The impact of formal and informal peers on academic performance

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September 23, 2012

Abstract

This paper uses random assignment of students to study groups and residential apartments to study the impact of formal and informal peers on academic achievement. We find that informal social interaction with residential peers has a significant positive impact on academic achievement while formal interaction in study groups has no discernible impact, a result driven by group heterogeneity in ability. We also find that lower ability students benefit from high ability students but not vice versa. Finally, we show that analyzing formal peers but excluding informal peers leads to an omitted variable bias in peer effect estimates.

Keywords: Peer effects. Social networks. Management education.
JEL Codes: I23, L23.

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1 Introduction

The impact of peers on individual academic outcomes is a key research question addressed by a growing empirical literature.[1] While this literature has established that peer effects are significant in academic settings, less is known about the effects of intra-group incentives on peer interaction and influence.[2] This paper analyzes the simultaneous impact of formal study groups and informal residential groups on grades at a business school. To our knowledge, this is the first paper that examines the simultaneous effect of multiple peers groups with different intra-group incentives on educational outcomes of students.

We report four main findings. First, we find that informal social interaction with residential peers has a positive impact on academic achievement whereas the effect of formal interaction in study groups is small and insignificant. Second, we find that greater variance in roommate ability is positively associated with higher grades. Third, we find that the impact is heterogenous in student ability, where academically weaker students benefit more than the stronger students from their peers. Finally, in our analysis, we find that excluding the informal interaction between roommates and including only the study group peers leads to an omitted variable bias. In particular, our initial finding of significant positive impact of study group peers on students' grades is overturned when residential peers are included in the specification.

The source of the data for our analysis, described in more detail in subsequent sections, is a full-time, residential graduate general management program located in India. A key advantage of this institutional setting is that students are randomly assigned to two separate groups – a formal study group and an informal residential group. The study group, typically consists of four or five students who are required to jointly complete formal academic tasks such as homework assignments for which they receive common grades. The residential group is formed by the assignment of individuals to apartments shared by three other students (forming "quads"). In contrast to the study group, roommates have no formal academic commitments towards each other, and interact voluntarily. This assignment helps us to address two out of the three concerns raised

[1] See surveys of the literature on peer effects in education by Epple and Romano (2011) and Sacerdote (2011).

[2] See Carrell, Sacerdote, and West (2012) for a discussion on the challenges of understanding mechanisms with regression estimates.

by Manski (1993) – "endogenous group membership" where identification of peer effects in most observational data is difficult because of the tendency of individuals with shared attributes to associate with each other, and the "correlated unobservables" which is the possibility of incorrectly attributing the influence of shared environment to the influence of peers. However, we cannot separately identify the direction of peer effects within the group since we estimate reduced form regressions.

There are several further advantages to using this data for answering our research question. First, in most settings, the population from which formal peers are drawn from, for example workplace colleagues, can be very different from the population corresponding to professional and social networks. Therefore, researchers cannot cleanly identify whether peer effects are due to joint responsibility and rewards in formal groups or the lack thereof in informal groups, or due to inherent differences in characteristics of individuals in the two networks. However, in our setting, as mentioned previously, students are simultaneously and exogenously assigned to formal and informal groups, all of whom are in the same program and therefore share similar characteristics. Second, given the specialized nature of the graduate program, it is unlikely that off-campus social networks influence our main measure of student performance, which is grades earned in the core terms. Finally, we have complete administrative data which contains a rich set of covariates allowing us to control for other factors that might potentially impact academic outcomes in this setting.

Our study bridges the literature on peer effects in informal and formal settings.[3] Pioneered by Sacerdote (2001), the most convincing studies of peer effects in academic settings avoid endogenous selection into groups by exploiting exogenous or random assignment of students to various groups. This strategy is used to estimate the impact of informal roommates in residential college dormitories on academic and career outcomes (Zimmerman 2003; Foster 2006; Stinebrickner and Stinebrickner 2006; Lyle 2007; Carrell, Fullerton, and West 2009). Lugo (2011) employs a slightly different strategy by using the random assignment of students to classrooms to estimate the asymmetric impact of peer heterogeneity in wealth and finds that poor students perform better when their

[3] Although in their setting the formation of connections is unlikely to be exogenous, Chidambaran, Kedia and Prabhala's (2011) study of CEOs and directors compares the impact of professional connections formed by serving on corporate boards with the influence of social networks formed in college on corporate fraud.

classmates are wealthier, but not vice versa. Lerner and Malmendier (2011) and Shue (2012) use the random assignment of students to first year sections at Harvard Business School to estimate the impact of peers on entrepreneurship, executive compensation and firm performance. Alternative methodologies use instruments for peer characteristics (Evans, Oates, and Schwab 1992), or include fixed-effects for group and institution-specific characteristics (Hanushek, Kain, Markman, and Rivkin 2003; Lavy and Schlosser 2011).

Similar strategies are also used to understand the impact of formal groups. A key policy question in the context of formal groups is the design of the incentives for joint output by the group. Lavy (2002) evaluates a team-based incentive program for teachers in Israel and finds that such incentives improve academic performance and are cost-effective compared to increasing school resources. A more recent randomized control trial in Benin compared the effectiveness of team incentives to individual incentives for secondary school students (Blimpo 2010). Jain and Narayan (2011) conduct a laboratory experiment to address distributional issues that emerge when teachers' compensation is in the form of team incentives. Our paper uses simultaneous random assignment of students to multiple peer groups to study the effect of formal and informal peers.

The rest of the paper is organized as follows. Section 2 introduces the institutional setting where the study is located, the assignment process that is the heart of our identification strategy and a description of the data. Section 3 analyzes this data in detail, including a discussion of the results and robustness checks. Section 4 concludes with a discussion of the policy implications.

2 Institutional description and data sources

Estimating peer effects in academic outcomes requires data where each student is reliably and exogenously matched with a set of peers. In order to test the relative impact of peer groups in formal versus informal environments, we need at least two sets of such peer assignments in the dataset. The dataset should contain information from each node in the network, not from a partial sample of the network, to avoid biased estimates in case the structure of the network is inaccurately or incompletely mapped (Chandrasekhar and Lewis 2011). Finally, the dataset should contain information on academic and career outcomes, as well as a rich set of covariates that describe each student's ability, skills, professional background and demographic characteristics. The next three sections describe the data that satisfies these requirements, and allows for estimation of the size of peer effects.

2.1 Institutional description

Our data source is the flagship post-graduate business program at the Indian School of Business (ISB). ISB is a large, independent provider of post-graduate management education established in 2001 with a one year, full-time residential diploma program. Since 2009, the *Financial Times* newspaper has ranked the program among top 20 MBA programs in the world. ISB was established in 2001 in academic collaboration with the Wharton School of the University of Pennsylvania, Kellogg School of Management at Northwestern University and London Business School (LBS), and shares many institutional academic policies with these schools.

An application to ISB consists of GMAT scores, essays, letters of recommendation, undergraduate and graduate transcripts and an interview. Although drawing from a pool of applicants predominantly from India, Table 1 shows that student characteristics at ISB are comparable with those at a number of leading international business schools. The mean GMAT score at ISB is 712, which is slightly below Harvard Business School and Stanford GSB (both 730), comparable to Kellogg (715), Chicago Booth (715) and MIT Sloan (710), and a few points higher than INSEAD, Darden, Fuqua and LBS (703, 701, 698 and 694, respectively). The fraction of female students (28 percent) is slightly lower than the norm in the United States (35 to 38 percent). Finally, the average candidate has five years of work experience before enrollment, which is typical of many North American and European business schools. Although the Business Week data does not capture this, students arrive with wide variation in educational background and skills.[4] Hence, ISB is arguably similar to a number of major international business schools on observable characteristics. There might be a number of factors, such as location in a developing country, which differentiate ISB from other major management schools. However, without sector-wide

[4] In contrast to many colleges and universities located in India, ISB neither implements preferential affirmative action quotas for Scheduled Caste or Scheduled Tribe candidates. Sekhri (2011) analyzes peer effects with affirmative action and finds that better average quality of high caste students has a negative impact on the performance of low caste students.

Table 1: **Indian School of Business compared to major international business schools**

	GMAT (Mean)	Years of work experience	Female (Fraction)	Class size
Harvard Business School	724	4.0	39%	901
Stanford GSB	730	4.1	34%	401
Wharton (UPenn)	720	6	36%	823
Kellogg (Northwestern)	715	5	35%	475
Booth (UChicago)	715	4.6	35%	1177
IIM Ahmedabad PGPX	713	10	7%	86
Indian School of Business	**712**	**4.9**	**28%**	**560**
MIT Sloan	710	5	35%	396
INSEAD	703	6	33%	988
Darden (University of Virginia)	701	4.7	29%	328
Fuqua (Duke)	698	5.0	37%	887
London Business School	694	5.6	25%	319

Note: Data is for the Class of 2011 for the full time MBA programs (or equivalent) for all schools. Source: School websites and `http://www.businessweek.com`.

microdata from a large number of international schools, the impact of location, institutional or cultural factors that might be correlated with the impact of peers is difficult to estimate.

Classes at ISB are held for 50 weeks without any significant break, and are divided into eight terms of six weeks each. In the first four terms, students take a common “core” of 16 non-elective classes covering a range of management topics. In the next four terms, students choose various elective courses that allow them to concentrate (or “major”) in the areas of entrepreneurship, finance, IT management, operations, marketing or strategy.

Instructors at ISB award course grades on a four point scale. The highest grades is an A, corresponding to 4 grade points. Below this are A- (3.5 grade points), B (3 points), B- (2.5 points), C (2 points), D (1 point) and F (0 points). An F is a failing grade which requires the student to repeat the course. Instructors are required to maintain a class grade point average between 3.25 and 3.30 across all sections that they teach. While student achievement is assessed on relative performance,[5] the comparison set is all students in the sections that an instructor teaches (typically, 280 students in four sections) and not the students within the study group or even within the section. This implies that a student's objective is to earn the maximum score possible, regardless of the relative performance of the other members of the study or residential groups.

2.2 Administrative data

The Academic Services Administration (ASA) at ISB maintains detailed records on the courses that each student enrolls in, the grades achieved in these courses as well as assignment of students to study groups and residential facilities. We obtained a complete record of all enrolled students for four years from 2007-08 to 2010-11. One advantage of selecting this period was the absence of significant changes in the curriculum or administrative policies during this time.

Student assignment, coursework and grade data is supplemented with data from admissions records that contain each student's academic (undergraduate and graduate institutions and associated majors and GMAT scores), professional (sector and firm of employment, employment duration, earning and functional role) and demographic backgrounds (year of birth, gender, marital status and citizenship). Also included is data from the on-campus placement process. We record the earnings associated with the job offer received by students at the end of the PGP program.

Table 2 summarizes select variables from the data. Students have an average of 4.9 years of full time work experience when they join. Seventy three percent of students are single at an average age of over 28.7 years. Twenty six percent of the students are women, and 96 percent are Indian citizens. The average salary drawn before enrolling at ISB was Rs. 996,000 whereas the average salary reported on graduation was Rs. 1400,000, corresponding to 41 percent increase in compensation after one year of study.[6]

This combined dataset offers a number of features that makes it attractive for analyzing formal and informal peer effects on the academic performance of business school students. First, the administrative source of the data allows us to map the entire set of formal and informal peers for each student, and avoid

[5] The correspondence between the class score and letter grades is not known to students during the term and determined at the end of the term.

[6] At the time of writing, US $1 = Rs. 50.

potentially biased estimates due to partial sampling from the network (Chandrasekhar and Lewis 2011). Since all administrative records are mandated to be complete and truthful, self-reporting bias, measurement error and missing data do not threaten our analysis. Finally, in the one year PGP program, attrition is negligible and student cohorts do not overlap. Therefore, non-random attrition from the sample as well as serial correlation due to overlapping peers across years are not significant concern.[7]

The data also suffers from a few shortcomings. First, since students who conduct their own job search do not report earnings to ISB, the placement data is incomplete. If, for example, the most ambitious students or those who were unsuccessful in receiving an offer on-campus are more likely to conduct off-campus searches, this data will suffer from selection bias. Furthermore, students who conduct their own job search are most likely to rely on professional and social peers, especially off-campus networks, which implies that estimates of influence of peers on earnings at graduation will suffer from systematic biases. Finally, information on students' family characteristics such as caste, religion or parental education that are potentially important in determining educational achievement are unavailable in this data.

Nonetheless, the unique advantages of this dataset allow us to perform econometric analysis that helps uncover peer effects in student performance while at business school.

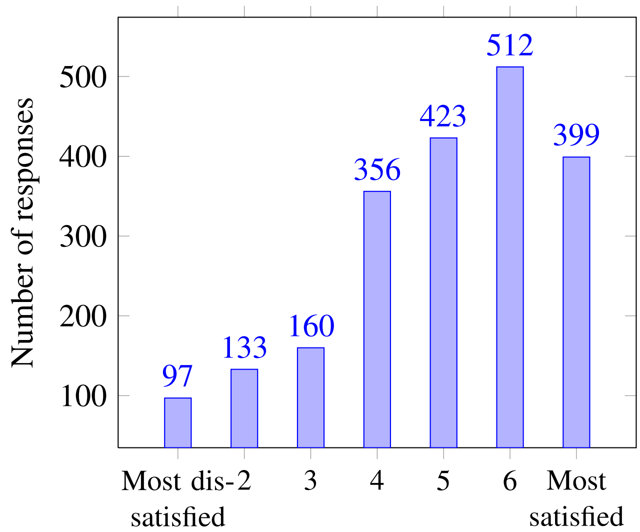
2.3 Assignment of formal and informal peers

A unique feature of this data that makes it appropriate for analysis of peer effects is that students are simultaneously and randomly assigned into two separate and mutually exclusive sets of peers – the study group and the residential group. We designate the study group as "formal" peers because students are expected to perform graded class assignments collectively with other members of the group. The residential group is "informal" as students are not expected to perform any academic tasks together. To the best of our knowledge, this is the only dataset used to estimate peer effects among management students with such a feature.

Before the start of core classes, ASA assigns students to a study group,

[7] In the entire sample period, only 3 students joined the program but left before completion.

Figure 1: **Value of study group experience**



Notes: Ratings are responses to "Please rate your experience with the ISB PGP curriculum on the following dimensions: Value of your core term study group experience". Mean response is 4.92 and standard deviation is 1.68. N = 2080 from classes of 2007-08 to 2010-11. Data source: ISB Dean's survey.

which is then assigned randomly to a section of approximately 70 students.[8] This assignment is fixed for the duration of the four core terms. Members of the study group work together to understand the coursework, as well as to complete specific group-based assignments. The share of the overall grade that is determined by group grades ranges from 0% to 50%, with 30% share in the median course. In the elective terms, students choose their own courses, which might be different from those of their study group peers. Data from a survey conducted at the end of the program suggests that students value these study groups, with the modal student responding that they were "very satisfied" with the study group experience (Figure 1).

In assigning students to study groups, ASA relies only on observable characteristics of students, following two simple sequential rules.[9] First, groups are assigned either two women, or none at all. Next, the groups are balanced

[8]The number of sections increased from six in the 2007-08 and 2008-09 class years to eight in 2009-10 as the school increased enrollment from 416 students in 2007-08 to 436 students in 2008-09 and 565 students in 2009-10 and 2010-11.

[9]One of the authors observed this process and verified that the staff member had only demographic information for each student during the assignment process.

in terms of the previous work experience (function and sector) of the students. Each group consists of either four or five students due to these restrictions. With these assignments, the data contains 90 study groups in the 2007-08 and 2008-09 class years, and 120 groups in the 2009-10 class year. ASA does not consider any measure potentially correlated with ability, such as GMAT scores, elite undergraduate college or Master's degree while assigning students to groups, nor does ASA assign students based on any characteristic that is unobservable to the researchers such as ability, motivation or potential for interaction with peers. Hence, due to the administrative process, the assignment of individuals to groups is statistically random on unobservable characteristics.

In addition to the formal peers in the study group, students are also assigned to an informal peers in the residential dormitories. Unlike many international business schools, all students at ISB are required to stay on campus in housing provided by the school throughout the length of the program. Roommates are not expected to work together on academic assignments, and involvement in each other's coursework is voluntary. Students can elect to stay in either four room quads with a shared kitchen, dining and living spaces or single apartments.[10] Students who elect group housing are randomly assigned to quads, with two observable assignment rules. First, each quad is single sex. Second, roommates cannot overlap with study group peers. Once assigned, students stay in the same quad throughout the eight terms. Although there are more apartments than quads, most students live in quads – in the sample, 1697 out of 2281 students live in shared residences.[11]

Figures 2 and 3 show that the distribution of study group and roommate GMAT scores are very similar. This is not surprising, since the two groups are drawn from the same population and that the allocation rules are very similar.

However, given the importance of random assignment in obtaining unbiased estimates, we check the effectiveness of the administrative process described above in the data. For this, we regress group mean GMAT and quad mean GMAT scores on individual GMAT scores, including year dummies as control variables. To verify that the administrative process is also random with respect to an alternative measure of ability, we include a second set of regressions where

[10]Single apartments are assigned to students with cohabiting family members or those with special needs. ISB does not solicit data on roommate preferences.

[11]Each quad is located in a "block" which consists of up to six quads. Further, each quad is located in a "student village" which consists of up to 12 blocks.

group mean pre-earnings and quad mean pre-earnings are regressed on individual pre-earnings. Since gender is the primary criteria for assignment of students to study groups and quads, we report results separately for women and men. Table 3 shows low correlation between a student's GMAT score and mean group and quad GMAT scores. For women, the t-statistics associated with a test of the null hypotheses that mean study group GMAT scores and mean quad GMAT scores are uncorrelated with a student's GMAT score are 0.91 and -0.72, respectively. The corresponding t-statistics for men are 0.45 and 0.51, respectively. The pre-earnings test also reveals similarly that earnings before matriculation are uncorrelated across groups. These results support our belief that the administrative randomization process led to the formation of formal and informal groups where ability was uncorrelated.

3 Empirical analysis

The objective of the empirical exercise is to investigate on the role of peers on academic outcomes, separating out the impact of formal and informal groups. We first demonstrate that core terms grades are an appropriate outcome variable for our setting. We next estimate a full model of the individual, study group and roommate characteristics on core term grades, with particular emphasis on heterogeneity in peer effects, and report the results. We then show that a specification which includes only characteristics of formal peers and excludes informal peer characteristics as explanatory variables suffers from omitted variable bias. In addition, we conduct a number of robustness checks to verify that the results are not driven by factors unobserved in the data.

3.1 Core terms GPA as outcome measure

We select students' grade point average during core terms as the outcome measure because the formal study groups and the informal roommate assignments operate concurrently only during the core terms. We cannot use elective terms GPA or job placement outcomes (such as salary or sector of employment) since the study groups are disbanded while the roommates remain in place during elective terms and the job interviews. Hence, we cannot compare the parallel impact of the two types of peer groups on elective GPA or earnings at graduation.

Nonetheless, if students' true objective is to maximize earnings, which is quite possible in a graduate business program, then academic learning as measured by core terms grades is a good outcome variable only if it is correlated with earnings. Thus, we examine the association between core terms GPA and the value of the job offered during on-campus placement, controlling for other student characteristics that might determine earnings. To do so, we specify the following OLS model for student i in cohort t.

$$earnings_{it} = \delta_0 + \delta_1 core\_gpa_{it} + \delta_2 \mathbf{X}_{it} + year_t + \mu_{it} \tag{1}$$

In this model, $earnings_{it}$ is the value of the job offer reported by a student after on-campus job interviews. Although a student might receive multiple job offers, we use the salary associated with the accepted job. The coefficient of interest is δ_1 which represents the impact of a student's cumulative GPA at the end of core terms on the salary. The coefficients represented by δ_2 represents the impact of other individual factors, such as the number of years of experience, marital status, age, female, GMAT score, last salary before business school and citizenship status. We also include indicator variables for students who attend either Delhi University or Indian Institute of Technology, since the largest fraction of students attended these universities for undergraduate studies. Note that the coefficients of this model cannot be interpreted as causal estimates since we cannot rule out the impact of unobserved factors that impact both $core\_gpa_{it}$ and $earnings_{it}$.

Table 4 reports the results of the estimation exercise and shows that core terms GPA (scale of 0 to 4) is very strongly correlated with salary. Increasing GPA by one point is associated with an increase of Rs. 483,073 in salary reported, an estimate that is statistically different from the null at the 1% level. This result is not surprising. In contrast to several major business schools which follow grade non-disclosure policies, ISB permits students to report their GPAs to potential employers who use this information to screen interview candidates.[12]

[12]For example, see the section on education from a sample resume in Figure 4. Anecdotal evidence suggests that consulting firms, which hire approximately one third of students, screen on the basis of GPA only, and often ignore other factors such as past work experience or specialization.

Other characteristics that significantly influence reported salaries are work experience and citizenship. However, since neither of these factors can be changed by a student while at ISB, these results suggest that students are strongly motivated to maximize their GPA in the core terms.

3.2 Impact of formal and informal peers on core terms GPA

We specify the following model to estimate the impact of formal and informal peers on the academic outcomes. Given the design and structure of the experimental data as described earlier, identification of peer effects is not a significant obstacle. Although the dependent variable is theoretically truncated at 4.0 (the maximum GPA) and 0.0 (the minimum GPA), there are no observations at these points in the data. Therefore, OLS estimates will be consistent in reporting the impact of study group characteristics on student outcomes.

$$y_{ijt} = \beta_0 + \beta_1 \mathbf{X}_{ijt} + \beta_2 \overline{\mathbf{X}}^S_{-ijt} + \beta_3 \mathbf{Z}^S_{jt} + \beta_4 \overline{\mathbf{X}}^R_{-ijt} + \beta_5 \mathbf{Z}^R_{jt} + year_t + \epsilon_{ijt} \qquad (2)$$

In this specification, the outcome variable, y_{ijt} is the grade point average (GPA) from core term courses for student i in group j in cohort t. $\mathbf{X}_{ijt}$ is a vector of individual characteristics that includes the student's age, the number of years of full time experience and last salary prior to joining the program. We expect that these variables capture student maturity, experience with solving business problems, and success in the corporate workplace, respectively. We also include observed demographic characteristics such as whether the student is female, single, and a citizen of India. The student's GMAT score is included as a proxy for academic ability, especially quantitative and verbal skills, among the variables in $\mathbf{X}_{ijt}$. $\overline{\mathbf{X}}^S_{-ijt}$ represents the mean of the same variables for study group j, excluding the characteristics of student i. Student achievement might be influenced by heterogeneity in peer characteristics, especially in ability. Therefore, we include $\mathbf{Z}^S_{jt}$, which captures within-group variance in study group GMAT scores, age, previous salary in Indian Rupees and years of experience. As with the group mean, the variance is calculated across all other members of group j excluding student i. $\overline{\mathbf{X}}^R_{-ijt}$ and $\mathbf{Z}^R_{jt}$ capture the corresponding group mean and variance in residential peer characteristics. We include year fixed effects to control for observed and unobserved factors, such as academic policies or macroeconomic conditions, that are common for an entire cohort of students. Finally, we include an i.i.d. normal error term to account for factors such as motivation, study skills and personality that might impact a student's academic and professional outcomes, but are unobserved in the data. In this specification, the coefficients of interest are β_2, β_3, β_4 and β_5 which represent the impact of the mean and variance in study group and roommate characteristics on y_{ijt}.

Table 5 reports the results from estimation of equation (2). As expected, a number of individual characteristics are correlated with academic performance, including the individual's GMAT score, years of experience and salary before entering business school. A student's GMAT score has a large impact on GPA, with a 10 point increase in GMAT increasing GPA by 0.029 points. The coefficient associated with this result can be distinguished from the null at the 1 percent level, and indicates that quantitative and analytical intelligence as measured by the GMAT exam is important for success in business school classes. In addition to exam scores, students with higher salaries before joining business school are also likely to earn higher grades. GPA decreases with greater experience (and age), perhaps reflecting the difficulty faced by more experienced students in returning to an academic environment and mastering the study skills required to earn high grades. The table also reports coefficients for a number of demographic characteristics. Women have slightly higher grades than men. Married students have 0.05 grade points more than unmarried students, a result which is consistent with a well-established empirical observation that married workers have higher earnings than unmarried workers (Lundberg and Rose 2000). Finally, Indian citizens have significantly higher GPAs, which is due to efforts to diversify and internationalize the student body by admitting foreign nationals even with poorer academic skills.

The coefficients under the headings labeled "Study group (Mean)" and "Study group (Variance)" in Table 5 report the influence of the study group on student performance. The coefficients under the title "Study group (Mean)" represent β_2, the linear-in-means impact of study group peers. The coefficients under the title "Study group (Variance)" represent β_3, the impact of variance in study group characteristics on core GPA. We find that a one-point increase in the mean GMAT score of the group is associated with a 0.00036 increase in grade point average. Although this result is not statistically significant, the coefficient suggests that the influence of mean ability of study group peers is approximately 15% of individual ability. The only coefficient under "Study group (Mean)" that can be statistically distinguished from the null is the impact of earnings before joining business school, which have a positive influence on core term grades. Under "Study group (Variance)", the coefficient for variance in GMAT scores of the study group is 0.0000067, which cannot be statistically distinguished from the null. As before, the only statistically significant variable is earnings before joining business school.

In contrast to the study group, the coefficients under "Roommates (Mean)" show that the linear-in-means GMAT score for roommates has a large and significant impact on student GPA. A one-point increase in roommates' GMAT score increases student GPA by 0.0097 points, a result which is significant at the 10% level. The magnitude of this effect is one-third of the impact of own GMAT score. Most importantly, we find that variance of roommates' GMAT score positively and significantly affects core terms GPA. The coefficient associated with variance of roommate GMAT is 0.000015, which is both statistically significant at the 5% level and more than twice the magnitude of coefficient associated with variance in study group GMAT scores.

These results suggest that peer ability (as measured by GMAT scores) within the study group do not significantly influence student grade outcomes. One explanation for this finding is that students free-ride extensively on group assignments when effort is costly and the rewards are shared by all the members of the group (Holmstrom 1982). As a result, active engagement within the study group members is low, and students do not learn from higher ability peers. Simultaneously, the coefficients on both the mean and variance of roommate ability are significant, which suggests that the informal environment of the quad perhaps encourages interactive learning and students are able to learn from peers and improve grade outcomes.

In addition to the GMAT, we also find a consistent effect of "last salary" which reports a student's earnings prior to joining business school and represents job and industry-specific ability different from intellectual ability captured by the GMAT score. In both the study group as well as the quad, a thousand rupee increase in mean earnings is associated with a 0.004 higher grade point average (the coefficient associated with the study group is 0.00461 and that with the roommates is 0.00347, which are statistically not different from each other).

However, increase in variance in this measure has a significant negative impact on academic performance in both peer groups. A potential explanation for this result is that differences in earnings reflect differences in financial expectations or career goals within the group, leading to dysfunctional relationships that negatively impact academic performance.

3.3 Heterogenous impact of peers

The previous section reports the impact of peers for the average student over the entire core period. However, the effects might be different for students who are different in terms of ability and different over time. Assuming that the specification for determining peer effect in the previous section yields unbiased and consistent estimates, we use it to analyze heterogeneity in the impact of formal and informal peers in more detail.

We first explore the differential impact of peers on students of different ability. Students who have below mean GMAT scores might be more willing to learn from students with above average GMAT scores than vice versa. Table 6 reports the heterogeneous impact of peers on core GPA by estimating the main specification (equation 2) for students who are above and below the respective mean of either the study group ($\overline{GMAT}^S$) or the residential peers ($\overline{GMAT}^R$). We find that the mean and variance of the study group's GMAT score is insignificant for both students who are above and below the mean. In contrast, the impact of variance in the residential group's GMAT score is asymmetric. The coefficient associated with students who are below the quad average is 0.0000325, which is significant at the 1% level, and twice the magnitude of the average effect reported in the previous section. Simultaneously, the coefficient for above mean students is very close to the null and statistically indistinguishable from it.

This result suggests that increases in peer human capital disproportionately benefits weaker group members, that stronger students are not affected by the presence of academically weaker students and that informal settings are more conducive for academic peer interaction than formal settings. These empirical patterns are consistent with higher ability students transferring specific knowledge to lower ability students through, for example, direct tutoring. Our findings are consistent with studies such as Duflo, Dupas, and Kremer (2011) and Lyle (2009) who also report that relatively weaker students benefit more from high ability peers compared to stronger students.

We next explore the impact of formal and informal peers on a student's grade point average over each of the four core terms. Peer effects might amplify over time if students benefit from their initial interaction, or dampen if otherwise. Table 7 reports the impact of the peer group's GMAT scores on the GPA for each core term. As expected, own GMAT score has a positive, significant and persistent impact on academic performance. The coefficient declines over the first three terms, suggesting that students who arrive with relatively weak academic preparation catch up over time. The impact of the mean study group GMAT score is negative in the first term, although statistically insignificant. This offers a potential explanation why the coefficient on mean study group GMAT score is persistently small and insignificant. If initial interactions within the group do not enhance learning, for example, due to a extensive free-riding problems, then the study group ceases to be the setting for positive interactions. Instead, the coefficients on residential peer GMAT scores suggest that the quad becomes the setting for academic learning. The impact of residential peers is positive and significant in Term 1, so students increasingly interact in the quad, leading to amplification of peer effects in subsequent terms.

Table 8 reports the impact of core-term study groups and roommates on elective terms grade point average. In the elective terms, students continue with the same set of roommates, but the core-term study groups are disbanded and groups are self-selected in all courses. The results indicate that roommates continue to influence academic performance even if all students are not taking the same set of course. However, none of the characteristics of the core-term study groups are significant, indicating that these groups do not have a persistent impact. This is not surprising. If the formal study group did not influence students' grades in the terms when the group is required to work together, it is unlikely to do so once this requirement is removed.

3.4 Robustness checks

A concern with the analysis presented in the previous sections is that the impact of the immediate peers reflects, in Manski's (1993) words, "*correlated effects*, wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments." In this case, such similar institutional environments might consist of students beyond the study group and the quad.[13]

We conduct two exercises to address these concerns. In the first exercise, we augment equation (2) with variables representing peers beyond the immediate study groups and roommates to check whether other students who share the same environment also influence grades. In the second exercise, we conduct a falsification exercise where students are randomly reassigned to groups and quads in the data. We expect that peer effects should be absent in these results.

In order to address environmental concerns more completely, we exploit two features of the dataset. First, since the data is from an administrative source, we observe every node of the network. This feature allows us to map the environment for each student completely. Second, study groups are assigned to sections and residential groups are placed in blocks randomly, with no consideration of any observed or unobserved characteristics. Thus, we modify equation (2) to include additional variables that represent section and block characteristics to check the impact of these factors. The error term factors is clustered at the student village level (μ_{jt}).

$$\begin{aligned} y_{ijt} \;=\; & \beta_0 + \beta_1 \mathbf{X}_{ijt} + \beta_2 \overline{\mathbf{X}}^{S}_{-ijt} + \beta_3 \mathbf{Z}^{S}_{jt} + \beta_4 \overline{\mathbf{X}}^{R}_{-ijt} + \beta_5 \mathbf{Z}^{R}_{jt} \\ & + \beta_6 \overline{\mathbf{X}}^{Sec}_{-ijt} + \beta_7 \mathbf{Z}^{Sec}_{jt} + \beta_8 \overline{\mathbf{X}}^{Block}_{-ijt} + \beta_9 \mathbf{Z}^{Block}_{jt} + year_t + \mu_{jt} + \epsilon_{ijt} \end{aligned} \tag{3}$$

Table 9 reports the results of this estimation. Our first finding is that addition of the section and block variables does not alter the main results reported earlier significantly. Second, while the coefficient associated with the section's mean GMAT is negative and that with the block's mean GMAT is positive, neither of these contrasting effects can be statistically indistinguishable from the null. The effect of section or block GMAT variance is also statistically insignificant. These results suggest the absence of correlated effects beyond the study group or residential quad.

Our second robustness check is a falsification exercise to rule out that the results are driven by spurious correlations or factors unobserved in the data. We

[13]While we cannot rule out that students form networks beyond ISB, it is unlikely that these influence the outcome variable given the specific nature of material in core graduate management classes.

construct placebo study and residential groups by randomly shuffling the formal and informal group assignment in the data. We then estimate equation (3) with placebo groups. We expect that estimated coefficients associated with various peers will be both smaller in magnitude and statistically indistinguishable from the null. Table 10 does not find any discernible evidence of peer effects when estimated with the randomized groups. This falsification exercise leads to greater confidence that the estimation exercises in the previous sections correctly identified the impact of proximate study groups and roommates and not unobserved correlated effects.

3.5 Omitted variable bias in peer effect estimates

This section shows that estimating peer effects in a specification that includes only formal peers but excludes informal peers may lead to an overestimation of the influence of formal peers. Workers assigned to formal peer groups in most settings also have informal peers in the form of professional and social networks (or vice versa) that impact productivity but remain unobserved to the researcher. Thus, estimates of peer effects might suffer from omitted variable bias if the two types of peers are substitutes for each other. First consider the following specification, which is representative of many studies that estimate the impact of formal peers only.

$$y_{ijt} = \beta_0 + \beta_1 \mathbf{X}_{ijt} + \beta_2 \overline{\mathbf{X}}^{S}_{-ijt} + \beta_3 \mathbf{Z}^{S}_{jt} + year_t + \epsilon_{ijt} \tag{4}$$

In this specification, the formal peers are represented by the vectors $\overline{\mathbf{X}}^{S}_{-ijt}$ and $\mathbf{Z}^{S}_{jt}$, which contain the same variables as described in section 3.2. Column A in Table 11 presents the results of estimating this equation with core terms GPA as the outcome variable. The coefficient associated with the mean GMAT score of the study group is 0.000814, which is statistically significant at the 10% level. Simultaneously, the coefficient associated with variance in the study group's GMAT scores is 0.0000159, which is different from the null at the 5% level. Based on these results, a researcher who is interested in examining the impact of peers in an academic setting might ascribe significant influence to the study group, especially variation in ability.

We next consider a specification that includes only the characteristics of the informal peers, and excludes characteristics of formal peers. A number of studies that estimate the impact of roommates on academic achievement use similar specifications.

$$y_{ijt} = \beta_0 + \beta_1 \mathbf{X}_{ijt} + \beta_4 \overline{\mathbf{X}}^R_{-ijt} + \beta_5 \mathbf{Z}^R_{jt} + year_t + \epsilon_{ijt} \tag{5}$$

In this specification, $\overline{\mathbf{X}}^R_{-ijt}$ and $\mathbf{Z}^R_{jt}$ are included as the linear-in-means and variance of the same roommates' characteristics as described in section 3.2. Column B reports the results from estimating equation (5). We find that the point estimates for most components of β_1 differ only slightly from Column A. However, we find that both the mean and variance of GMAT scores of the quad have significant, positive influence on a student's GPA. Based on these results, a researcher interested in examining the impact of roommates on academic outcomes, might conclude that roommates have significant influence on student performance.

However, if the influence of one set of peers is a substitute for the other, then the estimates of peer ability presented in Columns A and B might suffer from omitted variable bias. If roommates substitute for the study group, then we will overestimate the impact of the study group in equation (4), and vice versa. In Column C, we present the coefficients from the full specification (equation 2) which includes both the study group and roommate peers.

Column C shows that including both study group and roommate ability in the specification changes our key finding of peer effects. The difference in coefficients between Column B and C are small, but large between A and C. Instead of finding that study group ability has a significant impact on student performance, we conclude that the effect of study group ability is relatively small and insignificant, but the impact of variance in roommate ability is large, positive and statistically significant. The difference in coefficient associated with the variance in study group scores is statistically significant (p=0.004). This suggests that roommate ability substitutes for study group ability in determining academic output of students, but not vice versa. Thus, our correct conclusion is that the primary set of peers who influence academic outcomes are the roommates, and not the study group as the results in Column A would suggest.

The results in this section suggest that excluding informal peers from a specification to estimate the impact of formal peers may lead to omitted variable bias, even insofar to overturn the original findings. Thus, researchers interested in examining peer effects in various situations should attempt to map and obtain data from the complete set of formal and informal peers who might influence individual outcomes.

4 Conclusion

This paper investigates the impact of peers on academic outcomes using data from an elite business school in an emerging economy. We analyze the impact of both formal and informal peers, as represented by study groups and roommates, respectively. To overcome potential endogeneity in group formation, we exploit the random assignment of students to roommates and study groups in the core terms. Thus, we are able to exploit a randomized experimental design where the characteristics of the other students in the group are uncorrelated with unobserved student characteristics, yielding unbiased and consistent estimates for peer effects.

We report three main results. First, we find that both informal peers, represented by roommates in residential dorms, have a significantly greater impact on academic performance than formal peers represented by the core terms study group. This suggests that social interaction is more effective in boosting academic outcomes than formal peer groups that are designed for learning. Second, we report that core term grades are driven by heterogeneity in group ability, since variance in GMAT scores within the group has a positive and significant impact on student performance in addition to the linear-in-means measure of ability. Third, we find an asymmetric impact of the benefits of peer ability. Low ability students benefit significantly more from variance in peer GMAT scores than high ability students. Finally, we show that including both informal and formal peers in the specification is important to avoid omitted variable bias in the estimated coefficients since the two types of groups are potentially substitutes for each other.

These results imply that informal settings without expectations of joint production may be conducive to academic exchange in peer groups. In contrast, formal situations where students are expected to work together may suffer from classic free-riding problems that inhibit learning. This is true even among business school students who are arguably more open to, and perhaps even seek out, peer influences compared to undergraduate or secondary school students.

Our findings should be read with a few caveats. First, we do not address selection into a business career or into business school, and the impact of formal and informal peers might be very different for individuals who are not observed in our sample. A related issue is that just because we uncovered evidence of peer effects in this setting among a certain cohort of students does not imply that these findings can be readily generalized for all situations. Second, while we examine academic performance, due to group design and data limitations we do not report salary or career path outcomes that might be important from an economic perspective. Third, in the absence of a complete structural model of behavior or the ability to conduct experiments, we cannot perform counterfactual simulations that either create optimal group assignments or predict the impact of specific academic policies to improve student outcomes.

Nonetheless, we can conclude from these findings that business schools and other educational institutions that wish to maximize learning should focus on out-of-classroom group activities in addition to, or as substitutes for formal situations within the class. Second, we suggest that group composition is important, and educational institutions should compose heterogenous groups where weaker students can learn from academically stronger peers.

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Table 2: **Summary statistics**

Variable	Observations	Mean	Std. Dev.
Full time experience (years)	1997	4.86	2.22
Single	1997	72.76%	0.45
GMAT	1997	709.0	40.2
Delhi University	1997	15.32%	0.36
IIT	1997	14.37%	0.351
Age (years)	1997	28.71	2.78
Female	1997	25.8%	0.44
Citizen of India	1997	95.74%	0.202
Last salary (Rs. '000s)	1845	996.1	1195.0
Salary at graduation (Rs. '000s)	1759	1399.8	869.3

Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

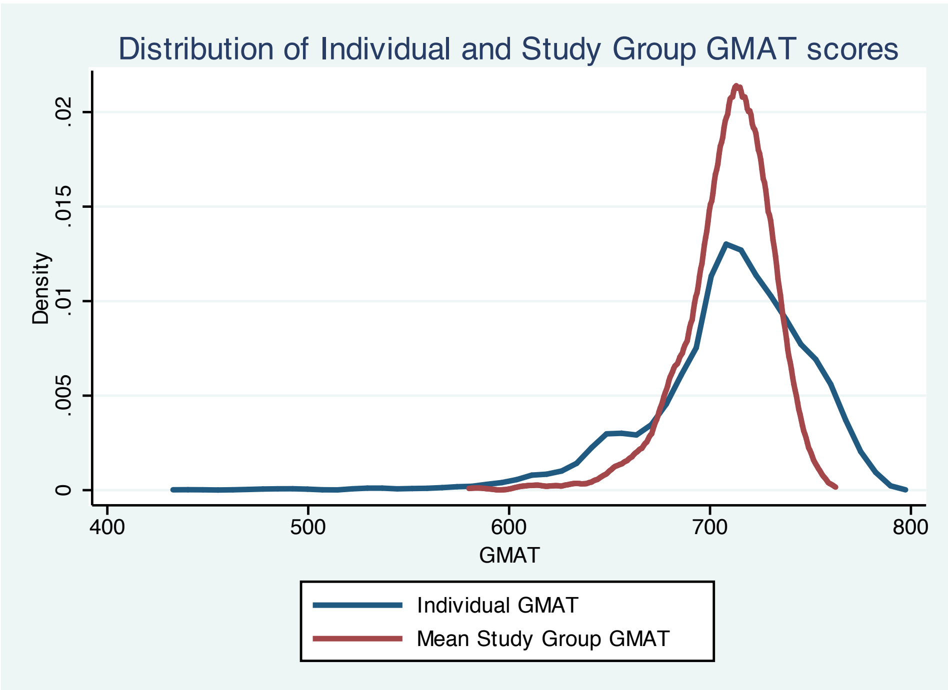

Figure 2: **Distribution of individual and study group mean GMAT scores**

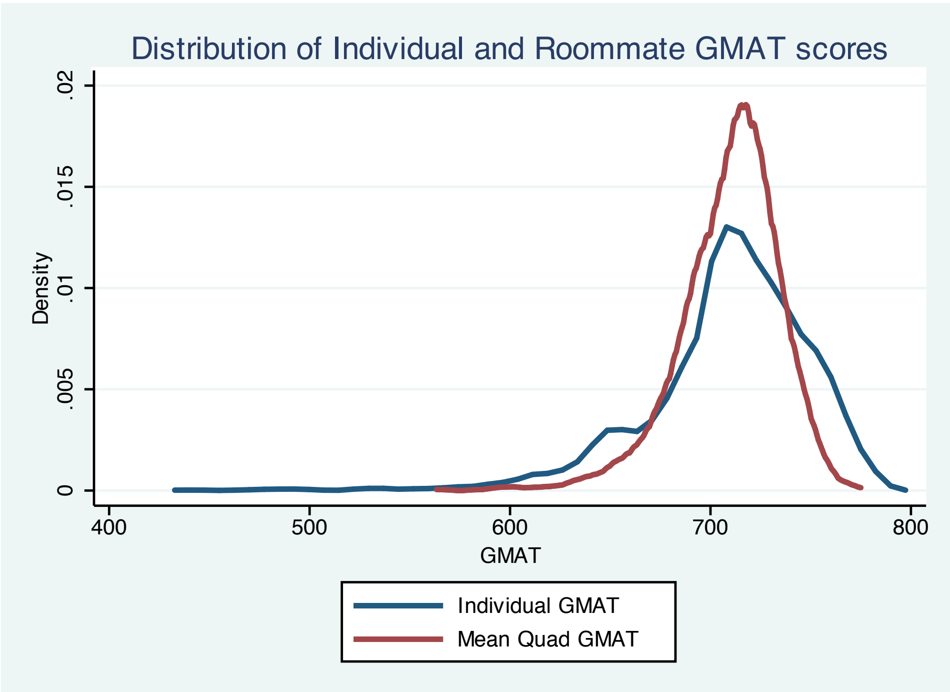

Figure 3: **Distribution of individual and residential group mean GMAT scores**

Table 3: **Randomization check in study group and quad assignments**

	Female		Male	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**
Panel A. Dependent variable is GMAT score				
Mean study group GMAT	0.0879	0.91	0.0239	0.45
	(0.0970)		(0.0536)	
Mean quad GMAT	-0.0579	-0.72	0.0258	0.51
	(0.0807)		(0.0503)	
N	440		1075	
R^2	0.04		0.04	
Panel B. Dependent variable is pre-earnings				
Mean study group pre-earnings	0.0665	0.48	0.000923	0.02
	(0.137)		(0.0455)	
Mean quad pre-earnings	0.0233	0.28	-0.0561	-1.03
	(0.0843)		(0.0544)	
N	412		998	
R^2	0.01		0.06	

Note: OLS regressions include year fixed effects. Standard errors in parentheses. $*p < 0.01$, $**p < 0.05$, $***p < 0.01$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 4: **Determinants of earnings at graduation**

Dependent variable: Value of on-campus offer		
	Coeff.	**Std err.**
Core terms GPA	**483074.6*** **	(127312.8)
Full time experience (years)	**92381.2** **	(30221.2)
Age (years)	-2536.3	(25543.9)
GMAT	-938268.5	(674017.8)
IIT	64929.1	(103942.4)
Delhi University	-80739.1	(93078.9)
Single	41959.9	(92103.7)
Female	-28039.3	(43916.6)
Citizen of India	**548740.5** **	(182623.1)
Last salary	0.00750	(0.0305)
R^2	0.16	

Notes: Table reports coefficients obtained from OLS estimation of equation (1). Regression includes year fixed effects. $N = 1753$. $*p < 0.01$, $**p < 0.05$, $***p < 0.01$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

EDUCATION

Indian School of Business **April 2009–to date**

Post Graduate Program in Management (Major- Finance & Marketing)

- **CGPA: 3.59/4.0 (Top 16%)**; GMAT: 760/800 (99 percentile)
- Developing the growth strategy for Staples-Future Group JV to achieve 40% growth in revenues through the retail channel
  - Designed the Customer Acquisition and Retention programme to be implemented across stores nationwide
  - Carried out extensive market and competitor analysis to come up with a new sales and operations model
- Undertook a consulting engagement with ISB Operations and Marketing teams to redesign the ISB Merchandize Store
  - Project being implemented for Solstice'09- annual ISB alumni meet
- Working on a Research Project on the transformation of State Bank of India through Business Process Re-engineering

Indian Institute of Technology, Kanpur **May 2002-May 2006**

Bachelor of Technology (B.Tech), Electrical Engineering

- **CGPA: 8.4/10;** Among the **top 0.1%** in IIT Joint Entrance Exam (All India Rank 255)
- Summer Training at ITC Ltd.: Designed a benchmark cigarette factory based on Lean manufacturing principles (Capex proposal of $23 million). Project adjudged among the top 3 projects (from 20+ projects) in the division

Delhi Public School, R.K. Puram **April 2001- March 2002**

- Secured **93.2%** in CBSE, AISSCE; **Ranked 7/889** in school; Awarded National CBSE Merit Scholarship and Gold Medal

Figure 4: **Sample resume**

Table 5: **Impact of own and peer characteristics on core terms GPA**

Dependent Variable: Core terms GPA		
	Coeff.	**Std err.**
I. Individual		
GMAT	**0.00291*** **	(0.000228)
Last salary (Rs. '000s)	**0.00435*** **	(0.000827)
Experience (years)	**-0.0239** **	(0.00794)
Age (years)	-0.0107	(0.00628)
Female	0.0379	(0.0882)
Single	-0.0502	(0.0337)
Citizen of India	**0.186*** **	(0.0479)
II. Study Group (Mean)		
GMAT	0.000356	(0.000466)
Last salary (Rs. '000s)	**0.00461** **	(0.00176)
Experience (years)	-0.0127	(0.0149)
Age (years)	-0.00478	(0.0122)
Female	0.0698	(0.0361)
Single	-0.0371	(0.0451)
Citizen of India	0.102	(0.0770)
III. Study Group (Variance)		
GMAT	0.00000671	(0.00000646)
Last salary (Rs. '000s)	**-0.0000228* **	(0.0000106)
Experience (years)	0.00102	(0.00234)
Age (years)	0.000900	(0.00155)
IV. Roommates (Mean)		
GMAT	**0.000970* **	(0.000398)
Last salary (Rs. '000s)	**0.00347* **	(0.00169)
Experience (years)	-0.00116	(0.0133)
Age (years)	-0.00215	(0.0109)
Female	-0.0947	(0.0895)
Single	-0.0484	(0.0418)
Citizen of India	-0.0470	(0.0706)
V. Roommates (Variance)		
GMAT	**0.0000150** **	(0.00000486)
Last salary (Rs. '000s)	**-0.0000243** **	(0.00000920)
Experience (years)	-0.000886	(0.00334)
Age (years)	-0.000201	(0.00198)

Notes: Table reports coefficients obtained from OLS estimation of equation (2). Regression specification includes year fixed effects, as well as coefficients for gender, marital status, citizenship and age in each of the categories labelled I-V. $N = 1845$. $R^2 = 0.20$. *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 6: **Heterogenous impact of peer GMAT scores**

	Dependent Variable: Core terms GPA			
	$GMAT_i < \overline{GMAT}^S$	$GMAT_i > \overline{GMAT}^S$	$GMAT_i < \overline{GMAT}^R$	$GMAT_i > \overline{GMAT}^R$
GMAT	**0.00352*****	**0.00288*****	**0.00375*****	**0.00309*****
	(0.000575)	(0.000573)	(0.000530)	(0.000606)
GMAT (Mean, Study group)	-0.000531	0.000966		
	(0.000814)	(0.000796)		
GMAT (Variance, Study group)	0.0000261	0.00000500		
	(0.0000140)	(0.00000885)		
GMAT (Mean, Residential peers)			0.000645	0.000530
			(0.000688)	(0.000700)
GMAT (Variance, Residential peers)			**0.0000325*****	0.00000583
			(0.00000878)	(0.00000752)
R^2	0.20	0.15	0.24	0.15

Notes: Table reports coefficients obtained from OLS estimation of equation (2) performed separately individuals above and below respective group medians. Regression specification includes year fixed effects, as well as variables for years of experience, last salary, gender, marital status, citizenship and age in each category. Standard errors in parentheses. $N = 1845$. *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 7: **Impact of GMAT scores over terms**

	Core GPA	**Term 1 GPA**	**Term 2 GPA**	**Term 3 GPA**	**Term 4 GPA**
GMAT	**0.00291***** (0.000228)	**0.00363***** (0.000294)	**0.00249***** (0.000228)	**0.00230***** (0.000251)	**0.00323***** (0.000247)
GMAT (Mean, Study group)	0.000356 (0.000466)	-0.000142 (0.000600)	**0.000940*** (0.000466)	0.000478 (0.000512)	0.000163 (0.000504)
GMAT (Variance, Study group)	0.00000671 (0.00000646)	0.00000288 (0.00000831)	0.00000884 (0.00000646)	0.00000630 (0.00000710)	0.00000514 (0.00000699)
GMAT (Mean, Residential peers)	**0.000970*** (0.000398)	0.000915 (0.000513)	**0.00110**** (0.000398)	0.000782 (0.000438)	**0.00116**** (0.000431)
GMAT (Variance, Residential peers)	**0.0000150**** (0.00000486)	**0.0000188**** (0.00000625)	**0.0000123*** (0.00000485)	**0.0000124*** (0.00000534)	**0.0000165**** (0.00000525)
R^2	0.20	0.21	0.18	0.16	0.18

Notes: Table reports coefficients obtained from OLS estimation of equation (2). Regression specification includes year fixed effects, as well as variables for years of experience, last salary, gender, marital status, citizenship and age in each category. Standard errors in parentheses. $N = 1845$. *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 8: **Impact of peers on elective terms GPA**

	A: Core GPA		B: Elective GPA	
	Coeff.	**Std Err.**	**Coeff.**	**Std Err.**
I. Individual				
GMAT	**0.00291*** **	(0.000228)	**0.00148*** **	(0.000216)
Experience (years)	**-0.0239** **	(0.00794)	-0.00643	(0.00750)
Last salary (Rs. ’000s)	**0.00435*** **	(0.000827)	**0.00261*** **	(0.000781)
II. Study Group (Mean)				
GMAT	0.000356	(0.000466)	0.0000657	(0.000440)
Experience (years)	-0.0127	(0.0149)	0.0195	(0.0140)
Last salary (Rs. ’000s)	**0.00461** **	(0.00176)	0.00222	(0.00166)
III. Study Group (Var)				
GMAT	0.00000671	(0.00000646)	0.00000267	(0.00000610)
Experience (years)	0.00102	(0.00234)	-0.00269	(0.00221)
Last salary (Rs. ’000s)	**-0.0000228***	(0.0000106)	-0.0000163	(0.00000998)
IV. Roommates (Mean)				
GMAT	**0.000970***	(0.000398)	**0.00112** **	(0.000376)
Experience (years)	-0.00116	(0.0133)	0.00261	(0.0125)
Last salary (Rs. ’000s)	**0.00347***	(0.00169)	0.00124	(0.00160)
V. Roommates (Var)				
GMAT	**0.0000150** **	(0.00000486)	**0.00000965***	(0.00000459)
Experience (years)	-0.000886	(0.00334)	0.00139	(0.00315)
Last salary (Rs. ’000s)	**-0.0000243** **	(0.00000920)	-0.00000425	(0.00000868)
R^2	0.20		0.07	

Notes: Table reports coefficients obtained from OLS estimation of equation (2). Regression specification includes year fixed effects, as well as variables for gender, marital status, citizenship and age in each category labeled I-V. $N = 1845$. *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 9: **Impact of extended networks**

	Core GPA	**Term 1 GPA**	**Term 2 GPA**	**Term 3 GPA**	**Term 4 GPA**
GMAT	**0.00293*** **	**0.00367*** **	**0.00248*** **	**0.00230*** **	**0.00323*** **
	(0.000313)	(0.000431)	(0.000321)	(0.000218)	(0.000373)
GMAT (Mean, Study group)	0.000443	-0.000197	0.000915	0.000793	0.000328
	(0.000541)	(0.000888)	(0.000490)	(0.000559)	(0.000549)
GMAT (Variance, Study group)	0.00000447	-0.00000167	0.00000723	0.00000815	0.00000491
	(0.00000666)	(0.0000104)	(0.00000593)	(0.00000846)	(0.00000568)
GMAT (Mean, Section)	-0.00376	-0.00196	-0.00127	**-0.00814** **	-0.00435
	(0.00176)	(0.00186)	(0.00180)	(0.00232)	(0.00331)
GMAT (Variance, Section)	0.00000773	0.0000451	0.0000229	-0.0000592	0.00000297
	(0.0000191)	(0.0000243)	(0.0000233)	(0.0000295)	(0.0000360)
GMAT (Mean, Residential peers)	**0.000931***	0.000729	**0.00102***	0.000735	**0.00122***
	(0.000382)	(0.000549)	(0.000425)	(0.000486)	(0.000424)
GMAT (Variance, Residential peers)	**0.0000171*** **	**0.0000200*** **	**0.0000120***	**0.0000139** **	**0.0000221*** **
	(0.00000306)	(0.00000413)	(0.00000463)	(0.00000418)	(0.00000458)
GMAT (Mean, Block peers)	0.000510	0.00112	0.000504	0.000265	0.000118
	(0.00104)	(0.00133)	(0.00107)	(0.00108)	(0.00127)
GMAT (Variance, Block peers)	-0.00000522	-0.000000393	0.000000788	-0.00000243	**-0.0000180***
	(0.00000739)	(0.00000946)	(0.0000129)	(0.00000803)	(0.00000635)
R^2	0.24	0.24	0.19	0.17	0.19

Notes: Table reports coefficients obtained from OLS estimation of equation (3). Regression specification includes year fixed effects, as well as variables for years of experience, last salary, gender, marital status, citizenship and age in each category. Standard errors in parentheses are clustered at the student village level. N = 1845. *** p < 10%, ** p < 5%, * p < 10%. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 10: **Randomized allocation of study groups and quads**

	Core GPA	**Term 1 GPA**	**Term 2 GPA**	**Term 3 GPA**	**Term 4 GPA**
GMAT	**0.00307*****	**0.00411*****	**0.00298*****	**0.00274*****	**0.00336*****
	(0.000435)	(0.000398)	(0.000267)	(0.000356)	(0.000403)
GMAT (Mean, Study group)	-0.000722	-0.000378	-0.000511	-0.000603	-0.000201
	(0.000515)	(0.000606)	(0.000459)	(0.000542)	(0.000370)
GMAT (Variance, Study group)	-0.00000253	0.00000965	0.00000798	0.00000155	0.0000100
	(0.00000530)	(0.00000846)	(0.00000553)	(0.00000634)	(0.00000618)
GMAT (Mean, Residential peers)	0.000355	0.000171	0.000166	-0.000237	-0.0000134
	(0.000426)	(0.000496)	(0.000354)	(0.000344)	(0.000197)
GMAT (Variance, Residential peers)	0.00000827	0.00000524	0.00000399	0.00000485	0.00000318
	(0.00000546)	(0.00000940)	(0.00000395)	(0.00000765)	(0.00000386)
R^2	0.26	0.24	0.19	0.19	0.21

Notes: Table reports coefficients obtained from OLS estimation of equation (3). Regression specification includes year fixed effects, as well as variables for years of experience, last salary, gender, marital status, citizenship and age in each category. Standard errors in parentheses are clustered at the student village level. N = 1845. *** $p < 10\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.

Table 11: **Omitted variable bias**

	Dependent Variable: Core terms GPA					
	A: Formal peers only		**B: Informal peers only**		**C: Formal and informal peers**	
	Coeff.	**Std err.**	**Coeff.**	**Std err.**	**Coeff.**	**Std. err.**
I. Individual						
GMAT	**0.00294*****	(0.000187)	**0.00288*****	(0.000224)	**0.00291*****	(0.000228)
Experience (years)	**-0.0189****	(0.00602)	**-0.0244****	(0.00786)	**-0.0239****	(0.00794)
Last salary (Rs. '000s)	**0.00327*****	(0.000638)	**0.00380*****	(0.000780)	**0.00435*****	(0.000827)
II. Study Group (Mean)						
GMAT	**0.000814***	(0.000398)			0.000356	(0.000466)
Experience (years)	-0.0146	(0.0127)			-0.0127	(0.0149)
Last salary (Rs. '000s)	**0.00458****	(0.00151)			**0.00461****	(0.00176)
III. Study Group (Var)						
GMAT	**0.0000159****	(0.00000527)			0.00000671	(0.00000646)
Experience (years)	0.00129	(0.00191)			0.00102	(0.00234)
Last salary (Rs. '000s)	**-0.0000264****	(0.00000893)			**-0.0000228***	(0.0000106)
IV. Roommates (Mean)						
GMAT			**0.00107****	(0.000396)	**0.000970***	(0.000398)
Experience (years)			-0.00306	(0.0132)	-0.00116	(0.0133)
Last salary (Rs. '000s)			**0.00395***	(0.00166)	**0.00347***	(0.00169)
V. Roommates (Var)						
GMAT			**0.0000158*****	(0.00000472)	**0.0000150****	(0.00000486)
Experience (years)			-0.000708	(0.00332)	-0.000886	(0.00334)
Last salary (Rs. '000s)			**-0.0000289****	(0.00000895)	**-0.0000243****	(0.00000920)
R^2	0.21		0.19		0.20	

Notes: Columns A, B and C report coefficients obtained from OLS estimation of equation (4), equation (5) and equation (2), respectively. Regression specification includes year fixed effects, as well as coefficients for gender, marital status, citizenship and age in each of the categories labeled I-V. $N = 1845$. *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$. Source: ISB administrative records from 2007-08, 2008-09, 2009-10 and 2010-11 class years.