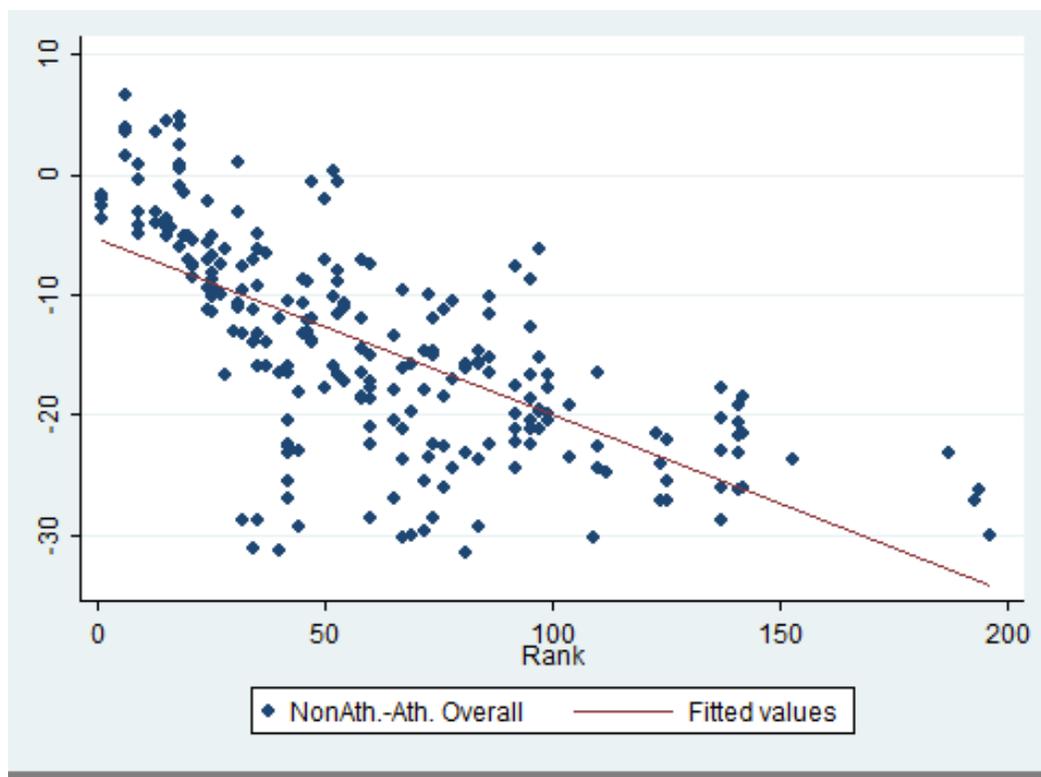
As the avgsatverbal increases, the gap increases positively, indicating that college athletes perform better at schools with an academically weaker student body. As the incoming class becomes academically smarter (higher SAT verbal), the gap in graduation rates increases.

Graph twoway scatter nonathathoverall avgsatmath || lfit nonathathoverall avgsatmath



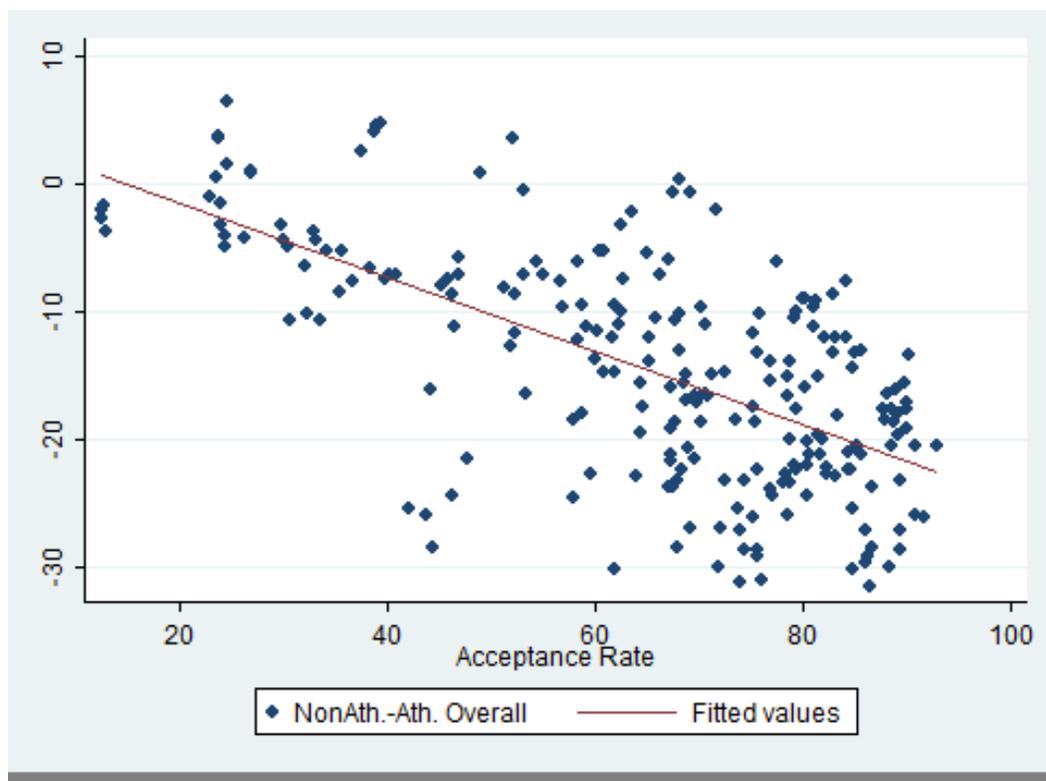
As the avgsatmath increases, the gap increases positively, indicating that college athletes perform better at schools with an academically weaker student body. As the incoming class becomes academically smarter (higher SAT math), the gap in graduation rates increases.

Graph twoway scatter nonathathoverall rank || lfit nonathathoverall rank



At the academically stronger schools (lower rank number), the gap in the graduation rates between the entire student body and college athletes is large and positive. As the academic rank of the school worsens (the rank number goes up), the gap shrinks and eventually becomes negative. This means that college athletes can compete better in the classroom better with a weaker academic student population.

Graph twoway scatter nonathathoverall acceptancerate || lfit nonathathoverall acceptancerate



As the acceptance rate increases (% of applicants that are accepted into the school increases), the gap in the graduation rates between the entire student body and college athletes decreases and becomes negative.

Effects Across Different Conferences For the Different Sports Teams

The earlier analysis grouped all of the schools together, which did not account for potential unobservable differences across athletic conferences. In this section, we control for unobservable conference effects. The reason why this is important includes that it is possible that graduation rates may be affected by factors that are specific to conferences, but not captured by our independent variables.

Figure #6:

```
. reg nonathathoverall studentfac rank avgsatmath revenue acceptancerate confdum1 confdum2 confdum3 confdum4 confdum5, noconst
```

Source	SS	df	MS	Number of obs = 171		
Model	40526.8771	10	4052.68771	F(10, 161) = 151.73		
Residual	4300.25285	161	26.709645	Prob > F = 0.0000		
				R-squared = 0.9041		
				Adj R-squared = 0.8981		
Total	44827.13	171	262.146959	Root MSE = 5.1681		

nonathathoverall	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
studentfac	.0760532	.1626731	0.47	0.641	-.2451951	.3973014
rank	-.1244714	.019997	-6.22	0.000	-.1639616	-.0849812
avgsatmath	.0165031	.0201112	0.82	0.413	-.0232127	.0562189
revenuefromsports	-5.62e-08	2.70e-08	-2.08	0.039	-1.10e-07	-2.86e-09
acceptancerate	-.2086933	.0376706	-5.54	0.000	-.2830855	-.1343012
confdum1	-1.510782	15.64977	-0.10	0.923	-32.41608	29.39451
confdum2	-3.30933	15.43064	-0.21	0.830	-33.78188	27.16322
confdum3	2.341248	15.84963	0.15	0.883	-28.95872	33.64122
confdum4	-1.00126	15.15566	-0.07	0.947	-30.93079	28.92827
confdum5	1.5956	15.42949	0.10	0.918	-28.87468	32.06588

Figure #9:

<u>Performance Rank</u>	<u>Conference</u>	<u>Coefficient Value</u>	<u>P-Value</u>
1	Big 10	-3.30933	.830
2	ACC	-1.510782	.923
3	Pac 12	-1.00126	.947
4	SEC	1.5956	.918
5	Big 12	2.341248	.918

After generating dummy variables for the different conferences (See Figure #5), this test analyzed the five main conferences and their relationship to the graduation gap. Thus, a positive coefficient on the dummy variable means a larger gap (Mean of the Regular Undergraduate Students' Graduation Rate – Mean of the Overall NCAA Athletes' Graduation Rate) for that conference and a negative coefficient means that the gap shrinks for that specific conference. Figure #6 shows the regression results and figure #9 ranks the conferences in order from best to worst. The best conference for the graduation gap is the Big 10, with a negative coefficient of -3.30933, meaning college athletes actually graduate at a higher rate than the undergraduate

student body. The worst conference for the graduation gap is the Big 12, with a positive coefficient of 2.341248, indicating that student-athletes graduate at a much lower rate when compared to the rest of the undergraduate student body.

Joint Test for Confidum Variables

See Figure #4

$$F(5, 161) = 3.35$$

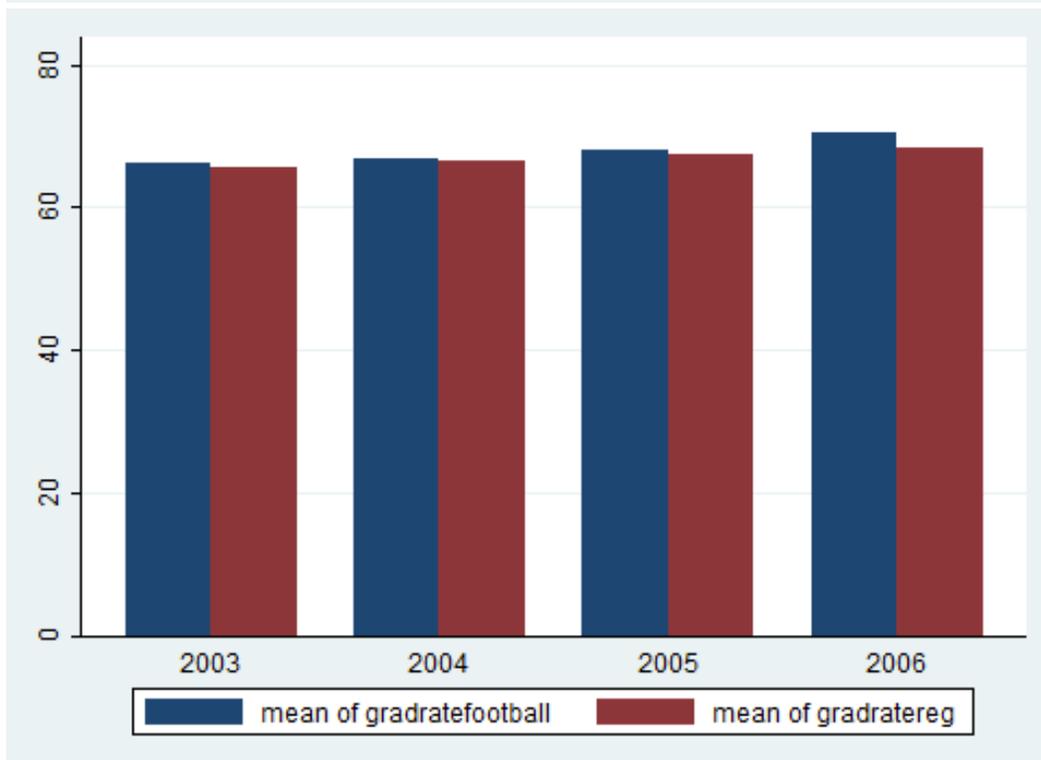
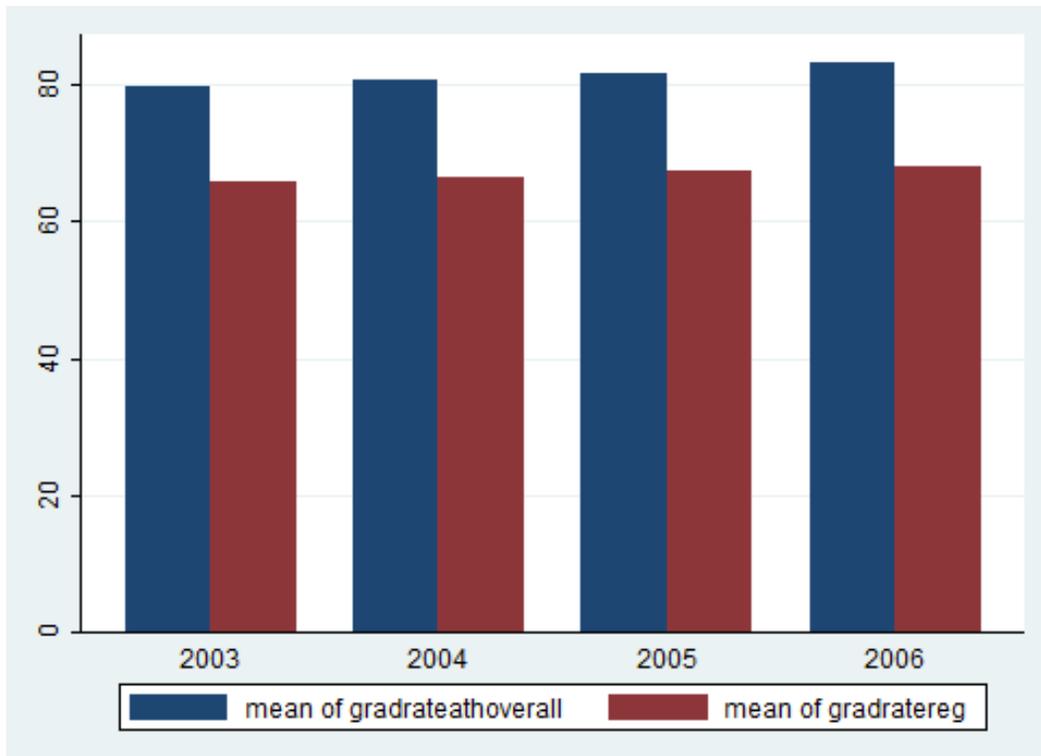
$$\text{Prob} > F = .0066$$

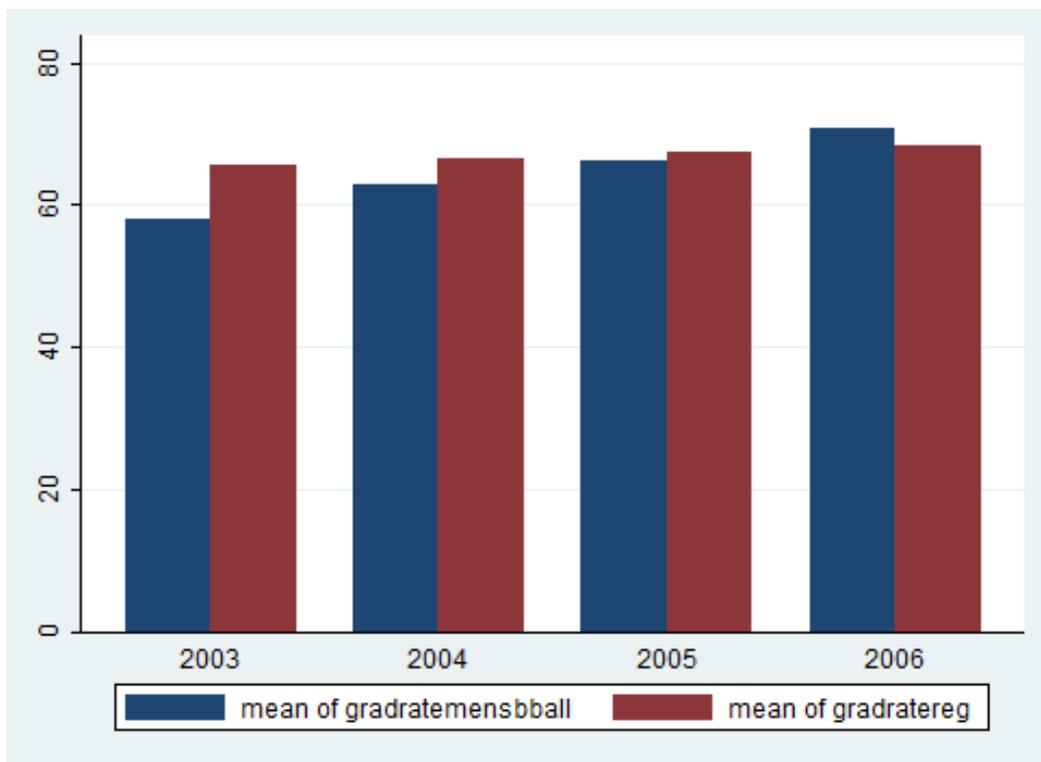
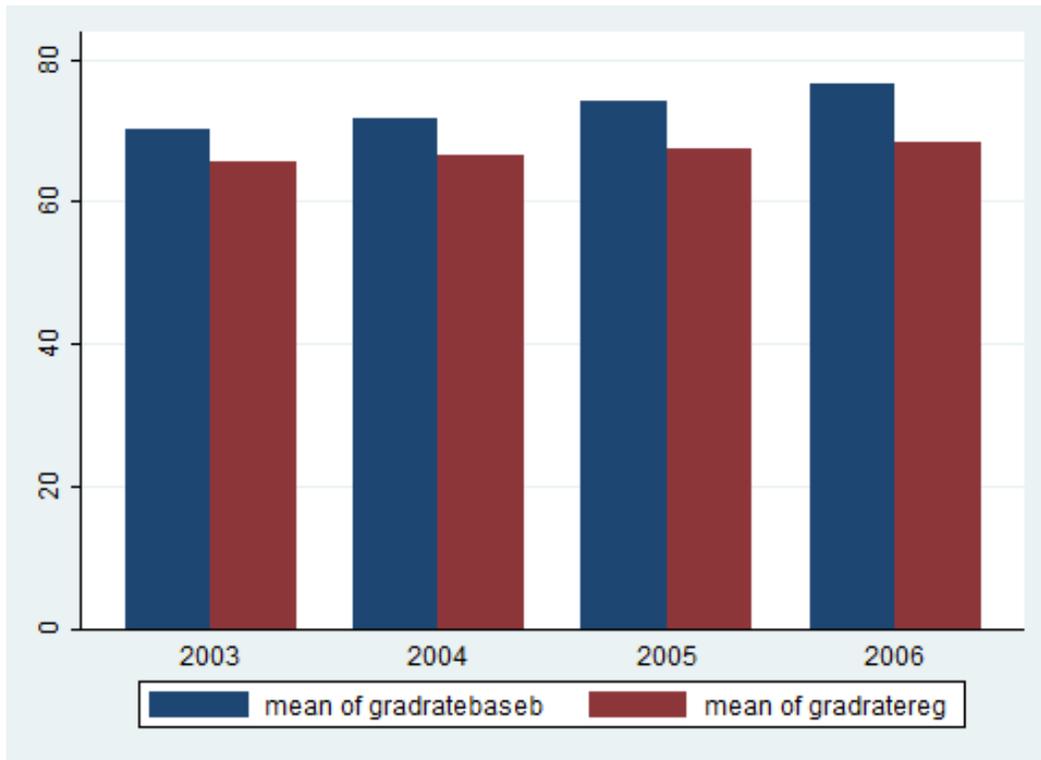
This test is included in my analysis because when considered individually, none of the conference dummy variables were significant in any of the regressions. The probability is small ($\text{Prob} > F = .0066$), so we reject the hypothesis that the conference dummies as a group have no effect. Thus, there is a good probability that when considered together, the confidum dummy variables are significant.

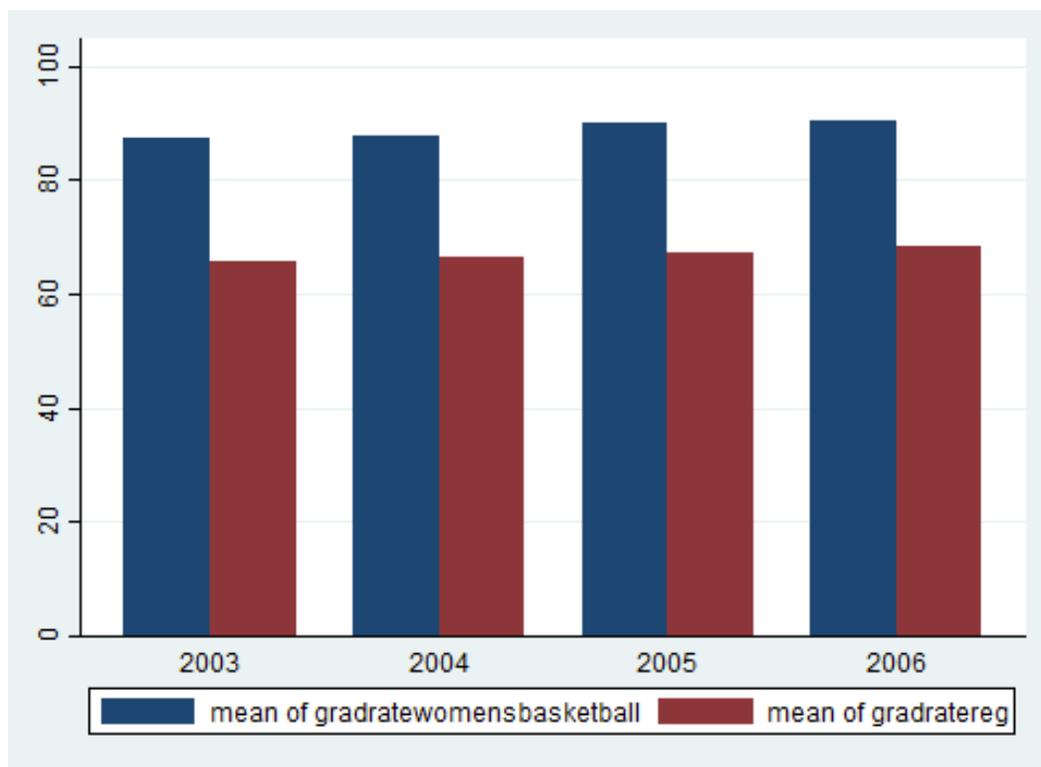
Effects Across Different Sports Teams

The following bar charts show the mean of the graduation rates for the entire student body (pictured in red) relative to the mean of the graduation rate for the all NCAA athletes and the women's basketball, men's basketball, football, and baseball team.

It is important to note that the mean graduation rate for the baseball and women's basketball teams was consistently greater than the mean of the overall undergraduate graduation rate for 2003 to 2006. This indicates that on average and over this time period, these teams were graduating their student-athletes at a higher rate than the average graduation rate for the institution.







VI. Conclusion

Some of the results of the random linear effects regressions are accurate and consistent with the hypothesis and related literature. Although we were unable to successfully find a significant relationship⁹ between a school's revenue from their athletic program and the graduation gap, this study produced two major relationships between a school's incoming characteristics and the graduation gap.

The most important finding in this study comes from the relationship between the academic rank of a school (where #1 is best) and the graduation gap between the overall undergraduate population and student-athletes. The rank variable was consistently significant at the 5% level for the overall NCAA athlete population and all of the teams analyzed in this study. The coefficients on the rank variable for each of the random linear effects models were

⁹ Revenue had the right sign for the random linear effects model with women's basketball. It was significant at the 10% level for men's basketball.

consistently negative across each regression. This indicates that as the rank of the school increases, the gap in graduation rates between undergraduate students and student-athletes decreases, so students would be academically better off attending weaker academic institutions, where they can compete better in the classroom and graduate at the same or a higher rate than the rest of the student body. These results for the rank variable were consistent with my hypothesis that college athletes should attend weaker academic institutions because they can compete better in the classroom with the overall undergraduate student body and thus have a better chance of succeeding relative to their fellow classmates. This study's findings for the rank variable are also consistent and better than Mallory Heydorn's (2009) findings in her paper, "Explaining the Graduation Gap – Athletes vs. Non-Athletes: A study of the Big Ten and Missouri Valley Conferences" because we were able to find a significant relationship between the rank variable and the graduation gap.

The independent variable, *acceptancerate*, was one incoming characteristic that we chose to test for the first time in this study. Although the acceptance rate of a school relates to its academic ranking, this variable still has an important relationship with the graduation gap because it was significant at the 5% level and had a negative coefficient for the overall NCAA population, an institution's football team, and its women's basketball team. The negative coefficient for the *acceptancerate* variable indicates that as the acceptance rate at a school increases, the gap in graduation rates between the undergraduate student body and student-athletes decreases. This is consistent with the results found for the rank variable in this study and in Mallory Heydorn's (2009) paper, assuming that as the acceptance rate of a school increases, the academic rank of the school would also increase (worsen) because it is a less academically competitive institution.

Although the revenue from a school's athletic program was the primary focus of this study, it was consistently insignificant at the 5% level and often had the wrong sign¹⁰. As we expressed before, there are several possible explanations for this. First, revenue differs greatly from one athletic program to another based on their popularity, size, and history. The scatter plot for the revenue from sports and nonathletic overall variables shows that there is not a strong relationship between the graduation gap and an institution's revenue from their sports programs. The lack of uniformity and correlation between the two variables explains why we found no statistical significance for revenue from sports at the 5% level.¹¹ Future research could employ better revenue data for a school's athletic program, perhaps broken down by individual sport or by trying other explanatory variables for the success of a school's athletic program, hopefully leading to statistically significant findings for this topic.

Aside from attempting to find a significant relationship between the success of a school's athletic program and the graduation gap, future studies on this topic are necessary because there are many more avenues to explore. First, the data are lacking in completeness in some aspects due to availability, so one avenue for the future could be to find a more complete dataset to analyze this issue. This study found a new and statistically significant variable to explain the graduation gap, namely through the acceptance rate variable. Future research could explore additional incoming characteristics of an institution, such as an institution's endowment or incoming student GPA, to name a few. As Cook and Pullaro (2010) stated, "Because of the importance of these factors to truly assessing the effectiveness of an institution at graduating its students, using any of the databases mentioned in this report individually may paint an

¹⁰ Revenue had the right sign for the random linear effects model with women's basketball. It was significant at the 10% level for men's basketball.

¹¹ Revenue had the right sign for the random linear effects model with women's basketball. It was significant at the 10% level for men's basketball.

incomplete picture of institutional quality.” That said, exploring other independent variables would help to increase the depth of this topic and provide a better understanding of why this graduation gap exists between an institution’s undergraduate student body and student-athletes, hopefully leading to policies that will improve the future academic success of NCAA athletes.

Appendix

Figure #1:

```
. xtreg nonathathoverall studentfac rank avgsatverbal avgsatmath revenue acceptancerate

Random-effects GLS regression                Number of obs   =       171
Group variable: schl                        Number of groups =        46

R-sq:  within = 0.0082                      Obs per group:  min =         1
        between = 0.6236                      avg =           3.7
        overall = 0.5923                      max =           4

Wald chi2(6) =       58.95
corr(u_i, X) = 0 (assumed)                  Prob > chi2     =       0.0000
```

nonathathoverall	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.0039521	.1388042	-0.03	0.977	-.2760033	.2680991
rank	-.0974082	.025476	-3.82	0.000	-.1473402	-.0474761
avgsatverbal	-.010687	.0480265	-0.22	0.824	-.1048173	.0834433
avgsatmath	.02659	.0429568	0.62	0.536	-.0576039	.1107838
revenuefromsports	-1.07e-08	2.06e-08	-0.52	0.603	-5.10e-08	2.96e-08
acceptancerate	-.1110636	.0368901	-3.01	0.003	-.1833668	-.0387604
_cons	-9.727076	17.1814	-0.57	0.571	-43.40201	23.94785
sigma_u	5.367742					
sigma_e	1.9034334					
rho	.88830032	(fraction of variance due to u_i)				

```
. xtreg nonathathoverall studentfac rank avgsatverbal avgsatmath revenue acceptancerate, fe

Fixed-effects (within) regression              Number of obs   =    171
Group variable: schl                          Number of groups =     46

R-sq:  within = 0.0299                        Obs per group:  min =     1
        between = 0.0392                       avg =           3.7
        overall = 0.0385                       max =           4

corr(u_i, Xb) = -0.3277                       F(6,119)        =     0.61
                                                Prob > F         =     0.7212
```

nonathathoverall	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
studentfac	-.0279895	.1486988	-0.19	0.851	-.3224279	.2664489
rank	-.012274	.0496018	-0.25	0.805	-.1104904	.0859425
avgsatverbal	-.012893	.0556634	-0.23	0.817	-.123112	.0973261
avgsatmath	-.0382903	.0516193	-0.74	0.460	-.1405017	.0639211
revenuefromsports	9.22e-09	2.41e-08	0.38	0.702	-3.84e-08	5.69e-08
acceptancerate	-.065857	.0412041	-1.60	0.113	-.1474452	.0157312
_cons	22.01263	23.80833	0.92	0.357	-25.13025	69.15551
sigma_u	8.927929					
sigma_e	1.9034334					
rho	.95652207	(fraction of variance due to u_i)				

F test that all u_i=0: F(45, 119) = 26.10 Prob > F = 0.0000

Figure #2:

```
. xtreg nonathathoverall studentfac rank avgsatmath avgsatverbal revenue acceptancerate

Random-effects GLS regression              Number of obs   =    171
Group variable: schl                          Number of groups =     46

R-sq:  within = 0.0082                        Obs per group:  min =     1
        between = 0.6236                       avg =           3.7
        overall = 0.5923                       max =           4

corr(u_i, X) = 0 (assumed)                   Wald chi2(6)    =    58.95
                                                Prob > chi2     =     0.0000
```

nonathathoverall	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.0039521	.1388042	-0.03	0.977	-.2760033	.2680991
rank	-.0974082	.025476	-3.82	0.000	-.1473402	-.0474761
avgsatmath	.02659	.0429568	0.62	0.536	-.0576039	.1107838
avgsatverbal	-.010687	.0480265	-0.22	0.824	-.1048173	.0834433
revenuefromsports	-1.07e-08	2.06e-08	-0.52	0.603	-5.10e-08	2.96e-08
acceptancerate	-.1110636	.0368901	-3.01	0.003	-.1833668	-.0387604
_cons	-9.727076	17.1814	-0.57	0.571	-43.40201	23.94785
sigma_u	5.367742					
sigma_e	1.9034334					
rho	.88830032	(fraction of variance due to u_i)				

Figure #3:

```
. test avgsatverbal=avgsatmath

( 1) - avgsatmath + avgsatverbal = 0

      chi2( 1) =      0.18
      Prob > chi2 =    0.6697
```

Figure #4:

```
. reg nonathathoverall studentfac rank avgsatmath revenue acceptancerate confdum1 confdum2 confdum3 confdum4 confdum5, nocons
> t
```

Source	SS	df	MS			
Model	40526.8771	10	4052.68771	Number of obs =	171	
Residual	4300.25285	161	26.709645	F(10, 161) =	151.73	
Total	44827.13	171	262.146959	Prob > F =	0.0000	
				R-squared =	0.9041	
				Adj R-squared =	0.8981	
				Root MSE =	5.1681	

nonathathoverall	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
studentfac	.0760532	.1626731	0.47	0.641	-.2451951	.3973014
rank	-.1244714	.019997	-6.22	0.000	-.1639616	-.0849812
avgsatmath	.0165031	.0201112	0.82	0.413	-.0232127	.0562189
revenuefromsports	-5.62e-08	2.70e-08	-2.08	0.039	-1.10e-07	-2.86e-09
acceptancerate	-.2086933	.0376706	-5.54	0.000	-.2830855	-.1343012
confdum1	-1.510782	15.64977	-0.10	0.923	-32.41608	29.39451
confdum2	-3.30993	15.43064	-0.21	0.830	-33.78188	27.16322
confdum3	2.341248	15.84963	0.15	0.883	-28.95872	33.64122
confdum4	-1.00126	15.15566	-0.07	0.947	-30.93079	28.92827
confdum5	1.5956	15.42949	0.10	0.918	-28.87468	32.06588

```
. test confdum1 confdum2 confdum3 confdum4 confdum5
```

```
( 1) confdum1 = 0
( 2) confdum2 = 0
( 3) confdum3 = 0
( 4) confdum4 = 0
( 5) confdum5 = 0

      F( 5, 161) =      3.35
      Prob > F =    0.0066
```

Figure #5:

```
. tabulate conf, gen(confdum)
```

Conference	Freq.	Percent	Cum.
ACC	108	20.89	20.89
Big10	101	19.54	40.43
Big12	104	20.12	60.54
Pac12	94	18.18	78.72
SEC	110	21.28	100.00
Total	517	100.00	

Figure #6:

```
. reg nonathathoverall studentfac rank avgsatmath revenue acceptancerate confdum1 confdum2 confdum3 confdum4 confdum5, nocons
> t
```

Source	SS	df	MS	Number of obs =	171
Model	40526.8771	10	4052.68771	F(10, 161) =	151.73
Residual	4300.25285	161	26.709645	Prob > F =	0.0000
				R-squared =	0.9041
				Adj R-squared =	0.8981
Total	44827.13	171	262.146959	Root MSE =	5.1681

nonathathoverall	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
studentfac	.0760532	.1626731	0.47	0.641	-.2451951	.3973014
rank	-.1244714	.019997	-6.22	0.000	-.1639616	-.0849812
avgsatmath	.0165031	.0201112	0.82	0.413	-.0232127	.0562189
revenuefromsports	-5.62e-08	2.70e-08	-2.08	0.039	-1.10e-07	-2.86e-09
acceptancerate	-.2086933	.0376706	-5.54	0.000	-.2830855	-.1343012
confdum1	-1.510782	15.64977	-0.10	0.923	-32.41608	29.39451
confdum2	-3.30993	15.43064	-0.21	0.830	-33.78188	27.16322
confdum3	2.341248	15.84963	0.15	0.883	-28.95872	33.64122
confdum4	-1.00126	15.15566	-0.07	0.947	-30.93079	28.92827
confdum5	1.5956	15.42949	0.10	0.918	-28.87468	32.06588

Figure #7:

```
. xtreg nonathathoverall studentfac rank avgsatmath revenue acceptancerate
```

```
Random-effects GLS regression                Number of obs   =   171
Group variable: sch1                        Number of groups =    46

R-sq:  within = 0.0081                      Obs per group:  min =    1
        between = 0.6223                    avg           =    3.7
        overall = 0.5915                    max           =    4

Wald chi2(5)                               =   59.14
corr(u_i, X) = 0 (assumed)                  Prob > chi2     =   0.0000
```

nonathathoverall	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.0023238	.1381801	-0.02	0.987	-.2731519	.2685042
rank	-.0977459	.0253666	-3.85	0.000	-.1474636	-.0480283
avgsatmath	.0184987	.0229724	0.81	0.421	-.0265264	.0635239
revenuefromsports	-1.18e-08	1.99e-08	-0.59	0.553	-5.07e-08	2.71e-08
acceptancerate	-.1097103	.0363203	-3.02	0.003	-.1808968	-.0385238
_cons	-11.11453	15.94849	-0.70	0.486	-42.373	20.14393
sigma_u	5.3524457					
sigma_e	1.895913					
rho	.88851942	(fraction of variance due to u_i)				

```
. xtreg nonathfootball studentfac rank avgsatmath revenue acceptancerate
```

```
Random-effects GLS regression           Number of obs   =       172
Group variable: schl                   Number of groups =        46

R-sq:  within = 0.0091                 Obs per group:  min =         1
        between = 0.4677                avg =           3.7
        overall = 0.3802                max =           4

                                           Wald chi2(5)    =       35.13
corr(u_i, X) = 0 (assumed)             Prob > chi2     =       0.0000
```

nonathfootball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.1323734	.2877875	-0.46	0.646	-.6964266	.4316797
rank	-.1008932	.0424615	-2.38	0.017	-.1841162	-.0176701
avgsatmath	.0211545	.0415813	0.51	0.611	-.0603432	.1026523
revenuefromsports	-5.23e-08	4.09e-08	-1.28	0.201	-1.32e-07	2.78e-08
acceptancerate	-.1504181	.0724955	-2.07	0.038	-.2925066	-.0083296
_cons	8.710353	29.88439	0.29	0.771	-49.86197	67.28268
sigma_u	7.7671605					
sigma_e	4.5024566					
rho	.74848773	(fraction of variance due to u_i)				

```
. xtreg nonathbaseball studentfac rank avgsatmath revenue acceptancerate
```

```
Random-effects GLS regression           Number of obs   =       172
Group variable: schl                   Number of groups =        46

R-sq:  within = 0.0483                 Obs per group:  min =         1
        between = 0.1312                avg =           3.7
        overall = 0.1097                max =           4

                                           Wald chi2(5)    =       12.48
corr(u_i, X) = 0 (assumed)             Prob > chi2     =       0.0287
```

nonathbaseball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.6150282	.575931	-1.07	0.286	-1.743832	.5137758
rank	-.2958496	.1005544	-2.94	0.003	-.4929326	-.0987667
avgsatmath	-.1014238	.0927681	-1.09	0.274	-.2832459	.0803983
revenuefromsports	-2.06e-08	8.23e-08	-0.25	0.803	-1.82e-07	1.41e-07
acceptancerate	.1504957	.1502793	1.00	0.317	-.1440463	.4450378
_cons	81.23775	64.91282	1.25	0.211	-45.98904	208.4645
sigma_u	21.114527					
sigma_e	8.3633854					
rho	.86438474	(fraction of variance due to u_i)				

```
. xtreg nonathmbball studentfac rank avgsatmath revenue acceptancerate
```

```
Random-effects GLS regression           Number of obs   =       172
Group variable: schl                    Number of groups =        46

R-sq:  within = 0.1242                   Obs per group:  min =         1
        between = 0.1774                                     avg =         3.7
        overall = 0.1308                                     max =         4

                                           Wald chi2(5)     =       22.57
corr(u_i, X) = 0 (assumed)               Prob > chi2      =       0.0004
```

nonathmbball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	.1384866	.6860668	0.20	0.840	-1.20618	1.483153
rank	-.2632405	.0931467	-2.83	0.005	-.4458047	-.0806764
avgsatmath	-.0263806	.0939613	-0.28	0.779	-.2105414	.1577802
revenuefromsports	-2.65e-07	9.77e-08	-2.72	0.007	-4.57e-07	-7.38e-08
acceptancerate	-.1435199	.1690344	-0.85	0.396	-.4748212	.1877815
_cons	58.20168	68.46996	0.85	0.395	-75.99697	192.4003
sigma_u	15.451301					
sigma_e	11.096398					
rho	.65974216	(fraction of variance due to u_i)				

```
. xtreg nonathwbbball studentfac rank avgsatmath revenue acceptancerate
```

```
Random-effects GLS regression           Number of obs   =       172
Group variable: schl                    Number of groups =        46

R-sq:  within = 0.0574                   Obs per group:  min =         1
        between = 0.4156                                     avg =         3.7
        overall = 0.3871                                     max =         4

                                           Wald chi2(5)     =       37.38
corr(u_i, X) = 0 (assumed)               Prob > chi2      =       0.0000
```

nonathwbbball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.1940106	.3849228	-0.50	0.614	-.9484454	.5604242
rank	-.1236035	.0618931	-2.00	0.046	-.2449116	-.0022953
avgsatmath	-.0008499	.0587934	-0.01	0.988	-.1160829	.114383
revenuefromsports	1.82e-08	5.47e-08	0.33	0.739	-8.91e-08	1.26e-07
acceptancerate	-.3331145	.0988743	-3.37	0.001	-.5269047	-.1393243
_cons	11.3507	41.67415	0.27	0.785	-70.32912	93.03053
sigma_u	11.986429					
sigma_e	5.6934231					
rho	.81591715	(fraction of variance due to u_i)				

Figure #8:

```
. xtreg nonathmball studentfac rank avgsatmath revenue acceptancerate

Random-effects GLS regression           Number of obs   =       172
Group variable: schl                    Number of groups =        46

R-sq:  within = 0.1242                  Obs per group:  min =         1
        between = 0.1774                  avg =           3.7
        overall = 0.1308                  max =           4

Wald chi2(5)                            =       22.57
Prob > chi2                              =       0.0004

corr(u_i, X) = 0 (assumed)
```

nonathmball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	.1384866	.6860668	0.20	0.840	-1.20618	1.483153
rank	-.2632405	.0931467	-2.83	0.005	-.4458047	-.0806764
avgsatmath	-.0263806	.0939613	-0.28	0.779	-.2105414	.1577802
revenuefromsports	-2.65e-07	9.77e-08	-2.72	0.007	-4.57e-07	-7.38e-08
acceptancerate	-.1435199	.1690344	-0.85	0.396	-.4748212	.1877815
_cons	58.20168	68.46996	0.85	0.395	-75.99697	192.4003
sigma_u	15.451301					
sigma_e	11.096398					
rho	.65974216	(fraction of variance due to u_i)				

```
. xtreg nonathwball studentfac rank avgsatmath revenue acceptancerate

Random-effects GLS regression           Number of obs   =       172
Group variable: schl                    Number of groups =        46

R-sq:  within = 0.0574                  Obs per group:  min =         1
        between = 0.4156                  avg =           3.7
        overall = 0.3871                  max =           4

Wald chi2(5)                            =       37.38
Prob > chi2                              =       0.0000

corr(u_i, X) = 0 (assumed)
```

nonathwball	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
studentfac	-.1940106	.3849228	-0.50	0.614	-.9484454	.5604242
rank	-.1236035	.0618931	-2.00	0.046	-.2449116	-.0022953
avgsatmath	-.0008499	.0587934	-0.01	0.988	-.1160829	.114383
revenuefromsports	1.82e-08	5.47e-08	0.33	0.739	-8.91e-08	1.26e-07
acceptancerate	-.3331145	.0988743	-3.37	0.001	-.5269047	-.1393243
_cons	11.3507	41.67415	0.27	0.785	-70.32912	93.03053
sigma_u	11.986429					
sigma_e	5.6934231					
rho	.81591715	(fraction of variance due to u_i)				

Figure #9:

<u>Performance Rank</u>	<u>Conference</u>	<u>Coefficient Value</u>	<u>P-Value</u>
1	Big 10	-3.30933	.830
2	ACC	-1.510782	.923
3	Pac 12	-1.00126	.947
4	SEC	1.5956	.918
5	Big 12	2.341248	.918

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