Formal versus informal peers: Evidence from the random assignment of business school peers

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Abstract

We investigate the impact of formal and informal business school peers on academic outcomes using random assignment of students to study groups and group residential facilities. We find that informal social interaction with residential peers has greater impact on core term grades than formal interaction in study groups. The result is driven by group heterogeneity in ability, with greater impact of more diverse peers. Further, the impact is asymmetric as low ability students benefit more from their peers than high ability students.

Keywords: Peer effects. Management education.
JEL Codes:

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1 Introduction

In this paper, we estimate the determinants of success in business school, and study the impact of peers on student academic achievement. Our analysis of peer effects takes into account two peer groups that are exogenously assigned – study and residential groups. The study group requires members to perform formal academic tasks such as group assignments. The residential group is formed by the assignment of individuals to apartments shared by three other students. We find that formal study groups have a negligible impact on the academic performance of students. In contrast, the informal residential peer groups have a significant impact on academic performance. Moreover, this effect seems to be larger for those students who are below the peer group average in terms of GMAT scores.

This study is part of a large recent literature on peer effects in education. A number of studies argue that the influence of peers on academic outcomes is a potentially omitted variable with significant impact (Case and Katz 1991; Hoxby 2000; Hanushek, Kain, Markman, and Rivkin 2003). However, estimation of peer effects in most observational data is difficult because of the "reflection problem", the potentially endogenous tendency of individuals with shared attributes to associate with each other (Manski 1993). Hence, random or exogenous assignment of peers is important to correctly identify the impact of peers. Pioneered by Sacerdote (2001), the most convincing studies of peer effects exploit exogenous or random assignment of students to residential dormitories by colleges to estimate the impact of peers on academic and career outcomes (Zimmerman 2003; Stinebrickner and Stinebrickner 2006; Lyle 2007; Lyle 2009; Carrell, Fullerton, and West 2009). Lerner and Malmendier (2011) and Shue (2011), two recent studies that use data from Harvard Business School, take a slightly different strategy by using the random assignment of students to first year sections to estimate the impact of peers on entrepreneurship, executive compensation and firm performance.

Our study contributes to the existing literature in a number of ways. First, the structure of exogenous peer assignments in our data allows us to simultaneously estimate the differential impact of two sets of peers. We observe both formal peers through study group assignments, as well as informal peers through residential assignments. As a result, our study is one of the first to examine the impact of multiple peer sets on students' academic performance. Second, we examine the role of group variance in predicting student performance, which differs from most papers that examine peer effects through a linear-in-means framework. Third, ours is one of the first studies that looks at the asymmetric impact of peers on students who differ in terms of GMAT scores.

This study is also related to the production of managerial talent in an emerging economy. It has long been suspected that the lack of managerial skills could potentially explain differences in total factor productivity between developed and emerging economies. However, empirical evidence to establish this is scarce. A notable exception is a study by Bloom, Mahajan, McKenzie, and Roberts (2010) who use a randomized control trial to study the impact of managerial techniques on firm productivity in India. They find that randomly implementing modern practices in factory operations, quality control and inventory, human resource and sales and order management increased average firm productivity by 11 percent in one year, primarily through improved quality and efficiency and reduced inventory and without any investment in new plant or equipment. Our study contributes to this small but growing literature on business skills by analyzing the impact of peer effects on the performance and productivity of future managers.

The rest of the paper is organized as follows. The next section describes the data generating process at the business school as well as a summary 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 Data and institutional description

Estimating the impact of peers on 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 formal and informal peers, we need at least two sets of such peer assignments in the dataset. In addition, 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.

We obtain administrative data from the flagship post-graduate business program at the Indian School of Business (ISB) which satisfies these requirements. ISB is a large, independent provider of post-graduate management education established in 2001 with a one year, full-time residential diploma program. Classes 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. The next four terms are elective terms where students choose their classes while concentrating in the areas of entrepreneurship, finance, IT management, operations, marketing or strategy.

At ISB, instructors 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.

A unique feature of this data that makes it appropriate for analysis of peer effects is that students are simultaneously and randomly assigned to two separate and mutually exclusive peer sets – "formal" peers in the study group, and "informal" peers in the residential dormitories. To the best of our knowledge, this is the only dataset used to estimate peer effects among management students with such a feature.[1]

Before the start of core classes, the Academic Services Administration (ASA) assigns students to a study group, which is then assigned randomly to a section of approximately 70 students.[2] Members of the study group work together to understand the coursework, as well as to complete specific group-based assignments. In assigning students to study groups, ASA relies only on the observable demographic characteristics of students, following two simple se-

[1]Another advantage of the one year program is that student cohorts do not overlap and therefore serial correlation of peer effects across the years is not a significant concern.

[2]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.

quential rules.[3] First, groups are assigned either two women, or none at all. Next, the groups are balanced 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, the assignment of individuals to groups is statistically random on the unobservables.

In addition to the formal study group peers, students are also assigned to 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. Students can elect to stay in either single apartments or four room "quads" with shared kitchen, dining and living spaces. Single apartments are assigned to students with co-habiting family members or those with special needs. The remaining students are randomly assigned to quads, with two observable assignment rules. First, each quad is single sex. Second, roommates cannot overlap with study group peers.[4] 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, 1038 out of 1422 students live in shared residences.

The data has a number of limitations that potentially impact our estimates of peer effects. First, ISB records career outcomes only for those students who receive offers on-campus. Detailed career outcomes for students who received offers off-campus or return to family owned businesses are not available in the data. A related issue is that ISB reports only the first job after business school, whereas long-term outcomes might also be relevant but are not observed in the data. Second, we do not observe potential students who considered business school but did not apply, nor those who applied but were not admitted. Hence, we cannot address se-

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

[4]This restriction prevents us from using an identification strategy that uses peers-of-peers as an instrument (De Giorgi, Pellizzari, and Redaelli 2010).

lection of individuals into our sample. Finally, since our sample is from a single school, we cannot compare differences in institutional or cultural characteristics across business schools that might be correlated with the impact of peers. One reason why this is not a major concern is because ISB was established in academic collaboration with the Wharton School, Kellogg and London Business School (LBS), and shares institutional DNA (for example, academic policies and administrative structure) with them. To confirm that the shared institutional features also led to similar student attributes, Table 1 compares student characteristics at ISB with those at a number of top-ranked 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 little higher than INSEAD and LBS (703 and 694, respectively). In addition, the average candidates has five years of work experience before enrollment, which is typical of many North American and European business schools. The fraction of female students (28 percent) is slightly lower than the norm in the United States (35 to 38 percent). 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 cause ISB's results to be unique. However, without sector-wide data from a large number of international schools, it is not possible to estimate the impact of location or other unobservable factors.

Nonetheless, the unique advantages of this dataset allow us to perform econometric estimations that help uncover the role of peer effects. Table 2 summarizes the data. Seventy two percent of students are single at an average age of over 28 years. Nearly 25 percent of the students are women, and 96 percent are Indian citizens. The average salary drawn before enrolling at ISB was Rs. 649,000 whereas the average salary reported on graduation was Rs. 1,669,000, corresponding to 157 percent increase in compensation over one year of study.

The next section describes the econometric analysis performed on this data to estimate the impact of peer effects on academic performance.

3 Empirical analysis

The objective of the empirical exercise is to determine the factors that impact academic and professional performance. Along with individual factors, we investigate the role of peer characteristics in student outcomes, separating out the impact of formal and informal group assignments. In addition, we conduct robustness checks to ensure that the results are not driven by spurious correlation in the data.

3.1 Econometric specification

To estimate the impact of study group and residential peers on student outcomes, we specify the following model for student i in group j in cohort t.

$$y_{ijt} = \beta_0 + \beta_1 \mathbf{X}_{ijt} + \beta_2 \overline{\mathbf{X}}^S_{-ijt} + \beta_3 \mathbf{Z}^S_{jt} + \beta_4 \overline{\mathbf{X}}^R_{-ijt} + \beta_5 \mathbf{Z}^R_{jt} + year_t + \epsilon_{ijt} \tag{1}$$

In this specification, y_{ijt} is the outcome of interest, which is grade point average (GPA) from core term courses and elective courses. $\mathbf{X}_{ijt}$ is a vector of individual characteristics that includes the student's age, the number of years of full time experience before joining the program and previous salary. 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. We include the student's log GMAT score 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 the study group.[5] We are also interested in examining the impact of peer heterogeneity on student outcomes. So we include $\mathbf{Z}^S_{jt}$, which captures the within-group variance in study group GMAT scores, age, previous salary and years of experience.[6] $\overline{\mathbf{X}}^R_{-ijt}$ and $\mathbf{Z}^R_{jt}$ are the corresponding vectors for residential peer characteristics. We include year fixed effects to control for observed and unobserved characteristics that are common for an entire cohort

[5] The mean is taken across all other members of group j excluding student i.

[6] As with the group mean, the variance is calculated across all other members of group j excluding student i.

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.

The coefficients of interest are β_2, β_3, β_4 and β_5, which represent the impact of the group mean and variance in peer characteristics on y_{ijt}. Given the design and structure of the experimental data, identification of peer effects is not a significant obstacle. Therefore, OLS estimates will be unbiased and consistent in reporting the impact of peers on student outcomes.

We estimate this specification separately for students who are above and below the mean GMAT of the group. Since a student can simultaneously belong to both a study group as well as a quad, we report two versions. $\overline{GMAT}^S$ is the mean of the study group in the first version and $\overline{GMAT}^R$ is the mean GMAT of an individual's roommates in the second.

3.2 Results

Table 3 presents OLS estimates from equation (1) using the grade point average for the core terms as the outcome variable. The column labeled "Own characteristics" reports the vector of coefficients β_1. GPA decreases in both greater experience as well as age, indicating the difficulty faced by older and more experienced students in returning to an academic environment and mastering the study skills required to earn high grades. Although women have lower grades than men, the result cannot be statistically distinguished from the null. Students who are married have higher grades, a result that corresponds with a well-established empirical observation that married workers have higher earnings than unmarried workers (Korenman and Neumark 1991; Cornwell and Rupert 1997; Lundberg and Rose 2000; Chun and Lee 2001). Our result indicate that married students have greater productivity than unmarried students, potentially due to returns to specialization after marriage or greater motivation for higher grades.[7] Finally, Indian citizens have significantly higher GPAs, which is due to efforts to internationalize the

[7] A related issue is the impact of children on productivity. The data on whether students have children or not is incomplete, hence this variable is not included in the main analysis. However, regression results that include this variable indicate that the GPAs of students with children is lower than those students who are married without children. This indicates that specialization rather than motivation is a better explanation for the marriage result. Without panel data, we are unable to address selection into marriage.

student body by admitting more foreign nationals even if they have poorer academic skills.

The two most precisely estimated coefficients are those for the impact of pre-salary and GMAT scores on core GPA. Students with higher salaries before joining business school are also likely to earn higher grades. Since we have controlled for age and length of professional experience, this suggests that workplace skills such as tenacity and creativity rather than maturity or perspective drive performance in business school classes, leading to higher grades. Finally, GMAT scores have a large and statistically significant impact on GPA. This indicates that quantitative and analytical intelligence is key to success in business school classes.

The column labeled "Study group characteristics" in Table 3 reports the impact of the study group peers on a student's core term GPA. The coefficients under the title "Group mean" represent β_2, the linear-in-means impact of study group peers. The coefficients under the title "Group variance" represent β_3, the impact of study group variance on core GPA. We find almost no statistically significant impact of study group characteristics on core GPA, either as group mean or variance. However, the coefficients for residential peers, reported under the column labeled "Roommate characteristics", show that both group mean as well as group variance for GMAT matter significantly (at the 10 percent and 5 percent level, respectively) in predicting core term performance. The linear-in-means impact of the residential group (+0.78) is more than twice as large as the impact of the study group (+0.30). This result suggests that the intellectual ability of informal peers, as measured by GMAT, has a significantly greater influence on academic performance than the abilities of formal peers.

Table 4 reports the impact of peer GMAT scores on the GPA for each of the four core terms, as well as the elective terms (where students choose their own courses). As expected, own GMAT score has a significant and persistent impact on academic performance, although the coefficient declines over time. The impact of the study group GMAT remains insignificant, except in Term 2. This is potentially because a larger fraction of the evaluation in this term is determined by group rather than individual submissions. The impact of residential peers is persistent in both the core and elective terms, and shows no decline over time.

In Table 5, we report the heterogeneous impact of peers on core GPA. The fifth shows that students whose GMAT score is below the mean for their group benefit significantly from greater variance in GMAT, both in the study group as well as in their quad. This effect is especially large for students who are in the bottom half of their residential group peers (+11.40 and statistically significant at the 5 percent level) compared to those who are in the bottom half of their study groups (+6.37 and statistically significant at the 10 percent level). This suggests that the benefit of heterogenous peers accrue disproportionately to weaker rather than stronger students, especially among informal peers.

4 Conclusions

This paper investigates the impact of peers on academic outcomes using data from a 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 quasi-random 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 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, whereas linear-in-means does not. 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.

These results should be read with a few caveats. First, we do not address selection into a business career or into ISB. Selection on observed or unobserved characteristics might be important to determine validity of these results outside this sample. Second, while we examine academic performance, due to data limitations we do not report salary or career path outcomes which might be important from an economic perspective. Third, in the absence of a complete structural model of behavior, we cannot construct counter-factual simulations that predict the impact of specific policies to improve student outcomes.

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

	GMAT (Mean)	Years of work experience	Female	Class size
Harvard Business School	730	4	38%	908
Stanford GSB	730	3.9	36%	370
Wharton	720	6	36%	823
Kellogg	715	5	35%	475
Chicago Booth	715	4.6	35%	1177
IIM Ahmedabad PGPX	713	10	7%	86
Indian School of Business	**712**	**5**	**28%**	**560**
MIT Sloan	710	5	35%	396
INSEAD	703	6	33%	988
London Business School	694	5.6	25%	319

Note: Data is for the Class of 2010 for all schools. Source: School websites and `http://www.businessweek.com`.

Table 2: **Summary statistics**

Variable	Obs.	Mean	Std. Dev.
Full time experience (years)	1427	4.9	(2.3)
Single	1427	72%	(0.4)
Age (years)	1427	28.7	(2.8)
Female	1427	25%	(0.4)
Citizen of India	1427	96%	(0.2)
Last salary (Rs. '0000)	696	64.9	(45.6)
Salary at graduation (Rs. '0000)	1056	166.9	(168.4)

Source: Administrative records.

Table 3: **Impact of own and peer characteristics on Core GPA**

Dependent Variable: Core GPA					
Own characteristics		**Study group characteristics**		**Roommate characteristics**	
		Group Mean		*Group Mean*	
Age (years)	**-0.015***	Age (years)	0.000	Age (years)	-0.002
	(0.007)		(0.014)		(0.013)
Experience (years)	**-0.025****	Experience (years)	-0.010	Experience (years)	0.000
	(0.009)		(0.017)		(0.015)
Female	-0.136	Female	0.018	Female	0.041
	(0.119)		(0.042)		(0.121)
Single	**-0.071***	Single	-0.046	Single	-0.048
	(0.035)		(0.048)		(0.047)
GMAT	**1.693*****	GMAT	0.304	GMAT	**0.780***
	(0.177)		(0.375)		(0.311)
Citizen of India	**0.250*****	Citizen of India	0.045	Citizen of India	-0.069
	(0.055)		(0.096)		(0.087)
Last salary (Rs. ’0000)	**5.69*****	Last salary (’0000 rupees)	**4.31***	Last salary (’0000 rupees)	3.25
	(1.09)		(2.16)		(2.04)
		Group Variance		*Group Variance*	
		Experience (years)	0.002	Experience (years)	0.001
			(0.003)		(0.004)
		GMAT	5.012	GMAT	**5.944****
			(2.938)		(1.951)
		Last salary (’0000 rupees)	0.000	Last salary (’0000 rupees)	0.000
			(0.000)		(0.000)
		Age (years)	0.001	Age (years)	-0.001
			(0.002)		(0.002)

Notes: $N = 951$. Regression specification includes year fixed effects. Standard errors in parentheses. *** $p < 10\%$, ** $p < 5\%$, * $p < 10\%$. Data source: Administrative records.

Table 4: **Impact of GMAT scores over terms**

	Core GPA	**Term 1 GPA**	**Term 2 GPA**	**Term 3 GPA**	**Term 4 GPA**	**Elective GPA**
GMAT	**1.693*****	**2.137*****	**1.451*****	**1.333*****	**1.820*****	**0.748*****
	(0.177)	(0.234)	(0.194)	(0.211)	(0.196)	(0.174)
GMAT (Mean, Study group)	0.304	-0.102	**0.883***	0.524	-0.0570	0.120
	(0.375)	(0.495)	(0.411)	(0.448)	(0.415)	(0.370)
GMAT (Variance, Study group)	5.012	4.652	**6.922***	5.244	3.163	1.215
	(2.938)	(3.879)	(3.219)	(3.505)	(3.247)	(2.895)
GMAT (Mean, Residential peers)	**0.780***	**0.869***	**0.834***	0.498	**0.915****	**0.695***
	(0.311)	(0.410)	(0.340)	(0.371)	(0.343)	(0.306)
GMAT (Variance, Residential peers)	**5.944****	**7.490****	**4.713***	**4.769***	**6.703****	3.538
	(1.951)	(2.576)	(2.137)	(2.327)	(2.156)	(1.922)

Notes: N = 951. Regression specification includes year fixed effects. Standard errors in parentheses. *** $p < 10\%$, ** $p < 5\%$, * $p < 10\%$. Data source: Administrative records.

Table 5: **Heterogenous impact of peer GMAT scores**

	Dependent Variable: Core GPA			
	$GMAT_i < \overline{GMAT}^S$	$GMAT_i > \overline{GMAT}^S$	$GMAT_i < \overline{GMAT}^R$	$GMAT_i > \overline{GMAT}^R$
GMAT	**1.767*****	**1.601*****	**1.714*****	**2.279*****
	(0.455)	(0.446)	(0.396)	(0.468)
GMAT (Mean, Study group)	-0.528	**1.266***	-0.597	0.824
	(0.674)	(0.612)	(0.527)	(0.589)
GMAT (Variance, Study group)	10.62	5.804	1.271	5.596
	(6.931)	(3.906)	(4.306)	(4.677)
GMAT (Mean, Residential peers)	0.0394	**0.985***	0.845	0.118
	(0.479)	(0.446)	(0.565)	(0.502)
GMAT (Variance, Residential peers)	**6.371***	3.210	**11.40****	-0.230
	(3.186)	(2.965)	(3.594)	(2.862)
N	423	528	434	517

Notes: Regression specification includes year fixed effects. Standard errors in parentheses. *** $p < 10\%$, ** $p < 5\%$, * $p < 10\%$. Data source: ISB administrative records.

Table 6: **Quantile regression results**

	Dependent Variable: Core GPA		
	25th quantile	**50th quantile**	**75th quantile**
GMAT	**1.747*****	**1.811*****	**1.737*****
	(0.176)	(0.241)	(0.251)
GMAT (Mean, Study group)	0.0704	0.412	0.325
	(0.377)	(0.515)	(0.533)
GMAT (Variance, Study group)	3.124	5.422	5.764
	(3.070)	(3.923)	(3.893)
GMAT (Mean, Residential peers)	**0.723***	0.787	0.749
	(0.309)	(0.423)	(0.460)
GMAT (Variance, Residential peers)	**5.079***	3.824	**7.991****
	(2.008)	(2.650)	(2.619)

Notes: Regression specification includes year fixed effects. Standard errors in parentheses. *** $p < 10\%$, ** $p < 5\%$, * $p < 10\%$. Data source: ISB administrative records.