PEER EFFECTS AT COLORADO COLLEGE

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Abstract

Peer effects in institutions of higher education are often measured in terms of differences in student achievement after interaction with able peers. This paper uses an empirical approach to analyze peer effects on student achievement in classrooms at Colorado College. Under an ordinary least squares model, student academic rating is employed as a proxy for ability – understood to be student "quality" for the purposes of this paper – and the 4.0 GPA scale-equivalent of the grade received in a class is employed as a proxy for achievement. Specific focus is placed on the potential effects that international students and student athletes may have on the achievement of their peers. If these focus groups pose any effects, how do these effects vary with course division (humanities, natural sciences, social sciences)? This paper finds evidence of the existence of peer effects at Colorado College; specifically, international students have a large positive effect on the achievement of non-international students, and the greatest benefit from peer effects occurs in humanities courses.

KEYWORDS: (Peer effects, Higher education, Student athlete, International student)
JEL CODE: I00, I2

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Introduction

In determining the quality or quantity of an individual's performance, several factors must be taken into account; the individual's characteristics alone cannot realistically determine performance levels. Peer effects is a term which encompasses the idea that an individual's performance is affected by the qualities of her peers and not solely by the individual's traits. The concept of peer effects is applicable to workplaces, prisons, and schools – anywhere where interactions with other people are commonplace. At schools, student performance is affected by teachers and their peers – fellow students. This idea is acknowledged even outside of academia, as both students and parents know that the quality of a student body plays an important role in the student's educational experience. A student who works closely with a particularly bright peer is likely to have some academic benefit just as a particularly bright student in a class full of poor students may suffer academically.

The study of peer effects in education has largely centered on primary and secondary schools. Although peer effects in higher education are just as valuable to examine, they are more difficult to model because students choose which institution to attend and then which courses to take. Higher education peer effects studies are thus plagued with the econometric issues surrounding selection bias. It cannot be determined whether a student is performing a certain way because of observable environmental factors or because of underlying characteristics not noted by the data. The lack of a perfectly random quality and the possibility of unobservable variables render the results of peer effects studies difficult to interpret.

Nonetheless, this paper aims to study the peer effects of first-year students at Colorado College. Peer effects studies in higher education often focus on first-year roommate effects, which is made possible by quasi-random roommate assignment. However, the model will utilize Colorado College's unique block plan calendar to examine effects within the small intimate classes provided at the liberal arts school. Specifically, the objective of this paper is to study the effect international students and student athletes may have on the academic performance of students without those qualities.

Literature Review

While literature on peer effects in higher education draws from the large base of studies on peer effects in K-12 schools, studies in higher education have a more difficult task in avoiding selection bias in their empirical analysis. Many K-12 studies including Hoxby (2000) and Hanushek (2001) focus on classroom effects, but the majority of higher education analysis utilizes roommate interactions as the platform on which to examine peer effects. This is because many schools implement a random or quasi-random roommate assignment process, effectively minimizing if not eliminating selection bias in choosing roommates. In contrast, most institutions of higher education allow students to pick their own classes. In order to illustrate the selection problem Manski (1993) developed and analyzed linear, non-linear, and dynamic mathematical models while assuming that peer effects are determined solely by academic achievement. In other words, greater achievement for one student is balanced by lower achievement for another. He concluded that in order to identify peer effects, it is necessary to have large amounts of detailed data so that the model may control for various factors.

To give a few examples of peer effect studies in elementary schools, Hanushek et al. (2001) and Hoxby (2000) used data from the University of Texas Dallas (UTD) Texas Schools Project to estimate the effect of student and school characteristics (largely demographic) on student performance as measured by grades. Hanushek concluded that the achievement of a student's peers have a significant effect on that student's learning even while the precise nature of peer effects remained ambiguous. Meanwhile, Hoxby tested for various econometric issues, including time trends, nonlinear time patterns, idiosyncrasies, and teacher shocks. Ultimately, Hoxby was able to minimize or dismiss these issues by manipulating the abundant data to find that black and Hispanic students have a negative peer effect on other races, but a larger negative effect on themselves, while females have a slightly positive peer effect on both sexes.

Peer effect literature in higher education commonly relies on proxies to measure both student academic ability and student academic achievement. By running an OLS model of a student's academic achievement against the academic ability and achievement of that student and that student's peer(s), it is possible to interpret whether or not peer effects exist, and if they do exist, in what form. Several of the more recent articles note that peer effects include those effects on students' habits at least as strongly as those direct effects on students' academic performance.

Many of the studies in regards to peer effects in higher education have focused on the effects that roommates have on one another. Sacerdote (2001), Zimmerman (2003), Stinebrickner and Stinebrickner (2006), McEwan and Soderberg (2006), Foster (2006), and Griffith and Rask (2014) utilized random or quasi-random roommate assignment processes at various universities to explore the possibility of peer effects. However, conclusions differ across the studies. It is unclear whether this lack of unanimity signifies that peer effects are specific to a university or that they are not being measured appropriately.

Sacerdote (2001) uses data from Dartmouth College to examine the peer effect of first-year roommates on one another's social life and study habits. Through ordinary least squares (OLS) analysis, Sacerdote runs regressions of one student's GPA or social outcome (for example, major or whether they joined a Greek house) against their own level of academic ability (measured by an academic index), their roommate's GPA, their roommate's level of academic ability, and the students' answers to housing questionnaires. While Sacerdote found that roommates had a linear effect on the decision to join a Greek house, he found academic effects only when allowing for nonlinearities and interaction variables of the roommate's characteristics with the student's own ability. Analysis showed that the effect of top-performing students was limited to bottom- and other top-performing students.

Zimmerman (2003) uses a similar model with data from Williams College but estimates only the presence of small effects for middle-ability students. Similar to Sacerdote, Zimmerman uses a mixture of SAT scores and answers to housing questionnaires as a measure of students' academic ability and college GPA as a measure of students' academic achievement. The study ran OLS while allowing for nonlinearities so that academic ability was split into three tiers: students who had high, medium, and low SAT scores. Although small in magnitude, the study yielded consistent statistically significant values showing that medium-SAT students who shared a room with low-SAT students tended to obtain worse grades than would otherwise have been expected of them. Zimmerman's study identified a potential issue with the model in that Williams College is a highly selective school, implying a greater level of homogeneity in student performance than that which could be found at a less selective school.

Stinebrickner and Stinebrickner (2006) elaborated on the highly-selective-school issue, theorizing that there may not be enough range in their abilities for students to show significant signs of effecting one another. This study also focused on the possible inadequacy of previous studies in addressing the identification issue, as most of those studies were based in schools with imperfectly random roommate assignment processes.

These believed inadequacies led Stinebrickner and Stinebrickner to use data from Berea College from the period 1991-1996, when roommate assignment was "unconditionally random," (p. 1439) without any questionnaires or systematic placement. As in other studies, this model used standardized test scores and high school GPAs to proxy for academic ability but added retention values to college GPA as the measure for academic achievement. The study found evidence for the existence of peer effects, and that these effects varied depending on the students' gender. The Stinebrickners also collected additional information on students' habits as well as the amount of time a student spent with his roommate versus non-roommates. In regards to the latter, they found that almost half of students reported spending more time with their roommate than with any other friend, which adds to the validity of the inferences made from the model. As for the former, when running specifications with students' habits as the endogenous variable, the study found that standardized test scores were not as effective as predicting the changes in habits as were high school GPA.

In light of the last finding, Griffith and Rask (2014) further emphasized the importance of including both high school GPA and standardized test scores as the proxies for academic ability. Otherwise, Griffith and Rask modeled their study similarly to others, choosing to focus on roommates in two highly selective universities and finding that peer effects exist most strongly for students that are male, part of an ethnic minority, or receiving financial aid. As in the aforementioned studies, Griffith and Rask regress a student's academic achievement on the academic ability and characteristics of themselves and their roommate, using students' high school GPA and standardized test scores as a measure of academic ability and students' college first-year GPA as a measure of academic achievement. Griffith and Rask took their study a step further by creating and comparing subsamples in order to explore whether peer effects were more prominent inside of the classroom than in the dorm room. This separate analysis found that peer effects (as defined in the study) were not more prominent in the classroom than in the dorm room, implying that students have more of a positive effect on one another's habits than a direct effect on grades. The study also makes a note that "students are only significantly impacted by roommate ability if they get along well." (p. 74) In other words, only friends have a significant academic effect – direct or not – on one another.

Foster (2006) emphasized the importance of social proximity – what she identified as friendship – that was tested for in Stinebrickner and Stinebrickner (2006) and later echoed in Griffith and Rask (2014). Foster used data from the University of Maryland both for the diverse range of student ability as defined in previous studies and to take advantage of the fact that some students were able to choose who they would like as their roommate. Foster defined the relationship between two students who had chosen the other as their roommate to be friendship, and inferred that these friends would spend more time together (increasing social proximity). In order to overcome the selection bias particularly presented by this autonomy, the study used the characteristics of randomly assigned peers in the freshman class as instrumental variables. For the analysis, Foster compared the effects of students who were paired with a friend to the effect of students who were paired randomly. However, the study yielded no robust results even when allowing for nonlinearities, signifying that friends were less effective at having an impact on one another than was true of students who were paired randomly. At the same time, the study did not find any results when regressing student performance against other characteristics without regard to the friend relationship, so it is possible that peer effects may not exist solely for the University of Maryland.

McEwan and Soderberg (2006) also failed to yield evidence supporting the existence of robust peer effects at Wellesley College, where roommate assignment was quasi-random. The OLS specifications followed the pattern found in previously discussed studies, including dummy variables for various student characteristics and assigned dormitories. McEwan and Soderberg listed multicollinearity as a primary source of error in the model, and concluded that peer effects in terms of freshman roommate pairings did not exist at Wellseley College.

Given the mixed results and questionability of the relevance of roommates in forming peer effects, a few studies have attempted to center their analyses on effects taking place between classmates. Because students in institutes of higher education are generally able to select their own classes, such studies are limited because they are plagued with errors of selection bias. A common mechanism used in studies is to analyze students in mandatory courses where student allocation is mostly random. For example, Androushchak, Poldin, and Yudkevich (2013) used data on students in the economics department of a Russian university and found statistically significant peer effects, particularly for high ability students in a class of many other high ability students.

Hoel, Parker, and Rivenburg (2006) used data from the mandatory Humanities 101 course at Reed College to drive their analysis. This study controlled for student academic and demographic characteristics and included dummy variables to capture students' eventual area of study (major) and class year to further control for grading discrepancies across disciplines and grading trends over time, respectively. This study was unique in emphasizing the various transformations of the endogenous variable, GPA, and running regressions against various combinations of exogenous variables despite the fact that these nonlinear transformations and combinations rendered the results difficult to interpret. Nonetheless, the study found evidence for the existence of peer effects for specific groups of students: students with high measurements of academic ability had a positive effect in classes with relatively low variances in classmate ability. In somewhat of a contrast to Griffith and Rask (2014), Hoel, Parker, and Rivenburg found that a greater female presence in a classroom had a greater effect in raising the achievement of female students. However, because this study only allowed for interpretations concerning direct academic effects, any effects that students may have had on one another's habits went unnoticed.

Parker, Grant, Crouter, and Rivenburg (2010) expanded the 2006 study not only in sample size by including data from three different liberal arts colleges, but also in interpretation by noting that students' attitudes seemed to have a stronger role in shaping peer effects than did their academic ability even though the study was unable to account for these factors. Unlike the 2006 article, this study ultimately found no evidence of peer effects at Reed College, Lewis & Clark College, or Whitman College. This study also brought to attention the issue of the "curve effect," (p. 7) where the academic performance of a student's classmates could have an effect on that student's grade.

The majority of peer effects studies suffer from imperfect models due to the various forms of selection bias found in institutions of higher education and lack of ideal proxies for student ability and achievement. There are a few studies that are able to minimize these imperfections.

Goethals (2001) used a laboratory setting to test the effect of various levels of homogeneity in a students' peer group on that student's academic performance. The study characterized students as either top- or bottom-half depending on the student's academic rating as assigned by the Office of Admissions. Goethals mixed students into groups of three so that there were four different possible combinations of top- and bottom-half students and had the groups read articles, discuss them, and then write about what they had learned. Data for the model came from evaluations of the discussions and the writing assignments. The study found that students who belonged to a homogenous group (all belonging to the top half or all belonging to the bottom half) had greater performance than those students who belonged to a heterogeneous group. These differences varied slightly by gender, with males benefiting more from homogenous groups than females. The results from Goethals' experiment leads to the conclusion that peer effects are stronger when peers are alike in academic ability as opposed to when they are not.

Carrell, Fullerton, and West (2009) took advantage of the program at the United States Air Force Academy where students are, condition to a few demographic variables, randomly assigned to peer groups (squadrons) of about 30 students. While this study used a similar basic model and similar proxies, unlike in the studies focusing on roommates, students within each squadron are guaranteed to spend the majority of their time with one another. The model also had controls for year of entrance and other demographic characteristics. Interestingly, the study found that academic peer effects existed in larger magnitudes, and had a greater possibility of existing in nonlinearities, than was found in previous literature. By accounting for the type of course (first year students are assigned to their mandatory schedule by the registrar), the study was able to find that peer effects were largest in math and science courses and nonexistent in physical education and foreign language courses.

Both the methodological similarities and discrepancies found in peer effect literature are helpful in outlining various important factors to include in the model used by this paper. Although the study in this paper may not be centered on a situation as ideal as those in Carrell, et al. (2009) and Goethals (2001), it is still possible to judge the potency of the results by testing for the certain qualities mentioned in those two studies.

Theory

The basis of any model aimed to measure peer effects lies in elementary microeconomic theory. Like other markets, the market for higher education has both a cost and a production function. Where students are involved, the objective of an institution's production function is to produce high levels of learning. The factors of production (learning) include not only a student's own characteristics, but also those of the learning environment. In other words, a student's learning is determined not only by the student herself but also by outside determinants. These outside determinants include course characteristics and characteristics of the class, of which peer effects are included.

A student with more advantageous characteristics – for example, nonminority or higher initial academic ability – will have the benefit of increased learning, and the same is true for a student in a class with peers who have more advantageous backgrounds. Distinct from class characteristics, course characteristics involve subject matter, subject level, and professor variables. A higher subject level or particularly difficult professor may provide a more challenging atmosphere for the student to learn while student preferences for subject matter can also affect the student's performance. The education production function can thus be represented by the following function:

$$L = S_1 + S_2 + S_3 + \mathrm{Z} \qquad (1)$$

L represents a measure of learning, S_1 represents the base student's characteristics, S_2 represents a peer's characteristics, S_3 represents other environmental characteristics, and Z is an error term. S_2 is distinct from the other factors because it holds the characteristics of the peer whose effects on the base student are to be quantified.

Peer effects can manifest in numerous ways. In its purest form, they occur when students directly teach one another. Meanwhile, one major possible indirect peer effect lies in habits: a student may be influenced by the good or poor studying habits of her peers. Both of these possible origins of influence are theoretically captured in the S_2 term. The collective characteristics of the students in a class may similarly have an effect on each individual, and class dynamics also make up an important part of peer interactions and thus, effects. For example, a professor may consider a class to be brighter than average and consequently modify the curriculum to reflect higher expectations – the same is true of an opposite situation. These, and other class characteristics, are captured by the S_3 term.

Data Discussion

Data for this paper is taken from Colorado College, a small and increasingly selective liberal arts college located in Colorado Springs. The unique block plan calendar adopted by the school contributes to its optimal position for this study. By allowing for only one course every 3 ½ weeks, the block plan forces students to focus intensely on one subject. Students are more likely to work closely with one another given the rigor of the block plan and the intimate size of the classes made possible by the small student population at Colorado College. This environment theoretically fosters a greater amount of student interaction, and thus a greater amount of peer effects can potentially occur.

A total of 20,311 observations encompass data from first-year courses of the school years between 2009 and 2014. Student grades, quantified on the 4.0 scale, are identified by the characteristics of the student, course, and classmates. The dataset excludes explicit identification of a student, as the topic of interest is whether students with certain characteristics (athlete, international) impose an effect on students without those characteristics. Observed student characteristics include the demographic variables: minority, gender, legacy status, and financial aid reception are each represented by dummy variables. Minorities and females constitute 28.94% and 56.63% of this sample, respectively. As a variable with a likely predictive value for student grades, the dataset also includes students' academic rating, a value assigned by the Colorado College Admission Office which comprises the student's SAT score and high school GPA upon applying to Colorado College. A higher academic rating indicates a more competitive applicant – an applicant of higher "quality" as defined for the purposes of this paper.

Observed course characteristics are: class size, year of course, block sequence, course level, and academic division. The sample's average class size is about 17 students with the largest observed class capped at 35 students. For academic division, there are 8,515 humanities courses, 4,660 social sciences courses, 5,868 natural sciences courses, and 1,268 unaffiliated courses represented in the sample set.

The qualities of interest in this paper are noted as dummy variables for both international students and student athletes. It should be noted that not all classes have athletes or international students; of the 20,311 total observations, only 634 represent international students and 3,748 represent student athletes. These populations constitute 3% and 18%, respectively, of the total observed student population. The maximum number of international students in an observed class is 5. There are an average of about 3 student athletes in each class, with the maximum amount of athletes in an observed class being 15. Although student athletes are also identified by the type of athletic activity, subsamples divided by activity would be too small for study. To gauge the "quality" of international students and student athletes, the average academic ratings of these students in an applicable class are also noted. Both academic ratings had a maximum value of 65.

Model and Methodology

Potential Econometric Issues

Because students select their own courses, any economic model attempting to capture and quantify peer effects must navigate a variety of econometric issues. The difficulty of separating peer effects from other influences and of identifying the actual peer interactions to be observed poses econometric issues including multicollinearity, serial correlation, and omitted variable bias. Peer effects studies are also rampant with unobservable factors – even within small classes, students are likely to have greater interaction with others who have similar interests and backgrounds. Given these persistent reflection problems, this study must in its methodology hold constant as many variables as possible.

Model

Models used to analyze peer effects commonly have a measure of student achievement as a function of peer characteristics while controlling for various demographic and other course-related variables. The model analyzed in this paper follows previous studies in using ordinary least squares to estimate the effect of focus students on other student performance. A student's earned grade stands as a proxy for achievement and students' academic rating stands a proxy for ability or "quality." Other characteristics are represented by the remaining variables observed in the dataset, which are discussed below. A general equational form of the model can be represented as:

$$G = \beta_1 X_1 + \beta_2 X_2 + \beta_n X_n + \mathrm{Z} \qquad (2)$$

In this equation, G represents the grade received by a base student, X_1 represents the number of focus (international or athlete) students in the base student's course, X_2

represents the average academic rating of focus students in the base student's course, X_n represents other control variables, and Z represents the error term.

X_1 allows the examination of the effect produced by each additional focus student while X_2 allows for the effect produced by the average "quality" of focus students in a course. Control variables included within the X_n term are academic rating, which stands as the base student's "quality," and demographic dummy variables: minority, female, from Colorado, legacy, and recipient of financial aid. The X_n term accounts for both grade inflation over time with a course-year variable, and student grade improvement with a sequence variable which captures when within a school year the course was taken. Possible differences in grades received in introductory versus non-introductory courses are captured in course-level dummies, and grading differences due to differing class sizes are accounted for as well.

Methodology

The model is run first for international students, ignoring the student athlete variables. The same methodology is used for student athletes, and international student variables are likewise ignored. In order to prevent the average academic rating variable from being dropped in the regression, an interaction variable between average focus-student academic rating and number of focus-students in a class was created. This interaction term replaced the average academic rating variable.

This paper employs three forms of the model in analyzing potential peer effects. The first runs the model for a sample which omits observations for focus students in order to gauge the effect of focus students on non-focus students. The second runs the model for a sample which omits both observations for focus students and observations where the number of focus students in the course equals zero. This sub-model aims to examine solely the effect focus students have on non-focus students who are in the same class. The third and final sub-model runs the regression for the full sample but includes an interaction variable between the focus student dummy variable and the variable for the number of focus students in the course. The estimate on this interaction variable represents the effect international students have on other international students.

Because grading policies in courses across the four divisions – unaffiliated, humanities, natural sciences, and social sciences – reflect the disparate qualities of the learning material in these divisions, the model runs four separate regressions. This is in line with holding constant as many things as possible in order to account for other potential sources of academic effects. While observations in unaffiliated courses are left in the sample, the small quantity of these observations render the sample size for this regression unreliable. Therefore only the regressions for humanities, natural sciences, and social sciences are reported in the results section.

Estimates attached to the focus variables are the most significant for the purposes of this paper, but estimates attached to other control variables also hold importance. If those values attached to control variables are logical and in line with the theory behind the variables, it holds that results for the focus variables can also be reported with confidence.

Results

Regression results for international students and student athletes are summarized in the tables following their respective sections.

Peer Effects of International Students

Model 1 – Effects on Non-International Students. The number of international students proved significant in determining non-international student grades at the 1% confidence level. For example, each additional international student in a humanities course improves non-international student grades by 0.397 GPA points. Beyond its statistical significance, this value is economically significant because it is larger than the 0.3-point difference between received grade levels (for example, A and A-).

In contrast, the effect of the average academic rating of international students within a humanities course proved to decrease grades received by 0.007 GPA points, which is again statistically significant at 99% confidence. The negative direction of this correlation suggests that the greater the "quality" of international students, the lower the grades of non-international students. The direction of the effect can be initially confusing, but is likely a sign of a curve effect where better-performing classmates make it more difficult to receive a higher grade. However, the magnitude of the estimate is so small that it does not hold much weight in effecting received grades.

Results estimated in models for natural and social sciences mimicked the relationships obtained in the humanities model but had estimates of a lower magnitude with a lower confidence level.

Model 2 – Effects on Non-International Students in the Same Class. Each additional international student in a humanities course raised the received grade of non-international students in the same course by 0.497 GPA points with 99% confidence. The value is higher than the effect found in Model 1, implying that the presence of international students has a positive effect for non-international students' received grades. As in Model 1, the presence of an international student with a 1-point higher academic rating resulted in a decrease in received grade. However, the small magnitude of 0.009 again renders the estimate unimportant.

The same pattern held for the natural and social sciences divisions, but the estimates had smaller magnitudes and were held with 95% confidence.

Model 3 – Effects on other International Students. Following the pattern of the previous two models, each additional international student in humanities courses had the effect of a 0.39 point increase in the received grades of all students within the division. The estimation on the effect of international students' academic rating was also statistically significant, but the small negative value holds no real economic significance.

Of interest, each additional international student increases another international student's grade by .059 GPA points in humanities courses at the 1% confidence level. It appears that international students have more of a positive effect on non-international students than they do on one another. The model yielded similar results for the other divisions, but of lower magnitude and at the 5% confidence level.

Table 1.1

Estimated Effect of International Students on Peer Grades (on 4.0 GPA scale)

Parameter	Model 1			Model 2			Model 3		
	H	NS	SS	H	NS	SS	H	NS	SS
No. of International	0.397***	0.183	0.151	0.497***	0.137	0.177	0.390***	0.284*	0.166
	(4.26)	(1.51)	(1.38)	(5.16)	(1.09)	(1.42)	(4.57)	(2.46)	(1.61)
Academic Ranking of International	-0.00784***	-0.00363	-0.00318	-0.00907***	-0.00303	-0.00377	-0.00773***	-0.00562*	-0.00352
	(-4.35)	(-1.55)	(-1.49)	(-4.91)	(-1.24)	(-1.60)	(-4.68)	(-2.52)	(-1.76)
International * No. of International							0.0586**	0.0331	0.0385
							(3.03)	(1.57)	(1.83)
Academic Ranking	0.0204***	0.0394***	0.0285***	0.0226***	0.0408***	0.0307***	0.0204***	0.0392***	0.0285***
	(22.29)	(28.15)	(21.98)	(10.84)	(14.55)	(12.59)	(22.59)	(28.14)	(22.23)
Minority	-0.0555***	-0.0744***	-0.111***	-0.0307	-0.0507	-0.102**	-0.0524***	-0.0717***	-0.107***
	(-4.25)	(-3.81)	(-5.61)	(-1.02)	(-1.35)	(-2.94)	(-4.10)	(-3.70)	(-5.53)
Female	0.0661***	0.00267	0.0723***	0.0415	-0.00766	0.0454	0.0674***	0.0104	0.0747***
	(6.01)	(0.17)	(4.64)	(1.53)	(-0.23)	(1.52)	(6.25)	(0.65)	(4.87)

Note. T-statistics appear in parenthesis

* p<0.05   ** p<0.01   *** p<0.001

Table 1.2

Estimated Effect of International Students on Peer Grades (on 4.0 GPA scale), Continued

Parameter	Model 1			Model 2			Model 3		
	H	NS	SS	H	NS	SS	H	NS	SS
From CO	0.0542***	0.0192	0.0315	0.0302	-0.108*	0.0585	0.0539***	0.0180	0.0308
	(3.64)	(0.87)	(1.44)	(0.71)	(-1.98)	(1.25)	(3.64)	(0.82)	(1.42)
Legacy	0.0483**	0.0221	-0.00154	-0.0000771	-0.0461	-0.0581	0.0485**	0.0217	-0.000737
	(3.15)	(0.93)	(-0.07)	(-0.00)	(-0.92)	(-1.27)	(3.19)	(0.91)	(-0.03)
Receives	0.0140	0.00569	0.0408*	0.0210	-0.0184	0.0316	0.0128	0.00339	0.0423*
Fin. Aid	(1.12)	(0.31)	(2.23)	(0.71)	(-0.50)	(0.91)	(1.04)	(0.18)	(2.36)
Class Size	-0.00805***	-0.00824***	-0.000675	-0.00575**	-0.00999*	0.000725	-0.00832***	-0.00796***	-0.000918
	(-9.36)	(-5.13)	(-0.48)	(-2.66)	(-2.55)	(0.22)	(-9.85)	(-4.98)	(-0.67)
Intro Course	-0.0340	-0.0388	-0.0558	-0.167**	0.376	0.123	-0.0338	-0.0429	-0.0447
	(-1.80)	(-0.35)	(-1.64)	(-2.67)	(0.62)	(1.59)	(-1.81)	(-0.39)	(-1.33)
200 Course	-0.113***	-0.0800	-0.0700*	-0.222***	0.290	0.106	-0.112***	-0.0775	-0.0594
	(-6.07)	(-0.71)	(-2.10)	(-3.58)	(0.48)	(1.39)	(-6.14)	(-0.68)	(-1.81)
Block Sequence	0.0214***	0.00586	0.0116***	0.0376***	0.00807	0.00624	0.0220***	0.00517	0.0123***
	(9.96)	(1.64)	(3.37)	(6.67)	(1.06)	(0.89)	(10.44)	(1.46)	(3.61)
School Year	0.0170***	-0.00758	0.0117*	0.0221	0.0123	0.0244	0.0179***	-0.00725	0.0136**
	(4.97)	(-1.42)	(2.27)	(1.81)	(0.84)	(1.93)	(5.28)	(-1.36)	(2.67)

Note. T-statistics appear in parenthesis

* p<0.05   ** p<0.01   *** p<0.001

Peer Effects of Student Athletes

Model 1 – Effects on Non-Athlete Students. Each additional student athlete in humanities courses increased the received grade of non-athletes by 0.142 GPA points with 99% confidence. The value represents little more than a third of a grade-level difference and can thus be taken as economically significant. Like the results for international student peer effects, every additional academic rating point for a student athlete resulted in a small decrease in the expected grade of non-athletes.

Results in the natural sciences division yielded similar, if smaller in magnitude, results at 99% confidence. However, peer effects estimations in social sciences were not statistically significant. It is possible that this is due to the greater number of student athletes enrolled in social sciences courses as opposed to humanities or natural sciences. The large portion of student athletes in the social sciences division would have caused a large number of observations to be dropped – extinguishing the sample size and otherwise throwing off sample characteristics.

Model 2 – Effects on Non-Athlete Students in the Same Class. Results for the effect of student athletes in humanities courses on non-athletes in the same course followed the pattern set in Model 1. Each additional student athlete raised the received grade of a non-athlete in the same course by 0.132 GPA points, while a greater academic rating for student athletes had a small negative effect.

Results in the natural sciences division were the same but with lesser magnitudes at 99% confidence. In social sciences, the analysis again could not claim peer effects with confidence.

Model 3 – Effects on other Student Athletes. Estimated peer effects of student athletes on other student athletes were smaller in magnitude than those effects on non-athletes. In humanities courses, non-athletes benefited from a 0.116 increase per additional student athlete with 99% confidence. With 95% confidence, each additional student athlete in a humanities courses decreased another athlete's received grade by 0.0095 GPA points. Although the value is still small relative to the more significant effects, the idea that student athletes may harm one another's grades is interesting. This might be due the fact that when there are more student athletes in a class, they are likely to form groups amongst themselves. When these athletes miss class because they are off-campus for competitions, they do not have non-athlete students in their group to catch them up on missed material.

The model for natural sciences yielded the same results in smaller magnitudes, and the model for social sciences again found no statistically significant results.

Table 2.1

Estimated Effect of Student Athletes on Peer Grades (on 4.0 GPA scale)

Parameter	Model 1			Model 2			Model 3		
	H	NS	SS	H	NS	SS	H	NS	SS
No. of Athletes	0.143***	0.0831**	-0.00872	0.134***	0.0825**	-0.0119	0.116***	0.0822***	0.0436
	(5.41)	(2.94)	(-0.31)	(5.02)	(2.89)	(-0.41)	(5.19)	(3.42)	(1.89)
Academic Ranking	-0.00335***	-0.00167**	0.000477	-0.00281***	-0.00174**	0.000657	-0.00278***	-0.00162***	-0.000574
of Athletes	(-6.09)	(-2.99)	(0.80)	(-4.97)	(-3.09)	(1.07)	(-5.94)	(-3.41)	(-1.18)
Athlete * No. of Athletes							-0.00951*	-0.00911*	-0.00800
							(-2.21)	(-2.33)	(-1.92)
Academic	0.0180***	0.0383***	0.0270***	0.0203***	0.0383***	0.0282***	0.0203***	0.0396***	0.0287***
Ranking	(17.16)	(21.83)	(16.79)	(15.47)	(21.04)	(15.80)	(21.67)	(27.30)	(21.56)
Minority	-0.0758***	-0.0839***	-0.138***	-0.0802***	-0.0816***	-0.145***	-0.0523***	-0.0704***	-0.104***
	(-5.55)	(-3.86)	(-6.41)	(-4.66)	(-3.61)	(-6.08)	(-4.10)	(-3.65)	(-5.44)
Female	0.0708***	0.00506	0.0911***	0.0680***	-0.00129	0.0648***	0.0650***	0.0103	0.0798***
	(6.12)	(0.28)	(5.26)	(4.71)	(-0.07)	(3.40)	(6.03)	(0.65)	(5.17)

Note. T-statistics appear in parenthesis

* p<0.05   ** p<0.01   *** p<0.001

Table 2.2

Estimated Effect of Student Athletes on Peer Grades (on 4.0 GPA scale), Continued

Parameter	Model 1			Model 2			Model 3		
	H	NS	SS	H	NS	SS	H	NS	SS
From CO	0.0496**	0.0346	0.0347	0.0330	0.0306	0.0147	0.0522***	0.0191	0.0309
	(3.14)	(1.37)	(1.39)	(1.61)	(1.16)	(0.53)	(3.54)	(0.87)	(1.42)
Legacy	0.0509**	0.00942	-0.00128	0.0509*	0.0190	-0.0111	0.0454**	0.0213	0.000542
	(3.15)	(0.36)	(-0.05)	(2.50)	(0.69)	(-0.40)	(2.99)	(0.89)	(0.02)
Receives Fin. Aid	0.0279*	-0.00576	0.0596**	0.0247	-0.00876	0.0487*	0.0144	0.00480	0.0434*
	(2.05)	(-0.27)	(2.77)	(1.44)	(-0.39)	(2.03)	(1.17)	(0.26)	(2.39)
Class Size	-0.00671***	-0.00835***	-0.00223	-0.00668***	-0.00688**	-0.00315	-0.00579***	-0.00764***	-0.00369*
	(-6.56)	(-4.21)	(-1.28)	(-4.77)	(-3.17)	(-1.49)	(-6.00)	(-4.28)	(-2.38)
Intro Course	-0.0288	-0.0277	-0.0419	-0.0384	-0.121	0.0155	-0.0348	-0.0556	-0.0485
	(-1.48)	(-0.22)	(-1.09)	(-1.40)	(-0.70)	(0.34)	(-1.88)	(-0.50)	(-1.44)
200 Course	-0.108***	-0.0664	-0.0466	-0.0964***	-0.154	0.0225	-0.107***	-0.0801	-0.0547
	(-5.63)	(-0.51)	(-1.25)	(-3.57)	(-0.88)	(0.50)	(-5.86)	(-0.71)	(-1.67)
Block Sequence	0.0187***	0.00282	0.0135***	0.0202***	0.00250	0.0157***	0.0202***	0.00476	0.0132***
	(8.48)	(0.73)	(3.69)	(7.03)	(0.62)	(3.81)	(9.54)	(1.35)	(3.94)
School Year	0.0197***	-0.00422	0.00715	0.0221***	-0.00224	0.00877	0.0200***	-0.00784	0.00575
	(5.63)	(-0.77)	(1.29)	(4.98)	(-0.39)	(1.42)	(6.19)	(-1.60)	(1.18)

Note. T-statistics appear in parenthesis

* p<0.05   ** p<0.01   *** p<0.001

Control Variable Estimations

Several control variables consistently yielded similar results at the 1% confidence level. The academic rating of the base student proved to have a positive correlation with grade received across all models and sub-models, with the smallest estimate representing a 0.017 GPA point increase in grade per additional academic rating point and the largest estimate representing a .04 GPA point increase. This pattern makes logical sense, as a student with higher ability as measured by their academic rating would receive better grades.

The minority dummy variable was also consistently statistically significant at the 1% confidence level. The range of estimations were -0.05 to -0.14 GPA points, although the value was not significant in some divisions under Model 2. The suggestion that minority students are at a disadvantage academically is a familiar notion in studies of those students with socioeconomic disadvantages.

Other control variables with a trend in most of the models include the female and course level dummy variables, class size, and the sequence and year time variables. In general, females were shown to have an advantage in humanities courses. Because females have historically had a greater association to subjects classified as humanities than they did with either of the sciences, such an advantage may be expected and is likely not unique to students at Colorado College. Larger class sizes yield slightly lower GPA scores in alignment with the theory that a smaller more intimate class is beneficial for the student's learning. In the models and in real life, two-hundred-level courses are more difficult and thus harder to receive A's in than are introductory courses.

Lastly, estimates on the temporal variables indicate both grade inflation and first-year students adapting to college – both the year and sequence variables have a positive effect on grades. First year students adapt to college life with experience, as courses taken later in the school year were more likely to have higher received grades than courses taken earlier in the school year.

Conclusion and Possible Improvements

Results for this study support not only the existence of peer effects of international students and student athletes at Colorado College, but also the importance of these effects. The simple presence of international students in a course benefits the grades of all students within that course by at least one level, especially non-international students. Each additional international student in a class has enough of a positive effect on non-international students that they are bumped from one grade level to another. Because the nature of interaction between international and non-international students have not been observed, it is unclear whether this peer effect stems from influences on habit, direct tutoring, or stimulating discussion.

Student athletes demonstrated smaller peer effects than international students overall, even if those effects were both statistically and economically significant. One explanation for this disparity lies in the likelihood that characteristics of student athletes are similar to the characteristics of non-athletes. If there aren't many differences between athletes and non-athletes, the observed peer effect could be the effect that any Colorado College student has on another. In contrast, the differences between the backgrounds of international students and non-international students are likely many in number and large in significance.

No matter the focus group, peer effects were most predominant in the humanities division. Because the curriculum in humanities courses generally offer more open-ended learning goals and discussion, there are greater amounts of interaction – and thus greater opportunities for peer effects – between students. At the same time, courses in the natural and social sciences often teach towards specific learning objectives and, being largely lecture-based, have less room for discussion. On the other hand, it is possible that the greater perceived effect of peers in humanities courses is actually a result of more forgiving grading policies.

Because the estimations yielded by the model proved theoretically sound for well-studied control variables, it follows that the peer effect estimations are also theoretically sound. However, the consistent finding that increased “quality” of focus students had a small and negative effect on base students could be a point of concern as theory would suggest that higher quality peers would benefit a student’s grades. Although the curve effect is one possible explanation behind this phenomena, it is also a potential indication of missing or unobserved variables in the model.

In future studies of peer effects at Colorado College, improvements can be made by examining a larger sample size, collecting more information on the nature of peer interactions, and focusing more on possible unobservable characteristics. It would also be interesting to include roommate studies and other focus groups in examining peer effects. Peer effects in higher education are important to analyze because a thorough understanding of their workings can help institutions form policies to make student body distribution processes more efficient. For example, admissions processes could be aimed towards a certain distribution to maximize the benefits of peer effects. But for now, the existence and potency of peer effects at Colorado College is supported by the statistical evidence in this paper.

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