Peer Effects: Do First-Year Classmates, Roommates, and Dormmates Affect Students' Academic Success

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Abstract

We use data on ten years of entering students at Reed College to test for peer effects among three groups of peers: roommates, residents in the same dorm grouping, and classmates in a required freshman class. In each case, peer groupings are apparently random, allowing us to avoid statistical problems that often make testing for peer effects impossible. We find strong effects of the academic quality of roommates and dormmates on student achievement. We do not find evidence of classmate peer effects.

1. INTRODUCTION

Colleges and their applicants believe that the quality of one's classmates matters. Most colleges and universities strive to admit the highest-quality students they can attract; increasing selectivity is often an institutional goal. Better students enable a more challenging curriculum and, so the story goes, a better education through interaction with peers inside and outside the classroom.

Applicants usually choose to attend the "best" school to which they are admitted, provided it is financially feasible. While outstanding faculty instructors are surely part of the reason, high-quality peers are valuable as well—both for the positive educational effect they may have and also because identification with a school known for high-quality students may enhance a student's post-graduate opportunities.

While the behavior of participants in the higher-education market demonstrates faith in the importance of peer effects, very little research is available to support this belief.[1] This paper examines the effects of a student's classmates in a required first-year course on his or her subsequent academic success. The sample comprises ten years of entering first-year students at Reed College, a selective liberal-arts college. Each first-year student at Reed is assigned (effectively) randomly to a "conference" section of Humanities 110. We explore whether the academic qualifications of a student's classmates in this conference are associated with higher or lower achievement.

In addition to classmates, residential peers may have an important influence on a student's educational environment. Studious roommates may provide good role models and be less likely to distract their partners from their studies. A dorm that is oriented strongly toward academics may actively discourage noisy or rowdy behavior, providing a more productive environment for all its residents. We examine residential peer effects using first-year roommates and dormmates using a five-year sub-sample of our data.

We find that the academic qualifications of roommates and dormmates seem to have substantial effects on student performance, both contemporaneously in the first year and

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[1] In contrast, peer effect interactions on values, lifestyles, and purchasing have long been the focus of marketing research. The notion of "birds of a feather flocking together" is the basis of most geo-demographic marketing. See Weiss (1989).

even extending through the student's undergraduate career. However, we are unable to detect any effect of classmate peer effects in Hum 110 conferences.

The paper is organized as follows. Section 2 examines the theoretical basis for peer effects in higher education and discusses some relevant literature. The third section describes our basic model of student achievement, which is used to predict a student's grade-point average based on his or her own characteristics. The fourth section presents our peer-effect results; section five concludes.

2. PEER EFFECTS

2.1. Between vs. within-college peer effects

In principle, one can think of peer effects at two levels: between schools and within schools. The strongest peer effects in higher education are probably those between institutions. The general characteristics of a college's student body constrain its curriculum. Schools with bright and motivated students are able to assign more challenging materials and teach courses at a higher level than colleges whose students are academically less able. However, between-institution peer effects are impossible to measure unless one can distinguish between the educational effects of differences in peers and the effects of all the other characteristics that differ across schools.

This study examines peer effects within a single institution—Reed College. Differences among peer groups within the population of Reed students are surely less striking than the differences between groups of Reed students and those at, say, a state university. Nonetheless, there are likely some groups of Reed peers whose effects are more conducive to high academic achievement than if one interacted with other groups. We have all participated in classes in which the classroom interaction among students has contributed strongly to learning—and classes where the peer dynamic has been less supportive. We have all known students whose academic careers suffered because of the behavior of roommates, neighbors, or friends—and others whose performances have improved due to their interaction with these peers.

2.2. Choice of peers and the reflection problem

Estimation of peer effects is made impossible in most higher-education settings because most college students choose their peers. If a student's peers have unobserved characteristics that are systematically related to his or her own, then estimation of peer effects is made impossible by what Charles Manski (1993) calls the "reflection problem." For example, if smart students systematically tend to choose smart peers, then it becomes impossible to distinguish statistically between the effects of the student's own smartness and the effect of peers' smartness.

College students always choose their friends and they often choose roommates, neighbors, and classmates. They are likely to choose peers whose unobservable characteristics are systematically related to their own. Even when the choice of peers is not explicitly voluntary, there may be associations between characteristics of peers. For example, by enrolling in a difficult course (or an advanced or honors section of a course) a good student would surround himself or herself with good peers.

The reflection problem can be overcome by using peer groups where one of the following conditions holds: (a) selection into groups is random, or at least independent of variables related to achievement; or (b) selection into groups is based only on measurable characteristics that can be used as controls in estimation. Neither of these conditions will be fulfilled in situations where students select their peers. Thus, the estimation of peer effects must be based on externally (and, ideally, randomly) assigned peer groups.

2.3. Studies of peer effects

Students in primary and secondary schools may be assigned into classrooms in a way that is not related to achievement. Thus, studies of classroom peer effects at these levels are more common. Among the studies finding positive classroom peer effects are Coleman et al. (1966), Henderson, Mieszkowski, and Sauvageau (1976), Hoxby and Terry (2000), Zimmer and Toma (2000), Checchi and Zollino (2001), Robertson and Symons (2003), and McEwan (2003). These studies find that having better peers tends to improve a student's own academic performance and many find the effects to be larger for low-ability students than for those with high ability.

Random class assignment is unusual in higher education, which makes testing for classroom peer effects more difficult. García-Diez (2000) estimates positive peer effects among first-year economics students in a Spanish university. Because the primary purpose of the study was assessment of a change in curriculum rather than estimation of peer effects, the author does not address issues of selection bias.

Selection issues are addressed explicitly in two recent studies of residential peer effects at U.S. colleges. Bruce Sacerdote (2001) and David Zimmerman (2003) examine the effects of the characteristics of first-year roommates at, respectively, Dartmouth College and Williams College on academic achievement.

Zimmerman finds some evidence of positive roommate and dormmate peer effects for some categories of students. Using combined SAT scores as his measure of peer quality, he finds that having a roommate with low SAT scores will diminish the academic performance of the student near the middle of the SAT distribution. Students at the low end of the distribution are adversely affected by having a low-SAT-average dorm.

Sacerdote finds that one's own and one's roommate's first-year GPA outcomes are strongly correlated, but because of the reflection problem that does not imply peer causality. Linear effects of roommate admission characteristics are not significant, but he finds evidence of some nonlinear effects: having a roommate whose admission index is in the top 25% raises one's first-year GPA by 0.06 and is statistically significant.

3. A MODEL OF STUDENT PERFORMANCE

We begin discussion of our empirical work by presenting a basic model of student performance, which we developed as a baseline specification to which we later add measures of peer ability. The model is estimated using data on all students who enrolled in Humanities 110 as freshmen between the fall of 1988 and the fall of 1997.[2] The basic model explains a student's performance as a function of his or her own admission credentials, demographic characteristics, and entry year.

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[2] A few first-year students do not enroll in Hum 110. For example, students whose prior training in chemistry allows them to enroll in organic chemistry cannot take Hum 110 due to a time conflict with the humanities lecture. Any student who did not take Hum 110 in his or her first full-time semester is excluded from our sample, but is included in peer statistics for the sections of Hum 110 in which he or she enrolled.

3.1. Admission variables

We use five variables that are criteria for admission at Reed. Most basic are the mathematics and verbal scores on the Scholastic Aptitude Test (SAT), which is reported for 3,045 of the 3,142 students in our data set.[3]

We observe a high-school grade-point average for 2,429 of our observations, so including this variable is costly in terms of sample size. Moreover, it is difficult to compare GPAs across high schools because of differences in standards and in grading scales. Reed converts high school GPA to a 4.0 basis when the high school provides sufficient information to do so, but the presence of many observations above 4.0 and a handful above 5.0 suggests that some unconverted values are also present.[4]

The fourth admission credential we use is a dummy variable indicating whether the student was ranked in the top 5% of his or her high school class.[5] We have class-rank data on 2,233 students, so including this variable is also costly in terms of observations lost. However, most of the observations for which class rank is missing are also missing high-school GPA, so we have 2,022 observations for which both are observed.

The final admission variable is a summary measure of admissibility called "reader rating." This variable is the average rating assigned by the (usually three) admission deans who read the applicant's file. It is the variable upon which admission decisions are made. Our reader-rating variable is measured on a scale with 5 being the highest rank and 1 the lowest.[6] It is observed for all students in the sample.

Summary statistics and correlations among the five admissions variables are presented in Table 1. Perhaps the most striking result is the relatively low degree of

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[3] The College Board changed the scaling of SAT scores during our sample period to compensate for accumulated drift in the distribution of scores over time. We use "recentered" scores for the earlier period, so all reported SAT scores are comparable and measured according to the new scale.

[4] Many of the GPAs that are greater than 4.0 result from a policy of giving higher grade values for advanced courses such as Advanced Placement courses. Thus, to some extent, GPAs greater than 4.0 may be informative. Upon the advice of Reed's admission staff, we exclude from our sample the six observations with GPA greater than 5.0 under the assumption that these reflect non-standard grading systems, but retain the 280 observations between 4.0 and 5.0.

[5] This variable proved empirically to be more predictive of student success than the actual percentile value.

[6] The actual ranks used by the Reed admission office are reversed with 1 being the highest and 5 the lowest. We inverted the variable so that strong students would have a larger numerical ranking, corresponding to the other admission variables.

correlation among these measures, each of which attempts to measure the student's academic quality. Although we anticipated the possibility of severe multicollinearity among these measures, this does not appear to be the case.

Table 1. Sample statistics and correlations among admission variables

Variable	Mean	Std. Dev.	Min	Max	Correlation with:				
					SAT math	SAT verbal	HS GPA	Top 5%	Reader Rating
SAT math	642.6	72.7	380	800	1.00	0.37	0.27	0.18	0.36
SAT verbal	681.8	71.5	360	800	0.37	1.00	0.16	0.11	0.37
HS GPA	3.67	0.38	2.29	4.93	0.27	0.16	1.00	0.53	0.53
Top 5%	0.312	0.463	0	1	0.18	0.11	0.53	1.00	0.44
Rdr Rating	3.25	0.52	1.5	5	0.36	0.37	0.53	0.44	1.00

A regression of reader rating on the other four measures yields significant coefficients of the expected sign on each variable, but an R-square value of only 0.41. The result is reported in equation (1), with *t* statistics shown in parentheses below the coefficient estimates. (SAT scores have been divided by 100 to make the scaling of the coefficients more consistent. The coefficient of 0.154 on verbal SAT indicates that an increase of 100 points in the verbal score would raise the reader rating by 0.154 rating points.)

$$RR = -0.328 + 0.099\,SATM + 0.154\,SATV + 0.504\,HSGPA + 0.225\,TP5\%$$
$$(-2.5)\quad (7.7)\qquad\quad (12.1)\qquad\quad (17.6)\qquad\quad (10.2)$$
$$N = 1946, \quad \bar{R}^2 = 0.41, \quad \hat{\sigma} = 0.38. \tag{1}$$

It is clear that the Reed admission office utilizes non-quantitative information in the student's file alongside test scores and high-school grades in evaluating applicants. The first principal component of the five variables explains only 46% of the collective variation and the first two explain just 68%. Although it is unwieldy to retain five measures of a student's pre-Reed academic quality, choosing a measure with lower dimensionality would discard potentially significant information.

The use of both reader rating and the variables that affect it in the student achievement model would make interpretation of the effects difficult. For example, an increase of one point in a student's high-school GPA might affect achievement both directly *and* by raising the reader rating one-half point. To facilitate the interpretation of the basic

results, we replace the reader rating by the residuals from equation (1). The reader-rating residual measures the aspects of the file *other than SAT and high-school grades* that the admission deans used in assigning the rating—presumably essays, letters of recommendation, interviews, and the reputation of the student's high school are some of the factors included. This allows the total effects of SAT scores and high-school credentials to be read directly as their coefficients, while the coefficient of the reader-rating residual represents the components of reader rating that are orthogonal to these variables.

3.2. Other basic variables

In addition to the admission variables, our basic specification includes dummy variables for gender, ethnicity (Asian, African-American, Hispanic, Native American, and Caucasian, with unknown as the omitted category), U.S. citizenship, and eligibility for financial aid. In order to account for possible year-to-year variations in the assignment of admission ratings or grades, we include dummies for year of entry. We also add dummy variables for the area of the student's major (natural sciences and math, social and behavioral sciences, or arts and humanities, with undeclared as the omitted category) to account for the possibility of differences in grading standards across disciplines. The percentages of the sample in the various demographic categories are given in Table 2.

Table 2. Percentage of students in demographic categories

Variable		Percentage of "one" values in sample
Ethnicity	Asian	8.2
	African-American	1.2
	Caucasian	76.0
	Hispanic	3.6
	Native American	0.6
	Other or unknown	10.4
Eligible for financial aid		53.0
U.S. citizen		93.5

3.3. Academic outcome variables

Our principal outcome variable is undergraduate grade-point average. The basic GPA variable includes all undergraduate graded classes taken at Reed.[7] We also examine first-year GPA to see if first-year classmates and living conditions have a stronger influence in the short term than over a student's entire Reed career.[8] Because classroom peers are based on a first-year humanities course, we also look at GPA in humanities-related courses as an academic outcome.[9] For tests of classroom peer effects, grades in Humanities 110 are excluded.[10] We view GPA as a continuous variable and thus use least-squares regression to model the GPA variables.[11] Table 3 shows the summary statistics for the GPA measures.

Table 3. Summary statistics for GPA measures

Variable	Mean	Std. Dev.	Minimum	Maximum
Undergraduate GPA	2.94	0.61	0.00	4.00
Undergraduate GPA (no Hum 110)	2.93	0.64	0.00	4.00
1st Year GPA	2.91	0.63	0.00	4.00
1st Year GPA (no Hum 110)	2.86	0.68	0.00	4.00
Hum-related GPA	3.00	0.63	0.00	4.00

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[7] Ungraded classes, such as pass/fail classes, withdrawals, and incompletes, are excluded.

[8] The first year is defined to be the academic year in which the student receives a grade for Humanities 110 in the fall semester, even if the student was not enrolled in the spring. We define the variable in this way because we hope to capture the immediate effects of peers in the humanities conference on contemporaneous academic performance. In a few cases, this period does not correspond to the student's first two semesters of coursework at Reed. During our sample, 13 local students took one or two courses as high school seniors, which we do not consider to be a true first-year college experience. When such students enroll full-time at Reed, they are considered to be first-time students, and they are included in our sample. Transfer students, even if they take Hum 110, are excluded from our sample, though they are included in the class averages from which peer variables are calculated. The first-and-second-year GPA is calculated over the student's first four semesters in which the student finishes (successfully or unsuccessfully) at least one course, again beginning with the first semester of enrollment in Humanities 110.

[9] We considered a range of possible boundaries for closeness of the relationship to humanities. The narrowest was courses directly relating to the content of Hum 110: literature, history, philosophy, religion, classical languages, art history, and political philosophy. The broadest included all classes except natural sciences and mathematics.

[10] There is some evidence in our data that having classmates with stronger academic credentials is associated with receiving a lower grade in Hum 110. This is plausible if some instructors grade on a relative scale (a "curve") so that a student of given quality would receive a higher grade if he or she were the best student in a weak class than as a lower-ranked student in a strong class.

[11] Truncation is not a serious problem at Reed. Our sample of over 3000 students contains only three observations with a GPA of 4.00 and eleven with a GPA of 0.00.

3.4. Basic GPA regression results

Our basic model of student performance relates the outcome measure, GPA, to the admission variables, demographic dummies, and dummy variables for year of entry and area of major. There is no reason to expect that the effects of variables such as SAT scores, high-school GPA, and the reader-rating residual should be linear.[12] To allow for non-linear effects, each continuous regressor was examined using a linear, quadratic, and cubic specification. The only significant non-linearities we found were for SAT scores in the full undergraduate and hum-related GPA equations, where GPA was best fit as a cubic function of the math score and a quadratic function of the verbal score.

Table 4 presents the results of estimating a basic model of student GPA. Results are shown for the three major variants of GPA: total undergraduate, first-year, and humanities-related.[13] In all cases, each of the admission variables contributes significantly and in the expected direction to explaining GPA. Some of the ethnic dummies have significant explanatory power, as do the gender dummy (men do worse) and, marginally, the U.S. citizen variable (U.S. citizens do slightly worse).

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[12] Both Zimmerman (2003) and Sacerdote (2001) find non-linearities to be important in their study of peer effects.
[13] The results with the undergraduate GPA without Hum 110 and first-year GPA without Hum 110 are very similar to those reported in Table 4.

Table 4. Basic GPA regressions

		Dependent variable		
		(1) Undergraduate GPA	(2) First-year GPA	(3) Hum-related GPA
Admission variables	SAT math/100	3.614 (1.89)*	0.067 (3.13)***	4.729 (2.23)**
	SAT math/100 squared	-0.628 (2.07)**		-0.790 (2.35)**
	SAT math/100 cubed	0.036 (2.27)**		0.043 (2.46)**
	SAT verbal/100	0.502 (2.10)**	0.086 (4.31)***	0.804 (3.03)***
	SAT verbal/100 squared	-0.033 (1.84)*		-0.054 (2.72)***
	Reader rating residual	0.260 (7.77)***	0.291 (8.15)***	0.220 (5.92)***
	High-school GPA	0.417 (10.14)***	0.394 (8.98)***	0.347 (7.59)***
	Top 5% of HS class	0.155 (4.98)***	0.188 (5.68)***	0.148 (4.31)***
Demographic variables	Asian	-0.110 (1.85)*	-0.106 (1.68)*	-0.052 (0.77)
	Black	-0.252 (1.92)*	-0.195 (1.43)	-0.303 (2.09)**
	Caucasian	0.029 (0.67)	0.006 (0.13)	0.003 (0.06)
	Financial aid eligible	-0.006 (0.23)	-0.022 (0.81)	-0.032 (1.12)
	Hispanic	-0.107 (1.46)	-0.080 (1.03)	-0.048 (0.59)
	Male	-0.113 (4.31)***	-0.130 (4.65)***	-0.152 (5.23)***
	Native American	-0.029 (0.20)	-0.165 (1.08)	0.059 (0.38)
	U.S. citizen	-0.109 (1.73)*	-0.122 (1.83)*	-0.115 (1.64)
	Observations	1938	1935	1868
	R-squared	0.24	0.22	0.17

Absolute value of t statistics are in parentheses.
*significant at 10%; ** significant at 5%; *** significant at 1%
Regressions also include constant term, dummies for year of entry, and dummies for area of major.

The non-linearity of the SAT effects in equations (1) and (3) of Table 4 are difficult to interpret based only on the coefficient values. Figure 1 shows the implied relationship between undergraduate GPA (column (1) of Table 4) and SAT scores, with all other variables held at their means. Both SAT effects are mainly positive, but there is a striking

difference. Math SAT scores have little effect below 700, but those at the very top end earn markedly higher grades. The verbal score has little effect above 640, but those substantially below that level end up with lower outcomes.

Figure 1. Partial effects of SAT scores on undergraduate GPA
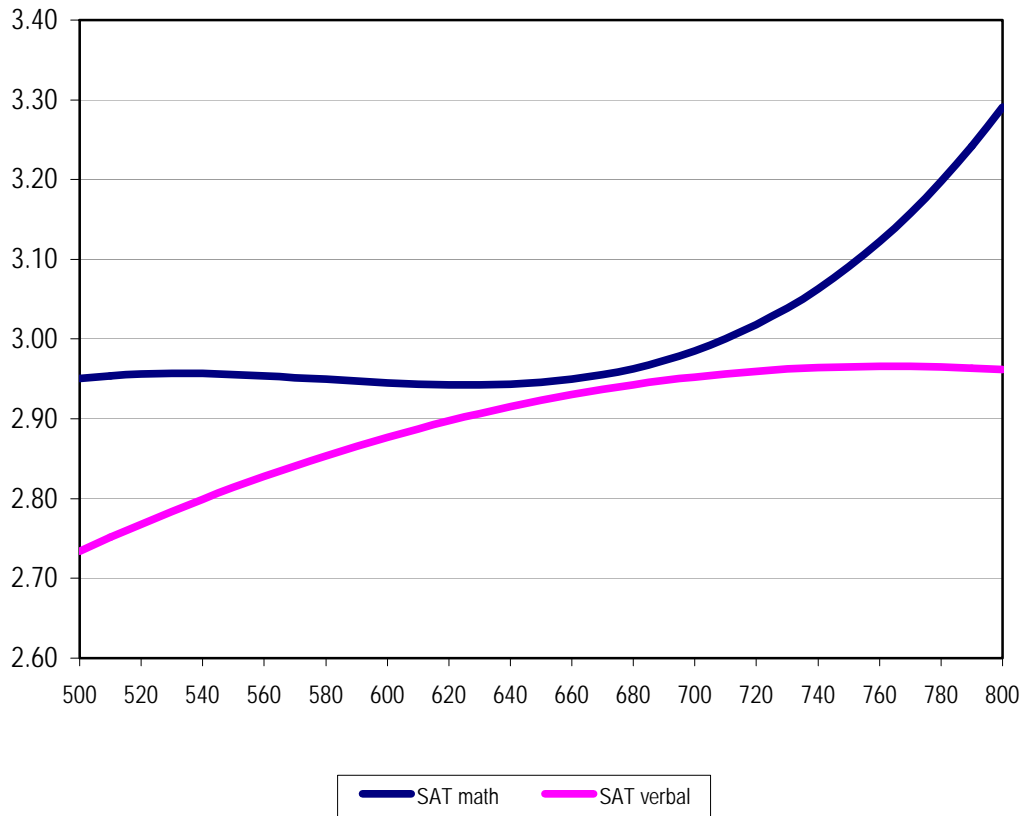
This result is consistent with the structure of degree requirements at Reed. Because no one is required to take a quantitative course, a low mathematical aptitude may have little effect on GPA—those with math SATs below 650 may simply specialize in non-quantitative courses—whereas students with high math ability are able to excel. Verbal ability is more pervasive across the curriculum, including the required freshman humanities course, two additional required courses in humanities, and the senior thesis, which together account for nearly one-quarter of the total units required for graduation. Thus, it is impossible for

students with low verbal ability to avoid reading and writing oriented courses, which probably lowers their GPAs.

4. PEER EFFECTS ON GPA

4.1. Measuring peer effects

We attempt to measure the effects of three groups of peers on student performance: classmates in a student's first-year humanities conference, the student's roommate(s), and the student's fellow dorm residents. Many characteristics of one's peers may be relevant for academic success. In their studies of roommate peer effects at Dartmouth and Williams, Sacerdote (2001) and Zimmerman (2003) use SAT scores or an index of SATs and high-school GPA to measure the roommate's academic quality. We found above that five admission variables all have independent predictive power for Reed GPAs. We have explored two alternative procedures for measuring peer effects: considering each peer characteristic (SAT, HS GPA, etc.) individually or constructing an index of predicted Reed GPA based on admission and demographic variables. Because of its simplicity, we prefer the latter and report only selected results of individual peer characteristics. In addition to measuring the mean quality of a student's peers, we also examine the effects of greater dispersion (higher standard deviation) and the student's position in the class distribution (how many standard deviations the student is above or below the class mean).

To construct a single indicator of student academic quality, we use a variant of the basic GPA regression reported in column (1) of Table 4. To avoid any possible endogeneity bias, the prediction equation uses only information about the student's pre-Reed characteristics—the dummy variables for major are omitted. A predicted GPA is calculated for each student based on this equation.[14] The student's average peer quality is then measured as the average value of predicted GPA among the student's peers.[15]

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[14] Because of missing data, predicted GPA could not be calculated for nearly half of some humanities conferences using the basic equation. In order to provide a more complete description of each student's peers, predicted values were created for student with missing data based on similar prediction equations in which the missing variables were omitted. Thus, a student with no high-school GPA would have a Reed GPA prediction based on a regression excluding high-school GPA. This student's predicted GPA is then included as part of the class, room, or dorm quality distribution.

4.2. Humanities 110

All Reed College first-year students are required to enroll in Humanities 110 for the entire first year.[16] The course meets for six hours per week. Three hours per week are a lecture in which all 350 or so students meet together; the other three hours are a conference section of approximately 16 students led by a faculty member. This yearlong course introduces Reed students not only to classical scholarship in the humanities, but also to the "conference" style of teaching and learning that is common at Reed.

Conference sections are offered at various times of the week. Students sign up for a humanities conference section at their initial meetings with their academic advisors. Instructors' names are not shown in the published class schedule, so the choice of conference section is essentially a choice of time. The required lecture is held at 9am on Mondays, Wednesdays, and Fridays, with most conference sections being at later times on those same days. Thus, a desire to avoid early-morning classes (which might be correlated with late-night partying and low academic motivation) has little effect on the choice of conference time. However, the conference time must not conflict with other courses that the student takes. Introductory courses in biology, chemistry, physics, and psychology have a lecture component that all students in the course must attend, so this imparts some selectivity into the choice of Hum conference times. For example, no student who takes introductory chemistry in his or her first year could enroll in an 11am MWF humanities conference because it would conflict with the intro chemistry lecture.

Once students and their advisors have agreed on a preferred conference time, the registrar's office places students into sections. When multiple sections are offered at the same time, the sections are filled sequentially in the order in which the students are registered, which depends on the advising appointment times assigned to the students by the

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However, because of the missing data, the student's own observation would not be included in the estimation sample.

[15] Note that we exclude the student's own value from the average—we average the *other* members of the students group: class, room, or dorm.

[16] A few first-year students do not enroll in Hum 110. For example, students whose prior training in chemistry allows them to enroll in sophomore-level organic chemistry cannot take Hum 110 due to a time conflict with the humanities lecture. Any student who did not take Hum 110 in his or her first full-time semester is excluded from our sample, but is included in peer statistics for the sections of Hum 110 in which he or she enrolled.

student services office.[17] When all sections at a requested time are full, subsequent students requesting that time are assigned to a section at another time that does not conflict with the students' other classes. Once a tentative assignment into sections has been made, the registrar's office re-assigns students to achieve approximate gender balance in each section.

Thus, the assignment of conference classmates in Humanities 110 can be thought of as nearly random with respect to variables that are likely to affect academic success. As Zimmerman (2003) shows, bias in peer effects can be avoided by including any non-random selection criteria as control variables. We tested dummy variables for the time of the humanities conference along with other characteristics of the conference to control for such bias. None of these characteristics were statistically significant, so they were dropped from the final specification.

4.3. Roommates and dormmates at Reed

The roommate and dormmate peer variables are constructed in a manner similar to the classmate variables. Our data set contains housing information only for the last five years of first-year cohorts. This cuts our sample for estimating residential peer effects to roughly half the size of the ten-year sample we use for classmate effects.

We did not have access to information that would allow us to control for roommate selection effects based on pre-enrollment housing surveys. Thus, to the extent that (1) roommates or dormmates are systematically matched according to survey responses (e.g., liking to get up early or listening to loud music) and (2) these responses are correlated with student academic characteristics and outcomes, our estimates of residential peer effects may be biased. For example, if two roommates who like loud music are paired together and if students who like loud music tend to have lower GPAs, then because the loud-music characteristic is omitted from the sample but correlated with the roommate's characteristics, its effect may be mistakenly picked up as a peer effect. The Reed housing staff claims that this information is used less formally in the roommate-matching process at Reed than

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[17] There is considerable bunching of sections at popular times. Nearly 44% of the students in our sample enrolled in conferences meeting at the two most popular times: 10am and 11am on Mondays, Wednesdays, and Fridays compared with only 28% total in the five afternoon time slots.

appears to be the case in the roommate studies at Williams and Dartmouth. Nonetheless, our estimates of roommate effects may contain some bias from this source.

Roommate effects may be weaker at Reed than at many other schools. Most Reed dorm residents, including first-year students, live either in single rooms or in "divided doubles," in which two students share a common room entry but have separated sleeping spaces. This may limit the degree of influence that roommates have on one another. Among the students in our sample, 7.0% lived in single rooms, 73.4% in doubles (mostly divided), and 15.4% in triples (also mostly divided). The remaining 4.3% lived off campus.

We classify dormitory rooms into groups according to the domains of the student house advisors. Because of variations in dorm architecture, these groups of "dormmates" are sometimes located on a single floor of a traditional dormitory or sometimes groupings of proximate rooms located on multiple floors. These dormmate groups (which we will call "dorms" although they do not usually comprise the entirety of a physical building) often participate together in social activities and have considerable group identification for their members. They range in size from 8 to 33 students with a mean of 22.3.

4.4. Peer variables

As shown in Table 5, the average academic quality of students varies considerably across Hum 110 conferences. Average predicted GPA has a range of 0.46 grade points, average SAT scores vary across conferences by 120–150 points, and more than one point of high-school GPA and the reader-rating residual.

Table 5. Sample statistics for classmate peer averages

	Variable	Mean	Std. Dev.	Minimum	Maximum
Classmate peer average of:	Predicted GPA	2.93	0.080	2.71	3.17
	SAT math	640.4	21.1	576.7	703.6
	SAT verbal	679.8	20.7	602.9	746.7
	Reader-rating residual	0.0058	0.160	-0.468	0.771
	HS GPA	3.65	0.129	3.04	4.38

The distribution of roommate peers mirrors closely the general distribution of student admission variables shown in Table 1. For dorm peers, the distribution of dorm averages is shown in Table 6. As with classmates, there is considerable variation in the distribution of average characteristics across dorm groups.

Table 6. Sample statistics for dormmate peer averages

	Variable	Mean	Std. Dev.	Min	Max
Dorm peer average of:	Predicted GPA	2.94	0.074	2.74	3.15
	SAT math	648.2	16.9	594.8	699.0
	SAT verbal	678.8	19.2	608.5	750.0
	Reader-rating residual	−0.023	0.107	−0.33	0.44
	HS GPA	3.68	0.11	3.29	3.96

4.5. GPA regressions with classmate peer effects

To test for classroom peer effects, we add to the basic GPA regressions of Table 4 the classmate average predicted GPA (possibly in polynomial specification). In each of these regressions, the dependent GPA variable is measured without the grade in Hum 110, to avoid any possible effects of a grading "curve" in this course. The results are reported in Table 7 for three GPA outcomes.

Table 7. Classmate average predicted GPA effects

	(1) Undergraduate GPA excluding Hum 110	(2) First-year GPA excluding Hum 110	(3) Hum-related GPA excluding Hum 110
Classmate peer average predicted GPA	-392.791 (1.17)	322.055 (0.83)	-229.421 (0.62)
Classmate peer average predicted GPA squared	132.314 (1.15)	-107.540 (0.82)	78.347 (0.62)
Classmate peer average predicted GPA cubed	-14.846 (1.14)	11.962 (0.80)	-8.910 (0.62)
Observations	1931	1934	1868
R-squared	0.24	0.20	0.17
Absolute value of t statistics in parentheses. Other variables included as in Table 4, but not shown.			

Table 7 fails to demonstrate any significant effects of Humanities 110 classmate peers' average ability on student achievement, measured by any of the three GPA measures. Results with quadratic and linear specification are equally negative. Detailed peer characteristics such as SAT scores, high-school GPAs, and reader-ratings are equally unsuccessful in helping to predict student achievement.

Some statistically significant effects were found for sub-samples of the dataset using specifications of both peer average and the individual student's position in the class distribution. However, these results seem quite fragile and do not confirm a consistent

pattern of peer effects across variables and sub-samples. Additional exploration may uncover a model in which humanities classmates' have a strong effect on academic achievement, but based on our work to date, we cannot claim to have found such an effect.

4.6 GPA regressions with residential peer effects

Table 8 shows the results of adding roommate (in a cubic specification) and dormmate (quadratic) average predicted GPA to the basic specifications of Table 4 for undergraduate GPA and first-year GPA. In contrast to the negative results for classmate peers reported above, residential peer effects seem to be quite strong at Reed. Roommate effects are statistically significant at the 1% level; dormmate effects are significant at the 5% level for first-year GPA and the 10% level for overall GPA. As expected, considering that the peers are first-year residential peers, the magnitude and significance of the coefficients is greater for the first-year GPA than overall.

Because the effects in Table 8 are non-linear, they are difficult to interpret by examining the coefficients. Figure 2 and Figure 3 show the cubic and quadratic effects of roommate and dormmate average predicted GPA on one's own overall GPA outcome. The effects on first-year GPA are similar, but slightly stronger. In both diagrams, the bold section in the middle reflects the range of peer values between the 10th and 90th percentiles, with the fine curves at the ends representing the tails of the peer distribution.

Table 8. Effects of residential peer variables on own GDP

	(1) Undergraduate GPA	(2) First-year GPA
Roommate mean predicted GPA	-24.181 (3.08)***	-26.859 (3.24)***
Roommate mean predicted GPA squared	8.425 (3.15)***	9.281 (3.28)***
Roommate mean predicted GPA cubed	-0.969 (3.20)***	-1.059 (3.30)***
Dormmate mean predicted GPA	-30.276 (1.93)*	-37.106 (2.23)**
Dormmate mean predicted GPA squared	5.151 (1.92)*	6.351 (2.24)**
Observations	919	917
R-squared	0.29	0.27
Absolute value of t statistics in parentheses. *significant at 10%; ** significant at 5%; *** significant at 1% Other variables shown in Table 4 are included in regressions but not shown.		

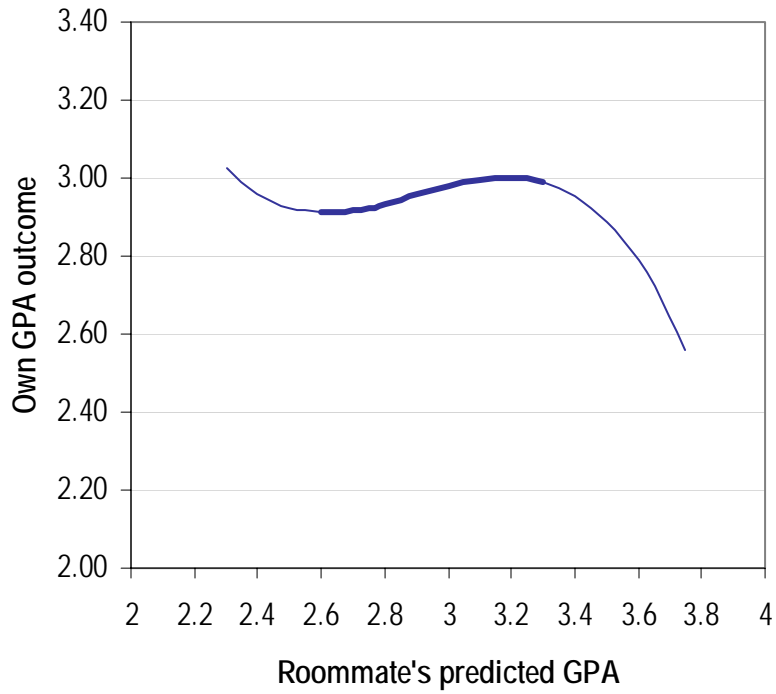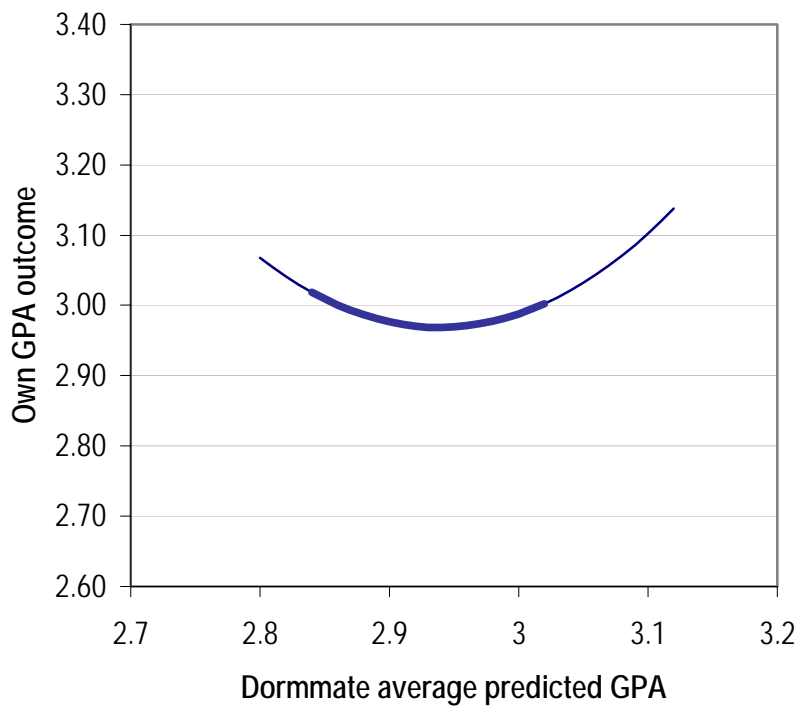**Figure 2. Effects of roommate's predicted GPA on own overall GPA**

Figure 3. Effects of dormmates' average predicted GPA on own overall GPA

The roommate effects in Figure 2 are particularly interesting. For the middle 80% of the roommate population, having an academically stronger roommate is a small benefit, potentially raising one's overall GPA about one-tenth of a point as one rises from the 10th percentile of roommate abilities to the 90th. However, the tails of the distribution behave quite differently. In particular, having a roommate at the very top of the predicted GPA seems to lead to substantially lower academic performance. Reed students who have seen these results have suggested that these "reversed peer effects" could be due to the intimidating effects of having peers who are "too good."

The dormmate effects shown in Figure 3 suggest that most of the effects of dormmate predicted GPA comes in the tails of the distribution. Within the 10–90th percentile range, one's GPA responds by 0.05 points or less to fluctuations in the dorm average academic ability. However, having either a high-ability dorm or a low-ability dorm seems to be associated with a better academic outcome.[18]

In view of the results of Sacerdote (2001) and Zimmerman (2003), the nonlinearity of these results is expected. However, the statistical significance of the effects is somewhat surprising, given the weaker effects found at Dartmouth and Williams coupled with the "divided double" nature of most roommate arrangements at Reed and the fact that these effects are estimated over a sample of just five years.

5. CONCLUSION

We have used data on ten years of Reed first-year students to examine the effects of academic qualifications of three sets of peers on a student's academic achievement, measured by his or her grade-point average. Our results suggest that residential peers may exert strong effects on student performance, but that classmates in a required first-year humanities class have no measurable impact.

We are encouraged to think that peer effects are important by the apparent strong effects of roommates and dormmates on student performance. These results are stronger than those of earlier studies. They may have implications for residence-hall staff in assigning

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[18] A third-order term, which would have allowed for asymmetries in these effects, was statistically insignificant (*t* statistic of 0.23).

first-year students to rooms and dorms. Exploration of those implications is on our agenda for future work.

This absence of classroom peer effects may be explained by any of several possibilities. First, recall that our GPA prediction equation, on which the classmate data are predicted, explains less than one-quarter of the variation in GPA. Although our admission variables have strong statistical significance, most of the variation in academic achievement cannot be explained by our data. Thus, if true quality is demonstrated by GPA outcome, we are assessing peer quality by a very noisy measure. Considerations of simultaneity bias prevent us from using actual peer GPA in the model. However, refinement of the measure of peer quality may enable presently invisible effects to emerge.

Second, while the peers with whom one participates in discussions may be very important, their overall academic ability may not be the most significant characteristic. Students who are outgoing and well-mannered discussion partners may contribute strongly to their peers' learning even if they are not academic superstars. Similarly, exceptionally talented students whose classroom style is either highly introverted or brashly abrasive may induce negative peer effects despite their abilities.

Third, there are many ways in which classroom peer effects may be manifested for different groups of students. Earlier work has suggested that students near the top and bottom of the distribution of abilities may be affected quite differently by their peers. We have only begun to explore the possible effects of a student's position in the class distribution on his or her outcomes. Similarly, work remains to be done in examining how effects may differ across various sub-populations of students. Educational scholars have long argued that girls respond differently to classroom stimuli than boys, so analyzing results by gender may be fruitful. Another measure of academic success is persistence; we are in the process of looking at the possible effects of peers on persistence to the second year and to graduation. We also hope to examine how peers may influence the choice of majors.

Finally, it is entirely possible that peer effects in first-year humanities are simply not important. Despite all of the attention Humanities 110 receives as a "centerpiece" of Reed's curriculum, it is but one course among several that each student takes in the first year. While it may be a formative and defining experience for some, others (especially students aiming

toward majors in mathematics, economics, and the natural sciences) find it far less relevant to their academic enterprise.

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