Do College Teammates Make Good Academic Peers? A Study of Peer Effects Among Division III Athletes

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Abstract

College student-athletes spend a great deal of time with teammates, at every level of collegiate athletics. In this paper, we look at these teammates as peer group memebers in a common core curriculum class and measure the size and persistence of peer effects on student-athlete academic achievement. First, we demonstrate that peer assignment is as good as random. Using high school GPA as a measure of peer quality, we find significant and persistent peer effects. Finally, as a robustness check, we look at the potential that the peer effects are exherted by a broader range of peers, demonstrating that teammates are most important peer group.

1 Introduction

At a small liberal arts college, such as the one which we study in this paper, among the highlights that are mentioned to prospective students are the unique opportunities to interact with peers and learn in a collaborative setting. While peer effects have been studied in other, slightly larger universities, most notably Carrell et al. (2009), and Lyle (2007), as well as Sacerdote (2001), at the USAFA, West Point and Dartmouth respectively, there are no published studies of peer effects at a small liberal arts college. In each of the aforementioned studies, the authors seek to define a cohesive peer group - Carrell et al. and Lyle use squadrons (or the equivalent), since virtually all of a student's time is spent with those peers. Sacerdote's papers investigate the peer effects exherted by roommates. In this paper, we also use a well-defined peer group of Lewis & Clark students, teammates enrolled in the same section of the common core curriculum class.

For a student-athlete, this peer group is important for a number of reasons. Close teammate relationships spill over into the formation of lasting peer groups for both academic and social purposes. Anecdotally, one of the authors noticed that as a college athlete, he spent the lion's share of his time with his teammates and other athletes, particularly in the first year. Teammates advise their peers academically, help to match teammate desires for professors, courses, and support and

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This is a working paper draft - comments are welcome and appreciated.

assist each other's academic efforts.

Students in our study are from Lewis & Clark College, a small liberal arts college with a NCAA Division III athletic program. This study focuses on athlete peer groups formed during the student's fall semester, in a common core curriculum class titled "Inventing America," which we refer to as Core 110 for the remainder of the paper.

For the peer group we study, peer assignment appears to be a random subset of the larger group of potential peers, an issue we discuss at length in section 4.

This paper makes use of the data set generated by a similar peer group study, supported by the TEAGLE Foundation, which researched the effects on student achievement from peer groups formed in the freshman core courses at Whitman, Lewis & Clark and Reed Colleges.

The remainder of this paper is organized as follows. Section 2 summarizes previous research. We provide background to athletics at Lewis & Clark College in section **??**. Section 3 describes the students in our dataset by intercollegiate athlete status, academic characteristics at the time of entry into college, and college achievement characteristics. We test the hypothesis that peer assignment is random in section 4, while our regression specifications are detailed in section 5. We discuss our results in Section 6. Afterwards, in section 7, we look at other potential peer groups through which these peer effects may be exherted. Finally, we draw conclusions and discuss possible extensions to this research in Section 8.

2 Literature Review

There have been a number of studies of peer effects at every level of education. There are studies on primary school peer effects, such as Rangvid (2003); Vigdor and Nechyba (2004), studies on peer effects in secondary schools, (Ding and Lehrer, 2006), and studies on peer effects in universities, such as Winston and Zimmerman (2003), Sacerdote (2001), Lyle (2007) and Carrell et al. (2009). We draw on all these studies in this research, as well as a few studies that look more specifically at the academic acheivement of athletes.

Central to the literature on peer effects is the observation made by Manski (1993) that there is a potential in all studies of peer effects to encounter the "reflection problem." Functionally the reflection problem arises when peers share common background characteristics; then outcomes of individuals in a peer group cannot be unambiguously attributed to the peer group. This would occur in our research if peers systematically share unobserved characteristics such as socio-economic background. Manski stresses in his paper that such a situation would prohibit unbiased or consistent estimation of peer effects. Most successful peer group research tries to exploit randomization (or psuedo-randomization) in order to address this empirical issue.

While most of the original peer effects research was done at the elementary school level, particularly the Boston METCO project (Angrist and Lang, 2004), recent work on peer effects has focused

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on peer effects at the university level. In much of this research, the focus is on having a well-defined peer group that is plausibly randomly assigned. Winston and Zimmerman (2003) and Sacerdote (2001) both study the effects that rommmates have on those that live with them, at Williams and Darmouth Colleges, repectively. Winston and Zimmerman find that the academic achievements of a student in the school's lowest 15% of SAT scores are generally negatively affected if their roommate is in the same category. Students in the middle 70% are also affected negatively by a roommate in the bottom 15%, although this effect is less frequently statistically significant. They use quantile regressions in order to account for any non-linearity in the effects of peers on own acheivement. However, their roommate assignments are not truly random, and so they note that ideal data would incorporate an element of random roommate assignment. Following that paper, Zimmerman (2003) also looks at roommate randomization at Williams College, and finds that students in the middle 70% of the distribution of SAT scores do worse than predicted when their roommates are in the bottom 15%.

Sacerdote (2001) looks at peer effects for roommates at Dartmouth College, which randomly assigns roommates to one another, conditional on a few parameters. Sacerdote finds positive peer effects for a student in the bottom 25% whose roommate is in the top 25%, while bottom and middle roommates exert a roughly similar sized peer effect. Sacerdote also finds that student achievement improves if both roommates are in the top 25% of the distribution of abilities.

One of the critiques of this peer effects research is that a roommate might not be a very influential peer, as there is no way of measuring whether the student actually spends time with his roommate, or even takes similar classes. Two recent papers address both the randomization of peer groups and the problem of finding a group of peers that is actually influential. In the first study, Lyle (2007) looks at peer effects at the squadron level at West Point Military Academy. He finds that while there are no peer effects in terms of acheivement gains or losses, social groups do influence choice into studying engineering, as well as the decision to stay in the Army after the required commitment is finished. In the second paper, Carrell et al. (2009) look at the peer effects for the Air Force Academy (AFA). Carrell et al. argue convincingly that the peer groups are sufficiently random, and that the structure of the first year for students makes these peer groups academically influential. They find large peer effects, in terms of magnitude and statistical significance, in science and math classes, but little to no peer influence in foreign language courses. They note that "peer effects may be working through study partnerships versus a social norm of effort." This is important for our paper, since our peer group is one that forms a natural study group for the common core class. However, because our class is a humanities class, we expect our peer effects to be smaller in magnitude, since the potential for knowledge transfer is lower for a humanities class than science and mathematics.

2.1 Athlete Academic Acheivement in College

There is also a large literature addressing the academic achievement of athletes. Both Maloney and McCormick (1993), researching a Division I-A college, and Robst and Keil (2000), who investigate athlete performance at a Division III college, note that it is important to measure the ease of classes that athletes take throughout their four years of college. Additionally, McCormick and Tinsley

We do something similar in our regressions, controlling for area of major. The controls for major area are Arts and Humanities, Math and Science, and Social Sciences. A double-major across disciplines is counted as half of one area and half of another, while a minor is one-fourth of that area.

(1987) argue that there is a symbiotic relationship between academics and athletics, implying that skills learned in athletics are transferrable to the academic arena and vice-versa. Garrett (2000) finds that the sport in which one participates is not significant to academic performance, and both he and Sedlacek (1992) argue that athletes need to be viewed as non-traditional students, whose college performance is not accurately predicted by test scores and high school GPA.

Since both SAT and high school GPA are sometimes troubling measures of college achievement, Kotlyarenko and Ehrenberg (2000) utilize a measure of ability used by most admissions offices called the academic index, which factors in SAT I performance, SAT II performance and class rank. This index paints a more complete picture of a student, and so is useful as a predictor of achievement in college. We also use a similar variable, known as the admission rating, which is discussed later in the paper and explained in full detail in the appendix. Finally, Robst and Keil (2000) find that the average student-athlete at the Division III college researched takes harder classes and maintains a higher GPA than his or her non-athletic peers, controlling for SAT scores, racial background and high school rank.

3 Description of Data Set

Our data set includes the admissions and academic records of all Lewis & Clark College students who entered the college as full-time, first-year students from 1995 through 2002. Admissions information provides the following data for each student: home demographic information, high school information (high school GPA, high school rank, and when available, high school type and size) and a numerical admissions rating constructed by the admissions staff. SAT or ACT test scores are optional for admission at Lewis & Clark College, though most students choose to submit them. Those who do not submit them have chosen to apply to the college through the college's Portfolio Path, which does not require a student to submit test scores. A table of summary statistics is in Table 2 in the tables appendix.

These missing data on test scores presents us with a unique problem, because the test score data is missing in a way that is non-random, making imputation tricky. Instead, in order to measure the background characteristics of an individual, we use the student's high school GPA, which is required to be submitted for admission. This measure is available in our data for almost every student, and when it is missing, as far as we can surmise, it is random.

Additionally, we have data on every class a student took while at the college, the professor for the class, and at what time of day each class was offered, as well as what grade was received in

Sixty-nine percent of our sample has SAT scores that are not coded as missing. Thirty percent of our sample has ACT scores that are not coded as missing. Together, eighty-eight percent of our sample has either SAT or ACT scores recorded.

For more information on the Portfolio Path, please visit `http://college.lclark.edu/offices/admissions/apply/portfolio_path/`

In results not shown here, we tested if SAT non-submittal was random, with the regression $SATMISSING_i = \beta X_i + \epsilon_i$. We found that over three-fourths of the individual characteristics we include on the RHS are statistically significant, confirming our suspicion that it is non-random.

Every student in our data set was admitted into the school, and therefore had to have High School GPA. There were 20 student-athletes in our sample who did not have a high school GPA reported; we drop these students.

the class. From these data, we construct our acheivement variables, which are as follows: Core 110 grade, first semester GPA, first and second year GPA, cumulative GPA and persistence to graduation within six years.

In our main regressions, we include only student-athletes who have at least one other teammate in their section, because we can then have a peer group. Therefore, our sample size is 428 for all of our main regressions. We do not have to drop anyone in our robustness checks, looking at the peer group of athletes and the peer group of classmates, since the peer group always has at least one individual in it.

3.1 Background on Lewis & Clark College

Just over 22 percent of students at Lewis & Clark College participate in a varsity athletic sport, which means that there are ample opportunities for peer groups to form within the athlete community. Furthermore, about seventy-five percent of the athletes that participate in an intercollegiate sport have been recruited to do so. Much of this recruiting emphasizes the peer group a student-athlete would gain by choosing to attend Lewis & Clark College. The distribution of academic acheivement both before and during college varies significantly by sport, and so in our regressions we include sport fixed-effects.

Competing at the NCAA Division III level means that no athletic scholarships can be given. Applicants interested in competing in intercollegiate athletics must be granted admission to the college on their own academic merits. This means that we should expect that athletes' academic and admissions records honestly represent them. There are currently nineteen varsity sports at the college, however during the years covered by our research there were only eighteen varsity sports (women's soccer was added in 2004).

3.2 Peer Variables of Interest

We construct the following variables for our peer group of interest. We intend these variables to capture empirically the different dimensions of possible peer effects that have been discussed in the literature. As mentioned above, we use high school GPA as our measure of peer quality.

First, for each student we calculate the mean of peer mean as the mean value for all other members in one's peer group. This variable helps address questions related to the effect of average peer group ability on one's academic achievement. Second, we calculate the standard deviation of the peer group's high school GPA; *Standard Deviation* is the sample standard deviation of the background characteristic for all peer group members. This variable is important because it will address to what extent the dispersion in quality of a peer group affects student achievement.

Lewis & Clark College has roughly 2000 students, and so there are around 440 student athletes in any given year.

This statistic excludes Men's and Women's Crew, since very little recruiting occurs until students are on campus, partially due to the low number of high school crew programs around the United States, particularly on the West Coast.

Parker et al. (forthcoming) find this to be an important peer characteristic in their study, which uses the same data

In previous versions of this paper, we also controlled for the individual's position in the peer group. But if we are controlling for peer mean, SD and own high school GPA, it is unclear how the coefficient on position would be

Now that we have discussed the peer variables that we measure, we discuss our tests for random assignment.

4 Random Assignment to Core 110 Section

In this section, we discuss the techniques that we used to verify that peer assignment was effectively random for the peer group of teammates in the same Core 110 section. While clearly there are high correlations between teammates in terms of ability, we argue that peer assignment is effectively random for two reasons. First, incoming students register for their Core 110 class before they arrive on campus. Second, because of this, we posit that any teammates in a Core 110 section are a random sub-sample of the broader group of teammates. We test this assertion in section 4.2.

4.1 Signing up for Core 110

Every summer, incoming first-year students fill out a preferences sheet online in order to sign up for a section of the common curriculum class, Core 110. The preference sheet lists only the professor's name and the time of the class. The student then submits a list of five prioritized classes. In enrolling students in classes, the registrar attempts to honor these priorities. If a student does not submit his or her list of classes, class assignment is random, conditional on space constraints (Class sizes average around 18 students).

Important to note is that in five years of our data (1998-2002), there were special morning sections of Core 110 for which fall athletes were encouraged to sign up, so that their classes would not conflict with potential practice times. Whether this affects peer randomness is ambiguous. It certainly increases the likelihood of having more teammates in one's class, but that merely implies that one's peer group will include a larger percentage of one's potential peers. In the next subsection, we explicity test this question, of whether having special morning sections affected the randomness of the assignment to classes.

4.2 Testing for Effective Random Assignment

To test the hypothesis that students are effectively randomly assigned peers from their team, we follow the methodology in Carrell et al. (2009), as shown in the regression equation below.

$$Y_{ijk} = \beta \bar{Y}_{-i,jk} + \delta_{jt} \tag{1}$$

The above equation will test whether the background characteristic of student i in section j and team k, Y_{ijk}, is correlated with the mean characteristics of teammates, $\bar{Y}_{-i,jk}$ in section j on team k, including team-by-year fixed effects, δ_{jt}. Our results are below, in table 1. Additionally, we control for the mean of the potential peer group, since otherwise our estimates of β will be biased downwards, as noted by Guryan et al. (2009). Column 1 tests randomization without year fixed-effects, while column 2 includes year-fixed effects, since the quality of the incoming class fluctuates year-to-year.

interpreted, since it necessarily means changing one of the other characteristics.

To test whether these fluctuations were substantial, we performed an ANOVA test on these quality measures by year. Our F-statistic was 5.45, so we reject the null hypothesis that the means from year-to-year are the same.

Table 1: Results of Randomization Tests

	(1)	(2)	(3)
High School GPA Peer Mean	0.0143	0.0143	0.0438
	(0.0359)	(0.0359)	(0.0325)
Year Fixed Effects?	No	Yes	No
Years Included	1995-2002	1995-2002	1998-2002

Robust Standard Errors are in Parentheses.

Regressions control for sport-by-year fixed effects, and potential peer group mean high school GPA

As shown in Table 1, we find that in all of our specifications, the , the correlation conditional on sport-year cohort is statistically insignificant. We also tested for random assignment specifically in the years where there were special morning sections for fall athletes, in 1998-2002. Our results are shown in column 3 of table 1. It shows that assignment to sections was just as random as in the previous years.

We also tested for random assignment specifically in the years where there were special morning sections, 1998-2000. Our results are shown in column 3 in table 1. It shows that assignment to sections was just as random as in the previous years, at least according to two of our measures. Therefore, we are relatively certain that presence of these special morning sections do not invalidate our results.

Clearly, there are some sports (e.g., golf) where there may be only one teammate of the same year of entry, and therefore, the subsample is not "random" in the above sense. However, since this is only a small proportion of our sample, it is unlikely to affect our results.

5 Regression Specifications

We model athlete peer effects as one of a number of variables affecting a student-athlete's academic achievement. We take Manski's (1993) linear model of endogenous social effects as our basic framework. This model attempts to identify and separate three effects on a student's achievement that are observationally correlated with his or her peer group. We want to identify endogenous effects (peer effects), which is the portion of a student's academic performance that varies with peer group performance. Also, we want to control for exogenous effects, which is the part of a student's acheivement that varies with exogenous background characteristics, as well as correlated effects, which are the portion of acheivement that is attributable to common shocks for the entire peer group.

Our general empirical model is below.

$$GPA_{ijk} = \alpha + \beta X_{ijk} + \gamma Peer_i + \theta_t + \mu_k + \epsilon_i \tag{2}$$

Where GPA_{ijk} is one of a number of different achievement measures for a student i in section j and sport k: Core 110 grade, first semester GPA, first and second year GPA, cumulative GPA and persistence to graduation. X_{ijk} includes all of an individual's own characteristics, including

Persistence to graduation is subject to many counfounding external shocks, such as loss of financial aid, inability

HSGPA, dummies for ethnicity and race, professor teaching Core 110, and type of high school. The vector, $Peer_{ijk}$, contains the peer group variables discussed in section 3.2. We also include year fixed-effects, sport fixed-effects (in our main results), and a dummy for taking a science class in the first semester.. The random error term is ϵ_{ijk}.

In all regressions including more than one peer variable, we perform an F-test to see if peer variables are jointly significant. This is reported at the bottom of the tables.

6 Regression Results

In the tables appendix, we present the results of our main regressions. Tables 3 - 7 present our main results. The first column in each table presents a regression of the outcome on own high school GPA and peer mean, including year fixed-effects, while the second column includes sport fixed-effects. Column (3) controls for SD of peer quality, omitting sport fixed-effects, and then column (4) includes sport fixed-effects.

A few patterns stand out from this analysis. First, when using high school GPA, we find statistically significant peer effects for all acheivement variables. Our point estimates are largest for term GPA, implying that the peer group formed in one class may spill over to concurrent classes. Furthermore, our results are robust to the inclusion of other peer characteristics, such as standard deviation and position within the peer group. Our tests for the joint significance of all peer characteristics are consistently significant, with the exception of Core 110 grade. Our point estimates of peer group standard deviation and position within peer group are also consistently positive, suggesting that a student gains from have a more diverse peer group, as well as being of higher quality when compared with teammates. We do find some evidence that peer effects dissipate over time, as point estimates for later achievement variables are smaller in magnitude, although not significantly different.

6.1 Alternative Specifications

We also performed the above regressions, restricting the sample to those athletes whose sports were played in the fall, which includes football, volleyball and cross-country. Our results are in table 8. There are similar patterns to the main results, although the point estimates do fall over time. However, because we lose so many observations by restricting our sample only to fall athletes, the standard errors are much larger. Overall, these results are inconclusive; there may be larger peer effects for fall sport athletes, particularly in the first semester of college (when the peer group is the most cohesive), but the effects regress to the mean, becoming similar to those of all athletes (the point estimates are almost identical for cumulative GPA, shown in table 6).

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to pay for tuition, family hardship, or not wanting to continue at Lewis & Clark College, and transferring. Since all of these are simply coded as not graduating from the College, it seems unlikely that peer effects play a large role in this situation. For this reason, we look at our regressions of persistence to graduation as a zero test. We suspect peers affect the academic outcomes only in terms of grades received.

We omit dummies for professors who only taught Core 110 once, since this dummy would absorb all of the difference at the section level between predicted and actual

When using sport fixed-effects, the dummy for football is always the ommitted variable

Another potential channel for peer effects is not the quality of peers who are teammates, but the mere presence of them. In order to test if the presence of peers who are teammates or athletes affected outcomes, we ran our original regression specification from equation 2, but now our $Peer_{ijk}$ is simply the fraction of your classmates who are teammates or athletes. The results of these regressions are in table 9. These results tell a much more interesting story. We can conclude certainly that the channel for peer effects of teammates is *not* merely the presence of peers, but the quality of those peers. However, it appears that the channel for peer effects for athletes may be the presence of peers; we find significantly negative effects on outcomes the larger the fraction of athletes in Core 110 section. We return to the idea of athlete peer effects in section 7

6.2 Discussion

Some work must be done to interpret the coefficients. Since the standard deviation of peer mean high school GPA is 0.29, our coefficient in table 6, column 6, says that a one standard deviation increase in peer quality will lead to about a 0.06 increase in cumulative GPA.

The magnitude of these peer effects are relatively large, compared to similar studies. This is particularly striking because Core 110 is a humanities course. Carrell et al. (2009) find peer effects only in math and sciences courses, where knowledge is easily transferrable. Since Core 110 is a humanities course (although not always taught by humanities professors), we would have expected that the peer effects woud be smaller. It may be that the peer group we are studying is simply a very effective peer group. As we mentioned, these peers share a lot of time together in all aspects of their college career, persisting on after the initial peer group formation (which is in contrast to Carrell et al. (2009), where peer groups are essentially dissolved after one year).

7 Robustness Checks

In order to ensure that our results for teammates are not simply random, we perform a variant of a permutation test, in the following manner. First, for each individual, we assign the peer group mean and standard deviation of some individual randomly chosen (with replacement) from the population of athletes that appear in our main regressions. Then, we run regression (4) from our main specifications, storing the coefficient and standard error from both peer mean and standard deviation, and then calculate the t-statistic. We replicate this process 1000 times. If there is some hidden bias that is driving our findings, we would expect the distribution of t-statistics to be centered at a value other than zero. The results of this permutation test are shown in table 10.

Clearly, the distribution of t-statistics are centered on zero in every case, and in fact the distribution is tighter that normal t-statistics show; in most cases, the 2.5 percentile and 97.5 percentile values of our t-statistics are close to the actual critical values of -1.96 and 1.96, respectively. This test serves for us as a falsification test. Since there should be no effect on average of assigning a student a random peer group that is not necessarily their own, we find that this is indeed the case. Therefore, this makes our findings more robust.

One potential story that would weaken our results is that the peer effects are being exherted by a larger peer group, of which teammates are a subgroup. There are two other potential peer groups

through which these peer effects might be exherted. First, they might be an effect of athletes in class section. Second, these peer effects may be exherted by the entire class. For this reason, we test for the presence of peer effects on these two peer groups.

First, we test that peer assignment is random. These results for both athletes and classmates are presented in table 11 of the tables appendix. and 13, respectively. We find that overall, our results are similar to our earlier findings of peer randomization. In our test of randomization for classmates, year fixed-effects make a large difference, which should be the case; we want to measure random assignment conditional on being in the potential peer group, which is what year fixed-effects do in this case.

Second, we run the same regression specifications as before, only now the peer groups of interest are athletes in Core 110 section and Core 110 section classmates; these results can be seen in table 12. Overall, our results are encouraging for our original hypothesis. The only peer characteristic that is consistently significant for athletes is peer standard deviation.

Our results for peer effects where the peer group is all students in core 110 section can be found in table 13. We find that peer effecs are insignificant almost across the board, when controlling for peer group standard deviation. While the peer characteristics are jointly significant for the first semester and core 110 grade acheivement outcomes (not reported), this significance dissipates for later years, which is the exact opposite of our main results; for our main results, the peer effects begin small, but the point estimates grow over time. The significance of peer standard deviation is consistent with the findings of Parker et al. (forthcoming), which uses the same methodology and data as our current paper; this shows that our method is consistent

Overall, our results show that the channel through which the peer effects are exherted is almost certainly the teammates in the same section of Core 110.

8 Conclusion

In this paper, we have looked at a particularly unique peer group, teammates in a common core curriculum class at a liberal arts college. Because this peer group interacts regularly inside and outside of class, we would expect that peer effects would be most strongly exherted by this peer group. In order to ensure that our results are not being driven by a selection problem, we test for random assignment of peers, and find that peers are as good as randomly assigned to the common core curriculum class. In our main results, we find that there are positive peer effects, and even more surprisingly, we find that peer effects are persistent and grow in magnitude over time. This conflicts with the findings of Carrell et al. (2009), who find that peer effects dissipate significantly after the first year of interaction.
This conflict is significant, because in both of the current paper and Carrell et al., the peer group is very cohesive, capturing more of the total peer influence by which a student is impacted. However, our findings may differ because of the continuing peer influence in our study. In Carrell et al., students are reassigned to a new peer group after their first year, limiting the impact that their first-year peers can have. However, in our study, students have the opportunity of continued interaction with the peer group throughout college.

Therefore, our paper is able to look at how peer effects are exherted over long-term interactions. It may be that because many papers focus on short-run peer effects, they find very small values, because peer effects grow over time. This paper is the first step in understanding this interaction. We find that the effects grow throughout college, and hence that peer effects are more cumulative than thought previously.

This paper also suggests that other peer characteristics, besides peer mean, may also affect the student. We find that the dispersion of peer ability may also impact acheivement in a positive manner, suggesting that studies should ensure that they properly address these other potential channels for peer effects beyond the simple peer mean.

One potential extension of this project would be to find a university or college that has a common core curriculum class that is in the maths or sciences, in order to see if there are stronger peer effects in this type of course.

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A Tables Appendix

COMMENT: Do we want to combine these tables all into 1 table with 5 panels? Or do we want to keep these so we can have the f-tests shown?

Table 2: Summary Statistics by Athlete Status

	Athlete	Non-Athlete
SAT Verbal	610.10	636.86
	(70.61)	(73.89)
SAT Math	615.61	611.51
	(68.90)	(70.81)
HS GPA	3.56	3.50
	(0.38)	(0.41)
Core 110 Grade	3.028	3.061
	(0.648)	(0.725)
Cumulative GPA	3.07	3.12
	(0.53)	(0.55)
Grad. Rate	70.96%	64.75%
Observations	847	2933

Table 3: High School GPA - All Athletes

	Dependent Variable: Core 110 Grade			
	(1)	(2)	(3)	(4)
HS GPA	0.544***	0.542***	0.557***	0.585***
	(0.104)	(0.109)	(0.108)	(0.114)
Peer Mean HS GPA	0.0959	0.0250	0.117	0.0933
	(0.139)	(0.140)	(0.154)	(0.153)
Peer SD HS GPA			0.0871	0.321
			(0.225)	(0.225)
Sport FE	No	Yes	No	Yes
Sport F-Stat		2.86		4.11
p-value - Sport		0		0
Peer Char. F-Stat			.29	1.02
p-value - Peer			.75	.37
Adj. R-Squared	0.243	0.282	0.242	0.285
N	428	428	428	428

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: HS GPA - All Athletes

	Dependent Variable: Term GPA			
	(1)	(2)	(3)	(4)
HS GPA	0.671***	0.658***	0.729***	0.742***
	(0.0966)	(0.102)	(0.0962)	(0.103)
Peer Mean HS GPA	0.146	0.0818	0.239**	0.213**
	(0.0959)	(0.101)	(0.103)	(0.104)
Peer SD HS GPA			0.393**	0.619***
			(0.178)	(0.171)
Sport FE	No	Yes	No	Yes
Sport F-Stat		2.32		3.97
p-value - Sport		.02		0
Peer Char. F-Stat			3.72	6.98
p-value - Peer			.03	0
Adj. R-Squared	0.287	0.311	0.294	0.330
N	428	428	428	428

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: HS GPA

	Dependent Variable: First Two Year GPA			
	(1)	(2)	(3)	(4)
HS GPA	0.710***	0.700***	0.769***	0.778***
	(0.0794)	(0.0807)	(0.0713)	(0.0742)
Peer Mean HS GPA	0.113	0.0616	0.206*	0.183*
	(0.0970)	(0.101)	(0.105)	(0.104)
Peer SD HS GPA			0.396***	0.571***
			(0.137)	(0.130)
Sport FE	No	Yes	No	Yes
Sport F-Stat		2.7		4.11
p-value - Sport		.01		0
Peer Char. F-Stat			4.5	9.69
p-value - Peer			.01	0
Adjusted R-Squared	0.339	0.365	0.348	0.385
N	428	428	428	428

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Peer Effects for Teammates in Core 110 Section

	Dependent Variable: Cumulative GPA			
	(1)	(2)	(3)	(4)
HS GPA	0.691***	0.683***	0.747***	0.753***
	(0.0720)	(0.0723)	(0.0638)	(0.0656)
Peer Mean HS GPA	0.142	0.0944	0.231**	0.205*
	(0.100)	(0.103)	(0.110)	(0.107)
Peer SD HS GPA			0.373***	0.522***
			(0.139)	(0.130)
Sport FE	No	Yes	No	Yes
Sport F-Stat		3.27		4.45
p-value - Sport		0		0
Peer Char. F-Stat			4.11	8.24
p-value - Peer			.02	0
Adjusted R-Squared	0.344	0.372	0.352	0.389
N	428	428	428	428

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Peer Effects for Teammates in Core 110 Section

Dependent Variable: Persistence to Graduation				
	(1)	(2)	(3)	(4)
HS GPA	0.941*	1.010**	1.027**	1.096**
	(0.494)	(0.498)	(0.499)	(0.501)
Peer Mean HS GPA	0.569	0.549	0.709	0.689
	(0.467)	(0.523)	(0.482)	(0.527)
Peer SD HS GPA			0.544	0.540
			(0.637)	(0.631)
Sport FE	No	Yes	No	Yes
N	428	428	428	428

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Peer Effects Exerted by Teammates in Core 110 Section - Fall Athletes Only

	(1)	(2)	(3)	(4)
(a) Dependent variable: Core 110 Grade				
Peer Mean	0.450	0.236	0.644	0.430
	(0.292)	(0.373)	(0.391)	(0.450)
Peer SD			0.653	0.642
			(0.450)	(0.440)
(b) Dependent variable: Term GPA				
Peer Mean	0.246	0.0984	0.533*	0.432
	(0.273)	(0.342)	(0.292)	(0.342)
Peer SD			0.964***	1.099***
			(0.337)	(0.306)
(c) Dependent variable: First Two Year GPA				
Peer Mean	0.175	0.0386	0.348	0.216
	(0.215)	(0.245)	(0.266)	(0.299)
Peer SD			0.582*	0.584*
			(0.296)	(0.290)
(d) Dependent variable: Cumulative GPA				
Peer Mean	0.258	0.0795	0.429	0.249
	(0.216)	(0.257)	(0.273)	(0.316)
Peer SD			0.574*	0.559*
			(0.305)	(0.300)
(c) Dependent variable: Persistence to Graduation				
Peer Mean	0.931	0.306	1.661	1.083
	(0.788)	(1.038)	(1.067)	(1.342)
Peer SD			2.206**	2.080*
			(1.091)	(1.215)
Number of obs.	129	129	129	129

Standard Errors in parentheses, Clustered at the Sport-Year Level

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Testing the effect of presence of peers

	(1)	(2)	(3)	(4)
(a) Dependent Variable: Core 110 Grade				
Fraction Teammates	-0.0890	0.233		
	(0.120)	(0.161)		
Fraction Athletes			-0.414***	-0.267**
			(0.115)	(0.114)
(b) Dependent Variable: Term GPA				
Fraction Teammates	-0.125	0.103		
	(0.0972)	(0.178)		
Fraction Athletes			-0.463***	-0.349***
			(0.103)	(0.102)
(c) Dependent Variable: First Two Year GPA				
Fraction Teammates	-0.103	0.128		
	(0.0872)	(0.153)		
Fraction Athletes			-0.476***	-0.350***
			(0.0884)	(0.0847)
(d) Dependent Variable: Cumulative GPA				
Fraction Teammates	-0.0904	0.104		
	(0.0883)	(0.150)		
Fraction Athletes			-0.442***	-0.324***
			(0.0882)	(0.0842)
(e) Dependent Variable: Persistence to Graduation				
Fraction Teammates	-0.0170	0.0911		
	(0.0746)	(0.128)		
Fraction Athletes			-0.137	-0.0703
			(0.0860)	(0.0871)
N	826	826	826	826

Robust Standard Errors in parentheses

SEs Clustered at the Sport-Year Level for 1 and 2, heteroskedastic-robust in 3 and 4

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Summary of T-statistics from a 1000 replication modified permutation test

	Mean	SD	2.5 centile	97.5 centile
(a) Dependent variable: Core 110 Grade				
Peer Mean	-.007	1.05	-2.11	1.97
Peer SD	-.034	1.039	-2.160	2.0189
(b) Dependent variable: Term GPA				
Peer Mean	-.0337	1.0290	-2.075	2.0312
Peer SD	.00400	1.0175	-2.0733	2.0130
(c) Dependent variable: First Two Year GPA				
Peer Mean	-.03477	1.0172	-2.0068	2.0810
Peer SD	-.0213	.9728	-1.9205	1.9186
(d) Dependent variable: Cumulative GPA				
Peer Mean	-.03414	1.0030	-1.9727	2.0514
Peer SD	-.0200	.9685	-1.9426	1.8056
(c) Dependent variable: Persistence to Graduation				
Peer Mean	-.04106	1.0898	-2.1491	1.992
Peer SD	-.0664	1.0790	-2.2262	1.9216

Results of a modified permutation test, 1000 replications

In these regressions, heteroskedastic-robust standard errors were used.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Testing Randomization for Athletes and Classmates in Core 110 Section

	(1)	(2)
(a) Testing Randomization - Athletes		
Peer Group Mean	-0.0838	-0.00358
	(0.0675)	(0.0110)
Observations	809	809
(b) Testing Randomization - Section		
Peer Group Mean	-0.525***	0.00128
	(0.0464)	(0.00464)
Observations	3196	3196
Year Fixed Effects	No	Yes

Robust Standard Errors are in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Peer Effects Exerted by Athletes in Core 110 Section

	(1)	(2)	(3)	(4)
(a) Dependent variable: Core 110 Grade				
Peer Mean	-0.00267	-0.0267	0.106	0.0541
	(0.0916)	(0.0897)	(0.111)	(0.108)
Peer SD			0.300*	0.220
			(0.173)	(0.172)
(b) Dependent variable: Term GPA				
Peer Mean	-0.0171	-0.0292	0.155	0.124
	(0.0858)	(0.0862)	(0.107)	(0.106)
Peer SD			0.474***	0.417**
			(0.165)	(0.165)
(c) Dependent variable: First Two Year GPA				
[1em] Peer Mean	0.0324	0.0259	0.168*	0.142
	(0.0799)	(0.0804)	(0.0983)	(0.0986)
Peer SD			0.376***	0.317**
			(0.137)	(0.137)
(d) Dependent variable: Cumulative GPA				
Peer Mean	0.00986	0.00827	0.130	0.112
	(0.0789)	(0.0799)	(0.0992)	(0.100)
Peer SD			0.332**	0.282**
			(0.134)	(0.134)
(e) Dependent variable: Persistence to Graduation (LOGIT)				
Peer Mean	0.500	0.454	0.751	0.645
	(0.390)	(0.412)	(0.457)	(0.484)
Peer SD			0.692	0.519
			(0.653)	(0.684)
Number of obs.	808	808	808	808

Robust Standard Errors in Parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Peer Effects Exerted by Students in Core 110 Section

	(1)	(2)
(a) Dependent variable: Core 110 Grade		
Peer Mean	-0.372***	-0.189
	(0.140)	(0.173)
Peer SD		0.412
		(0.265)
(b) Dependent variable: Term GPA		
Peer Mean	-0.401***	-0.272*
	(0.130)	(0.159)
Peer SD		0.290
		(0.209)
(c) Dependent variable: First Two Year GPA		
Peer Mean	-0.132	-0.0122
	(0.108)	(0.135)
Peer SD		0.270
		(0.202)
(d) Dependent variable: Cumulative GPA		
Peer Mean	-0.101	0.0194
	(0.107)	(0.132)
Peer SD		0.271
		(0.197)
(e) Dependent variable: Persistent to Graduation		
Peer Mean	0.692	0.915*
	(0.442)	(0.534)
Peer SD		0.518
		(0.692)
Number of obs.	2273	2273

Robust Standard Errors in Parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$