

# PEER EFFECTS IN ACADEMIC OUTCOMES: EVIDENCE FROM A NATURAL EXPERIMENT

David J. Zimmerman\*

*Abstract*—I use data from Williams College to implement a quasi-experimental empirical strategy aimed at measuring peer effects in academic outcomes. In particular, I use data on individual students' grades, their SAT scores, and the SAT scores of their roommates. I argue that first-year roommates are assigned randomly with respect to academic ability. This allows me to measure differences in grades of high-, medium-, or low-SAT students living with high-, medium-, or low-SAT roommates. With random assignment these estimates would provide compelling estimates of the effect of roommates' academic characteristics on an individual's grades. I also consider the effect of peers at somewhat more aggregated levels. In particular, I consider the effects associated with different *academic environments* in clusters of rooms that define distinct social units. The results suggest that peer effects are almost always linked more strongly with verbal SAT scores than with math SAT scores. Students in the middle of the SAT distribution may have somewhat worse grades if they share a room with a student who is in the bottom 15% of the verbal SAT distribution. The effects are not large, but are statistically significant in many models.

## I. Introduction

PEER effects are central to many important issues facing higher (and lower) education. School choice, affirmative action, busing, distance learning, mainstreaming, selective admissions, and the rise of merit scholarships at elite schools, for example, all possess the potential to alter the distribution of students within the educational system. At the micro level, these policies can change the composition of one's classmates along various dimensions—making them more or less racially, socially, geographically, or intellectually diverse. These changes may effect, among other things, students' attitudes, values, or academic performance. In short, changes in the distribution of students may generate peer effects.

Peer effects may also be central to understanding the production of educational services and, through that, the structure of colleges and universities in the United States. The production of higher education is characterized by an unusual customer input technology whereby student quality is arguably a key input into the production of educational services—students may learn better when in the company of other strong students. The fact that students are themselves the only providers of this potentially key input in the production of education could explain why schools care so much about the characteristics of their customers and why elite schools create a queue of applicants from which to select by regularly setting their tuition well below the full cost of the education they provide (cf. Winston, 1996).

Received for publication July 11, 2000. Revision accepted for publication November 13, 2001.

\* Williams College and Williams Project on the Economics of Higher Education.

I would like to thank the Andrew W. Mellon Foundation for its generous financial support for this project through the Williams Project on the Economics of Higher Education. I am grateful for helpful comments from Jon Bakija, Henry Bruton, Al Goethals, Steve Shepard, and Gordon Winston.

Measuring peer effects is difficult. Student outcomes depend on a myriad of factors other than the characteristics of one's peers, and isolating peer influences is particularly problematic in that people typically choose those with whom they associate. Indeed, when students select a college to attend, they are importantly choosing the peers with whom they will live and learn for the duration of their college life.

In this paper I use data from Williams College to implement a quasi-experimental empirical strategy aimed at measuring peer effects in academic outcomes. In particular, I use data on individual students' grades, their SAT scores, and the SAT scores of their roommates. I argue that first-year roommates are assigned randomly with respect to academic ability. This allows me to measure differences in grades of high-, medium-, or low-SAT students living with high-, medium-, or low-SAT roommates. With random assignment these estimates should provide compelling estimates of the effect of roommates' academic characteristics on an individual's grades. These estimates, unlike those found in most studies of peer effects, are not tainted by selection bias. I also consider the effect of peers at somewhat more aggregated levels. In particular, I consider the effects associated with different *academic environments* in clusters of rooms that define distinct social units. In addition, I consider the effects of the differential academic abilities of *academic advisors* associated with these social units.

In the next section I provide some background on the academic literature related to peer effects. I then discuss empirical issues related to measuring peer effects and propose an empirical strategy. In section IV, I turn to a description of the data used in my analyses. Finally, I present the empirical results and offer some concluding comments.

## II. Background

The study of peer effects spans several academic disciplines. Sociologists have spent considerable time studying neighborhood effects—particularly in the contexts of urban poverty and substance abuse (cf. Jencks and Meyer, 1989; Rosenbaum, 1991; Wilson, 1987). A recurring debate in developmental psychology concerns the relative importance of peers versus parents in human development (cf. Harris, 1998). Medical researchers have considered how patient recovery rates from coronary bypass surgery depend on sharing a hospital room with a roommate who has already had a similar operation (Kulik et al., 1996).

Most of the research literature on peer effects in education has focused on elementary and secondary schools.<sup>1</sup> Certainly the most influential piece of social science research incorporating peer effects is the famous study *Equality of Educational Opportunity*, completed over thirty years ago (Coleman et al., 1966). Employing over half a million students from approximately three thousand elementary and secondary schools, Coleman and his associates sought to measure the features of school environment that led to differences in student attainment. A key finding of this study was that “. . . a pupil’s achievement is strongly related to the educational backgrounds and aspirations of the other students in the school.” Indeed, peer characteristics were found to be notably more important than teacher characteristics or nonsocial aspects of the school.

Henderson, Mieszkowski, and Sauvageau (1978) employed data from approximately seven thousand Montreal students between the first and third grades. Their study found compelling evidence that peer effects were both important and nonlinear. Student performance rose with the average classroom IQ score. The increase, however, slowed as the mean IQ rose. The nonlinearity of the effect is particularly interesting. As noted by McPherson and Schapiro (1990), it suggests that mixing rather than segregating students of different abilities may generate higher aggregate learning. Intuitively, the increase in learning from moving a weak student to a peer-rich environment exceeds the loss in learning from moving a strong student to a peer-poor environment. This logic parallels the justification for income equalization in a world with diminishing marginal utility of income.

A recent K–12 study, using the British National Child Development Survey data, related children’s standardized math and reading scores—taken at the ages of seven and eleven—to measures of parental and schooling inputs (Robertson and Symons, 1996). Peer effects were captured both by the varying socioeconomic background of the student’s peers and by the “streaming” of students by ability within some schools. They found clear evidence that peer effects were positive, and their data too suggested that they were nonlinear—that poor students were helped more than strong students were hurt. Given their own abilities, students were best off if they were in the top group of a school that sorted by ability and worst off in the bottom group of such a school. Betts (1996), by contrast, using data from the United States, finds tracking to have little effect on students’ achievement once controls are included for the ability level of students in the nontracking schools.

Epple and Romano (1998) develop and simulate a careful theoretical model of secondary-school choice that explicitly

allows for peer effects in the education production function. They note that the Pareto-efficient allocation of students depends on the extent of peer-group externalities and, in particular, on the degree of complementarity between a student’s own ability and that of his or her peers. They also note that there is a paucity of empirical evidence on the magnitude of such complementarities. Their computational results suggest that low-income, low-ability students are more likely to remain in public schooling and sustain losses. Low-income, high-ability students secure the greatest gains from vouchers.

Much of the literature contributed by economists focuses on the effect secondary school spending has on either grades or wages (Burtless, 1996). To disentangle the effects spending might have on student performance, it is necessary to control for other variables—such as the quality of the peer environment—that are likely to be correlated with spending. Peer effects are, for this task, simply a nuisance that must be statistically controlled to enable researchers to accomplish their chosen objective of measuring the benefits of additional spending. Typically, a measure of a school’s average student quality—usually average SAT scores—is included in wage or grade equations and usually has a significant and positive coefficient (cf. Ehrenberg and Brewer, 1996; Behrman et al., 1996; Turner, 1996).

There has been significantly less research done directly on peer effects within higher education. Hall and Willerman (1963), in a study similar in spirit to this one, contrast the grades of roommates at the University of Minnesota who were randomly assigned to groups of differing prior achievement as measured by their high school percentile rank. They found little evidence that higher-achieving roommates affected the academic performance of their roommates. Focusing on birth-order effects, they found some evidence that first-born students with high-ability roommates exhibited larger grade effects than later-born students.

Julian Betts and Darlene Morell (1999) use data from five thousand undergraduates at the University of California, San Diego, between 1991 and 1993 to analyze the determinants of students’ grade point averages. Their results indicate a significant relation between students’ grade point averages and their gender, ethnicity, parental income, and SAT scores. They also find neighborhood effects, indicators of the socioeconomic environment of the students’ high school being significantly related to grades. Interestingly, they find models of grade determination based simply on SAT scores to predict grades almost as well as more complex models including family background and high school environment variables. These findings might be combined with those of Loury and Garman (1995)—who find a 1-point rise in grade point average to be associated with a 10% increase in subsequent earnings—to assess the effect of SAT scores on earnings.

<sup>1</sup> My discussion will focus on peer effects defined by the academic characteristics of one’s peers. There is an interesting literature on the effect of desegregation in schooling that focuses on the effect of the racial characteristics of one’s peers (cf. Rivkin, 1997; Hoxby and Terry, 1999). For evidence on a variety of other peer effects in higher education see Pascarella and Terenzini (1991).

Hoxby (1998) decomposes the growing inequality of wages for college-educated Americans into three components—a part due to changes in the demographic composition of college attendees, a part due to an increasing return to aptitude, and a final part due to the increasing correlation between student quality and institutional expenditures. The latter effect is a peer effect in that high-ability students are increasingly likely to have high-ability classmates. Hoxby finds that about 40% of the growth in wage inequality amongst college graduates that can be explained is attributable to such peer effects.

Finally, the economics literature has considered an important methodological issue that is pervasive in all research on peer effects: people often select those with whom they associate. This contrasts sharply with an experimental situation in which we might randomly assign people to differing peer environments and then measure their effect on educational attainment. If the peers with whom a person associates share his or her attributes and also affect his or her attainment (and are unobservable to the researcher), then we might falsely attribute a peer effect where one does not exist. For example, suppose people who associate with low-ability friends tend to do worse in school. Perhaps they would have done poorly even if they didn't associate with such people. That is, what might at first look like a peer effect might really be a case of birds of a feather flocking together. At least two studies by economists have looked at the issue of such *selection bias* in peer effects. Evans, Oates, and Schwab (1992) studied peer effects in the context of teen pregnancy and school dropout behavior. Applying an instrumental variables estimator, they found that peer effects disappear once selection bias is controlled. Questioning these results, Rivkin (1997) showed that they are sensitive to the type of instrumental variable used. These papers indicate the importance of taking the selection issue seriously. They also suggest the value of a good experimental or quasi-experimental approach to the measurement of peer effects—something I pursue next.

### III. Empirical Strategy

Estimates of peer effects typically use a specification of the form

$$O_{ic} = \alpha + \beta_1 C_{ic} + \beta_2 C_{ic}^{\text{Peer}} + \epsilon_{ic}, \quad (1)$$

where  $O$  is some outcome of interest,  $i$  indexes individual students,  $c$  indexes cohorts,  $C$  is a vector of characteristic of the individual and the school, and  $C^{\text{Peer}}$  is some characteristic(s) of the individual's peer(s). For example,  $C$  might contain the race and gender of the student along with the school's per-student spending, average class size, and the like.  $C^{\text{Peer}}$  might contain the average SAT of the student body.

A principal empirical hurdle facing a model of this type is that peers are typically not randomly assigned. If there are characteristics of the individual or the school that are (a)

omitted from the model that affect  $O$  and (b) are correlated with  $C^{\text{Peer}}$ , so that  $\text{cov}(C_i^{\text{Peer}}, \epsilon_i) \neq 0$ , then the estimated peer effect ( $\beta_2$ ) will be biased. Such a situation is likely when school inputs affect the quality of the student body and it is difficult to control for all relevant school inputs.

To estimate SAT-based peer effects I relate the grades of students in their first and later semesters to their own SAT scores and to the SAT scores of their first-year roommate. More formally, I estimate regression models specified as

$$GPA_{ic} = \alpha + \gamma_c + \beta_1 SAT_i + \beta_2 SAT_i^{\text{RM}} + \beta_3 X_i + \epsilon_{ic}, \quad (2)$$

where  $GPA$  is the student's grade point average measured in the first year and also cumulatively to graduation,  $SAT$  is the student's own SAT score (sometimes entered separately for math and verbal scores, and also sometimes entered nonlinearly),  $SAT^{\text{RM}}$  is the student's roommate's SAT score (sometimes entered separately for math and verbal scores, and also sometimes entered nonlinearly), and  $X$  is a vector of other characteristics (such as race and gender) of the student.<sup>2</sup> If students are randomly assigned their roommate(s), then the estimated peer effect ( $\beta_2$ ) will be unbiased. More generally, the estimate will be unbiased if it is plausible that  $\text{cov}(SAT^{\text{RM}}, \epsilon_{ic}) = 0$ . I turn to this issue in more detail below.

There are a variety of possible explanations for why  $\beta_2$  may differ from zero in this model (cf. Goethals, Winston, and Zimmerman, 1999). Work in social psychology, by Festinger (1950, 1954) and others, suggests that people have a powerful need to evaluate their own opinions and values by comparing them with the opinions and values of others (see also Goethals, 1999). When such comparisons take place in group settings, there exists a strong tendency towards uniformity. Those inside the group can reward or punish the behavior of its members, and uniform standards of behavior come to be expected. Deviation from group standards may elicit sanctions of various kinds, including status, praise, shame, and exclusion. The movement toward uniformity within the group is mediated in various ways, but often by way of talking and listening (or observing). Interaction within the group transmits information, which may affect knowledge, values, beliefs, and aspirations. That is, participation within the group may effect change.

Within residential housing, a student's peers may affect how much he or she enjoys learning. Roommates may champion or deprecate the "life of the mind." Bull sessions may explore novel ideas, share insights and inspirations, or delve into the implications of classroom lectures or world and campus events. Or they may be superficial or discouraging or nonexistent. Peers may exhibit good or bad study

<sup>2</sup> An appealing alternative strategy would be to include the roommate's GPA in the regression. Such a variable might better measure actual rather than potential performance. The problem with including such a variable is that it is simultaneously determined within the roommate context. Using such a measure would introduce simultaneous-equation bias.

habits and may or may not offer help on assignments. They may also encourage other activities—some of which, like partying, can compete with learning.

In sum, it seems clear that there are strong reasons to expect students' peers to influence their own successes and failures. The empirical strategy I employ requires (a) that roommates be assigned in such a way that the error term in equation (2) remains orthogonal to the explanatory variables, (b) the roommate's SAT score is a reasonable measure of peer quality, (c) the student's room (and other spatial aggregates) are a meaningful context for locating such effects, and (d) grades are a useful measure of academic achievement.

#### IV. Empirical Results for Williams College

##### A. Housing Assignment

Each year, students at Williams College are asked to fill out a housing preference form. A copy of this form can be found in the Appendix. Students are asked whether they would like to live with a particular person, whether they have any specific health problems (for example, students with asthma are more likely to be assigned a room with hardwood floors), and whether they prefer a particular residence. They also indicate their preferences regarding a single versus a double room; whether they smoke, enjoy frequent visitors, and prefer classical music; and so on.

The housing office currently uses this information (alone) to allocate students to rooms and roommates.<sup>3</sup> Rooms are embedded within *entries* that are clusters of rooms sharing a common entrance or hall. Entries are typically assigned two *junior advisors* (JAs)—third-year students who live in the entry and offer help to the first-year students.

A guide to housing offered by the Housing Office defines entries as follows:

*Entry* (from the Latin word “habitus froshness”) n. as a frosh, you will live with a surrogate “family” which we at Williams call an “entry.” Imagine a house, filled with a group of frosh, with a couple of enthusiastic and seasoned juniors bringing everyone together. They can be either vertically or horizontally arranged, so you will either have these individual yet connected “houses” next door or up and downstairs from you.<sup>4</sup>

The Housing Office uses the following protocol in assigning rooms.<sup>5</sup> First, applications are separated by gender.<sup>6</sup> Within

gender groups, applications are separated by the preferred first-year housing units (i.e. the “hall preference” ranking on the form). Of the eight remaining items A–H on the forms, items A (preference for a single room) and B (smoker or nonsmoker) carry the most weight. Items C (attitude towards visitors), F (preference regarding noise), G (neatness), and H (sleep patterns) are treated as a group, and attempts are made to match people who are similar in these dimensions. According to the Housing Office, items D and E carry “significantly less weight” and tend to have a “very minor” effect on assignment.

These variables are of some importance in determining whether estimates of roommate effects will be biased. Consider, for example, the following example shown in figure 1. In this example there are 500 students, of whom 100 indicate (a fictitious) preference A on the housing form. Suppose preference A indicates that the student dislikes reading. The remaining 400 students indicate preference B, indicating that they like to read. Suppose nonreaders, holding their SAT scores constant, receive lower grades, on average, than readers. Suppose further that there is a correlation between students' preferences regarding reading and their SAT scores, such that of those who dislike reading 80% have low SAT scores and 20% have high SAT scores, and of those who like reading 10% have low SAT scores and 90% have high SAT scores. Students are then matched randomly with roommates indicating a similar preference.

If we contrasted the grades of low-SAT students living with low-SAT roommates with those of low-SAT students living with high-SAT roommates, we would generate a biased estimate of any peer effect, because the group consisting of two low-SAT students would consist of nonreaders, whereas the group consisting of two high-SAT students would consist of readers. Differences in grades between these two groups would reflect the effect of their housing preferences on grades along with any causal peer effect. Notice that this bias depends on the correlation between SAT and the housing preferences. It also depends on the housing attribute having an effect on grades after controlling for the student's SAT score.

Clearly, some preferences are more likely than others to create a bias, and it is worth noting that neither ethnicity, nor prior academic performance, nor athletic affiliations—all characteristics that might create a problematic selection bias—are used by the Housing Office in assigning students to rooms and roommates. If such factors do affect the allocation of first-year students, they must act indirectly through the categories present on the form.<sup>7</sup> It is also worth noting that estimates

<sup>3</sup> In the mid 1990s the Office of the Dean of Students shifted responsibility for student housing assignments to the Housing Office. The form currently used appears to capture the spirit of the approach used by the dean's office.

<sup>4</sup> Chris Bell '98, *WCHG 101F Introduction to the Twentieth Century Frosh Dorm*, Williams College Housing Office (1997).

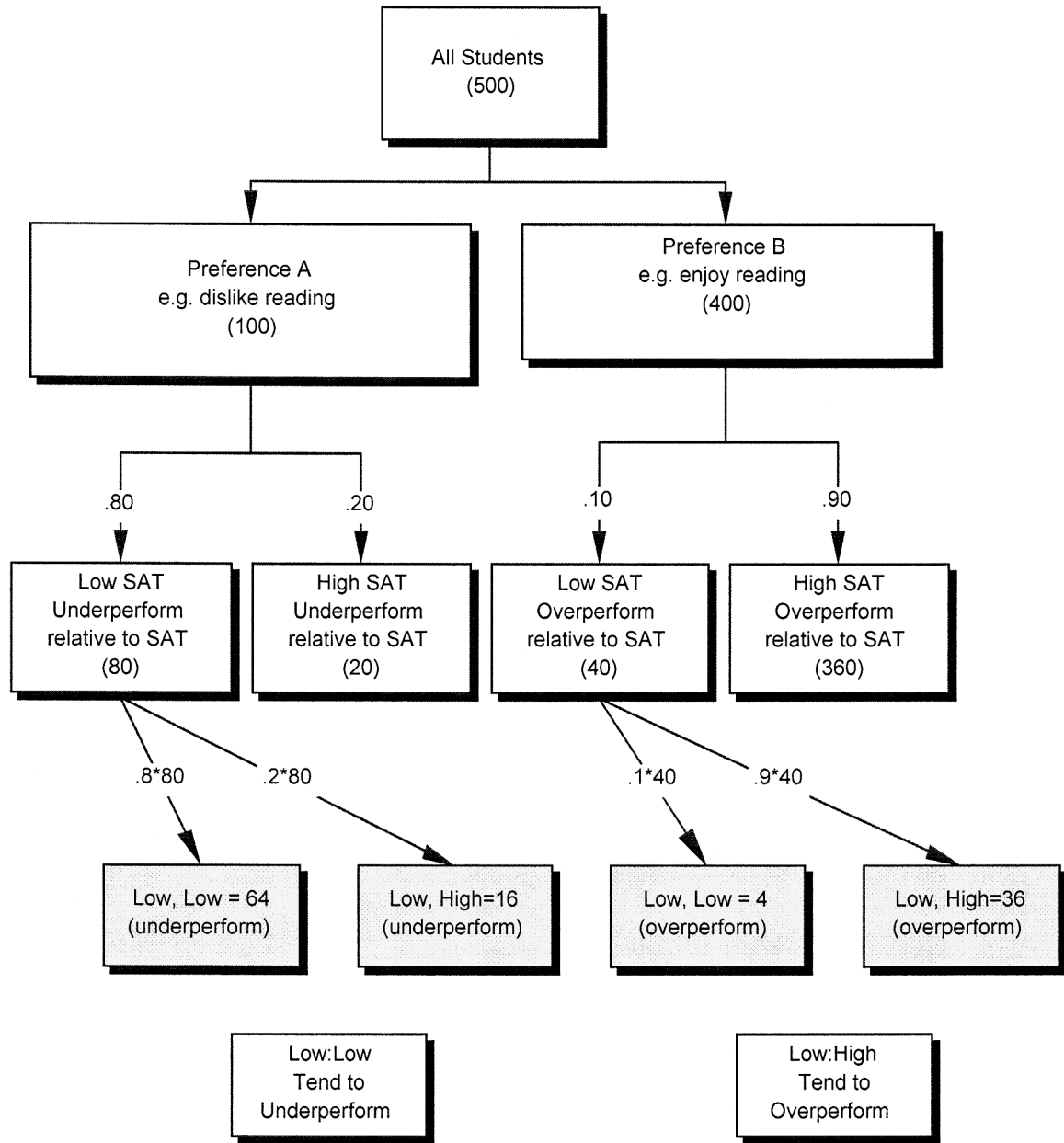
<sup>5</sup> Note that there is no price difference between units, and applications are not evaluated on a first-come, first-served basis.

<sup>6</sup> Entries (clusters of rooms connected by a stairway or hall and sharing a common room) were partly single-sex in the early years of the sample. For the classes of '90–'93 and '95 about one-third of the students were in

single sex entries. For the class of '94 about 10% of the students were in single-sex entries. All entries were mixed after '95. Virtually all rooms were single sex throughout the period. Controlling for single-sex entries has little effect on the results.

<sup>7</sup> Beginning with the class of '03, the Housing Office runs a check to make sure that entries are “diverse.” In particular, they aim to be sure that there is not a clustering of athletes or racial minorities in freshman dormitories.

FIGURE 1.—POTENTIAL BIAS FROM HOUSING ASSIGNMENT



could be similarly biased by self-selection if students were able to choose their roommates and did so based on characteristics that were associated with their prior performance (as measured by their SAT scores) or with future academic performance (as measured by grades with SAT scores held constant). The same problem arises if students can switch roommates. Fortunately for the analysis, the housing office strongly discourages students from changing roommates; only a handful of students move each year.

*B. Is the Use of SAT Scores Appropriate, and Is Housing Assignment Random?*

As noted, the mechanism used for making housing assignments could create a spurious correlation between a

students GPA and his or her roommate’s SAT. To see this more clearly, consider the following model:

$$GPA_{ic} = \alpha + \gamma_c + \beta_1 Q_i + \beta_2 Q_i^{RM} + \beta_3 X_i + \epsilon_{ic}, \quad (3)$$

where  $Q^{RM}$  is an index called *roommate quality*. Here, grades are assumed to depend on the academic quality of oneself and one’s roommate, together with other factors ( $X$ ) such as race or gender. Now, suppose it is the case that

$$Q_i = \delta_0 + \delta_1 SAT_i + \delta_3 H_i + v_i, \quad (4)$$

$$Q_i^{RM} = \gamma_0 + \gamma_1 SAT_i^{RM} + \gamma_3 H_i^{RM} + w_i, \quad (5)$$

where  $H$  is an index of the student’s housing preferences that are correlated with their peer quality. That is, SAT is a

proxy for student quality, which may also depend on housing preference variables.

Substituting equations (4) and (5) into equation (3), we have

$$\begin{aligned} GPA_{ic} &= \alpha + \gamma_c + \beta_1(\delta_0 + \delta_1 SAT_i + \delta_3 H_i + v_i) \\ &\quad + \beta_2(\gamma_0 + \gamma_1 SAT_i^{RM} + \gamma_3 H_i^{RM} + w_i) \\ &\quad + \beta_3 X_i + \epsilon_{ic} \\ &= \pi_0 + \beta_1 \delta_1 SAT_i + \beta_2 \gamma_1 SAT_i^{RM} + \beta_1 \delta_3 H_i \\ &\quad + \beta_2 \gamma_3 H_i^{RM} + \beta_3 X_i + \psi_{ic}. \end{aligned} \quad (6)$$

Suppose further that students' housing preference is correlated with their SAT and, because of the way roommates are assigned, with their roommate's housing characteristics. Thus,

$$\begin{aligned} H_i &= \lambda_1 SAT_i + \xi_1 H_i^{RM} + v_i, \\ H_i^{RM} &= \lambda_2 SAT_i^{RM} + \xi_2 H_i + v_i^{RM}. \end{aligned} \quad (7)$$

Substituting the equations in (7) into equation (6), we have

$$\begin{aligned} GPA_{ic} &= \pi_0 + \beta_1 \delta_1 SAT_i + \beta_2 \gamma_1 SAT_i^{RM} \\ &\quad + \beta_1 \delta_3 (\lambda_1 SAT_i + \xi_1 H_i^{RM} + v_i) \\ &\quad + \beta_2 \gamma_3 (\lambda_2 SAT_i^{RM} + \xi_2 H_i + v_i^{RM}) \\ &\quad + \beta_3 X_i + \xi_{ic} \\ &= \pi_0 + (\beta_1 \delta_1 + \beta_1 \delta_3 \lambda_1) SAT_i + (\beta_2 \gamma_1 \\ &\quad + \beta_2 \gamma_3 \lambda_2) SAT_i^{RM} + \beta_1 \delta_3 \xi_1 H_i^{RM} + \beta_1 \delta_3 v_i \\ &\quad + \beta_2 \gamma_3 \xi_2 H_i + \beta_2 \gamma_3 v_i^{RM}, \end{aligned} \quad (8)$$

which we can write simply as

$$GPA_{ic} = \Pi_0 + \Pi_1 SAT_i + \Pi_2 SAT_i^{RM} + \eta_i. \quad (9)$$

Notice that the coefficient on the SAT variable captures both the direct effect of SAT on grades and the indirect effect flowing through the correlation between SAT and the (omitted) housing preference variables. The main difficulty created in estimating equation (9) rests on the possible endogeneity created by a correlation between the complex error term and the roommates SAT variable. Such a correlation would bias estimates of the peer effect  $\Pi_2$ . This correlation could arise from the omitted housing preference variables.

Ideally, an instrumental variables estimator would be used in this context. In practice, no data are available to construct such an instrument. I am, however, able to present some suggestive evidence on the possible bias in the peer-effect variable flowing from the housing allocation method.

To do so, I gathered data from the Housing Office at Williams College on the housing preference form for the class of '02.<sup>8</sup> I use these data to present some available evidence on whether  $\delta_3$ ,  $\gamma_3$ ,  $\xi_1$ ,  $\xi_2$ ,  $\lambda_1$ ,  $\lambda_2$  are likely to be nonzero.<sup>9</sup> That is, if  $\delta_3$  and  $\gamma_3$  are zero, then the housing characteristics are not correlated with the quality of the roommate that affects grades. Further, even if  $\delta_3$  and  $\gamma_3$  are nonzero, it could be that  $\xi_1$  and  $\xi_2$  are zero. That is, particular housing characteristics may not be binding in forming roommate matches. Finally, it may be the case that  $\lambda_1$  and  $\lambda_2$  are zero. That is, housing preferences may be uncorrelated with SAT scores.

Tabulations of the students responses and their association with SAT scores and grades are found in Table 1. From the second column in this table we see that about 5% of students indicate a preference for a specific roommate (ten pairs, or 3.8% of students actually being granted this request) and a similar proportion indicate they have special needs. Almost 60% of students indicated they would prefer a single room (with about  $\frac{1}{3}$  of all students receiving a single room), 1.34% indicate they are smokers, and 2.87% indicate they prefer not to have visitors. Most students least like heavy metal music and video games, and most claim to be relatively organized. Few are morning people.

The third column presents simple regression coefficients for each housing preference when regressed on the student's combined SAT score. For example, smokers are found, on average, to have SAT scores 193 points lower than non-smokers. This difference is statistically significant. Similarly, students who prefer studying in "silence" have SAT scores about 237 points higher, on average, than students who like studying with "lots of noise." Again, the difference is statistically significant. From this column, we see that several of the housing preferences indicated by students are significantly related to SAT scores.

The fourth column shows the results of a set of multiple regressions—one for each of the student housing preferences. The dependent variable in these regressions is the student's cumulative GPA (as a proxy for  $Q$  in this case), and the explanatory variables are the indicated housing preference variable along with the student's race, citizenship, gender, and math and verbal SAT scores. This column helps identify those variables that are individually associated with a student's grades after controlling for the other measurable characteristics.<sup>10</sup> Most of the student housing variables are not statistically significant related to their grades. Although smokers have, on average, lower SAT

<sup>8</sup> The housing preference forms for earlier years had been destroyed.

<sup>9</sup> Even if these parameters are zero, an endogeneity could still result from unobservables that are correlated with the housing traits and the roommate's SAT variable.

<sup>10</sup> Ideally, I would control for the housing variables using the particular matching function (some linear or nonlinear function of the housing characteristics) employed by the housing office. Because the available data are limited, this is not feasible.

TABLE 1.—IS ROOM ASSIGNMENT RANDOM? WILLIAMS CLASS OF '02

Question	Distribution (%)	SAT Score	Cumulative GPA
Specific roommate requested? (1 = yes)	4.96	-171.32 (41.42)	-.014 (.082)
Special needs indicated? (1 = yes)	4.39	-14.31 (44.62)	-.143 (.083)
A. Would you prefer a single or a double? (1 = double)	58.43	-20.63 (18.64)	.062 (.035)
B. Are you a smoker or non-smoker? (1 = nonsmoker)	1.34	192.94 (85.58)	.018 (.162)
C. How do you think you will feel towards visitors to your room?			
1. Enjoy frequent visitors (excluded category)	27.72		
2. Like periodic visitors	69.41	24.58 (20.63)	.140 (.038)
3. Prefer not to have visitors	2.87	49.44 (56.78)	.204 (.105)
D. From the list below, please indicate in box D your least preferred activity.			
1. Cultural (theater, symphony, etc.)	29.29	84.00 (40.43)	-.259 (.077)
2. Video games	37.76	119.94 (39.63)	-.118 (.076)
3. Concerts (excluded category)	6.17		
4. Large parties	26.59	181.53 (40.78)	-.054 (.078)
E. From the list below, please indicate in box E your least preferred musical taste.			
1. Classical (excluded category)	10.17		
2. Rock/pop	3.03	97.58 (58.94)	.204 (.109)
3. Heavy metal	57.20	63.71 (30.81)	.186 (.060)
4. Oldies	4.03	-32.29 (54.22)	.126 (.101)
5. Rap	25.53	118.55 (33.56)	.286 (.064)
F. Place the number of your preferred study setting in box F.			
1. Lots of noise/people (excluded category)	1.53		
2. Some background noise/music	60.99	240.75 (74.29)	-.053 (.141)
3. Silence	37.48	237.18 (74.87)	-.011 (.142)
G. Place in box G the number which best describes the condition which you expect to keep your room.			
1. Impeccably neat (excluded category)	7.27		
2. Relatively organized	51.43	27.26 (36.05)	-.057 (.069)
3. Somewhat cluttered	36.90	74.95 (36.92)	-.084 (.071)
4. Hidden/buried floor	3.82	122.55 (57.44)	-.073 (.109)
5. Disaster area	.57	64.38 (124.70)	-.025 (.235)
H. Place in box H the number which best describes your wake/sleep patterns.			
1. Early riser/morning person (excluded category)	3.64		
2. Early riser/daytime person	19.92	67.38 (52.23)	-.068 (.097)
3. Early riser/evening person	20.69	39.11 (52.08)	-.139 (.097)
4. Late riser/daytime person	13.03	101.46 (54.28)	-.064 (.101)
5. Late riser/evening person	27.01	72.13 (51.12)	-.184 (.095)
6. Late riser/night person	15.71	50.02 (53.32)	-.296 (.098)
Sample size	519	519	519

## Notes:

- SAT regressions show the reported coefficient(s) from a bivariate regression of the student's combined SAT score on the relevant survey characteristic.
- GPA regressions show the reported coefficient(s) from a multiple regression of the student's cumulative GPA score on the relevant survey characteristic regression and controls for race, citizenship, gender, and own math and verbal SAT scores.
- Shaded coefficients are significant at the 5% level.

scores, this does not translate into lower grades once SAT scores and other characteristics are controlled for in the regression. Interestingly, grades are not related to how neat students are or to their sleep patterns or to their preferred level of noise during study times, once SAT scores and other controls are included in the model.

The discussion above suggests that estimates of the peer effect in equation (2) will be biased if a given housing preference is (a) significant in both SAT and GPA regressions and (b) a consequential determinant of a student's actual housing assignment. Only three characteristics are significant in both regressions—D1 (least-preferred activity is cultural) and E3, E5 (least-preferred music is heavy metal or rap). Importantly, these characteristics are associated with the preferences receiving the least weight by the Housing Office in determining assignments. According to the Housing Office, the practical effect of these particular responses is trivial. These results suggest that it is reasonable to assume that housing assignment is random for the purposes of this study. It should be noted that an alternative (and preferable) strategy to investigate the effect of the Housing Office's room allocation protocol on the estimated peer effect variable(s) would be to include the respondents' answers on the housing form (or some function of these answers) directly in equation (2). This strategy is not possible, on account of the limited data on housing response forms and the resulting small cell sizes when allowing for possible nonlinearity in the peer-effect variable(s).

In addition to the potential for endogeneity created by the housing preference variables, it is also possible that the admissions process itself could create a bias in the estimated peer effect. To see this, redefine the  $H$ -variables in equations (4) and (5) to be an index of a student's nonacademic qualities as considered by the admissions process. Such qualities might include athletic or musical or artistic prowess. Different schools will place different weights on these characteristics. Selective schools may admit low-SAT students only if they have high values of  $H$ . That is, SAT and  $H$  would be negatively correlated. This problem would be reduced by the fact that assignment to housing should be random with respect to this variable. It would, however, cause the variance in  $Q$  to be less than it would otherwise be. That is, the difference in  $Q$  between low- and high-SAT students would be smaller than it would be if SAT and  $H$  were uncorrelated. Further, it is possible that, because some of these nonacademic qualities may be associated with higher and some with lower grades, one has  $\gamma_3 = 0$ , in which case there will be no systematic bias.<sup>11</sup>

### C. Data and Descriptive Statistics

Table 2 provides summary statistics for the sample used. Data for the class of '90 through the class of '01 are used.

<sup>11</sup> Conversations with admissions officers at Williams suggests that this may be the case.

TABLE 2.—DESCRIPTIVE STATISTICS, WILLIAMS CLASSES OF '90-'01

Statistic	Standard			
	Mean	Deviation	Minimum	Maximum
Class cohort	1995	3.46	1990	2001
Class size	522	16.47	496	552
First-semester first-year GPA	3.10	0.510	1.08	4.17
Cumulative GPA	3.24	0.419	1.09	4.17
Own SAT score—verbal	708	73	360	800
Own SAT score—math	688	71	330	800
Own SAT score—combined	1396	123	830	1600
Black	0.073	0.260	0.058	0.099
Hispanic	0.058	0.234	0.027	0.085
Native American	0.002	0.047	0	0.005
Asian	0.094	0.293	0.058	0.101
Not a citizen of the United States	0.028	0.166	0.012	0.055
Female	0.472	0.499	0.429	0.510
Combined SAT score (lowest 15%)	1175	69	830	1250
Combined SAT score—middle 70%	1399	67	1260	1500
Roommate's verbal SAT score—lowest 15%	580	42	360	620
Roommate's verbal SAT score—middle 70%	699	36	630	750
Roommate's math SAT score—lowest 15%	568	41	330	610
Roommate's math SAT score—middle 70%	680	33	620	740
Entry's verbal SAT score—lowest 15%	671	16	628	686
Entry's verbal SAT score—middle 70%	707	10	687	724
Entry's math SAT score—lowest 15%	653	13	605	664
Entry's math SAT score—middle 70%	686	10	665	703
Entry size	22	4.99	11	35
Entry JA's verbal SAT score—lowest 15%	616	24	490	637
Entry's JA's verbal SAT score—middle 70%	709	30	640	755
Entry's JA's math SAT score—lowest 15%	577	50	430	610
Entry's JA's math SAT score—middle 70%	679	35	615	750

The average size of the entering class was 522 students over the eleven-year period. SAT scores—which were recentered—ranged from a low of 360 in the verbal test and 330 in the math test to a high of 800 in both tests. The average combined SAT score was 1396 over the period. These scores are high, putting the average student in the top 10% of the population of test takers. The table also shows the cutoffs for various percentiles of the Williams SAT distribution. For example, combined SAT scores below 1250 placed students in the lowest 15% of the pooled class. The average SAT score for this group was 1175, which, although in the lower tail of the distribution at Williams, would be at about the 75th percentile in the population.

Average math and verbal SAT scores were calculated for each entry in each year. Entries with average math SAT scores of 664 were at the 15th percentile of the distribution. Similarly, each year average SAT scores are calculated for the JAs associated with each entry.



TABLE 3.—YOUR GRADES AND YOUR ROOMMATE'S SAT SCORES, WILLIAMS CLASSES OF '90-'01

	GPA			
	First Semester	Cumulative	First Semester	Cumulative
Own SAT score/100	0.163 (0.007)	0.147 (0.006)		
Own SAT score—verbal/100			0.201 (0.013)	0.195 (0.011)
Own SAT score—math/100			0.120 (0.014)	0.092 (0.011)
Black	-0.249 (0.042)	-0.250 (0.034)	-0.261 (0.042)	-0.264 (0.033)
Hispanic	-0.220 (0.045)	-0.157 (0.036)	-0.222 (0.045)	-0.160 (0.035)
Native American	0.315 (0.116)	0.093 (0.169)	0.317 (11.44)	0.098 (0.175)
Not a citizen of the United States	0.184 (0.043)	0.079 (0.043)	0.198 (0.044)	0.099 (0.043)
Asian	-0.117 (0.029)	-0.092 (0.023)	-0.111 (0.029)	-0.085 (0.022)
Female	0.123 (0.016)	0.148 (0.013)	0.105 (0.017)	0.128 (0.013)
Major dummy variables	Yes	Yes	Yes	
Class cohort dummy variables	Yes	Yes	Yes	
Roommates SAT score/100	0.007 (0.006)	0.006 (0.005)		
Roommates SAT score—verbal/100			0.030 (0.012)	0.027 (0.010)
Roommates SAT score—math/100			-0.018 (0.013)	-0.016 (0.010)
Sample size	3151	3151	3151	3151
R <sup>2</sup>	0.324	0.369	0.328	0.378

Note: Standard errors are corrected for correlation within roommate cluster. Shaded peer coefficients are significant at the 5% level.

Finally, during this period, about half of the class were women, about 7% were black, and about 6% were Hispanic.

#### D. Roommate Effects?

Table 3 presents estimates of equation (2). In the first column the student's first-semester first-year grades are regressed on their own SAT score (divided by 100), race, gender, major, class cohort, and roommate's SAT score. The model includes controls for a student's major (which is selected in junior year) to provide some control for grade differentials arising from students taking different courses. Similarly, class cohort dummy variables provide a control for college-wide changes in grades over time.

The effect of student's own SAT score is large and statistically significant, with each 100-point increase translating into a 0.163 increment in grade point average. After controlling for SAT scores, black and Hispanic students score between a fifth and a quarter of a grade point below white students. Female students score 0.123 points higher than male students. The roommate's SAT score is found to have no effect.<sup>12</sup>

<sup>12</sup> Estimates are provided using only students living in doubles, that is, with a single roommate. This comprises the great majority of roommate situations at Williams. Including all observations for multiple-roommate rooms has virtually no effect on the results.

The second column repeats the same regression, but now uses a student's cumulative GPA rather than his or her first-year first-semester GPA. The results are similar—again showing no evidence of a peer effect. It is interesting to note that the effect of SAT scores on grades does not diminish over time.

In the third and fourth columns, a student's verbal and math SAT score are entered separately. In this case, the roommate's verbal SAT score is significant, but the roommate's math score is not. The effect is small, a 100-point increment in roommate's verbal score translating into a 0.03 increase in the student's GPA.<sup>13</sup> This effect is about 15% as large as a 100-point increment in the student's own verbal SAT score. Similar results are found using either first-semester or cumulative GPA as the dependent variable.

Table 4 reports estimates of equation (2) allowing the peer effect to depend on the student's own position in the SAT distribution. Panel A allows us to see whether weak, average, or strong students (as measured by their SAT scores) are more, or less, affected by roommates. The results in this panel suggest that neither weak nor strong students (those in the bottom or top 15% of the combined SAT distribution) are affected by their roommate's verbal or

<sup>13</sup> The effect, though small, could still be consequential if it moved a student below a grade cutoff for attending, for example, law or medical school.

TABLE 4.—YOUR GRADES AND YOUR ROOMMATE'S SAT SCORES BY SAT GROUP, WILLIAMS CLASSES OF '90-'01

	Combined SAT Score		
	Lowest 15%	Middle 70%	Top 15%
<b>A. Linearity in roommate's scores</b>			
Own SAT score—verbal/100	0.205 (0.039)	0.199 (0.015)	0.118 (0.055)
Own SAT score—math/100	0.065 (0.036)	0.112 (0.017)	0.045 (0.051)
Black	-0.181 (0.046)	-0.386 (0.053)	-0.800 (0.059)
Hispanic	-0.036 (0.059)	-0.254 (0.046)	-0.050 (0.274)
Native American	-0.238 (0.169)	0.212 (0.168)	dropped
Not a citizen of the United States	0.076 (0.091)	0.126 (0.055)	0.055 (0.066)
Asian	0.210 (0.120)	-0.065 (0.026)	-0.201 (0.047)
Female	0.262 (0.038)	0.103 (0.016)	0.107 (0.028)
Major dummy variables	Yes	Yes	Yes
Class cohort dummy variables	Yes	Yes	Yes
Roommates SAT score—verbal/100	0.006 (0.025)	0.043 (0.012)	-0.013 (0.021)
Roommates SAT score—math/100	-0.038 (0.028)	-0.021 (0.012)	0.030 (0.022)
Sample size	450	2072	629
R <sup>2</sup>	0.408	0.273	0.205
<b>B. Nonlinearity in roommate's scores</b>			
Own SAT score—verbal/100	0.203 (0.039)	0.201 (0.015)	0.119 (0.055)
Own SAT score—math/100	0.063 (0.035)	0.112 (0.017)	0.051 (0.051)
Black	-0.183 (0.045)	-0.387 (0.053)	-0.800 (0.058)
Hispanic	-0.034 (0.060)	-0.254 (0.046)	-0.074 (0.262)
Native American	-0.223 (0.175)	0.211 (0.181)	dropped
Not a citizen of the United States	0.066 (0.092)	0.125 (0.055)	0.035 (0.061)
Asian	0.212 (0.120)	-0.066 (0.026)	-0.194 (0.047)
Female	0.263 (0.037)	0.104 (0.017)	0.104 (0.027)
Major dummy variables	Yes	Yes	Yes
Class cohort dummy variables	Yes	Yes	Yes
Roommate's verbal SAT score—lowest 15%	-0.035 (0.055)	-0.077 (0.027)	-0.038 (0.047)
Roommate's verbal SAT score—middle 70%	-0.010 (0.045)	-0.011 (0.016)	0.038 (0.027)
Roommate's math SAT score—lowest 15%	0.092 (0.055)	0.048 (0.026)	0.007 (0.046)
Roommate's math SAT score—middle 70%	0.004 (0.045)	0.023 (0.019)	-0.028 (0.027)
Sample size	450	2072	629
R <sup>2</sup>	0.410	0.272	0.209

Dependent variable is cumulative GPA.

Standard errors are corrected for correlation within roommate cluster.

Shaded peer coefficients are significant at the 5% level.

math SAT scores. Students in the middle 70% of the distribution, however, show a positive peer effect associated with their roommate's verbal SAT score. Within this group, a 100-point increase in roommate's verbal SAT score translates into a 0.043 increase in GPA.

Panel B allows the peer effect to be nonlinear. That is, it allows us to see whether weak, average, or strong students (as measured by their SAT scores) are more, or less, affected by having roommates who are weak, average, or strong in terms of their math and verbal SAT scores. Again, no peer

TABLE 5.—YOUR GRADES AND YOUR ROOMMATE'S SAT SCORES BY GENDER WILLIAMS CLASSES OF '90-'01

	Combined SAT Score		
	Lowest 15%	Middle 70%	Top 15%
<b>A. Men</b>			
Own SAT score—verbal/100	0.249 (0.067)	0.217 (0.023)	0.055 (0.075)
Own SAT score—math/100	0.052 (0.049)	0.129 (0.026)	0.021 (0.066)
Black	-0.175 (0.071)	-0.410 (0.078)	-0.850 (0.071)
Hispanic	0.065 (0.099)	-0.288 (0.071)	-0.111 (0.380)
Native American	-0.066 (0.272)	-0.333 (0.047)	dropped
Not a citizen of the United States	0.044 (0.136)	0.138 (0.076)	0.014 (0.083)
Asian	0.489 (0.409)	-0.001 (0.043)	-0.190 (0.064)
Female			
Major dummy variables	Yes	Yes	Yes
Class cohort dummy variables	Yes	Yes	Yes
Roommate's verbal SAT score—lowest 15%	-0.040 (0.083)	-0.088 (0.041)	-0.093 (0.060)
Roommate's verbal SAT score—middle 70%	-0.019 (0.076)	-0.012 (0.026)	0.003 (0.036)
Roommate's math SAT score—lowest 15%	-0.009 (0.087)	0.015 (0.040)	0.003 (0.057)
Roommate's math SAT score—middle 70%	-0.044 (0.070)	0.028 (0.027)	-0.039 (0.032)
Sample size	230	1044	411
$R^2$	0.423	0.274	0.213
<b>B. Women</b>			
Own SAT score—verbal/100	0.180 (0.046)	0.187 (0.021)	0.230 (0.099)
Own SAT score—math/100	0.077 (0.050)	0.100 (0.022)	0.071 (0.094)
Black	-0.171 (0.060)	-0.356 (0.076)	dropped
Hispanic	-0.032 (0.076)	-0.211 (0.055)	-0.057 (0.092)
Native American	dropped	0.326 (0.092)	dropped
Not a citizen of the United States	0.163 (0.111)	0.117 (0.080)	0.090 (0.135)
Asian	0.267 (0.115)	-0.116 (0.033)	-0.185 (0.076)
Female			
Major dummy variables	Yes	Yes	Yes
Class cohort dummy variables	Yes	Yes	Yes
Roommate's verbal SAT score—lowest 15%	-0.040 (0.076)	-0.040 (0.039)	0.046 (0.082)
Roommate's verbal SAT score—middle 70%	0.014 (0.066)	-0.009 (0.022)	0.068 (0.043)
Roommate's math SAT score—lowest 15%	0.201 (0.076)	0.070 (0.035)	0.006 (0.085)
Roommate's math SAT score—middle 70%	0.068 (0.059)	0.029 (0.027)	0.038 (0.054)
Sample size	220	1028	218
$R^2$	0.360	0.254	0.349

Dependent variable is cumulative GPA.

Standard errors are corrected for correlation within roommate cluster.

Shaded peer coefficients are significant at the 5% level.

effects are found for students at the top and the bottom of the combined SAT distribution. Students in the middle 70% of the distribution are found to have grades lower by 0.077—after controlling for own SAT scores, race, gender,

and so on—when they have a roommate in the bottom 15% rather than the top 15% of the verbal SAT distribution. This effect, while statistically significant, is not large. It would lower a student at the median of the GPA distribution to

TABLE 6.—YOUR GRADES AND YOUR ENTRY'S OR JUNIOR ADVISOR'S SAT SCORES, WILLIAMS CLASSES OF '90-'01

Statistic	(1)	(2) Combined SAT Score			(3) Combined SAT Score			(4)	(5)	(6)	(7)
	Cumulative GPA	Lowest 15%	Middle 70%	Top 15%	Lowest 15%	Middle 70%	Top 15%	Lowest 15%	Middle 70%	Top 15%	
Own SAT score—verbal/100	0.191 (0.011)	0.170 (0.039)	0.200 (0.016)	0.120 (0.057)	0.116 (0.047)	0.213 (0.018)	0.054 (0.073)				
Own SAT score—math/100	0.097 (0.011)	0.064 (0.035)	0.119 (0.018)	0.056 (0.051)	0.040 (0.052)	0.123 (0.023)	0.001 (0.068)				
Black	-0.264 (0.034)	-0.187 (0.046)	-0.390 (0.056)	-0.771 (0.063)	-0.158 (0.067)	-0.459 (0.066)	-0.766 (0.083)				
Hispanic	-0.159 (0.036)	-0.051 (0.060)	-0.257 (0.046)	-0.093 (0.254)	0.032 (0.067)	-0.306 (0.054)	-0.491 (0.337)				
Native American	0.091 (0.180)	-0.324 (0.181)	0.213 (0.187)	Dropped	Dropped	0.521 (0.222)	Dropped				
Not a citizen of the United States	0.099 (0.043)	0.070 (0.089)	0.126 (0.057)	0.034 (0.064)	0.035 (0.140)	0.118 (0.075)	0.135 (0.089)				
Asian	-0.083 (0.022)	0.196 (0.126)	-0.065 (0.026)	-0.192 (0.047)	0.162 (0.099)	-0.053 (0.031)	-0.185 (0.060)				
Female	0.124 (0.014)	0.252 (0.037)	0.096 (0.017)	0.102 (0.027)	0.212 (0.046)	0.092 (0.019)	0.068 (0.035)				
Major dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes				
Class cohort dummy variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes				
Roommate's verbal SAT score—lowest 15%	-0.057 (0.022)	-0.014 (0.056)	-0.076 (0.028)	-0.027 (0.049)	-0.084 (0.069)	-0.062 (0.032)	-0.032 (0.059)				
Roommate's verbal SAT score—middle 70%	0.000 (0.014)	-0.002 (0.045)	-0.013 (0.017)	0.037 (0.027)	-0.048 (0.056)	-0.010 (0.021)	0.019 (0.033)				
Roommate's math SAT score—lowest 15%	0.046 (0.021)	0.087 (0.057)	0.046 (0.026)	0.015 (0.046)	0.153 (0.071)	0.041 (0.032)	0.028 (0.061)				
Roommate's math SAT score—middle 70%	0.004 (0.015)	-0.006 (0.046)	0.022 (0.019)	-0.027 (0.027)	-0.008 (0.053)	0.034 (0.023)	-0.036 (0.036)				
Entry's verbal SAT score—lowest 15%	-0.059 (0.026)	-0.192 (0.072)	-0.028 (0.032)	-0.064 (0.065)	-0.114 (0.106)	0.029 (0.044)	0.025 (0.087)				
Entry's verbal SAT score—middle 70%	0.008 (0.016)	-0.036 (0.059)	-0.002 (0.020)	0.035 (0.027)	-0.002 (0.069)	0.028 (0.026)	0.037 (0.038)				
Entry's math SAT score—lowest 15%	0.034 (0.025)	0.034 (0.070)	0.047 (0.031)	-0.013 (0.052)	0.024 (0.082)	0.028 (0.041)	-0.020 (0.066)				
Entry's math SAT score—middle 70%	-0.002 (0.019)	0.025 (0.061)	0.014 (0.023)	-0.041 (0.030)	-0.003 (0.067)	0.025 (0.033)	-0.054 (0.042)				
Entry JA's verbal SAT score—lowest 15%					-0.151 (0.093)	-0.019 (0.036)	-0.021 (0.060)				
Entry's JA's verbal SAT score—middle 70%					-0.086 (0.064)	0.010 (0.028)	-0.011 (0.040)				
Entry's JA's math SAT score—lowest 15%					0.183 (0.126)	-0.009 (0.054)	0.090 (0.074)				
Entry's JA's math SAT score—middle 70%					0.103 (0.113)	0.010 (0.045)	0.016 (0.056)				
Sample size	3117	443	2049	625	280	1294	404				
R <sup>2</sup>	0.384	0.432	0.276	0.219	0.389	0.318	0.237				

Standard errors are corrected for correlation within roommate cluster.  
Shaded peer coefficients are significant at the 5% level.

about the 42nd percentile. These results are robust to moderate variations in the percentile cutoffs used to define the groups.<sup>14</sup> Further, it is worth noting that comparing coefficients across equations it is not possible to say that middle students are hurt more than high SAT students by having a verbally weak roommate. The difference between these coefficients (-0.077 versus -0.038) is not significant at conventional levels.

<sup>14</sup> The model has also been estimated using house fixed effects. In this case, peer effects are estimated using within dorm variation. The results are very similar to those reported. In addition, the overlap between the academic rating used by the admissions office in making admissions decisions and the broad bins established for the SAT variable is almost 100%.

Table 5 reports estimates of equation (2) separately for men and women. Again, peer effects are only found for the middle 70% of the SAT distribution. Estimates for men are shown in Panel A. For men, having a roommate in the lowest 15% of the verbal SAT distribution is associated with a reduction in GPA of 0.088 points. This would lower a student at the median of the GPA distribution to about the 38th percentile.

Estimates for women are shown in panel B. Here the results are somewhat different. No peer effects are found for women in the top or bottom 15% of the SAT distribution. Within the middle 70% of the SAT distribution, however, women with roommates in the lowest 15% of the math

distribution show grades 0.070 points higher. This effect is significant at the 5% level. No significant peer effects are associated with verbal scores.

### E. Entry Effects?

Table 6 reports estimates that incorporate entry effects along with characteristics of the entries' JAs. Similar to the roommate effects, entries and JAs are classified by whether they are in the lowest 15%, middle 70%, or top 15% of their SAT distributions. Estimates in the first column do not separate students by their SAT scores. Again, peer effects are found at the roommate level. Having a roommate in the lowest 15% of the verbal SAT distribution is associated with grades being lowered by 0.057. Entry effects are also found. In this case, living in an entry characterized as being in the lowest 15% of verbal SAT scores of all entries is associated with a 0.059 reduction in grades.

In columns (2) through (4), this model is estimated for each of the three SAT groups. In this case, the lowest 15% of students are found to have lower grades if they live in a low-verbal-SAT-score entry. The entry effect is significant and large. It would drop a median student in this SAT group from about the 17th percentile to about the 10th percentile of the grade distribution. No entry-level peer effects are found for the other two groups.

Columns (5) through (7) report estimates of equation (2) that allow for peer effects associated with the average SAT scores of the JAs living in the entry.<sup>15</sup> Again, negative peer effects—associated with low verbal SAT scores—are found at the roommate level. Low-SAT students are also found to perform better in the presence of low-math-SAT roommates. There is no evidence of either entry or JA peer effects in these models.

## V. Conclusions

This paper investigates peer effects in the determinants of grades. In particular, I measure differences in grades associated with high-, medium-, or low-SAT students living with high-, medium-, or low-SAT roommates. I argue that housing assignment is random. This allows me to interpret any grade differences between the SAT groups as measuring a causal peer effect. The more robust findings suggest that in the context of residential housing:

1. Peer effects are almost always linked more strongly with verbal SAT scores than with math SAT scores.
2. Students in the middle of the SAT distribution may do somewhat worse in grades if they share a room with a student who is in the bottom 15% of the verbal SAT distribution.

3. The effects are not large, but are statistically significant in many models.

These results must be interpreted with some caution. First, it must be remembered that they are measured within the context of a highly selective school. Their applicability to several important issues in higher education must be tempered. For example, school choice might be characterized as moving the more able or motivated children from poorer schools into schools that are richer in both peer and other resources. In the context of this study, I measure the effect, on students who already attend resource-rich institutions, of having different peer environments in their residential housing situations. The nonlinearity of this effect—middle SAT students are affected, and others are not—is not the same as the nonlinearity involved in moving a weak student to a strong school and a strong student to a weak school. In that case, both peer and other educational resources are altered.

## REFERENCES

- Behrman, Jere R., Jill Constantine, Lori Kletzer, Michael McPherson, and Morton Owen Schapiro, "Impact of College Quality Choices on Wages: Are There Differences Among Demographic Groups?" Williams Project on the Economics of Higher Education discussion paper no. 38 (1996).
- Betts, Julian, and Darlene Morell, "The Determinants of Undergraduate Grade Point Average: The Relative Importance of Family Background, High School Resources, and Peer Group Effects," *Journal of Human Resources* 34:2 (Spring 1999), 268–293.
- Betts, Julian, and Jamie Shkolnik, "The Effects of Ability Grouping on Student Achievement and Resource Allocation in Secondary Schools," *Economics of Education Review* 19:1 (February 2000), 1–15.
- Burtless, Gary (Ed.), *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success*, Washington: Brookings Institution Press (1996).
- Coleman, James Samuel, E. Q. Campbell, et al. *Equality of Educational Opportunity*, U.S. Department of Health, Education, and Welfare, Office of Education, U.S. Government Printing Office (1966).
- Ehrenberg, R., and D. Brewer, "Does It Pay to Attend Elite Private Colleges? Evidence from the Senior High School Class of 1980," *Research in Labor Economics* 15 (1996), 239–271.
- Epple, Dennis, and Richard Romano, "Competition between Private and Public Schools, Vouchers, and Peer-Group Effects," *American Economic Review* 88:1 (March 1998), 33–62.
- Evans, W., W. Oates, and R. Schwab, "Measuring Peer Group Effects: A Study of Teenage Behavior," *Journal of Political Economy* 100:5 (1992), 966–991.
- Festinger, L., "Informal Social Communication," *Psychological Review* (1950), 271–282.
- , "A Theory of Social Comparison Processes," *Human Relations* 7 (1954), 117–140.
- Goethals, George, "Peer Influences among College Students: The Perils and the Potentials," Williams Project on the Economics of Higher Education DP-51 (1999).
- Goethals, George, Gordon Winston, and David Zimmerman, "Students Educating Students: The Emerging Role of Peer Effects in Higher Education," Williams Project on the Economics of Higher Education DP-50 (1999).
- Hall, R., and B. Willerman, "The Educational Influence of Dormitory Roommates," *Sociometry* 26 (1963), 294–318.
- Harris, Judith, *The Nurture Assumption*, New York: The Free Press (1998).
- Henderson, V., P. Mieszkowski, and Y. Sauvageau, "Peer Group Effects and Educational Production Functions," *Journal of Public Economics* 10:1 (1978), 97–196.

<sup>15</sup> The sample size is reduced somewhat in that JA SAT data are not available for classes prior to 1990. The class of '92 is the first class for which JA data are available.

Hoxby, Caroline M., and Bridget Terry, "Explaining Rising Income and Wage Inequality Among the College Educated," NBER working paper No. 6873 (1999).

Jencks, C., and S. Meyer, *The Social Consequences of Growing Up in a Poor Neighborhood: A Review*, Evanston, IL: Center for Urban Affairs and Policy (1989).

Kulik, James, Heike Mahler, and Phil Moore, "Social Comparison and Affiliation Under Threat Effects on Recovery From Major Surgery," *Journal of Personality and Social Psychology* 71:5 (1996), 967-979.

Loury, L., and D. Garman, "College Selectivity and Earnings," *Journal of Labor Economics* 13:2 (April 1995), 289-308.

McPherson, Michael, and Morton Schapiro, *Selective Admission and the Public Interest*. New York: The College Entrance Examination Board (1990).

Pascarella, E., and P. Terenzini, *How College Affects Students*. Jossey-Bass Publishers (1991).

Rivkin, Steven, "The Estimation of Peer Group Effects," Amherst College mimeograph (1997).

Robertson, D., and J. Symons, "Do Peer Groups Matter? Peer Group versus Schooling Effects on Academic Attainment," London School of Economics Centre for Economic Performance discussion paper 311 (1996).

Rosenbaum, J., "Black Pioneers—Do Their Moves to the Suburbs Increase Economic Opportunity for Mothers and Children?" *Housing Policy Debate* 2:4 (1991), 1179-1213.

Wilson, William, *The Truly Disadvantaged*, University of Chicago Press (1987).

——— "The Economic Structure of Higher Education: Subsidies, Customer-Inputs, and Hierarchy," Williams Project on the Economics of Higher Education discussion paper no. 40 (1996).

APPENDIX

Spring, 1999

Dear Incoming First Year Student:

On behalf of the Housing Office, welcome to the Class of 2003! We are looking forward to seeing you later in the summer.

Williams houses first year students and their JA's in six residential buildings. We try to create first year living units to reflect the variety found within the class. Thus, assignments to housing are made to foster the educational experience of living with classmates of different interests and backgrounds, while also recognizing the need for roommates to be compatible.

Enclosed is an informational booklet that will give you a peek at first year living at Williams. Please refer to it in the upcoming weeks as you gear up for dorm life, feeling free to direct any further inquiries to the Housing Office.

Also enclosed is a form that will give you the opportunity to provide information about yourself and your preferred rooming situation for next year. Please be mindful that while we will certainly consider your preference for a particular building, we cannot guarantee an assignment to it. The roommate matching questionnaire should be completed as carefully and honestly as possible, considering your general personality and behavior. Your choices should be made while imagining yourself living on your own without the structure to which you are accustomed. The form is to be completed and returned by June 25 to the Director of Housing, Williams College, 60 Latham St., Williamstown, MA 01267.

Please be sure to submit the preference form by June 25. We expect to mail first year room assignments in late July or early August. Meanwhile, should you have any questions or if you would like more information about residential living at Williams, please feel free to contact me. My e-mail address is *thomas.d.mcevoy@williams.edu*. Have a great summer and I look forward to seeing you soon.

Sincerely,

Thomas D. McEvoy  
Director of Housing

WILLIAMS COLLEGE  
HOUSING PREFERENCE FORM  
CLASS OF 2003

NAME (please type or print) \_\_\_\_\_  
 SEX male \_\_\_\_\_ female \_\_\_\_\_  
 SOCIAL SECURITY NUMBER \_\_\_\_\_  
 HOME ADDRESS \_\_\_\_\_  
 HOME PHONE NUMBER \_\_\_\_\_

**ROOMMATE REQUEST:** IF YOU WOULD LIKE TO LIVE WITH A SPECIFIC PERSON, PLEASE LIST THAT PERSON'S NAME BELOW. YOUR REQUEST WILL BE HONORED IF THE PERSON ALSO LISTS YOU.

---

**SPECIAL NEEDS:** ARE SPECIAL ROOMING ARRANGEMENTS ADVISABLE FOR YOU BECAUSE OF HEALTH PROBLEMS? IF SO, PLEASE EXPLAIN BELOW AND HAVE A PHYSICIAN'S STATEMENT MAILED BY JUNE 25 TO THE DIRECTOR OF HOUSING, WILLIAMS COLLEGE, 60 LATHAM ST., WILLIAMSTOWN, MA 01267. \_\_\_\_\_  
 \_\_\_\_\_  
 \_\_\_\_\_

**HALL PREFERENCE:** AGAIN, PLEASE REMEMBER THAT YOU ARE LISTING A PREFERENCE IT IS POSSIBLE THAT YOU WILL NOT RECEIVE YOUR FIRST CHOICE(S). PLEASE RANK YOUR PREFERENCES IN NUMERICAL ORDER WITH 1 BEING YOUR FIRST CHOICE AND 4 BEING YOUR FOURTH CHOICE. ENTER EACH NUMBER ONLY ONCE AND BE SURE TO RANK ALL FOUR CHOICES. FAILURE TO DO SO WILL CAUSE THE RANKING INFORMATION TO BE PROCESSED INCORRECTLY.

<input type="checkbox"/>	WILLIAMS OR SAGE ALSO CALLED THE FRESHMAN QUAD	6 VERTICAL ENTRIES, SINGLE AND DOUBLE ROOMS, MAINLY IN SUITES, SOME ROOMS OFF A HALLWAY.
<input type="checkbox"/>	MORGAN	4 VERTICAL ENTRIES, SINGLE, DOUBLE ROOMS, SOME IN SUITES AND SOME OFF A HALLWAY.
<input type="checkbox"/>	LEHMAN	2 VERTICAL ENTRIES, SINGLE AND DOUBLE ROOMS, MAINLY IN SUITES.
<input type="checkbox"/>	EAST OR FAYERWEATHER	3 HORIZONTAL ENTRIES, SINGLE AND DOUBLE ROOMS ALONG A HALLWAY →

**ROOMMATE MATCHING SURVEY:** PLEASE USE THE BOXES TO THE LEFT OF ITEMS A-H TO RECORD YOUR ANSWERS. FOR QUESTIONS C-H CHOOSE THE ONE THAT IS CORRECT MOST OF THE TIME.

- A. Would you prefer a single or a double? You must choose one of the choices listed below and place the appropriate response in box A.
  1. Single
  2. Double
- B. Are you a smoker or non-smoker? If you smoke at all, you are a smoker and you are likely to be housed near other smokers. You must choose one of the choices listed below and place the appropriate response in box B.
  1. I am a smoker
  2. I am a non-smoker

- C. How do you think you will feel towards visitors to your room? Please place the appropriate response in box C.
1. enjoy frequent visitors
  2. like periodic visitors
  3. prefer not to have visitors
- D. From the list below, please indicate in box D your least preferred activity.
1. cultural (theater, symphony, etc.)
  2. video games
  3. concerts
  4. large parties
- E. From the list below, please indicate in box E your least preferred musical taste.
1. classical
  2. rock/pop
  3. heavy metal
  4. oldies
  5. rap
- F. Place the number of your preferred study setting in box F.
1. lots of noise/people
  2. some background noise/music
  3. silence
- G. Place in box G the number which best describes the condition which you expect to keep your room.
1. impeccably neat
  2. relatively organized
  3. somewhat cluttered
  4. hidden/buried floor
  5. disaster area
- H. Place in box H the number which best describes your wake/sleep patterns.
1. early riser/morning person
  2. early riser/daytime person
  3. early riser/evening person
  4. late riser/daytime person
  5. late riser/evening person
  6. late riser/night person

Copyright of Review of Economics & Statistics is the property of MIT Press and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.