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ROOMMATE EFFECTS ON GRADES: Evidence from First-Year Housing Assignments

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This paper estimates the effect of students' background characteristics on the academic outcomes of their college roommates. It uses data from four classes of students at Wellesley College, where roommate assignment is credibly random, conditional on student responses to a housing preference form. In linear specifications, there are no peer effects on students' grade point averages. There is some evidence that students' SAT scores have nonlinear effect on their roommates' achievement, but the results are not robust. We conclude that roommate peer effects might exist among small groups of students, but they are not a key determinant of students' average academic outcomes at Wellesley College.

KEY WORDS: peer effects; roommates; natural experiment; liberal arts college; selection bias.

INTRODUCTION

A large literature examines whether a student's peer group—consisting of friends, classmates, or roommates—affects his or her academic outcomes. This research, in K-12 and higher education, often reports positive correlations between peer-group variables and individual outcomes, even when controlling for individuals' own ability or socioeconomic status.[1] It is usually difficult to ascertain whether these partial correlations merit a causal interpretation. The uncertainty exists because peer groups are formed by selection, whether by a student, family, or school administrator. In the presence of selection—perhaps on the basis of unobserved individual attributes that affect student outcomes—it is difficult to separate the causal effect of peer-group attributes from that

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of unobserved variables (Evans, Oates, and Schwab, 1992; Moffitt, 2001).

Confronted by this dilemma, Sacerdote (2001) and Zimmerman (2003) noted that assignment to one potential peer group in higher education is putatively random—or, at least, occurs on the basis of a small set of fully observed variables. When colleges and universities admit first-year students, they are randomly paired with their roommates. This frequently occurs after forming smaller groups of the students on the basis of responses to a housing questionnaire that explores individual preferences regarding smoking, noise levels, and so on. Thus, roommate allocation provides a unique natural experiment in which researchers might credibly estimate the causal effect of a particular peer group (college roommates) on students' college performance, often measured by grade point averages (GPAs).

A burgeoning literature in economics has used such experiments—in concert with institutional data—to estimate the effects of students' pre-college academic ability, gauged by admission test scores, on their roommates' academic outcomes (Foster, 2003; Gleason and Siegfried, 2003; Kremer and Levy, 2003; Sacerdote, 2001; Stinebrickner and Stinebrickner, n.d.; Winston and Zimmerman, 2004; Zimmerman, 2003). We will suggest that the cumulative findings of this research are far from conclusive. The cited research finds virtually no roommate effects when academic ability is entered linearly in regression specifications, and peer effects are rare among subsamples of females. Nonetheless, there are intriguing, though inconsistent, findings of nonlinear peer effects, as well as interactions of peer-group characteristics with students' own academic ability (e.g., Sacerdote, 2001; Zimmerman, 2003). In one case, the pre-college drinking behavior of roommates has substantial effects on academic performance even when academic ability does not (Kremer and Levy, 2003).

In light of this uncertainty, there are dividends to continued empirical study. This is especially true if the incipient estimates of peer effects are to be generalized beyond a small group of colleges, or meaningfully incorporated into models of education markets (e.g., Epple and Romano, 1998; Nechyba, 2000). This paper explores roommate effects at Wellesley College, a selective liberal arts institution in the Boston area that enrolls approximately 2,300 female undergraduates. We argue that roommate assignment is credibly random, conditional on a set of housing assignment preferences expressed by each student. The paper utilizes data from four recent classes of entering students to explore the effects of roommates' academic ability on GPA throughout a student's academic career, as well as the probability of withdrawal.

In some regards, the paper's findings are consistent with previous evidence. There is no evidence that roommates' academic ability, as gauged by SAT scores, has a linear effect on students' GPAs or probability of withdrawal. Like several recent papers, we find suggestive evidence of nonlinearities. In the present analysis, however, these findings are not robust across alternate specifications.

The paper proceeds in the following manner. Section 2 discusses the empirical approach used in this and other papers, while Section 3 reviews broad patterns of evidence from prior research. In Section 4, we discuss the Wellesley College data, as well as details of the roommate assignment process. Section 5 provides an overview of the main results, and Section 6 concludes and extracts some policy implications.

ESTIMATING PEER EFFECTS

Peer-Group Formation and Selection Bias

The seminal work of Newcomb (1966) specified factors that contribute to the formation of peer-groups. Most obviously, shared attitudes and interests may lead students to form peer groups within classrooms, nonclassroom groups, or residential settings such as fraternities and sororities.[2] This poses a considerable dilemma for the empirical researcher that wishes to estimate the effect of peer groups on student outcomes. When students share interests, they may also share unobserved motivations or characteristics that lead them to seek out like-minded peers. Thus, the effects of peer-group characteristics on individual outcomes are easily confounded with the effects of students' unobserved, individual characteristics (Evans, Oates, and Schwab, 1992; Moffitt, 2001).

Newcomb (1966) further notes that propinquity—or "chance" proximity to other students—may contribute to peer-group formation. A prominent example is student residential proximity in dorms, floors, or rooms, which is occasionally influenced by lotteries or well-specified administrative rules. Of course, residential relationships are merely one potential source of peer influence in a college setting. However, the estimation of residential effects is perhaps less susceptible to the selection bias just described, precisely because many residential decisions are not driven by selection on unobserved student characteristics. We argue below that focusing upon roommate effects provides important empirical leverage for the estimation of causal peer effects. However, there is a clear tradeoff in the richness of peer groups that can be explored.

Roommate Assignment as a Natural Experiment

With this caveat, the empirical problem can be formulated in more rigorous terms. The challenge is to estimate the *causal* effect of roommate characteristics on a student's academic outcomes. A starting point is the following linear regression specification:

$$O_i = \beta_0 + X_i\beta_1 + X_i^{\mathrm{RM}}\beta_2 + \varepsilon_i \tag{1}$$

where O_i is the college outcome of student i (such as GPA), X_i is a vector of the student's characteristics that potentially affect outcomes (such as SAT scores), X_i^{RM} is a vector of her roommate's characteristics, and ε_i is an error term. The β's are parameters to be estimated via ordinary least squares. We are particularly interested in β_2, the marginal effect of roommate characteristics on individual outcomes. Estimates of β_2 are unbiased if there is no correlation between observed roommate characteristics and the error term (i.e., $\mathrm{cov}(X_i^{\mathrm{RM}},\varepsilon_i) = 0$).

Such correlations are most likely to exist when roommates or members of other peer groups are allowed to self-select, perhaps basing their roommate choices upon characteristics that are unobserved by the researcher. For example, one could imagine that a highly-motivated student, already prone to obtain a higher GPA, chooses a roommate with high SAT scores. In this case, the unique influence of her roommate's SAT is difficult to separate from the effects of the student's existing, but unobserved motivation.

The economics literature has proposed several solutions to the problem of selection bias, usually in literature on K-12 peer effects. Some authors identify instrumental variables that are correlated with peer-group variables, but supposedly uncorrelated with the error term, thus identifying an exogenous source of variation in peer-group characteristics (Evans, Oates, and Schwab, 1992; Gaviria and Raphael, 2001; Robertson and Symons, 2003). Others have raised concerns about the validity of such instruments (Moffitt, 2001; Rivkin, 2001). Hoxby (2000) identifies a source of variation in peer-group characteristics—year-to-year variation in gender and race composition of classrooms—that is argued to be exogenous. Other authors compare the outcomes of siblings or twins that are exposed to different peer groups (Aaronson, 1998; McEwan, 2003). The empirical strategy introduces controls for unobserved student characteristics that are shared within families, eliminating a potential source of correlation between the peer-group variables and the error term.

The best means of ensuring that $\mathrm{cov}(X_i^{\mathrm{RM}},\varepsilon_i) = 0$ is the random assignment of students to roommate groups. A growing literature notes that some institutions undertake, sometimes inadvertently, a randomized experiment (Sacerdote, 2001; Zimmerman, 2003). Most institutions solicit students' preferences about their roommates (e.g., whether students prefer living with a smoker). Students are then placed in homogeneous groups according to their stated preferences. Within such groups, students are randomly assigned to one another as roommates. There is still selection, of course, but it occurs solely on the basis of observed variables. Conditional on students' group assignment—or, equivalently, their responses to the assignment survey—there should be no remaining correlation between students' unexplained outcomes and their roommates' characteristics. In the present analysis, we will further control for Z_i , a vector of variables indicating each student's response to the roommate assignment survey:

$$O_i = \beta_0 + X_i\beta_1 + X_i^{\mathrm{RM}}\beta_2 + Z_i\beta_3 + \varepsilon_i \tag{2}$$

Eq. (2) should provide credibly unbiased estimates of β_2. However, the effects gauged by β_2 could operate through two distinct causal channels. First, the outcomes of student i are directly affected by the exogenous background characteristics of her roommate (X_i^{RM}). Second, it is possible that student i is affected by her roommate's contemporaneous achievement (O_i^{RM})—which is, in turn, a function of X_i^{RM}. One cannot separately identify the effect of O_i^{RM} on achievement by simply including it as an independent variable, due the well-known problem of simultaneity (or "reflection," as it has been referred to in the peer-effects literature) (Moffitt, 2001; Sacerdote, 2001). To avoid this problem, we estimate a reduced-form regression, as in Eq. (2), but with the preceding caveat to interpretation.

In addition to the specification in Eq. (2), we will apply a range of alternative specifications to examine the robustness of our findings. In particular, we will test for nonlinearities in roommate effects, as well as interactions with own ability.

ROOMMATE EFFECTS IN HIGHER EDUCATION

The previous empirical approach has been applied to data from at least nine colleges and universities that vary by public and private status, selectivity, and size. Thus far, the most robust patterns in this growing literature are related to the *absence* of peer effects on students' GPAs. No author finds consistent evidence that admissions test scores or students' previous academic ability are linearly related to GPA. Moreover, a number of authors find that peer effects, when they do exist, are most pronounced among male students (Kremer and Levy, 2003; Stinebrickner and Stinebrickner, n.d.; Zimmerman, 2003). Several authors find that alternate specifications—allowing for nonlinearities or interactions with own ability—do yield peer effects (see especially Sacerdote, 2001; Winston and Zimmerman, 2004; Zimmerman, 2003). However, these estimates are not always consistent with one another.

Using data from recent Dartmouth classes, Sacerdote (2001) examined peer influences on students' GPAs. He found no evidence of peer effects when roommate characteristics were entered linearly, but he did find significant, positive results when he allowed for nonlinearities and interactions with own ability. Sacerdote found that having a roommate who was academically strong significantly increased a student's freshman year GPA, while having a weak roommate had no significant effect. Furthermore, he also found that strong students have significant, positive effects on other strong students and on weaker students. Students who were in the middle 50% for academic strength were neither helped nor hurt.

Zimmerman (2003) conducted a similar study at Williams College. Like Sacerdote, he found weak results in standard linear specifications. In other specifications, he found that students in the middle 70% of the SAT distribution perform worse when they have a roommate in the bottom 15% of the verbal SAT distribution. These effects appear to be driven by males rather than females. In subsequent work, Winston and Zimmerman (2004) employed data from three selective colleges—as gauged by SAT scores—drawn from the College and Beyond survey. When roommates' SAT scores are entered linearly, there are statistically insignificant or small effects at all institutions. In specifications that pool all institutions' data, peer effects are most robust among men in the middle 70% of their institution's SAT distribution.

Kremer and Levy (2003) found no effect of roommates' academic background on student performance among recent classes at a large state university. However, they did find that pre-college drinking among male students tended to negatively influence their roommates' GPAs, especially among lower-performing students. At Vanderbilt University, Gleason and Siegfried (2003) found no peer effects stemming from SAT score or high school GPA in linear specifications. They did find that the number of Advanced Placement (AP) courses that a student took in high school had a modest, positive effect on his or her roommate's GPA. In addition, the authors found that there was a substantial peer effect when academically strong students were paired with other academically strong students.

Foster (2003) found very limited evidence of peer effects among recent classes from the University of Maryland. In linear specifications, Foster found no peer effects for women, and only modest peer effects for men. The high school GPA of men was found to have a modest, positive impact on their roommates' college GPA. Unlike the other authors, Foster did not find evidence of peer effects when she allowed for nonlinearities. In the much less selective environment of Berea College, Stinebrickner and Stinebrickner (n.d.) found that roommates' ACT scores have no effect on students' grade point average. However, roommates' family income has some effect on female students' grades.

DATA AND INSTITUTIONAL BACKGROUND

Data Sources

The paper analyzes data from four entering classes of Wellesley College (2003--2006), drawn from three internal datasets. First, we obtained data on students' background characteristics from admission files. These variables include SAT scores; a series of dummy variables indicating race; a dummy variable indicating whether a student is a first-generation college student; and a series of dummy variables indicating the type of high school attended. High school class rank was included in the admissions data, but the variable was missing for a large portion of our dataset.

Second, we obtained data on outcomes, including students' GPAs and current enrollment status, from enrollment files. The files indicate each student's cumulative GPA at the end of consecutive spring semesters, ending in 2003. Thus, we were able to extract first-year GPAs for all four classes (2003, 2004, 2005, and 2006). However, we could only extract second-, third-, and fourth-year cumulative GPAs for subsets of the four classes. For example, cumulative fourth-year GPAs were only available for the class of 2003. The enrollment files were also used to construct a dummy variable indicating whether students have permanently withdrawn from the college. The GPA and withdrawal variables constitute the key outcome variables.

Third, we obtained students' responses to the housing preference survey forms—filled out by all incoming students—from the Wellesley Housing Office. The Housing Office maintains paper copies of the form, described further below, which contain student responses to a range of preferences about preferred characteristics of their rooms and roommates (the form is available from the authors). Besides the student's name and address, the forms contain no other background characteristics; hence, such data could not be used in the roommate assignment process. Each student's written responses were coded by hand.

We merged the three datasets using students' college-assigned identification numbers. We then created additional variables containing the background characteristics of each student's initially-assigned, first-year roommate. For the small number of first-year students housed in triple- or quadruple-occupancy rooms—about 13% of the sample—we matched each student with the mean background characteristics of their roommates.

Sample Definition

The initial sample contained observations on 2,356 students in four classes. It is slightly larger than the college's current enrollment, given that some of the entering students withdraw early. Table 1 reports descriptive statistics for this sample. Consistent with publicly-available data, it indicates that entering Wellesley students have high SAT scores (a mean of 1,348). They are racially and ethnically diverse, including a large proportion of Asian-American students (24%). Finally, a large proportion of students (about one-third) attended private independent high schools. Note that sample sizes decline for cumulative GPAs after the first year, given that data were not available for younger cohorts.

In the working sample used in this paper's analyses, we excluded 330 students because of obviously non-random roommate assignment or missing data. Nevertheless, as Table 1 suggests, the background characteristics of the working sample are similar to those of the original sample. First, a small number of students did not return a housing form, and were assigned non-randomly.[3] Second, some students made special roommate or dorm requests, despite the lack of an official policy to do so; such requests were granted in a few cases. Third, incoming members of the classes of 2003 and 2004 had the option of participating in a special academic cluster program. The participants were assigned roommates non-randomly, and they further received special classroom instruction. Fourth, some students were assigned single rooms and thus had no roommate peer group. Fifth, some students were missing an SAT score, usually because they only reported ACT scores in their application.

Roommate Assignment

In the spring before attending Wellesley, students respond to a housing survey that addresses topics such as smoking, preferences on guest

TABLE 1. Descriptive Statistics

	Full sample		Working sample	
	Mean	*N*	Mean	*N*
First year GPA	3.42 (0.37)	2,356	3.43 (0.37)	2,026
Second year cumulative GPA	3.44 (0.34)	1,724	3.44 (0.34)	1,480
Third year cumulative GPA	3.46 (0.31)	1,135	3.46 (0.31)	971
Fourth year cumulative GPA	3.50 (0.29)	559	3.49 (0.29)	489
First year withdrawal	0.00	2,356	0.00	2,026
Second year withdrawal	0.03	1,765	0.03	1,508
Third year withdrawal	0.05	1,191	0.04	1,006
Fourth year withdrawal	0.07	602	0.06	518
SAT/100	13.48 (1.07)	2,282	13.49 (1.08)	2,026
Math SAT/100	6.70 (0.66)	2,282	6.70 (0.67)	2,026
Verbal SAT/100	6.78 (0.70)	2,282	6.78 (0.70)	2,026
African-American	0.05	2,356	0.05	2,026
Asian-American	0.24	2,356	0.25	2,026
Latina	0.04	2,356	0.05	2,026
Other	0.19	2,356	0.18	2,026
White	0.48	2,356	0.47	2,026
First generation	0.10	2,356	0.11	2,026
Public HS	0.58	2,356	0.58	2,026
Private independent HS	0.32	2,356	0.32	2,026
Private religious HS	0.02	2,356	0.02	2,026
Other HS	0.08	2,356	0.08	2,026

Note: Standard deviations are in parentheses for non-dummy variables.

visitation, and musical tastes. Students are grouped according to their survey responses. According to the Housing Office, students' smoking preferences (whether or not they smoke and whether or not they would be willing to live with a student who smoked) and students' preferences regarding guests in their room figure most prominently in the initial grouping. Other survey questions such as preferences for music and extracurricular activities are given the least weight, and are considered "tie breakers" for forming sub-groups within the broad groups established by previous questions. Students are assigned a roommate from within the groups and sub-groups established by this matching process. No other individual variables are considered in the roommate assignment process.

In fact, this process occurs on a rolling basis as the housing assignment forms are received. Once a large number of forms is received, they are grouped by survey responses and roommates are assigned. First year students can be housed in double-, triple-, or quadruple-occupancy rooms, but the vast majority of students are placed in doubles. The roommate pairings are then assigned to a given dorm until it is filled, proceeding in the dorms' alphabetical order.[4] The process is repeated until all forms are received and assigned. Ideally, then, we should control for membership in each sequential assignment group in the empirical analysis, since "early-senders" may differ in unobservable ways from "late-senders." Because this information is not available, we instead control for a series of dorm dummy variables in all specifications. The dummy variables are a useful proxy for order of receipt, given the sequential assignment to dorms.

The dorm assignment process should not lead to systematic correlations between the background characteristics of roommate pairs, at least conditional on the housing assignment variables. The presence of correlations would imply some role for selection on observed and perhaps unobserved characteristics. This would cast doubt upon the causal validity of the natural experiment described above.

Table 2 tests this assertion by regressing the background variables of students, such as SAT and race, on a full set of their roommates' background variables—though initially excluding the housing assignment variables.[5] In the case of dummy dependent variables, we apply ordinary least squares and estimate a linear probability model, correcting the standard errors for heteroscedasticity. A number of individual coefficients are statistically significant at 5%, and the null hypothesis that coefficients are jointly equal to zero is rejected for three of 11 dependent variables. The results imply, for example, that Asian-American students are more likely, all else equal, to have Asian-American roommates. Since these initial specifications do not control for housing assignment variables, it is possible that the correlations are the results of shared preferences across sub-groups of students.

Table 3 tests this by controlling for a complete set of housing assignment variables.[6] Now, only five of 99 coefficients are statistically significant at 5%, and the null of jointly zero coefficients is rejected for only one variable. The results provide support for the notion that previously observed correlations are mainly the result of shared housing preferences. Conditional on such preferences, there is no remaining pattern of self-selection or sorting on observed student characteristics. This provides an additional measure of confidence that our empirical strategy is justified.

TABLE 2. Regressions of Own Characteristics on Roommate Characteristics

	SAT/100	African-American	Asian-American	Latina	Other	White	First generation	Private ind. HS	Public HS	Private rel. HS	Other HS
Roommate characteristics											
SAT/100	0.008	−0.000	−0.008	0.003	0.002	0.003	−0.002	−0.002	−0.005	0.004*	0.003
	(0.036)	(0.008)	(0.015)	(0.007)	(0.012)	(0.016)	(0.011)	(0.016)	(0.017)	(0.002)	(0.008)
African-American	0.095	0.014	0.095	0.022	−0.044	−0.086	0.126**	0.131*	−0.088	−0.013	−0.030
	(0.183)	(0.042)	(0.074)	(0.040)	(0.054)	(0.081)	(0.064)	(0.078)	(0.081)	(0.008)	(0.036)
Asian-American	−0.066	0.023	0.122***	−0.017	0.022	−0.150***	0.028	−0.009	−0.006	−0.000	0.014
	(0.088)	(0.018)	(0.036)	(0.015)	(0.032)	(0.040)	(0.025)	(0.036)	(0.039)	(0.010)	(0.023)
Latina	0.038	0.008	0.015	0.031	0.029	−0.083	0.038	0.012	0.031	−0.011	−0.033
	(0.185)	(0.039)	(0.070)	(0.042)	(0.064)	(0.081)	(0.057)	(0.080)	(0.084)	(0.008)	(0.034)
Other	−0.026	0.046**	0.103***	0.019	−0.005	−0.163***	0.059**	0.048	−0.032	−0.008	−0.008
	(0.100)	(0.021)	(0.038)	(0.020)	(0.033)	(0.043)	(0.030)	(0.041)	(0.043)	(0.008)	(0.022)
First generation	0.130	0.043	−0.009	0.009	−0.011	−0.032	−0.046	−0.019	0.023	0.002	−0.006
	(0.125)	(0.033)	(0.049)	(0.024)	(0.041)	(0.054)	(0.033)	(0.049)	(0.053)	(0.011)	(0.028)
Private ind. HS	0.066	0.016	0.010	−0.014	−0.008	−0.004	0.011	0.024	−0.011	0.001	−0.013
	(0.078)	(0.016)	(0.031)	(0.015)	(0.027)	(0.036)	(0.023)	(0.033)	(0.036)	(0.007)	(0.019)
Private rel. HS	−0.072	−0.048***	0.089	−0.020	0.091	−0.112	−0.080	−0.072	0.032	0.036	0.004
	(0.211)	(0.014)	(0.101)	(0.043)	(0.091)	(0.106)	(0.049)	(0.098)	(0.104)	(0.042)	(0.059)
Other HS	0.056	0.070*	0.096	−0.033	−0.074*	−0.059	−0.025	−0.008	0.047	−0.008	−0.031
	(0.145)	(0.039)	(0.058)	(0.022)	(0.041)	(0.061)	(0.036)	(0.057)	(0.061)	(0.005)	(0.028)
R^2	0.01	0.03	0.05	0.02	0.02	0.04	0.03	0.02	0.02	0.02	0.03
N	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050
p-value	0.90	< 0.01	0.02	0.61	0.59	0.01	0.20	0.62	0.92	0.19	0.72

Notes: All regressions include dummy variables for dorms and student cohorts. Robust standard errors are in parentheses. ***indicates statistical significance at 1%, **at 5%, and *at 10%. The p-value corresponds to a test of the null hypothesis that reported coefficients are equal.

TABLE 3. Regressions of Own Characteristics on Roommate Characteristics, with Controls for Housing Assignment Variables

	SAT/ 100	African-American	Asian-American	Latina	Other	White	First generation	Private ind. HS	Public HS	Private rel. HS	Other HS
Roommate characteristics											
SAT/100	−0.019	0.003	−0.009	0.007	0.004	−0.005	−0.003	0.007	−0.012	0.004	0.000
	(0.035)	(0.007)	(0.014)	(0.007)	(0.012)	(0.015)	(0.011)	(0.015)	(0.016)	(0.003)	(0.008)
African-American	0.197	−0.038	0.064	0.017	−0.063	0.020	0.131**	0.107	−0.063	−0.015	−0.030
	(0.180)	(0.039)	(0.070)	(0.043)	(0.058)	(0.079)	(0.065)	(0.084)	(0.087)	(0.010)	(0.039)
Asian-American	0.021	0.011	0.052	−0.021	0.011	−0.053	0.023	−0.021	0.010	0.002	0.009
	(0.088)	(0.016)	(0.036)	(0.017)	(0.031)	(0.037)	(0.027)	(0.036)	(0.040)	(0.011)	(0.025)
Latina	−0.005	0.023	0.001	0.032	0.054	−0.110	0.040	0.046	0.021	−0.005	−0.062**
	(0.187)	(0.036)	(0.067)	(0.042)	(0.065)	(0.074)	(0.061)	(0.082)	(0.084)	(0.010)	(0.030)
Other	−0.026	0.039*	0.068*	0.019	−0.017	−0.109***	0.054*	0.050	−0.027	−0.008	−0.015
	(0.098)	(0.021)	(0.037)	(0.019)	(0.035)	(0.041)	(0.031)	(0.041)	(0.043)	(0.009)	(0.023)
First generation	0.153	0.036	−0.012	0.004	0.002	−0.029	−0.050	−0.004	0.014	0.006	−0.016
	(0.127)	(0.027)	(0.046)	(0.026)	(0.042)	(0.051)	(0.035)	(0.053)	(0.056)	(0.013)	(0.027)
Private ind. HS	0.009	0.025	0.005	−0.008	−0.016	−0.005	0.016	0.006	0.016	0.000	−0.022
	(0.077)	(0.015)	(0.031)	(0.015)	(0.027)	(0.034)	(0.024)	(0.033)	(0.035)	(0.008)	(0.020)
Private rel. HS	0.043	−0.062**	0.077	−0.034	0.098	−0.079	−0.085	−0.072	0.027	0.038	0.008
	(0.212)	(0.029)	(0.100)	(0.047)	(0.090)	(0.109)	(0.054)	(0.099)	(0.106)	(0.043)	(0.060)
Other HS	0.124	0.071*	0.082	−0.024	−0.106**	−0.024	−0.024	−0.026	0.059	−0.009	−0.024
	(0.152)	(0.038)	(0.056)	(0.025)	(0.043)	(0.057)	(0.039)	(0.057)	(0.060)	(0.007)	(0.030)
R^2	0.14	0.19	0.18	0.08	0.12	0.27	0.08	0.12	0.12	0.04	0.09
N	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050	1,050
p-value	0.67	0.02	0.38	0.64	0.24	0.36	0.22	0.78	0.95	0.26	0.31

Notes: All regressions include dummy variables for dorms and student cohorts, as well as controls for housing assignment variables (see text for description). Robust standard errors are in parentheses. ***indicates statistical significance at 1%, **at 5%, and *at 10%. The p-value corresponds to a test of the null hypothesis that reported coefficients are equal.

RESULTS

First Year GPA

The results for Eq. (2), using first year GPAs as the dependent variable, are reported in Table 4. All specifications include dummy variables for student cohorts, as well as their assigned dormitory. Regressions in columns (1) and (3) do not include controls for housing assignment variables, while (2) and (4) do. The inclusion of controls makes little differences in the coefficient estimates. Nonetheless, we restrict our interpretations to specifications with housing controls, and all regressions in subsequent tables will always control for these variables.

As expected, students' own SAT scores have a positive and significant impact on their first year GPAs. A 100 point increase in a student's SAT score raises her first year GPA by 0.06 points (0.16 of a standard deviation). Columns (3) and (4) estimate separate coefficients for verbal and math SAT scores, but they are similar (one cannot reject the null hypothesis at 5% that math and verbal coefficients are equal). Students' own race plays a significant role in determining their first year college achievement. Students of African-American, Asian-American, and Latina descent have lower first year GPAs than white students. The effect is greatest for African-American students, with their first year GPA being 0.29 points lower (0.78 of a standard deviation). The results are generally consistent with comparable specifications from Williams College, another selective college (Zimmerman, 2003).

There is no evidence, however, of a peer effect. The SAT scores of student's roommates, while positively-signed, are small and statistically insignificant. None of the coefficients on other roommate variables are statistically significant. A potential concern is that multicollinearity is inflating standard errors and preventing the precise estimation of roommate effects. To assess this, Table A.1 reports bivariate correlations between the independent variables used in the regressions in Table 4.[7] The absolute value of most correlations is well under 0.4. The correlations between own-variables and roommate-variables are close to zero, consistent with previous evidence on quasi-random assignment of roommate pairs. Table A.1 also reports the tolerance for each independent variable, based upon the regression specification in Table 4 (column 1). The values suggest that more than 80% of the variance in each independent variable cannot be explained by the other independent variables. Thus, multicollinearity is unlikely to be driving the pattern of statistically insignificant coefficients.

TABLE 4. The Effects of Own Characteristics and Roommate Characteristics on First Year GPA

	(1)	(2)	(3)	(4)
Own characteristics				
SAT/100	0.065***	0.061***	–	–
	(0.008)	(0.009)		
Math SAT/100	–	–	0.066***	0.067***
			(0.014)	(0.014)
Verbal SAT/100	–	–	0.065***	0.056***
			(0.013)	(0.014)
African-American	−0.300***	−0.286***	−0.299***	−0.283***
	(0.051)	(0.055)	(0.051)	(0.055)
Asian-American	−0.066***	−0.066***	−0.066***	−0.069***
	(0.019)	(0.021)	(0.021)	(0.022)
Latina	−0.209***	−0.202***	−0.209***	−0.201***
	(0.048)	(0.048)	(0.048)	(0.048)
Other	0.021	0.019	0.021	0.017
	(0.022)	(0.022)	(0.023)	(0.023)
First generation	0.002	−0.009	0.002	−0.008
	(0.030)	(0.030)	(0.031)	(0.030)
Private ind. HS	0.001	−0.003	0.001	−0.004
	(0.018)	(0.018)	(0.018)	(0.018)
Private rel. HS	−0.031	−0.028	−0.030	−0.027
	(0.063)	(0.066)	(0.063)	(0.066)
Other HS	0.025	0.026	0.025	0.026
	(0.030)	(0.030)	(0.030)	(0.030)
Roommate characteristics				
SAT/100	0.007	0.006	–	–
	(0.009)	(0.009)		
Math SAT/100	–	–	0.006	−0.002
			(0.016)	(0.016)
Verbal SAT/100	–	–	0.009	0.013
			(0.013)	(0.013)
African-American	−0.051	−0.042	−0.052	−0.044
	(0.044)	(0.043)	(0.045)	(0.043)
Asian-American	0.005	0.002	0.006	0.006
	(0.021)	(0.021)	(0.022)	(0.023)
Latina	−0.032	−0.031	−0.032	−0.033
	(0.040)	(0.040)	(0.040)	(0.040)
Other	−0.016	−0.017	−0.016	−0.015
	(0.024)	(0.023)	(0.024)	(0.024)
First generation	−0.026	−0.036	−0.026	−0.037
	(0.029)	(0.030)	(0.029)	(0.030)

TABLE 4. (*Continued*)

	(1)	(2)	(3)	(4)
Private ind. HS	0.027	0.015	0.027	0.016
	(0.018)	(0.017)	(0.018)	(0.017)
Private rel. HS	−0.038	−0.039	−0.039	−0.041
	(0.065)	(0.066)	(0.065)	(0.067)
Other HS	−0.027	−0.028	−0.027	−0.028
	(0.035)	(0.035)	(0.035)	(0.035)
Assignment controls	No	Yes	No	Yes
R^2	0.12	0.18	0.12	0.18
N	2,026	2,026	2,026	2,026

Note: All regressions include dummy variables for dorms and student cohorts. Robust standard errors are in parentheses, adjusted for clustering within rooms. ***indicates statistical significance at 1%, **at 5% and *at 10%.

Alternate Specifications

Several previous studies suggest that peer effects are nonlinear, or vary according to students' own ability (Gleason and Siegfried, 2003; Sacerdote, 2001; Stinebrickner and Stinebrickner, n.d.; Winston and Zimmerman, 2004; Zimmerman, 2003). The authors test for nonlinearities by splitting roommate-ability into a series of dummy variables, although the exact specification varies.

We explore two nonlinear specifications in Table 5. Panel A reports a quadratic specification of math and verbal SAT scores (a full set of variables are included, but coefficients are not reported). In the full sample, the coefficients on math SAT scores imply statistical significance—but only at 10%—and a concave relationship. The implied marginal effect would reach zero at a math SAT of 648 (just below the sample mean). An increase of roommates' math SAT scores from 500 to 600 implies a substantial increase in GPA of 0.05. There are no effects of roommates' verbal SAT scores.

However, these effects are not robust to a variety of other specifications that allow for nonlinearities. In Panel B, roommates' SAT scores are divided into quartiles and none of the dummy coefficients are statistically significant (relative to the excluded category of the first quartile). In other results, not reported here, we replicated the specifications in Zimmerman (2003) and Sacerdote (2001). The first split roommates' SAT into the bottom 15%, middle 70%, and top 15%, while the second split the sample into the bottom 25%, middle 50%, and top 25%. None

TABLE 5. Alternate Specifications of Roommate Effects on First Year GPA

		Sample divided by quartile of own SAT			
	Full sample	1st	2nd	3rd	4th
Panel A: Quadratic specifications					
Roommate characteristics					
Math SAT/100	0.324* (0.185)	1.003** (0.449)	−0.066 (0.304)	−0.391 (0.420)	−0.121 (0.389)
Math SAT/100 squared	−0.025* (0.014)	−0.077** (0.034)	0.008 (0.022)	0.029 (0.032)	0.009 (0.030)
Verbal SAT/100	0.002 (0.169)	−0.118 (0.377)	0.179 (0.300)	−0.161 (0.314)	1.071*** (0.412)
Verbal SAT/100 squared	0.001 (0.013)	0.009 (0.029)	−0.013 (0.023)	0.015 (0.023)	−0.078** (0.031)
R^2	0.18	0.26	0.27	0.29	0.23
N	2,026	521	549	461	495
Panel B: Quartile specifications					
Roommate characteristics					
Math SAT/100 (2nd quartile)	0.011 (0.023)	−0.014 (0.055)	0.031 (0.043)	−0.016 (0.049)	0.061 (0.053)
Math SAT/100 (3rd quartile)	0.006 (0.023)	−0.006 (0.054)	0.027 (0.043)	−0.026 (0.050)	−0.002 (0.047)
Math SAT/100 (4th quartile)	−0.007 (0.026)	−0.076 (0.062)	0.058 (0.043)	0.006 (0.055)	0.009 (0.055)
Verbal SAT/100 (2nd quartile)	0.012 (0.024)	−0.051 (0.053)	−0.010 (0.044)	0.025 (0.055)	0.108** (0.050)
Verbal SAT/100 (3rd quartile)	0.018 (0.024)	0.016 (0.053)	0.027 (0.039)	0.035 (0.059)	0.021 (0.055)
Verbal SAT/100 (4th quartile)	0.014 (0.023)	−0.010 (0.059)	0.010 (0.041)	0.055 (0.056)	0.009 (0.050)
R^2	0.18	0.26	0.27	0.29	0.23
N	2,026	521	549	461	495

Note: All regressions include dummy variables for dorms and student cohorts, as well as controls for own characteristics (see Table 4) and housing assignment variables. Robust standard errors are in parentheses, adjusted for clustering within rooms. ***indicates statistical significance at 1%, **at 5% and *at 10%.

of the dummy variables in these specifications were statistically significant, relative to the lowest category.

Finally, we divided the sample by deciles of roommates' math SAT and included a series of dummy variables for deciles 2–10, doing the same for verbal SAT (full results are available from the authors). These less restrictive specifications indicate that the math-score quadratic results from Panel A are apparently driven by students in deciles three and five (although coefficients for these deciles are only significant at 10%). Other coefficients in the full sample are not statistically significant.

In other columns of Table 5, we divide the sample by quartiles of students' *own* SAT score, and re-estimate nonlinear specifications, thus allowing peer effects to vary according to a student's own academic ability. In Panel A, the apparent nonlinear peer effect of math scores in the full sample is driven by students in the bottom quartile of the own-SAT distribution. Moreover, a peer effect emerges for roommates' verbal SAT scores in the top quartile of the own-SAT distribution. As in the full sample, these results find inconsistent support in other nonlinear specifications (see Panel B). Moreover, there is no convincing explanation that would suggest why results should differ so dramatically across math and verbal scores.

Other Outcome Measures

It is possible that peer effects of first year roommates could influence student outcomes beyond the first year. Thus, we applied Eq. (2) to second, third, and fourth year cumulative GPAs (see Table 6). None of the coefficients for roommates' math SAT scores are statistically significant. Some positive peer effects appear for roommate's verbal scores, but these are only significant at the 10% level and only when we do not control for students' majors. Interestingly, these effects surface in students' third and fourth year GPAs. The appearance of peer effects in these two years is puzzling, since they were less evident in the full sample results for first-year GPA. In part, they may be explained by the fact that third- and fourth-year results are limited to the older cohorts in our sample. Rather than long-term effects, the results may simply indicate differential effects among the older cohorts. To further investigate this result, we repeated the previous regressions by cohort. The results of this exercise (not reported here) indicate that relatively larger point estimates, regardless of which year's GPA is examined, are generally concentrated among the older cohorts (the classes of 2004 and 2003).

In addition to examining peer effects with regards to student achievement, we also investigated the influence that students had on the

TABLE 6. Roommate Effects on Later-Year GPA

	Dependent variable					
	Second-year GPA		Third-year GPA		Fourth-year GPA	
Roommate characteristics						
Math SAT/100	0.295	0.310	0.314	0.281	0.130	−0.041
	(0.200)	(0.212)	(0.211)	(0.236)	(0.260)	(0.297)
Math SAT/100 squared	−0.022	−0.023	−0.023	−0.021	−0.009	0.003
	(0.015)	(0.016)	(0.016)	(0.018)	(0.019)	(0.022)
Verbal SAT/100	0.095	0.112	0.354*	0.285	0.533*	0.215
	(0.170)	(0.172)	(0.211)	(0.209)	(0.322)	(0.288)
Verbal SAT/100 squared	−0.006	−0.008	−0.026*	−0.022	−0.040*	−0.016
	(0.013)	(0.013)	(0.016)	(0.016)	(0.024)	(0.021)
Major fixed effects	No	Yes	No	Yes	No	Yes
R^2	0.22	0.28	0.24	0.33	0.33	0.50
N	1,480	1,480	971	971	489	489

Note: All regressions include dummy variables for dorms and student cohorts, as well as controls for own characteristics (see Table 4) and housing assignment variables. Robust standard errors are in parentheses, adjusted for clustering within rooms. ***indicates statistical significance at 1%, **at 5% and *at 10%.

likelihood that their roommates would withdraw from Wellesley College by the end of the second, third, or fourth year. Permanent withdrawal by the end of the first-year is extremely low. Even withdrawal by the fourth year is rare; only 7% of students do so. The results for linear probability specifications can be found in Table 7. While there were no significant effects for roommates' SAT scores, students with Asian-American roommates were statistically significantly more likely to withdraw by the end of their second and third years, and students with roommates who were first generation college students were significantly more likely to withdraw by the end of their second year.

SUMMARY AND IMPLICATIONS

This paper examined the effect that students have on their roommates' college achievement. We applied numerous specifications to a rich set of institutional data and examined effects both within the full sample of students and within sub-groups within the SAT distribution.

TABLE 7. Roommate Effects on Student Withdrawal

	Dependent variable		
	Withdrew by end of year 2	Withdrew by end of year 3	Withdrew by end of year 4
Roommate characteristics			
Math SAT/100	0.002	−0.013	−0.024
	(0.008)	(0.011)	(0.016)
Verbal SAT/100	−0.011	−0.004	−0.004
	(0.007)	(0.009)	(0.013)
African-American	0.053	0.019	−0.007
	(0.033)	(0.039)	(0.055)
Asian-American	0.025**	0.034*	−0.010
	(0.012)	(0.018)	(0.022)
Latina	0.017	−0.014	−0.027
	(0.023)	(0.028)	(0.039)
Other	0.001	−0.012	−0.035
	(0.012)	(0.019)	(0.037)
First generation	0.049**	0.030	−0.004
	(0.021)	(0.024)	(0.032)
Private ind. HS	−0.002	−0.012	0.006
	(0.009)	(0.013)	(0.022)
Private rel. HS	0.012	0.064	0.106
	(0.040)	(0.069)	(0.117)
Other HS	0.010	0.048	0.022
	(0.022)	(0.036)	(0.047)
R^2	0.07	0.13	0.17
Observations	1,508	1,006	518

Note: All regressions include dummy variables for dorms and student cohorts, as well as controls for own characteristics (see Table 4) and housing assignment variables. Robust standard errors are reported in parentheses, adjusted for clustering within rooms. ***indicated statistical significance at 1%, **at 5% and *at 10%.

Like previous studies, we find no evidence of linear peer effects on GPA or the probability of withdrawal. We find some weak evidence of non-linearities, but we also find that the results are not always robust to alternate specifications. We conclude that although roommate effects might exist among small groups of students, they are not a key determinant of students' average academic outcomes at Wellesley College. In particular, the magnitude of effects is substantially outweighed by the influence of individuals' own pre-college academic abilities and characteristics.

Research Implications

The findings do not support the notion that peer relationships are generally unimportant in determining student outcomes at Wellesley College. Rather, they suggest that if peer effects exist, they operate outside of first-year roommate pairings. The strong and relatively small academic community at Wellesley implies many possible sources of peer influence, including student government, extracurricular organizations, and residential relationships outside roommate pairs. This is not inconsistent with previous empirical research in higher education (see Pascarella and Terenzini, 2005 for a review).

The obvious research implication is to employ a richer set of peer-group measures. However, it bears emphasis that this would re-introduce the problem of selection bias. To circumvent this problem, a fruitful line of research—at Wellesley and elsewhere—would be to search for sources of exogenous variation in more relevant peer-group measures. Such variation may be the result of a natural experiment—as in roommate assignment—or the result of randomized or deliberate assignment on the part of institutional researchers. For example, Wellesley College makes peer mentoring groups available to first-year students. It would be feasible to assign incoming students to mentors based on observable variables (such as stated preferences or dorm).

Such a research agenda would supply the empirical leverage to credibly explore a larger range of possible peer influences. In so doing, it would bridge two disparate literatures on peer effects: (1) the recent economics literature that has emphasized valid causal inference, often at the expense of theoretical or practical relevance; and (2) the vast higher education literature that has employed rich measures of peer-group characteristics, perhaps accompanied by selection bias of an unknown magnitude.

Policy Implications

Like many colleges, Wellesley administers a quasi-random lottery to assign first-year roommates, but allows a larger degree of self-selection in later years. An important policy question is whether housing assignment policies should be modified in the presence of roommate-based peer effects on student outcomes. In particular, it is important to ask whether roommate sorting after the first year—perhaps leading to increasing segregation of roommates by ability—has negative consequences for the distribution or aggregate level of student outcomes.

Imagine that students with high SAT scores choose one another as roommates after the first year and, conversely, low-SAT students also form roommate pairs (regrettably, there is no direct evidence on roommate selection after the first year). In the presence of linear peer effects, this pattern of roommate sorting has distributional consequences, increasing the gap in outcomes between high- and low-ability students. Thus, maintaining random roommate assignment after the first year could improve the distribution of academic outcomes.

The recent economic literature, in K-12 and higher education, has further emphasized the possibility of nonlinear peer effects (e.g., McEwan, 2003; Zimmerman, 2003). In the presence of nonlinearities, roommate sorting—and segregation by academic ability—might affect *aggregate* academic outcomes, in addition to their distribution (Zimmerman, 2003). For example, it is plausible that the marginal effect of roommate-quality on individual outcomes diminishes at higher levels of roommate-quality (for evidence of this in K-12 education, see McEwan, 2003). In such a case, "the increase in learning from moving a weak student to peer-rich environment exceeds the loss in learning from moving a strong student to a peer-poor environment" (Zimmerman, 2003, p. 11). Thus, a better mixing of roommates by ability—as would occur through random assignment—could increase aggregate college outcomes.

This paper's results suggest that roommate effects are not an important determinant of academic outcomes at Wellesley College. Thus, roommate self-selection is unlikely to substantially affect either the distribution of student outcomes, or the aggregate level of outcomes. The current roommate allocation policies in the present research context appear largely benign. They may be less so at other institutions. Indeed, the roommate peer effects literature has produced mixed findings that warrant some caution in generalizing the same conclusion to other institutions. Above all, they highlight that roommate self-selection, in concert with positive and nonlinear peer effects, could have substantial implications for both the distribution and level of outcomes.

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END NOTES

1. For an overview of the peer-effects literature in K-12 education, see McEwan (2003). K-12 research usually measures peer-group quality by taking the average ability or socioeconomic status of all students in a school or classroom. In higher education, Pascarella and Terenzini (2005) review a large literature that documents positive partial correlations between proxies of nonclassroom peer interactions and student outcomes, such as measured or self-reported verbal or quantitative competence.
2. Many contemporary measures of peer-group interaction explicitly proxy shared interests. For example, Whitt et al. (1999) measure nonclassroom peer interaction by the degree to which students are involved in discussions with other students about political, religious, or academic issues. For overviews of the rich theoretical and empirical literature on college peer groups, see Pascarella and Terenzini (2005) and Renn and Arnold (2003).
3. According to our best information, students who do not return any housing preference form are listed in alphabetical order, contacted to confirm that they still plan to attend the college, and then matched in alphabetical order and assigned to rooms. This could potentially be resolved by conditioning on student characteristics used in the assignment (e.g., first letter of last name). However, remaining uncertainty about the assignment of such students leads us to exclude them from the analysis.
4. As each dorm is filled, one to two first year rooms are left vacant in each dorm to accommodate students who either fail to return their housing preference form, are taken off the admissions waiting list, or for some other reason require housing after the housing process has already been completed.
5. Following Kremer and Levy (2003), the sample includes only one member of each roommate pair.
6. In a few cases, students did not respond to a full set of housing assignment variables. In such cases, we replace the missing observation with the variable's mean, and further control for a dummy variable indicating missing values.
7. Table A.1 omits correlations and tolerances for dorm dummy variables and student cohort dummy variables, which were also included as controls in Table 4. The full results, available from the authors, suggest that multicollinearity is not problematic.
8. For more information on Wellesley, please see http://www.wellesley.edu/admission/admission/index.html.
9. Tutoring another student occasionally was the only pre-college behavior that had a significant effect on first year GPA in the full sample. These results appear to be largely confined to students with SAT scores in the 2nd quartile.

TABLE A.1. Correlations between Independent Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Own characteristics																		
1 SAT/100	1.00																	
2 African-American	−0.32	1.00																
3 Asian-American	0.17	−0.13	1.00															
4 Latina	−0.23	−0.05	−0.13	1.00														
5 Other	−0.07	−0.11	−0.27	−0.10	1.00													
6 First generation	−0.18	0.10	0.08	0.15	−0.03	1.00												
7 Private ind. HS	−0.07	0.04	−0.09	−0.03	0.15	−0.07	1.00											
8 Private rel. HS	−0.04	0.06	−0.05	−0.03	0.01	0.03	−0.09	1.00										
9 Other HS	−0.09	0.01	−0.05	0.08	0.05	0.08	−0.20	−0.04	1.00									
Roommate characteristics																		
10 SAT/100	0.00	0.00	−0.03	0.01	0.01	0.00	0.00	0.02	0.02	1.00								
11 African-American	0.00	0.02	0.00	0.01	0.02	0.05	0.04	−0.03	0.02	−0.32	1.00							
12 Asian-American	−0.03	0.02	0.08	−0.03	0.05	0.00	−0.03	0.02	0.05	0.16	−0.13	1.00						
13 Latina	0.00	0.02	−0.02	0.02	0.01	0.01	0.00	−0.01	−0.02	−0.23	−0.05	−0.13	1.00					
14 Other	0.01	0.02	0.04	0.02	0.00	0.04	0.03	0.01	−0.03	−0.06	−0.11	−0.27	−0.10	1.00				
15 First generation	0.00	0.06	0.01	0.00	0.03	−0.04	0.01	−0.02	−0.01	−0.17	0.07	0.10	0.15	−0.03	1.00			
16 Private ind. HS	0.01	0.03	−0.02	−0.01	0.02	0.01	0.04	−0.01	−0.02	−0.06	0.02	−0.08	−0.03	0.16	−0.07	1.00		
17 Private rel. HS	0.02	−0.03	0.02	0.00	0.01	−0.03	−0.01	0.04	0.00	−0.03	0.06	−0.05	−0.03	0.01	0.01	−0.09	1.00	
18 Other HS	0.02	0.03	0.05	−0.02	−0.03	−0.01	−0.02	−0.01	−0.03	−0.08	0.01	−0.06	0.09	0.04	0.08	−0.20	−0.04	1.00
Tolerance	0.79	0.81	0.82	0.86	0.83	0.91	0.90	0.97	0.92	0.79	0.82	0.82	0.87	0.83	0.92	0.90	0.97	0.92
Variance inflation factor	1.27	1.23	1.22	1.16	1.2	1.09	1.12	1.03	1.09	1.26	1.22	1.22	1.15	1.2	1.09	1.11	1.03	1.09

Note: The sample size is 2,026 for all correlations. The tolerance and the variance inflation factor (1/tolerance) for each independent variable are based upon the regression specification in Table 4 (column 1).

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