Peer Effects in MBA Program

Zinaida Foltin

October 5, 2017

[1]

1 Introduction

Despite the growing body of literature on the peer effects in education, there is still a lack of consensus on the existence and magnitude of peer effects on academic outcomes. Most of the traditional models of peer effects focus on cognitive peer characteristics or peer behaviour. To my knowledge, none of the research in the economics of education has incorporated the personality characteristics of student's peers when looking at possible mechanisms behind the peer effects. Very few researchers also have an opportunity to ask students directly about their behaviour and roles when it comes to interacting with their peers. Knowing more about how and why peers affect each other will help schools get closer to optimal allocation of students across groups.

Using unique data collected at a leading Canadian MBA program, I conduct an analysis of peer effects in small, administratively assigned groups called "learning teams". There are several features of my data that I am able to exploit in my research and that differentiate this paper from previous literature. First, I benefit from the exogeneous, stratified random assignment of students into small teams. Second, I obtained a rich dataset consisting of a number of students' demographic characteristics as well as their academic outcomes. Finally, I designed and administered a survey among three cohorts of MBA students and evaluated their study habits, preferences and non-cognitive characteristics (the Big Five personality traits). Having this information allows me to look for possible explanations for the peer effects I find in the data.

My results indicate that peers do have an effect on students' Managerial Finance grades. First of all, I find that high proportion of peers with science/engineering degrees has a

[1]This research was supported by the Social Sciences and Humanities Research Council of Canada.

negative effect on student's grade. Second, there is some evidence that students assigned to teams with low GPA peers perform better in finance course. Because of the nature of my dataset, I am able to explore the heterogeneities in the peer effects, in particular, how different types of students are affected by their peers. I find that peer effects are heterogeneous across students of different ability levels. In particular, academically weaker students benefit from having a high fraction of low admission GPA peers in their group, while stronger students have higher grades if they are in a team with top admission GPA peers. Meanwhile, high proportion of top GMAT peers has a negative effect on the grades of similar ability students. Heterogeneous peer effects indicate that there may be a better, Pareto improving way of allocating students across teams.

I use the survey data to explore two potential reasons for these findings. First, I look at the effect of peers on the number of hours students spend studying for the finance class alone and with the team. Students assigned to groups with top GMAT peers spend more time studying with their team. On another hand, students with peers who are domestic students spend more time preparing for class alone.

Second, I consider the non-cognitive characteristics of students and whether those could provide an explanation for the results. I find that GMAT scores are negatively correlated with "Agreeableness" score from the personality questionnaire. Domestic students and students with commerce/economics degrees also score one the lower end of "Agreeableness" scale. Using the answers to the question about the roles students take during group study, I find that students with the science/engineering background are the most likely to play "devil's advocate", argue the case points and challenge their colleagues.

Taking all of the results together, I posit that peers with top GMAT scores may be most likely to be critical and inflexible, thus creating suboptimal study atmosphere in the group. While they may encourage their teammates to spend time studying with the team, this time does not appear to be effective, and does not help students achieve better grades. Similarly, students with science/engineering background like to engage in arguments over the case points. While this behaviour may be good for study process in moderation, having many team members who enjoy to argue may create a hostile environment. Given also that students of similar ability levels (as measured by undergraduate GPA) perform better if they are placed in the same groups, I conclude that having a positive atmosphere during the study meeting where students are comfortable discussing their ideas and ask questions may be the key for the good performance in the course.

Many North American MBA programs divide students into learning teams. To my knowledge, these allocations are usually done by following a number of common sense rules, deemed appropriate by the administration. The main goal is to create diverse teams that would expose students to a variety of different peers and create a fair and equal learning environment. The findings of my paper will aid in improving the allocation rules: one clear implication is that mixing students of different abilities together may not be the most optimal way of creating teams. Instead, creating more uniform groups may be a way to improve students' experience. Another aspect of group formation that may need to be taken more seriously, is personality assessment of students. Students may need to be instructed on effective group work strategies, they should be warned against "steamrolling" over their teammates and taught how to deal with difficult groupmates without letting them affect the study process.

Finally, I address one of the potential issues with some of the peer effects in education research. Many of the papers on the subject use cumulative GPA or some other average grade as an outcome. Using grades for two different courses I show that focusing on an average grade may lead to false conclusions about absence of peer effects. This is an important issue to consider in any research that finds lack of peer effects when looking at any sort of average grade.

The rest of the paper is organized as follows: section 2 discusses the relevant literature on peer effects in higher education; section 3 describes the data used in this paper in detail; section 4 talks about the empirical strategy for the analysis and provides the results; section 5 includes the discussion of average GPA vs. individual course grades peer effects and section 6 concludes.

2 Literature Review

While there is a lot of research on peer effects in general, I will focus my attention on the branch of recent literature that deals with peer effects in education and higher education in particular.[2] Since the endogeneity of peer groups formation presents a significant hurdle in investigating the causality of peer effects, researchers try to identify the situations where peers are exogenously assigned such as the assignment of roommates in university/college residences or random distribution of students across classes and sections.

B. I. Sacerdote (2001) uses the data on random assignment of roommates in Dartmouth. He finds limited peer effects on academic achievement, however, he does find some evidence of peer effects on the social outcomes (e.g. fraternity choice). Another well-known paper on the subject by Zimmerman (2003) uses a similar setting of random assignment of roommates in Williams College to see whether different ability peers as measured by the SAT score influence their roommates. He finds that students in the middle of the SAT distribution are somewhat negatively affected by the low ability peers. Finally, Stinebrickner and Stinebrickner (2006)

[2]For a detailed survey of the literature on peer effects in education see Epple and Romano (2011)

use the Berea Panel Study and find evidence of peer effects on grade outcomes and drop-out decisions among the students of Berea College.

Alternative way of finding exogenously assigned peer groups is to consider class, cohort or squadron peers.Hoxby (2000) considers the peer effects in elementary school classroom setting. Using an identification strategy for peer effects using the gender and racial composition variation in the adjacent school cohorts, she finds some gender specific peer influence: for example, both males and females perform better in a class with a high proportion of females. With a similar strategy of using the variation in gender composition in adjacent school cohorts, Lavy and Schlosser (2011) present some evidence and mechanisms of gender peer effects. They also find that higher proportion of female students positively affects the academic achievement outcomes of all students. However, the effect of number of females in the classroom may or may not be the same at the college level as it is at the secondary education level. One particular paper that looks at the effect of female peers at the university level is Ooosterbeek and van Ewijk (2014). Authors run an experiment at the University of Amsterdam economics/business department. They randomly assign different proportions of females in different "sections" of the class and find no significant peer effects.

Carrell, Sacerdote, and West (2013) use a slightly different approach to deal with the endogeneity problem. They use a unique dataset from the US AirForce Academy, where students are randomly divided into squadrons of 30 people each. Authors first look at the historical data for estimation of peer effects and find that there is a positive effect of high ability peers on low ability students. This motivated an experiment: authors formed the squadrons in the following manner: some squadrons (treatment) consisted of mainly high and low ability students, while others (control) had high, middle and low ability participants. Surprisingly, the findings show lack of positive effect of high ability peers on the treatment groups. Authors explanation is that perhaps students form their own smaller subnetworks within a squadron by the ability level, thus limiting the effect of their peers with different levels of ability.

Finally, some researchers take advantage of experimental or quasi-experimental settings. There is usually a random (or quasi-random) peer group assignment and in some cases these groups are small, thus the aforementioned problems of students forming smaller subgroups can be avoided. However, these papers mainly document the presence (or absence) of peer effects rather than attempt to look into the mechanisms behind them. Hansen, Owan, and Pan (2015) consider knowledge spillover in an undergraduate management class. They find that male dominant groups perform worse than mixed or female dominant groups. Members of the groups that were more diversified in terms of age and gender perform better on exams. Lu and Anderson (2015) use a random assignment to the seats in a Chinese middle school to find evidence of peer effects. They document a positive effect of female peers on female students. Authors identify that a "boutique" model - where peers benefit from group homogeneity - would generate their results. Jain and Kapoor (2015) compare the two groups of peers: exogenously assigned study groups and roommates in an Indian university. They find that study groups have low impact on academic achievement, while informal social interactions with roommates have significant and positive effects. They indicate that low ability students benefit from high ability peers, but the relationship does not go the other way. Booij, Leuven, and Oosterbeek (2015) use data from an experiment where they manipulate the composition of tutorial groups according to students' ability levels. They find that while low ability students benefit from being in the groups with similar level students, while high ability students are not affected by the switch from mixed ability to similar ability groups.

One of the most recent papers on the subject of peer effects in education, Feld and Zolitz (2017) discovers an interesting thing. They say that peer effects appear to be channelled through the changes in group interaction rather than teacher's effort, for example. They find that in German university, where students are divided into sections of 16 students each, students allocated to sections with high ability students generally benefit. However, they note that this effect is heterogeneous. Low ability students are actually harmed by high ability peers, while high ability peers benefit from being grouped together. This finding is aligned with what I find in this paper as well. In addition, they use a survey to find evidence that peer effects might be due to the changes in group interaction dynamic. They do not incorporate personality characteristics, but in this paper, I use the results from the "Big Five" evaluation to find evidence that can be supportive of their claim.

3 Data

3.1 Program and Course Description

The dataset used in this paper is constructed using the demographic and administrative admission data from an MBA program at a leading Canadian University and the results of a survey of MBA students. The MBA program lasts one year and each year it admits approximately 120 students. Students are randomly divided into two sections, and students in each section take all the classes together. Professors teaching in two sections generally differ, however the syllabus and the material covered is the same. The data covers 6 cohorts of students who entered the program in 2011-2016. The data is available for one section for the year of 2011, and for both sections for 2012-2016, which results in the total of 611 observations.

The administrative data on the students of the MBA program includes students demographic and academic background characteristics, such as: gender, cumulative GPA from the previous degree ("Admission GPA", GMAT score, previous degree major, number of months of work experience and the industry in which the work experience has been acquired, mother tongue and immigration status. Approximately a third of students are female, and about 70% of students are Canadian citizens. Just under 20% are international students and the rest are Permanent Residents. Students come from a variety of academic backgrounds: 40% of students have some sort of business or economics related degree; a significant portion (about 30%) have engineering or hard science background; the rest have humanities or social science (other than economics) degrees. The average GPA grade from previous degree is 77%, and the average GMAT score is 660 (out of 800) points. The summary statistics are presented in the Table 1. In addition, I collect information on students' assigned learning teams and the grade in the Managerial Finance course, which I use as a main academic outcome.

Managerial Finance is an introductory finance course in which students learn basic corporate finance concepts, such as capital structure, asset pricing, interest rate calculation etc. The main teaching method employed for virtually all classes in MBA program is teaching with the use of "cases". A case describes a real or hypothetical firm which is facing a finance related problem and needs to make a decision. Students are asked to perform an analysis of a situation and present potential solutions to the problem. The case is taken up in class and all students are expected to participate in the discussion and offer their suggestions. This course is required for all students in the program and it runs in the first semester. The final grade for the Managerial Finance course consists of the weighted average grade for the written assignments: midterm and final exam, and the class contribution grade. While there is no explicit group component in the class, students are expected to work with their assigned learning teams to prepare for lectures and exams. A general format for the midterm is short answer questions: some questions test the knowledge of terms and definitions used in class, and some require calculations. Final exam on another hand consists of the analysis of a case study. It requires students to read a case describing a problem that a company is facing, provide the detailed analysis of the issues and make a recommendation. Class contribution is recorded in every class by a Teaching Assistant.[3] Students are given a grade of 3 for a significant, meaningful contribution; grade of 2 for an average insight; and grade of 1 for a quick comment or a definition. Students may have multiple contribution per class, although it is somewhat mediated by the instructor: he may cold call on a student with a low contribution level or pick a student with less contribution over the one with high contribution if there are several students willing to answer a question. The final grades are bell-curved

[3]Starting from 2015, the contribution grade is recorded by the instructor

with the mean of 80% and a standard deviation of 7. Students are told in advance about the bell-curving process.

I divide students into three groups according to their previous degree: commerce/economics, science/engineering and other, which includes mostly students with arts and humanities degrees, as well as a handful of students with degree in social sciences other than Economics. There are two reasons for this separation. First and foremost, these are main education background categories used to allocate students across groups. Second, since the outcome is a grade in an introductory finance class, students with Commerce degrees may already be familiar with concepts covered in class. Also, due to the quantitative nature of finance, I believe that students with Engineering or hard science backgrounds should be able to master the concepts faster than students who may need a refresher in math.

3.1.1 Learning Teams

After being divided into sections, students are assigned to learning teams by the administrative staff. The main criteria used in team assignment (in order of importance) are as follows: gender, previous degree major, work experience, immigration status, mother tongue.

The strictest requirement is the gender one. Based on the student experience from previous years, program administration reports that having two women per group results in the best student experience, especially for female students. Given the small number of female students in the program, each year there are some groups with no women.[4] While the rest of the criteria are important, the data suggests that there is a variation in number of science/engineer major students or the number of international students across groups. The reason for these allocation rules is to ensure some fairness when it comes to studying the commerce related subjects and to create diverse and safe environment. The main purpose for the learning team is to study and prepare for the various classes as a group as well as complete group assignments for some of the courses.

Students are not allowed to switch their teams. If conflict arises, students are expected to seek advice from their program coordinator and resolve the conflict. Only in the most extreme cases will the student be allowed to switch the team. According to the program coordinator, no such situation occurred within the last few years. Thus, students themselves have no input on how the learning teams are assigned.

During the interviews with some of the students (see section 3.2.2 for more information), I discovered that students are mostly working with the assigned teams in the beginning of the

[4]Due to some students dropping out of the program, there are some teams with only one female student. Especially in 2015, 4 students dropped out of the program and three were female. The drop outs usually happen very early in the semester and this should not be disruptive to student's work.

program. As time progresses, students get to know more of their peers in the program and they also get much busier (e.g. employment information sessions, interviews and networking events start near the end of the first semester). Because of this, students spend less time with their team and more time studying alone or with other friends. However, because I focus on the courses that run in the first semester, I believe that I capture any effects group mates have on each other.

Finally, students have a fixed, assigned seating in the classroom: students sit surrounded by their learning team members. Thus, if there are any peer effects that arise from a proximity of seating in a classroom, these effects will still come mostly from the learning team members.

3.2 Survey and Interviews

3.2.1 Survey

In order to gain some insight about potential mechanisms behind the peer effects, I ran a survey among the MBA students in June 2014, May 2015 and June 2016. The survey was conducted in person; students were first introduced to the topic and goal of the research project and then presented with the survey which they had 15 minutes to complete.

Aside from the standard demographic questions, there are three main parts to the survey. In order to establish student's social network, first question asked them to list up to 7 friends in the program. The last question of the survey asked them to indicate who, out of the given list of students, they talk to, with whom they study and with whom they socialize outside of school. Second, students were asked about their study habits, in particular, their study habits for the course of interest. I.e. how many hours a week do they study for all courses/Managerial Finance course; how many hours a week they spend studying alone/with their learning team; how many hours do they spend socializing with their friends outside of class. They were also asked about their beliefs about performance in Managerial Finance course. The goal was to approximate the students' effort levels when it comes to the class of interest.

Finally, students were asked questions about their non-cognitive characteristics, i.e. Big Five personality traits: extroversion, agreeableness, conscientiousness, emotional stability and openness. Extroversion measures how outgoing a student is; agreeableness score tells us whether a students is critical and inflexible; conscientiousness is a measure of being responsible and serious about studying; emotional stability tells how easily a person gets nervous or anxious and, finally, openness is a loose measure of creativity, openness to new experiences. Given the limited amount of time students had to fill out the survey, the shortened questionnaire developed by Gosling, Rentfrow, and Swann Jr. (2003) was used. This questionnaire included 10 simple questions, asking respondents to evaluate how closely given adjectives describe them. Each question measures one of the Big Five personality traits. Gosling et al. report good convergent correlations with longer tests of personality traits, especially for the traits which are most important for this research: extroversion, agreeableness and conscientiousness. Sample survey is provided in the Appendix.

The response rate for the survey was approximately 76% in 2014, 60% in 2015 and 67% in 2016. The summary statistics of the observable characteristics of respondents is presented in Table 2 [5]. In general, proportions of female students, international students and the proportions of students with various background degrees correspond to those in overall sample.

One common issue with any survey data is the measurement error due to the self-reporting: in particular, it is possible that students are not correctly reporting the number of hours they spend studying for course. For example, they could intentionally misreport the hours to appear more studious. I checked the study hours data for consistency in two ways. First, I added up the hours studied that student reported and checked that that number is less than the reasonable number of hours that a student may be expected to study outside of class over a week (I assumed that 60 hours is a maximum). Second, I checked whether or not the reported number of hours spent studying with the team makes sense given the reports of other team members. There are two caveats: first, there could be errors in individual reporting since students are reporting average weekly number of hours studied; second, I do not have data on all of the team members, and students do not have to study with all of the team mates for it to be considered "studying with a learning team". After these checks, I dropped from the sample one student who reported studying for 30 hours alone and 20 hours with the team for Managerial Finance, while his teammates reported number of hours close to the class average.

It may be non-trivial to check the validity of the personality characteristics evaluation. However, there are some checks that give me confidence in the correctness of the results. For example, Conscientiousness is positively related to the Admission GPA grade and the number of hours studied for Finance; Extroversion is positively and significantly related to the number of hours spent socializing with peers; Agreeableness have a positive relationship with team satisfaction. These correlations provide me with some evidence that the personality characteristics are measured more or less correctly.

[5] At the time of writing the full data about the cohort of 2016 was not available. The data from this cohort is used in some of the results in the following sections.

3.2.2 Interviews

Finally, in order to gain a deeper understanding of how the group study process works I conducted interviews with some of the students from the 2015-2016 cohort. I asked them a series of questions about their learning teams, other peers in the program and some of their study preferences. The detailed description of results is attached in the Appendix.[6]

There were three key pieces of information I was able to learn through the interviews. First, students spend most time studying with their learning teams in the beginning of the program. As term progresses, two things happen: students meet and get to know peers outside of the learning team, and students' schedule becomes busier due to the recruitment campaigns. But, since the course of interest, Managerial Finance, runs during the first term of the program, it is reasonable to believe that learning team peers affect the choices and outcomes of a student. Second finding is that students do not necessarily prefer studying with friends. Instead they may choose peers who they do not socialize outside of the program with, but who they consider to be good group members. While this fact may not directly impact the findings of this paper, I can conclude that students mostly study with their learning teams until they get a better understanding of other students' abilities, which may take longer than forming a friendship. Finally, I find that majority of students care about their performance in the course, since their grades may have a direct impact on their employment opportunities. Students who were interviewed, report that about half of the class is interested in a career in Finance or Consulting (which also aligns with the results of the survey), and that most companies hiring for consulting or finance roles request students transcripts. Thus, most students take the Managerial Finance course very seriously and put in effort in preparation for the class.

4 Empirical Strategy and Results - Administrative Data

To estimate the peer effects among the students in the MBA program I run the following regression on the different components of the Managerial Finance grade using the administrative data from the last five cohorts of MBA students.

$$y_i = \alpha_1 + \alpha_2 X_i + \alpha_3 \bar{X}_{-ij} + YearXSection_i + \epsilon_i \tag{1}$$

Where y_i is a grade (written or class participation) in Managerial Finance course, X_i is a collection of personal demographic and educational characteristics and $\bar{X}_{-ij}$ is a collection of learning team peer characteristics. The peer characteristics are defined as the average value

[6] The detailed transcripts of the interviews are available upon request.

for the student's learning team peers not including the student herself (e.g. for a students who has a science degree and is a member of a six person team which has two other science graduates, the value of the Fraction of peers with Science or Engineering degree will be 0.4).[7] In order to control for peers' ability levels, I generate four variables: fraction of learning team peers in the top 20% of class admission GPA distribution, fraction of learning team peers in the bottom 20% of class admission GPA distribution, and two variables of the fraction of learning team peers in top and bottom 20% of class GMAT distribution.

The results of the regression (1) are presented in Table 3. Column 1 shows the results on the written component of the Managerial Finance grade, and column 2 has the results of the regression on the class participation grade.

First, let's investigate the results of the regression on the written component. As expected, students with higher admission GPA and higher GMAT scores do better on Managerial Finance class tests. Students with background in Commerce or Economics, perform better as well, because the class of interest is an introductory Finance, and students with Commerce degrees are most likely familiar with at least some of the concepts covered. I also find that students with the degrees in hard sciences or engineering get higher grades on the written component of Managerial Finance course. Domestic students perform better than international students, which could be due to both language considerations and the similarity of undergraduate and MBA program courses. On another hand, female students do worse than male students on average.

In terms of peer effects, there are several interesting findings.

First of all, higher proportion of science/engineering peers is negatively correlated with the Managerial Finance written grade. This is curious, given that students with science and engineering backgrounds perform better than students with humanities and social science degrees. I would expect these students to be able to help their peers, at least when it comes to quantitative side of a finance course. This finding indicates that there are some non-trivial mechanisms behind the peer effects, and I investigate it further using the data from the survey.

Second, note that there is a significant positive effect of higher proportion of peers with bottom admission GPA scores. Once again, this is a bit of a puzzle, since one might expect that low admission GPA students may be more likely to benefit from having high ability peers, but it is unusual to see that low GPA student may actually be helpful, on average. I discuss this result in more detail later, when I show that this peer effect is heterogeneous across students of various abilities.

[7] I control for peers' educational background and for their ability levels. I tested a variety of specifications, including own and peers' work experience, and language. These variables do not influence the results, and thus I omit them in the final specification.

These findings call for further investigation. In the next section I look further into the effects of peers of different ability as well as science/engineering peers on students' grades by considering the possible heterogeneous peer effects.

Now, consider the results of regression (1) when the outcome is class participation grade. The coefficients on the personal characteristics are similar (if not in magnitude, then in sign) to the coefficients in column 1. However, no peer effects are significant at the usual levels. It is important to note that participation grade is different in nature than the written component grade: the driving force behind the participation grade is student's willingness to participate in class, not necessarily student's ability or even preparedness. Thus, I am not surprised by the lack of peer effects on this grade component. So, while I include the results on the participation grade in the Appendix, for the rest of the paper I focus my attention on the written component of the Managerial Finance class grade.

4.1 Heterogeneous effects

In addition to the regression on the full sample, in order to explore the potential heterogeneous effects across different types of students, I split the data according to the observable characteristics: gender, previous degree, immigration status, and terciles based on two measures of ability: GMAT score and admission GPA. I then run the same regression (1) on each subgroup. Note that I assign students to different grade (score) terciles based on their standing in class. [8] [9]

The results of these regressions are presented in tables below. I find the evidence of heterogeneous peer effects, which aligns with the previous findings in the literature. Since I have some puzzling results in the regression on the whole sample which I discussed above, I also look for potential explanations in the subsample regression results.

First, I separate the students by their ability levels as measured by their admission GPA scores. Recall, that the whole sample results showed the negative effect of science/engineering peers, as well as the positive effects of high proportions of bottom Admission GPA peers. Looking at the results in Table 4, we see that the negative effect of Science and Engineering students is the most pronounced for the students in the bottom tercile of admission GPA distribution. However, the coefficient is negative for students of all abilities, and is decreasing

[8] The terciles are determined by student's position in the *section* distribution of admission GPA (or GMAT scores), not the distribution of the overall sample. I believe that because students are graded on the curve, what matters is their relative standing in class, not the whole sample. It it useful to note, however, that the tercile split is not much different from year to year, and cut off values differ only by a couple percent across cohorts.

[9] The difference in the tercile sizes is due to the discrete nature of GPA and GMAT scores. A number of observations are grouped on the border between lower and middle tercile, around 75% or GMAT scores of 650, these observations are assigned to the lower terciles.

in value with the increase in GPA.

Peers with low admission GPA scores are benefitial for students on the same ability levels. We can also now see that top ability students also benefit from the top ability peers! This finding is aligned with what has been discovered in the previous literature as well, indicating that there might be a benefit from grouping students of the similar ability levels together. Recall, that Feld and Zolitz (2017) also find the heterogeneous peers effects, although they only see one side of it: the positive impact of high ability students being grouped together.

To sum up, Table 4 provides us with some interesting findings and some intuition regarding potential mechanisms behind the peer effects. First, I find that the peer effects are heterogeneous, with students benefiting from having similar ability peers in their teams. And second, the negative effect of Science/engineering peers stays negative for all types of students. My hypothesis is that grouping students by ability will improve confidence levels in low ability students, while allowing top ability students study at their higher pace. Students of similar ability may be more comfortable asking questions during their meetings and contribute to the discussion. Having a comfortable study atmosphere in a group may be the key to successful academic outcomes. The negative effect of science/engineering peers may be explained using similar logic. The stereotypical image of an engineering or a science student is someone who is confident, not afraid to ask questions or challenge ideas. Often, when it comes to hard sciences, there is one correct answer, so students with this type of background may be perceived as tough during group discussions. Perhaps, having a teammate who enjoys arguments during group discussion may be detrimental to the quality of study group meetings. I put this hypothesis to the test using the data from my survey in the following sections.

Another way of measuring students' ability as it pertains to the MBA program is to look at their GMAT scores. While GMAT scores are correlated with the admission GPA grades, the correlation is not perfect, with the correlation coefficient of 0.2036. There are a couple of reasons why this correlation coefficient is lower than might be expected. First, for some students GMAT may be less difficult than the courses they took in their undergraduate degree (for example for engineering students). So, these students will get high scores on GMAT even if their admission GPA is lower than average. The second reason could be that students with low undergraduate GPA may spend more time and effort preparing for the GMAT, which will result in a higher score. Plus, the GMAT can be taken multiple times, until a student is satisfied with their score.

So, Table 5 shows the results of regression (1) when the sample is split by GMAT tercile. Science/Engineering peers have a negative effect on Managerial Finance grades for students in the bottom and middle terciles of GMAT score distribution. Fraction of peers in the bottom of the admission GPA distribution has a positive effect on low GMAT students, while not significantly affecting the middle and top terciles of GMAT distribution. On the other hand, Fraction of LT peers in the top 20% of GMAT distribution has a strong negative effect on top GMAT students.

Thus, while peer effects still appear to be heterogenous for students with different GMAT levels, it does not seem that grouping top GMAT students together would result in better grades for them. In fact, we now see that the top GMAT students may actually be harmful to their peers with equal ability level. This is a counterintuitive finding that requires further investigation.

Next I look for the potential differences across peer effects of male/female students, international/domestic students and students with different degrees.

Interestingly, even own characteristics have different effects on written component of Finance grade for female/male students (Table 6). For example, while all students with science/engineering degrees perform better in finance than students with other degrees, this effect is stronger and statistically significant for male students. On another hand, domestic female students have stronger positive boost than male domestic students. It also seems that admission GPA is a better predictor for a higher finance grade for female students than for their male counterparts.

In terms of peer effects, most have the same sign for both genders, but significance and magnitude varies. Most notably, Science and Engineering peers have a much stronger negative effect on female students. Once again, this might point to the role of team dynamics and personality characteristics in the formation of peer effects.

Table 7 describes the results on regression (1) on international and domestic students. Once again, even the relationship between own characteristics and the grade in Finance class differs. While high admission GPA predicts a higher grade in Finance class for domestic students, it lacks the predictive power in the sample of international students. GMAT, on the other hand, is a stronger predictor of the grade for international students. This is not surprising, given that most international students who are accepted into the MBA program have high GPA scores, resulting in a small variance of the admission GPA scores among the international students. Female international students perform worse that their male counterparts and than the other female students in the program. There also appear to be some curious peer effects. First, the fraction of peers with commerce degrees has a strong negative effect on domestic students, while at the same time having a positive effect of similar magnitude on international students. Second, the fraction of science/engineering peers also has a negative effect on the written grade for domestic students, while not having a significant effect on the grades of international students. Higher fraction of lower ability peers is good for the grades of domestic students, while the high fraction of top GMAT peers has a negative effect on the international students' grades.

Finally, I show the peer effects on students with different undergraduate degrees (Table 8). It seems that students with commerce/economics background are the ones who are significantly negatively affected by the science/engineering peers. Other groups of students are also harmed by the high fraction of science/engineering peers, although these coefficients are not statistically significant at the usual levels.

Overall, looking into heterogeneous peer effects provided new findings and puzzles. First, it is clear that peer effects are, in fact heterogeneous, and pairing different students with same peers may result in different outcomes for these students. This indicates that there might be an improvement in how we allocate students across teams. The most stark result is that students of the similar ability levels (measured by the previous degree GPA), benefit from being assigned to the same teams. On another hand, some of the findings are still not very intuitive. Why do science/engineering peers have such negative effect on almost all groups of students? Why do top GMAT students do worse if paired with similar peers? I address these questions in the following sections using the data from the survey.

One thing to keep in mind while interpreting these results is that there are certain correlations in the data, either by the construction of the teams or due to the correlations between certain personal characteristics. For example, since administrators try to balance the group composition in terms of students' backgrounds or their immigration status, there necessarily will be a negative correlation between personal characteristic and average characteristic of peers. E.g. an international student is more likely to have a higher fraction of domestic student peers than a domestic student.

Similarly, there are some student attributes that are correlated. For example, international students are more likely to have a higher admission GPA and science/engineering students tend to have higher GMAT scores. I do not think that these correlations nullify my findings about existence of peer effects, but, the effects of individual characteristic may need to be interpreted with caution, keeping in mind the correlations I mentioned above. I include the complete correlation table of individual characteristics in the Appendix.

5 Empirical Strategy and Results - Survey Data

I assume that peers might influence the outcomes of their colleagues in two main ways. First, they could affect the number of hours students spend studying. For example,since the learning teams are encouraged to study together, peers with better study habits may increase the number of hours students spend studying in the group.

Second, peers may affect the effectiveness of studying in the group and alone. For example, a very intelligent peer may make it easier to understand the material and may be able to explain concepts to a struggling student. On another hand, a student who is behind in terms of class material may prevent his peers from studying effectively. In addition, different types of peers may affect the psychological atmosphere in the group. This could be influenced both by students' psychological characteristics and their ability levels. Obviously, a more argumentative peer may make it unpleasant to study in the group. But also, students who have peers of a similar ability to theirs may find it easier to study together rather than with peers of different ability.

Students, of course, could be affected through multiple channels at the same time. While I may not be able to identify the exact mechanisms behind the peer effects in this paper, I present some descriptive results that may serve as evidence for one or more mechanisms described above.

5.0.1 Study hours

One of the most straightforward ways students may affect each other's academic achievement is by studying together and thus increasing the number of hours a student spends preparing for the class. Using the survey data on individual study habits, I can see whether different types of peers affect the number of hours students choose to study alone or with their learning team. Combining this information with the findings from the previous section, we can get more insights into the possible mechanisms behind the peer effects.

Using the reported number of hours studied for Managerial Finance (alone or with the learning team) as an outcome, I run the following regression:

$$s_i^j = a_0 + a_1 X_i + a_2 \bar{X}_{peers} + Year * Section_i + \epsilon_i \tag{2}$$

Where $j \in \{Own, LT\}$, s_i is the number of hours student studies alone or with the team, X_i is a vector of observable characteristics of a person i, $\bar{X}_{peers}$ are the average of observable characteristics of the peers of the person i not including the student himself.

The results presented in Table 9 show some interesting information. Students in teams with many domestic peers tend to study by themselves. On another hand, students in the sample spend more time studying with their team if they have a high proportion of top GMAT score peers.

Although, these results need to be interpreted with some caution. Again, by the construction of the groups, the students with most domestic peers will be international students. International students are more likely to study by themselves, so this may be what is captured in the regression.

I find that while there is no strong effect of the number of hours spent studying with a team on the Finance grade, there still is a positive relationship (see Table 17 in Appendix). Thus, if top GMAT peers increase the number of hours students spend studying with the group, but also decrease the finance grade, the time students spend studying must be not very effective, which may explain their negative effect on the grades of other top GMAT students. To look further into this potential explanation I explore the data on personality traits.

5.0.2 Personality traits

When working with other people, be it on a research project or on a class assignment, personality of your colleagues may play a role equally or even more important than their level of knowledge and general cognitive ability. When it comes to peer effect research, however, the mechanism that is usually assumed is that peers may aid students in studying by either explicitly helping with the class work, being a study partner or, alternatively hinder student's success by being disruptive or distracting.

In particular, peer personality characteristics could shed light onto the puzzles in the results discussed above. To address these questions I turn to the results of the survey question aimed at evaluating students' Big Five personality traits. I run the OLS regression in order to find out whether any of the observable characteristics predict the personality traits. The results of the regressions can be seen in Table 10.

Admission GPA is positively related to the conscientiousness score, which is in line with the findings from previous literature, providing some reassurance that the measures of personality characteristics were more or less accurate. Interestingly, GMAT score is not related to conscientiousness. [10]

Another relevant result is that GMAT score is negatively correlated with "agreeableness" characteristic, providing some evidence that top GMAT peers might be difficult to get along.

One potential story that could explain these findings is that after controlling for admission GPA, GMAT score mainly measures student's motivation to be in the program. Since most students write GMAT specifically to enter this program, students with higher motivation to get in might want to spend more time preparing for the test, take it more seriously, which could result in a better score at the end. However, the strong motivation to do well in the program may cause these students to put pressure on their teammates, causing them to study

[10] If we think about what the "ability" means: it probably consists of some measure of knowledge and aptitude plus a measure of "grit" or conscientiousness. So, it's possible that GMAT, on another hand, is a measure of knowledge, aptitude and motivation.

longer hours, but not necessarily increasing their productivity or knowledge.

Interestingly, domestic students and students with commerce degrees also score lower than average on the "Agreeableness" scale. If we look back at the results of regression (1), we can see that both of these types of students have a negative, albeit not significant, effect on their peers' grades. Recall, though, that students with high fractions of domestic peers or peers with commerce/economics degrees also tend to study more alone on average, possibly counteracting the inefficient time spent studying with the team.

5.1 Roles on the Team and Team Dynamics

The number of hours students spend studying together may only tell us a part of the story. Not every hour spent studying will be effective, and it is especially clear if we consider that some students may be more disruptive than helpful during studying process. To better understand the roles different types of students play during team meetings, I directly asked survey participants how they behave or what do they do most often during study sessions with their Learning Teams. There were six possible answers and students were allowed to select as many answers as they wanted, but they did have to rank these behaviours in order of frequency, 1 being most often. The possible answers were: explaining concepts covered in class, leading the discussion, using work experience to provide examples, playing "devil's advocate" and arguing certain case point with colleagues, mostly listening rather than contributing and, finally, asking questions. Most students engage in more than one behaviour during the team meeting. I generated the indicator variables for each of these behaviours, and assigned the value of 1 if a student gave the behaviour a rank of 1 or 2, and zero otherwise.

In Table 11 I present the results of the logit regressions, where the outcome is the indicator variable of whether or not a student behaves in a certain way during the group meetings. It shows that different types of student have different behaviour styles during the group meetings. Female students prefer to ask questions, male students prefer to lead, international students share their work experience and science/engineering students like to play "devil's advocate". The results may shed some light on the curious negative effect of science/engineering students on their peers' finance grade. It appears that students with science/engineering background are most likely to play "devil's advocate" during the meetings, challenging their peers, arguing about points. While some students may enjoy some heated discussions, some may perceive this as a hostile group environment. In addition, if students argue with their peers for the sake of arguing, it does not add much to the discussion, and does not lead to good learning outcomes. Interestingly, science/engineering students do not score particularly low on the "agreeableness" scale of the Big 5 Personality traits evaluation.

Looking closer to what the questions are actually asking may give us some ides of why this the case. The question in the "Big 5" assessment asked students to rate how "critical, inflexible" they are; the question about roles on the team asked if they liked to play "devil's advocate". It is interesting that the students who consistently have a negative effect on their peers' grades perceive themselves as not too critical or inflexible and meanwhile enjoy the "devil's advocate" role on the team. It is also possible that "devil's advocate" was perceived by students as a more favourable characteristic than "inflexible or critical"; leading them to be more honest in their answers.

Overall, it appears that peers affect each other's grades not only through knowledge transfer, but also through the establishing a group environment that is conducive to learning. High number of argumentative peers, whether or not they are of high ability, has a potential to decrease students grades.

6 Average vs. Individual course Peer Effects

Students' success in the program is frequently measured by their cumulative GPA, so it comes as no surprise that research often focuses on the cumulative GPA or another average grade as the main outcome which peers might influence (e.g. Jain and Kapoor (2015), Carrel et al. (2013)). The results reported in the previous sections showed that even different components of the same course are differently influenced by the same peers, thus it is quite possible that different courses are affected in different ways. Therefore, focusing the analysis only at the average grade may miss crucial details. It is no secret that students may care more about some courses than others, and one reason for it is that grades in certain courses (often the ones with quantitative focus) may be requested by potential employers.

The data I collected allows me to compare and contrast the peer effects on two individual courses. One of them, Managerial Finance, is used for the analysis in the previous sections. The second course is called Leading People in Organizations ("LPO"), and is focused on developing student's leadership and managerial skills. The goal is to introduce students to a variety of situations a manager may be facing at work and guide them through finding solutions to these problems. As is probably clear from the description, the course is more qualitative than quantitative in nature and requires skills that are most likely different from the ones needed in Finance course. Thus, it is also expected that we might find different peer effects on the grades in this course. The total LPO grade is an equally weighted average of a group assignment score and a class participation grade. The group assignment is done together with the learning team.[11] I obtained the LPO grades for two cohorts.

[11] Recall that the learning team stays the same for all courses in one semester.

Table 12 shows the results of regression (1) on the final Managerial Finance grade, LPO grade and an average of the two - which is used as a proxy for cumulative GPA. Previous sections showed the results for the individual components of the Managerial Finance grade, and the results are similar for the final Managerial Finance score. To recap, students with higher admission GPA and GMAT scores do better, female students and non-domestic students perform worse, and students with the degree in Commerce get higher grades than students with other degrees. There are also some peer effects: negative effect of high fraction of science/engineering peers and peers with top GMAT scores. For there two cohorts there is also a positive effects from having peers with top admission GPA scores.

LPO grade is positively related to GMAT score; students with humanities degrees seem to do better. In terms of peer effects, there is only a slight negative effect of having a high fraction of top GPA peers in the group.

Now, column 3 in Table 12 shows the results of the regression of personal and peer characteristics on a generated average grade comprised of 50% Finance, 50% LPO grade. First, note that the personal characteristics coefficients decreased in significance. Because of such different nature of these courses, it's likely that different characteristics would matter the most. It is also possible that different types of students place different levels of importance on these courses, and therefore exert more or less effort in preparation for the class. Similarly, the significance and magnitude of peer effects changes as well.

This simple observation shows that we may be missing peer effects if we focus only on the average grade in the program or a semester. This is especially important for programs where grades for individual courses matter in the future job search.

7 Conclusion

Peer effects need to be taken into consideration when we divide students into groups, sections and classes. However, even though this research question has been given considerable attention, it is still not clear if peer effects exist, how strong and important are they and why might certain types of students affect each other. In this paper, I showed the existence and magnitude of peer effects in small exogeneously assigned groups in an MBA program. I find that students' grades are affected by the peers, and not all students are affected equally. Some important peer effects include the negative effect of science/engineering peers and possible positive effect of very low and very high GPA peers. I also find the evidence for heterogeneous peer effects, in particular, the possible benefits of grouping students of similar ability together. Using the unique survey data collected amount three cohorts of MBA students I found two potential explanations for these peer effects. First, top GMAT peers tend to increase the amount of time students spend studying for finance with their learning team, but it does not translate into higher grades. While exploring potential personality characteristics reasons for this puzzle, I find that GMAT scores are negatively correlated with "agreeableness" score. Thus, top GMAT peers might be more confrontational, making them less desirable as teammates. Second, science/engineering students are more likely than others to engage in "devil's advocate" behaviour, possibly creating a hostile study environment.

Finally, using grades for two vastly different courses, I find that peer effects differ across courses, meaning that if we focus on an average grade in a program as an outcome, we might falsely conclude that peer effects do not exists.

My future research will look into what possible students allocation rules can be implemented in order to improve students' outcomes. I also plan to incorporate the social network data to explore different sources of peer effects.

Table 1: Summary Statistics

VARIABLE	2012	2013	2014	2015	2016	2017
Female	33.9%	28.3%	22.9%	31.2%	26.8%	26.8%
Commerce Degree	41.3%	46.5%	46.7%	39.8%	47.8%	54.5%
Science/Engineering Degree	42.8%	43.3%	42.6%	51.61%	39.1%	36.5%
Canadian Students	68.3%	68.5%	71.3%	68.8%	73.9 %	73.6%
Admission GPA	76.4	77	77.33	77.6	77.29	77.16
GMAT	669	667	660	655	656	665
Number of observations	62	127	122	93	138	145

Table 2: Survey Participants Descriptive Statistics

	Cohort of 2015	Cohort of 2016	Cohort of 2017
Percentage of female students	28.13	29.89	23.00
	32	*26*	*29*
Percentage of students with commerce degree	39.7	37.21	43.00
	49	*39*	*54.48*
Percentage of students with engineering degree	45.45	43.02	42.00
	43	*42*	*36.55*
Percentage of Canadian or PR students	85.94	45.35	67.35
	68	*67*	*73.61*
Avg admission GPA	77.27	78.22	75.92
	(6.06)	(7.28)	(7.79)
	77.6	*77.28*	*77.15*
Avg GMAT score	654.03	667	671.97
	(47.89)	(45.81)	(48.38)
	655	*656*	*665.47*
Number of learning teams	18	24	24
Number of students (surveyed)	78	98	100
Number of students (registered)	103	130	143

Note: Standard deviations are in parenthesis. Cohort average is italicised.

Table 3:

VARIABLES	Written Grade in MF	Participation Grade in MF
Admission GPA	0.158***	0.217***
	(0.0433)	(0.0560)
GMAT score	0.0297***	0.0151**
	(0.00507)	(0.00626)
Degree related to commerce/economics	5.223***	2.831***
	(0.880)	(1.015)
Degree in hard science/engineering	2.056**	0.852
	(0.938)	(0.948)
Female	-1.848***	-2.450***
	(0.601)	(0.626)
Domestic student	2.924***	1.541**
	(0.575)	(0.608)
Fraction of LT Peers with Commerce/Economics degree	-2.890	-1.933
	(2.238)	(2.004)
Fraction of LT Peers with Sci/Eng degree	-5.250**	-1.031
	(2.187)	(2.125)
Fraction if LT peers who are domestic students	-0.306	-1.028
	(1.627)	(1.595)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	2.259*	-0.857
	(1.355)	(1.463)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.177	-0.00100
	(1.526)	(1.823)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.262	2.198
	(1.661)	(1.866)
Fraction of LT peers in the top 20% of GMAT distribution	-1.760	0.602
	(1.479)	(1.495)
Constant	46.69***	53.23***
	(5.039)	(6.925)
Observations	661	661
R-squared	0.172	0.092
F test model	7.166	3.065

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4:

VARIABLES	(1) Written Grade - All	(2) Written Grade - Bottom GPA Terc.	(3) Written Grade - Middle GPA Terc.	(4) Written Grade - Top GPA Terc.
Admission GPA	0.158***	0.341***	0.166	0.154
	(0.0433)	(0.110)	(0.349)	(0.227)
GMAT score	0.0297***	0.0262***	0.0187**	0.0493***
	(0.00507)	(0.00856)	(0.00887)	(0.0105)
Degree related to commerce/economics	5.223***	4.468***	5.695***	6.816**
	(0.880)	(1.245)	(1.462)	(2.736)
Degree in hard science/engineering	2.056**	2.241*	2.575	2.319
	(0.938)	(1.218)	(1.590)	(2.881)
Female	-1.848***	-3.157***	-0.495	-1.191
	(0.601)	(0.950)	(1.162)	(1.231)
Domestic Student	2.924***	2.620***	1.674	3.091***
	(0.575)	(0.979)	(1.221)	(1.060)
Fraction of LT Peers with Commerce/Economics degree	-2.890	-4.047	-3.155	-2.106
	(2.238)	(3.331)	(4.207)	(4.051)
Fraction of LT Peers with Sci/Eng degree	-5.250**	-6.981**	-5.421	-2.368
	(2.187)	(3.134)	(4.756)	(3.928)
Fraction if LT peers who are domestic students	-0.306	3.501	-1.142	-5.678*
	(1.627)	(2.373)	(2.809)	(3.047)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.177	-3.286	0.102	-3.025
	(1.526)	(2.856)	(3.202)	(2.587)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	2.259*	3.850*	-2.111	1.111
	(1.355)	(2.077)	(2.829)	(2.757)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.262	-1.000	-1.935	6.909**
	(1.661)	(2.580)	(3.180)	(2.804)
Fraction of LT peers in the top 20% of GMAT distribution	-1.760	-0.481	0.0613	-1.505
	(1.479)	(2.125)	(3.008)	(2.637)
Constant	46.69***	35.27***	54.22*	33.63*
	(5.039)	(9.192)	(29.48)	(18.96)
Observations	661	298	175	188
R-squared	0.172	0.194	0.219	0.320
F test model	7.166	6.300	2.959	3.794

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 5:

VARIABLES	(1) Written Grade - All	(2) Written Grade - Bottom GMAT Terc.	(3) Written Grade - Middle GMAT Terc.	(4) Written Grade - Top GMAT Terc.
Admission GPA	0.158***	0.252***	0.0990	0.146
	(0.0433)	(0.0648)	(0.0849)	(0.0944)
GMAT score	0.0297***	0.0261*	0.0535	0.0639***
	(0.00507)	(0.0133)	(0.0339)	(0.0211)
Degree related to commerce/economics	5.223***	4.772***	6.848***	5.934***
	(0.880)	(1.141)	(1.757)	(1.665)
Degree in hard science/engineering	2.056**	0.285	4.594***	3.782**
	(0.938)	(1.219)	(1.747)	(1.721)
Female	-1.848***	-1.068	-1.484	-2.380*
	(0.601)	(1.018)	(1.033)	(1.281)
Domestic Student	2.924***	4.536***	2.131*	2.407**
	(0.575)	(1.162)	(1.107)	(1.022)
Fraction of LT Peers with Commerce/Economics degree	-2.890	-2.009	-3.057	-1.116
	(2.238)	(3.788)	(4.293)	(3.526)
Fraction of LT Peers with Sci/Eng degree	-5.250**	-8.347**	-6.201	1.223
	(2.187)	(3.558)	(4.031)	(3.128)
Fraction if LT peers who are domestic students	-0.306	5.500**	-5.587*	-1.894
	(1.627)	(2.686)	(3.214)	(2.794)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.177	-2.548	-2.337	-0.194
	(1.526)	(3.270)	(3.073)	(2.203)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	2.259*	4.245*	0.616	2.027
	(1.355)	(2.401)	(2.481)	(2.023)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.262	1.105	2.627	0.883
	(1.661)	(2.415)	(3.160)	(2.766)
Fraction of LT peers in the top 20% of GMAT distribution	-1.760	1.661	-1.904	-5.656**
	(1.479)	(2.400)	(2.594)	(2.737)
Constant	46.69***	37.45***	37.38*	20.63
	(5.039)	(9.467)	(22.02)	(14.82)
Observations	661	257	201	203
R-squared	0.172	0.222	0.235	0.216
F test model	7.166	4.422	2.837	2.945

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 6:

VARIABLES	(1) Written Grade - Female	(2) Written Grade - Male	(3) Participation Grade - Female	(4) Participation Grade - Male
Admission GPA	0.338***	0.103**	0.295**	0.194***
	(0.0776)	(0.0521)	(0.113)	(0.0640)
GMAT score	0.0299***	0.0299***	0.00568	0.0176**
	(0.0109)	(0.00693)	(0.0131)	(0.00798)
Degree related to commerce/economics	5.402***	5.512***	3.480***	2.725
	(1.363)	(1.408)	(1.277)	(1.751)
Degree in hard science/engineering	1.220	2.502*	1.873	0.515
	(1.545)	(1.391)	(1.535)	(1.510)
Domestic Student	4.554***	2.269***	3.598***	0.883
	(1.113)	(0.735)	(1.007)	(0.769)
Fraction of LT Peers with Commerce/Economics degree	-5.244	-1.429	1.370	-2.429
	(4.559)	(2.740)	(4.226)	(2.564)
Fraction of LT Peers with Sci/Eng degree	-8.770**	-3.047	0.628	-0.826
	(3.802)	(2.551)	(3.788)	(2.805)
Fraction if LT peers who are domestic students	0.117	-0.697	-3.233	-0.636
	(3.172)	(2.329)	(2.887)	(2.136)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.307	-2.446	2.710	-0.560
	(3.525)	(1.696)	(3.859)	(2.049)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	3.491	2.102	-2.843	0.547
	(2.779)	(1.740)	(2.916)	(1.845)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.846	1.310	-1.092	4.294**
	(2.658)	(2.020)	(3.296)	(2.123)
Fraction of LT peers in the top 20% of GMAT distribution	-3.348	-1.551	-0.528	0.508
	(3.115)	(1.932)	(2.716)	(1.968)
Constant	32.45***	49.69***	48.80***	53.67***
	(8.726)	(6.978)	(10.31)	(8.851)
Observations	181	480	181	480
R-squared	0.307	0.140	0.179	0.075
F test model	6.237	4.006	2.805	1.864

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 7:

VARIABLES	(1) Written Grade - Canadian/PR	(2) Written Grade - Int'l	(3) Participation Grade - Canadian/PR	(4) Participation Grade - Int'l
Admission GPA	0.225***	0.00727	0.266***	0.143*
	(0.0571)	(0.0740)	(0.0651)	(0.0823)
GMAT score	0.0250***	0.0401***	0.0104	0.0241**
	(0.00628)	(0.0111)	(0.00819)	(0.0105)
Degree related to commerce/economics	4.680***	6.617*	2.616**	4.580*
	(0.906)	(3.420)	(1.122)	(2.527)
Degree in hard science/engineering	1.746*	2.929	0.565	2.644
	(0.924)	(3.577)	(1.010)	(2.646)
Female	-1.487**	-3.252***	-2.043***	-3.726***
	(0.688)	(1.175)	(0.756)	(1.072)
Fraction of LT Peers with Commerce/Economics degree	-6.491**	6.827*	-0.641	-4.279
	(2.905)	(3.835)	(2.646)	(3.795)
Fraction of LT Peers with Sci/Eng degree	-8.707***	5.623	0.0698	-1.983
	(2.816)	(3.735)	(2.550)	(4.061)
Fraction if LT peers who are domestic students	-0.00957	-3.146	-0.960	-2.053
	(2.117)	(3.202)	(2.016)	(2.938)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.587	-0.730	1.355	-2.779
	(1.862)	(2.848)	(1.967)	(3.471)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	3.543**	-1.572	-0.503	-1.443
	(1.639)	(2.434)	(1.734)	(2.935)
Fraction of LT peers in the top 20% of Adm. GPA distribution	0.979	0.587	1.710	2.766
	(2.052)	(3.097)	(2.056)	(3.570)
Fraction of LT peers in the top 20% of GMAT distribution	-1.685	-4.749**	1.444	-2.561
	(1.893)	(2.297)	(2.033)	(2.858)
Constant	49.94***	47.93***	52.42***	55.96***
	(6.171)	(9.756)	(7.977)	(10.64)
Observations	470	191	470	191
R-squared	0.182	0.251	0.086	0.180
F test model	6.932	2.487	2.516	2.293

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 8:

VARIABLES	(1) Written Grade - All	(2) Written Grade - Commerce/Econ	(3) Written Grade - Sci/Eng	(4) Written Grade - Other Degrees
Admission GPA	0.158***	0.246***	0.0826	0.361*
	(0.0433)	(0.0743)	(0.0661)	(0.180)
GMAT score	0.0297***	0.0251***	0.0396***	-0.00478
	(0.00507)	(0.00795)	(0.00820)	(0.0208)
Degree related to commerce/economics	5.223***			
	(0.880)			
Degree in hard science/engineering	2.056**			
	(0.938)			
Female	-1.848***	-1.763*	-2.274**	-1.692
	(0.601)	(0.900)	(0.985)	(2.106)
Domestic Student	2.924***	2.703***	2.821***	9.863**
	(0.575)	(0.870)	(0.824)	(4.300)
Fraction of LT Peers with Commerce/Economics degree	-2.890	-4.982	-1.167	1.398
	(2.238)	(3.414)	(2.946)	(10.89)
Fraction of LT Peers with Sci/Eng degree	-5.250**	-6.011*	-1.815	-8.265
	(2.187)	(3.391)	(2.813)	(6.917)
Fraction if LT peers who are domestic students	-0.306	-2.314	1.382	1.151
	(1.627)	(2.613)	(2.320)	(7.849)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.177	-3.005	-1.167	-0.186
	(1.526)	(2.629)	(2.346)	(6.544)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	2.259*	3.332	0.650	1.629
	(1.355)	(2.336)	(1.997)	(4.795)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.262	-0.478	0.405	6.484
	(1.661)	(2.291)	(2.592)	(5.056)
Fraction of LT peers in the top 20% of GMAT distribution	-1.760	-1.136	-2.044	-5.202
	(1.479)	(2.091)	(2.369)	(5.569)
Constant	46.69***	49.65***	46.07***	45.34**
	(5.039)	(8.505)	(7.604)	(19.26)
Observations	661	315	284	49
R-squared	0.172	0.150	0.164	0.357
F test model	7.166	2.140	2.505	1.836

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 9:

VARIABLES	(1) OLS on the Number of hours studying for Finance alone	(2) OLS on the Number of hours studying for Finance with LT
Adm. GPA	-0.0293	-0.0279
	(0.0458)	(0.0260)
GMAT	0.00778	-0.00161
	(0.00578)	(0.00304)
Female	0.157	0.306
	(0.482)	(0.380)
Sci/Eng Background	-0.695	0.536
	(0.748)	(0.370)
Comm/Econ Background	-0.845	0.0258
	(0.817)	(0.352)
Canadian or PR	-0.326	0.176
	(0.644)	(0.302)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	1.622	1.015
	(1.293)	(0.797)
Fraction of LT peers in the bottom 20% of GMAT distribution	0.232	0.0965
	(1.609)	(0.778)
Fraction of LT Peers with Sci/Eng degree	0.759	-0.940
	(2.335)	(1.436)
Fraction of LT peers who are Domestic Students	3.044*	0.154
	(1.563)	(0.907)
Fraction of LT Peers with Commerce/Economics degree	3.727	-1.144
	(2.392)	(1.401)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.188	1.442
	(1.507)	(0.948)
Fraction of LT peers in the top 20% of GMAT distribution	-0.206	2.644***
	(0.967)	(0.822)
Constant	-0.946	4.704
	(4.936)	(3.339)
Observations	191	191
R-squared	0.079	0.109
F test model	1.504	1.443
P-value of F model	0.140	0.165

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10:

VARIABLES	(1) Extroversion	(2) Agreeableness	(3) Conscientiousness	(4) Emotional Stability	(5) Openness
Adm. GPA	0.0195	0.00425	0.0343	0.0428	-0.0113
	(0.0326)	(0.0264)	(0.0239)	(0.0365)	(0.0229)
GMAT	-0.00562	-0.00953**	9.32e-05	-0.00829	-0.00623*
	(0.00486)	(0.00394)	(0.00357)	(0.00544)	(0.00341)
Comm/Econ Background	-0.170	-1.017**	-0.295	-1.189*	-0.490
	(0.621)	(0.504)	(0.457)	(0.696)	(0.436)
Sci/Eng Background	-0.904	-0.218	-0.167	-0.0901	-0.0990
	(0.622)	(0.505)	(0.457)	(0.697)	(0.437)
Female	-0.291	0.344	0.568	0.996*	0.332
	(0.522)	(0.424)	(0.384)	(0.585)	(0.367)
Canadian or PR	0.205	-1.329***	0.689**	0.711	-1.038***
	(0.474)	(0.384)	(0.348)	(0.531)	(0.333)
Constant	12.38***	17.61***	7.822***	8.894**	16.82***
	(3.964)	(3.216)	(2.914)	(4.442)	(2.783)
Observations	199	199	199	199	199
R-squared	0.035	0.095	0.050	0.063	0.066
F test model	1.157	3.351	1.686	2.141	2.256

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11:

VARIABLES	(1) Explain	(2) Lead	(3) Devil's Advocate	(4) Use Work	(5) Ask	(6) Listen
Adm. GPA	4.72e-05	0.00277	6.60e-05	-0.00111	-0.00166	-0.000408
	(0.00171)	(0.00172)	(0.00157)	(0.00164)	(0.00129)	(0.00155)
GMAT	4.34e-05	-0.000108	0.000649	-0.000631	-2.55e-05	-1.54e-05
	(0.000581)	(0.000584)	(0.000532)	(0.000557)	(0.000438)	(0.000526)
Comm/Econ Background	0.167	-0.0543	0.147	-0.137	-0.0982	-0.0937
	(0.120)	(0.121)	(0.110)	(0.115)	(0.0905)	(0.109)
Sci/Eng Background	-0.0251	-0.158	0.279**	-0.104	-0.0931	0.0260
	(0.122)	(0.123)	(0.112)	(0.117)	(0.0924)	(0.111)
Female	-0.292***	0.00925	-0.00816	0.0566	0.171**	0.0234
	(0.0912)	(0.0918)	(0.0836)	(0.0874)	(0.0688)	(0.0827)
Canadian or PR	0.0771	0.170**	-0.0670	-0.244***	0.0356	-0.139*
	(0.0832)	(0.0838)	(0.0763)	(0.0798)	(0.0628)	(0.0754)
Constant	0.376	0.284	-0.290	1.053**	0.309	0.399
	(0.429)	(0.431)	(0.393)	(0.411)	(0.323)	(0.389)
Observations	154	154	154	154	154	154
R-squared	0.089	0.069	0.080	0.073	0.065	0.046
F test model	2.384	1.804	2.140	1.942	1.707	1.182

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12:

VARIABLES	(1) Total MF	(2) Total LPO	(3) Avg Grade (MF and LPO)
Admission GPA	0.165***	-0.00883	0.0779*
	(0.0582)	(0.0429)	(0.0404)
GMAT score	0.0296***	0.00894*	0.0193***
	(0.00646)	(0.00466)	(0.00460)
Degree related to commerce/economics	4.076***	-2.367***	0.855
	(0.866)	(0.624)	(0.627)
Degree in hard science/engineering	1.116	-1.038*	0.0393
	(1.006)	(0.594)	(0.665)
Female	-1.532**	-0.126	-0.829*
	(0.717)	(0.468)	(0.487)
Domestic Student	1.755**	1.954***	1.854***
	(0.680)	(0.513)	(0.464)
Fraction of LT Peers with Commerce/Economics degree	-3.121*	-3.513	-3.317*
	(1.656)	(2.858)	(1.723)
Fraction of LT Peers with Sci/Eng degree	-6.319***	-0.194	-3.256*
	(1.573)	(2.904)	(1.714)
Fraction if LT peers who are domestic students	-1.511	1.458	-0.0264
	(1.298)	(2.096)	(1.379)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	1.366	-1.131	0.118
	(1.269)	(1.973)	(1.369)
Fraction of LT peers in the top 20% of Adm. GPA distribution	4.628**	-3.907	0.361
	(1.738)	(2.520)	(1.897)
Fraction of LT peers in the bottom 20% of GMAT distribution	-1.513	-1.157	-1.335
	(1.770)	(1.853)	(1.454)
Fraction of LT peers in the top 20% of GMAT distribution	-4.631***	1.259	-1.686
	(1.447)	(1.888)	(1.393)
Constant	49.91***	76.81***	63.36***
	(5.587)	(6.436)	(4.522)
Observations	280	280	280
R-squared	0.233	0.127	0.141
F test model	8.485	4.312	3.775

Standard errors are clustered at the learning team level.
Year and Section fixed effects are included in the regression.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

8 Appendix

8.1 Interview Results

8.1.1 Learning Teams

In the beginning of the program most students diligently study with their assigned learning teams. There are two reasons for this. First, a vast majority of students arrive at the program without knowing any other students in their cohort, so the assigned learning team serves as an initial peer group. Second, students are under the impression that they must study with their teams because the program requires it, and therefore follow the rules.

The organization of the team meetings varies across teams. There are some students who follow strict rules that they agreed upon in the beginning of the semester. There are also students who follow a more lenient approach and just decide what to do on the spot. During the team meetings students discuss the cases assigned as well as answer the assigned questions. They may discuss the models or go through calculations for the subjects that are more quantitative.

As the time progresses, the team meetings take more of review session form. Students may divide the assigned material among themselves and then teach the material to their teammates during the meeting. By the end of the second module (about 2-3 months into the program) most students do not meet with their teams, or meet very rarely.

The main reason for this as quoted by the students themselves is the intensity of the recruiting process which starts in June and reaches it's peak in August-September. Due to the high time demands from the recruiting events and because individual students may have to attend different recruiting sessions, the scheduling of the team meetings becomes very challenging. Other reasons for the drop in the learning team meetings frequency is that students start to study with their friends or other peers who have similar career interests, and that students overall stop seeing the benefits from working with their Learning Team. By the end of the summer most students only meet with learning teams to work on a few mandatory group projects.

8.1.2 Program and Recruiting

In terms of the class grades, students know that every class is "bell curved" with a mean of 80% and a standard deviation of 3-6 (depending on the class). They are also told that the top 25% of students usually get a grade of 82% and higher.

When it comes to the recruiting process, students are roughly (unofficially) divided into the groups according to their career goals. Most students are interested in either consulting stream or finance/investment banking stream. Other options may include entrepreneurship, corporate governance, HR, marketing or accounting. Because different types of companies have different types of interviews, students tend to have practice sessions with their peers who are interested in the same career stream. They may also do some of their other studying with them.

Consulting and Investment Banking firms have certain requirements for students' grades. In particular, in order to get an interview in one of these types of companies students need to be in the top quarter of the class. Some companies need students with an overall GPA in the top 25%, some others look for specific courses, most often Finance and Data Management and Analysis courses.

These recruiting rules generate competition among students. When asked whether or not they care about their class rank, most students say that they at least care whether or not they are above that cut-off grade of 82%. Some students who are not in these streams still care whether or not they are in the top half of the class. Only a small percentage of students do not care about their class rank, these are mostly students in the entrepreneurship stream.

8.1.3 Other peers in the program

Students are required to form their own teams on two occasions: to participate in the McKenzie case competition and for the consulting project.

Students seem to have two main ways of forming the groups for these projects. Some students report that they pick students who they are similar with, who they know they like to work with, with whom they can focus and finish the project fast and efficiently. Other students like to have a well-rounded team, so they pick students who complement their own abilities, so, for example a person with expertise in finance, may pick peers with accounting, HR and marketing experience. Finally, one student reported that he picked his team with a different goal in mind: he wanted to work with students who he has not worked with before. The reason for this was to expose himself to various types of people, as this student finds it very useful to learn how to deal with different types of colleagues in stressful situations.

One curious thing is that none of students indicated that they work with their friends on these group projects. It appears that in the MBA program students very clearly distinguish between the friends they socialize with and students they would like to work with. These two categories overlap, but not perfectly. This fact is also evident from the analysis of the survey data from 2014, where I also find a lack of overlap between the McKenzie case group composition and the groups of friends.

When it comes to the daily studying, students either prefer or are indifferent to being assigned to a team with various types of students. They do see the benefit in learning how to operate, lead and follow in a group that consists of people who are not similar to themselves. Some students value it more than others, but all of them agree that this is an important learning experience.

8.2 Additional Tables

Table 13:

VARIABLES	Participation Grade - All	Participation Grade - Bottom GPA Terc.	Participation Grade - Mid GPA Terc.	Participation Grade - Top GPA Terc.
Admission GPA	0.217***	0.294**	0.0401	0.100
	(0.0560)	(0.115)	(0.421)	(0.236)
GMAT score	0.0151**	0.0199**	0.0113	0.000647
	(0.00626)	(0.00988)	(0.0103)	(0.0132)
Degree related to commerce/economics	2.831***	1.441	4.505**	3.770
	(1.015)	(1.565)	(1.759)	(2.326)
Degree in hard science/engineering	0.852	0.225	2.295	0.954
	(0.948)	(1.665)	(1.711)	(2.195)
Female	-2.450***	-3.165***	0.827	-3.226***
	(0.626)	(1.089)	(1.212)	(1.074)
Domestic Student	1.541**	1.281	0.867	1.425
	(0.608)	(1.026)	(1.233)	(1.045)
Fraction of LT Peers with Commerce/Economics degree	-1.933	-4.296	-4.116	0.0634
	(2.004)	(3.574)	(3.829)	(4.505)
Fraction of LT Peers with Sci/Eng degree	-1.031	-3.354	1.168	-2.409
	(2.125)	(3.417)	(3.844)	(4.398)
Fraction if LT peers who are domestic students	-1.028	-1.019	0.611	-2.729
	(1.595)	(3.029)	(2.897)	(2.877)
Fraction of LT peers in the bottom 20% of GMAT distribution	-0.00100	-1.483	-1.080	0.912
	(1.823)	(2.931)	(2.795)	(3.192)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	-0.857	0.664	-5.085	-2.552
	(1.463)	(2.553)	(3.092)	(3.159)
Fraction of LT peers in the top 20% of Adm. GPA distribution	2.198	4.673	-4.669	1.321
	(1.866)	(4.202)	(3.340)	(3.360)
Fraction of LT peers in the top 20% of GMAT distribution	0.602	-0.289	3.010	0.480
	(1.495)	(2.414)	(2.804)	(2.727)
Constant	53.23***	47.17***	67.73**	74.82***
	(6.925)	(11.07)	(32.76)	(20.90)
Observations	661	298	175	188
R-squared	0.092	0.133	0.203	0.145
F test model	3.065	1.925	2.301	1.764

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 14:

VARIABLES	(1) Participation Grade - All	(2) Participation Grade - Bottom GMAT Terc.	(3) Participation Grade - Mid GMAT Terc.	(4) Participation Grade - Top GMAT Terc.
Admission GPA	0.217***	0.322***	0.243**	0.112
	(0.0560)	(0.0834)	(0.0980)	(0.0975)
GMAT score	0.0151**	0.0107	0.0570	0.0427*
	(0.00626)	(0.0168)	(0.0450)	(0.0247)
Degree related to commerce/economics	2.831***	3.544**	1.527	4.819**
	(1.015)	(1.401)	(2.051)	(2.183)
Degree in hard science/engineering	0.852	1.198	-0.569	2.660
	(0.948)	(1.479)	(2.214)	(2.106)
Female	-2.450***	-2.036**	-3.671***	-1.795
	(0.626)	(1.023)	(1.223)	(1.161)
Domestic Student	1.541**	2.927***	2.275*	0.717
	(0.608)	(1.106)	(1.165)	(1.145)
Fraction of LT Peers with Commerce/Economics degree	-1.933	0.411	-0.154	-2.061
	(2.004)	(3.591)	(4.514)	(4.226)
Fraction of LT Peers with Sci/Eng degree	-1.031	-0.763	1.408	-2.734
	(2.125)	(3.574)	(4.018)	(4.568)
Fraction if LT peers who are domestic students	-1.028	0.794	-1.368	-0.756
	(1.595)	(2.844)	(3.988)	(3.105)
Fraction of LT peers in the bottom 20% of GMAT distribution	-0.00100	-7.051**	5.894**	4.013
	(1.823)	(3.429)	(2.937)	(3.309)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	-0.857	3.515	-4.617	-0.475
	(1.463)	(2.961)	(2.905)	(2.517)
Fraction of LT peers in the top 20% of Adm. GPA distribution	2.198	5.874**	-0.978	0.215
	(1.866)	(2.846)	(3.547)	(3.715)
Fraction of LT peers in the top 20% of GMAT distribution	0.602	-1.685	5.301*	0.758
	(1.495)	(2.662)	(2.962)	(2.339)
Constant	53.23***	43.23***	22.21	40.54*
	(6.925)	(13.39)	(29.71)	(20.52)
Observations	661	257	201	203
R-squared	0.092	0.176	0.152	0.139
F test model	3.065	2.834	1.623	1.891

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 15:

VARIABLES	(1) Participation Grade - All	(2) Participation Grade - Commerce/Econ	(3) Participation Grade - Sci/Eng	(4) Participation Grade - Other Degrees
Admission GPA	0.217***	0.295***	0.174**	0.0209
	(0.0560)	(0.0906)	(0.0715)	(0.228)
GMAT score	0.0151**	0.00854	0.0183*	-0.00187
	(0.00626)	(0.00958)	(0.00956)	(0.0217)
Degree related to commerce/economics	2.831***			
	(1.015)			
Degree in hard science/engineering	0.852			
	(0.948)			
Female	-2.450***	-2.864***	-1.782*	-3.447
	(0.626)	(0.855)	(0.952)	(2.194)
Domestic Student	1.541**	1.672*	0.946	9.684*
	(0.608)	(0.936)	(0.816)	(5.290)
Fraction of LT Peers with Commerce/Economics degree	-1.933	-4.440	-1.655	2.421
	(2.004)	(3.178)	(3.582)	(11.20)
Fraction of LT Peers with Sci/Eng degree	-1.031	-1.981	-0.344	-2.417
	(2.125)	(3.233)	(3.331)	(8.724)
Fraction if LT peers who are domestic students	-1.028	-0.829	-0.458	-2.738
	(1.595)	(2.372)	(2.768)	(8.674)
Fraction of LT peers in the bottom 20% of GMAT distribution	-0.00100	3.050	-0.325	-15.83**
	(1.823)	(2.668)	(2.744)	(7.615)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	-0.857	-2.748	-0.249	5.134
	(1.463)	(2.271)	(2.112)	(4.806)
Fraction of LT peers in the top 20% of Adm. GPA distribution	2.198	0.907	4.527	7.419
	(1.866)	(2.116)	(3.078)	(7.940)
Fraction of LT peers in the top 20% of GMAT distribution	0.602	1.488	1.521	-1.192
	(1.495)	(1.856)	(2.762)	(8.107)
Constant	53.23***	54.81***	54.24***	73.91***
	(6.925)	(9.903)	(9.831)	(26.73)
Observations	661	315	284	49
R-squared	0.092	0.104	0.083	0.431
F test model	3.065	2.409	1.857	1.753

Standard errors are clustered at the learning team level.
YearXSection fixed effects are included in the regression.
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Correlations between personal characteristics

	(1) Admission GPA	(2) GMAT	(3) Female	(4) Domestic Student	(5) Commerce/Econ	(6) Sci/Eng
Admission GPA	1.00					
GMAT	0.19	1.00				
Female	0.08	-0.11	1.00			
Domestic Student	-0.25	-0.18	0.03	1.00		
Degree in Commerce/Economics	-0.09	-0.21	0.13	0.11	1.00	
Degree in Science/Engineering	0.08	0.25	-0.22	-0.20	-0.79	1.00

Table 17:

VARIABLES	(1) Written Grade in MF	(2) Written Grade in MF	(3) Participation Grade in MF	(4) Participation Grade in MF
Hours studied for MF by him/herself	-0.0281	0.0578	-0.130	-0.0871
	(0.129)	(0.188)	(0.125)	(0.186)
Hours studied for MF with LT	0.310	0.198	0.145	0.0982
	(0.189)	(0.234)	(0.229)	(0.273)
Adm. GPA	0.159**	0.181*	0.0381	0.0413
	(0.0792)	(0.0917)	(0.0782)	(0.0832)
GMAT	0.0306***	0.0283**	0.0200*	0.0188
	(0.0107)	(0.0127)	(0.0115)	(0.0128)
Comm/Econ Background	4.144***	4.060***	1.878	2.093
	(1.110)	(1.237)	(1.663)	(2.029)
Sci/Eng Background	0.147	0.776	1.199	1.752
	(1.135)	(1.295)	(1.490)	(1.658)
Female	-1.137	-1.049	-1.472	-1.475
	(0.912)	(0.935)	(1.080)	(1.040)
Canadian or PR	1.694	1.774	0.374	0.180
	(1.057)	(1.123)	(0.990)	(1.078)
Fraction of LT Peers with Commerce/Economics degree		-8.024		-0.851
		(5.079)		(5.153)
Fraction of LT Peers with Sci/Eng degree		-4.272		0.929
		(3.705)		(4.761)
Fraction of LT peers who are Domestic Students		0.394		-1.696
		(3.024)		(3.388)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution		-0.851		-0.492
		(2.485)		(3.064)
Fraction of LT peers in the bottom 20% of GMAT distribution		-2.066		-0.144
		(2.288)		(3.090)
Fraction of LT peers in the top 20% of Adm. GPA distribution		-1.452		-0.662
		(2.900)		(4.039)
Fraction of LT peers in the top 20% of GMAT distribution		2.172		1.438
		(2.267)		(2.831)
Section = 2	-1.074	-1.776*	-0.574	-0.904
	(0.978)	(0.928)	(0.900)	(0.983)
Constant	44.98***	50.30***	63.42***	64.98***
	(9.201)	(12.24)	(8.892)	(11.72)
Observations	185	176	185	176
R-squared	0.156	0.177	0.047	0.051
F test model	5.103	3.189	1.719	1.144
P-value of F model	3.36e-05	0.000494	0.103	0.337

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

References

Booij, A. S., Leuven, E., & Oosterbeek, H. (2015, January). *Ability peer effects in university: Evidence from a randomized experiment.* IZA DP No. 8769.

Burke, M. A., & Sass, T. R. (2008, June). *Classroom peer effects and student achievement.* Federal Reserve Bank of Boston Working Paper.

Carrell, S. E., Sacerdote, B. I., & West, J. E. (2013). From natural variation to optimal policy? the importance of endogeneous peer group formation. *Econometrica*, *81*(3).

Epple, D., & Romano, R. E. (2011). Peer effects in education: A survey of the theory and evidence. *Handbook of Social Economics*, *1B*.

Feld, J., & Zolitz, U. (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labour Economics*.

Gosling, S. D., Rentfrow, P. J., & Swann Jr., W. B. (2003). A very brief measure of the big-five personality domains. *Journal of Research in Personality*, *37*, 504-528.

Griffith, A. L., & Rask, K. N. (2014). Peer effects in higher education: A look at heterogeneous impacts. *Economics of Education Review*.

Hansen, Z., Owan, H., & Pan, J. (2015). The impact of group diversity on class performance: Evidence from college classrooms. *Education Economics*, *23*(2), 238-258.

Hoxby, C. M. (2000). *Peer effects in the classroom: Learning from gender and race variation.*

Hoxby, C. M., & Weingarth, G. (2005). *Taking race out of the equation: School reassignment and the structure of peer effects.*

Jain, T., & Kapoor, M. (2015). The impact of study ggroup and roommates on academic performance. *The Review of Economics and Statistics*, *97*(1).

Lai, F. (2007, December). *How do classroom peers affect student outcomes? :evidence from a natural experiment in beijing's middle schools.*

Lavy, V., & Schlosser, A. (2011). Mechanims and iimpact of gender peer effects at school. *American Economic Journal: Applied Economics*, *3*.

Lavy, V., Silva, O., & Weinhardt, F. (2012). The good, the bad and the average: Evidence on ability peer effects in schools. *Journal of Labour Economics*, *30*(2), 367-414.

Lu, F., & Anderson, M. L. (2015). Peer effects in microenvoronments: The benefits of homogeneous classroom groups. *Journal of Labour Economics*, *33*(1).

Manski, C. F. (1993, July). Identification of endogeneous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3).

Ooosterbeek, H., & van Ewijk, R. (2014). Gender peer effects in university: Evidence from a randomized experiement. *Economics of Education Review*.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? *Handbook of Economics of Education*, *3*.

Sacerdote, B. I. (2001, May). Peer effects with random assignment: Results for dartmouth roommates. *The Quarterly Journal of Economics*.

Stinebrickner, T., & Stinebrickner, R. (2006). What can be learned about peer effects using college roommates? evidence from new survey data and students from disadvantaged backgrounds. *Journal of Public Economics*.

Zimmerman, D. J. (2003). Peer effects in academic outcomes: Evidence from a natural experiment. *The Review of Economics and Statistics*.