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Peer Effects and Social Networks in an MBA Program

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Abstract

In this dissertation, I explore peer effects and social networks among MBA students in a Canadian business school. The unique feature of the data collected for this research is that the students are administratively assigned to small groups, providing plausibly exogenous variation that allows me to identify causal peer effects. Chapter 1, "Peer Effects in an MBA class", establishes the existence and magnitude of the effects of peer characteristics on academic outcomes of MBA students. It also shows that peer effects are heterogeneous across courses and student characteristics. Chapter 2, "Testing team allocation rules", takes the findings of the first chapter and uses them to find the allocations of students across teams that result in highest grades for the Managerial Finance course. After testing ten different allocation rules, I find that separating students by their admission GPA (a proxy for academic ability) may result in the best grades in Managerial Finance class. I discuss the role of the business school and posit that academic achievement may not be the only outcome that is important for business school graduates. Finally, in Chapter 3, "Comparison of the Two Methods of Social Network Data Collection", I compare two methods of social network data collection. A recollection method asks respondents to name a certain number of friends; while a recognition method asks respondents to pick peers from a provided list. First, I present descriptive results of the data collected by these two methods. Then I use the approach described in Comola and Fafchamps (2017) to estimate the true proportion of links by using the information from the discordant answers. I conclude by commenting on the appropriate uses of the two methods of social network data collection.

Keywords: Peer effects, social networks, methodology, education

Summary for Lay Audience

In this dissertation, I explore peer effects and social networks among MBA students in a Canadian business school. Peer effects describe the potential influence student's friends or classmates may have on their educational or social outcomes. The unique feature of the data collected for this research is that the students are administratively assigned to small groups, which allows me to avoid a common problem of students selecting their own peer groups. Chapter 1, "Peer Effects in an MBA class", establishes the existence and magnitude of the effects of peer characteristics on academic outcomes of MBA students. It shows that composition of student teams matters in some classes. It also shows that various types of students are influenced by their peers in different ways. Chapter 2, "Testing team allocation rules", uses these results to find the allocations of students across groups that produce the highest grades for the Managerial Finance course. I find that separating students by their admission GPA (a proxy for academic ability) may result in the best grades in Managerial Finance class. I discuss the role of the business school and posit that academic achievement may not be the only outcome that is important for business school graduates. Finally, in Chapter 3, "Comparison of the Two Methods of Social Network Data Collection", I compare two methods of social network data collection: a recollection method, where we ask respondents to name their friends, and a recognition method, where we ask them to pick friends from a given list. First, I present descriptive results of the data collected by these two methods. Then I use the approach described in Comola and Fafchamps (2017) to estimate the true proportion of links by using the information from the data where respondents disagree on whether or not they are connected. I conclude by commenting on the appropriate uses of the two methods of social network data collection.

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Introduction

Peers play an important role in any educational process. From kindergarten to graduate school, students who interact with each other on a daily basis may affect each other's social, personal and educational outcomes. The study of peer effects is complicated by the fact that in many cases students pick their groups of peers themselves, thus creating an endogeneity problem. Despite the growing body of research on this topic, there is still a debate on the importance of peer effects and their effect on different students. My dissertation contributes to the fields of economic of education and study of social networks, by providing evidence of existence of peer effect among students, establishing the best rules of allocating students across teams, comparing different ways of social network data collection and investigating the methods of estimation of the true social network size. It consists of three essays, related by the topic of peer effects and social networks.

Using unique data I 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 that differentiate this thesis from previous literature. First, I benefit from the exogenous, stratified random assignment of students into small teams. This plausibly exogenous variation allows me to identify causal peer effects. Second, I obtained a rich administrative 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, non-cognitive characteristics (the Big Five personality traits) and social networks. I use the grade in Managerial Finance class as the main outcome. This class is a mandatory core course that is taken in the first semester upon entering the program. It is one of the more quantitatively heavy courses and does not contain any explicit group project, allowing me to see a clearer picture of how peers affect individual outcomes, without worrying about potential "free-rider" problems that are common if the same grade is given to all members of a team. Grades in this class are also often requested by potential employers as a part of an application package, making students especially motivated to perform well. I was able to acquire grades from another course, called Leading People in Organizations for two years. This course is more qualitative, and focuses on developing students' soft skills.[1]

In Chapter 1, "Peer effects in an MBA program", I establish the existence of peer effects among the members of the same learning teams. I show that peer effects exist and are significant. First of all, I find that a high proportion of peers with STEM degrees has a statistically significant negative effect on student's grade. For illustration, substituting one commerce peer for a STEM peer in a learning team could decrease a student's grade for the written component of Finance class by approximately 1%. Second, there is some evidence that students assigned to teams with low GPA peers perform better in the finance course. Because of the nature of my dataset, I am able to explore heterogeneities in 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 (as measured by their admission GPA). 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 peers in the top of the admission GPA distribution. Meanwhile, a high proportion of top GMAT peers has a negative effect on the grades of students with similarly high GMAT scores. Heterogeneous peer effects indicate that there may be a Pareto improving way of allocating students across teams. After analysing the survey data, including the Big 5 personality characteristics of different students, I posit that peers with top GMAT scores may be most likely to be critical and inflexible, thus creating a suboptimal study atmosphere in the group. While they may encourage their teammates to spend time studying with the team, this study time does not appear to be effective and does not help students achieve better grades. Similarly, students with STEM background like to engage in arguments over the case points. While in moderation this behaviour may be good for study process, having many team members who enjoy arguing may create a hostile environment. Given 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 study meeting where students are comfortable discussing their ideas and ask questions may be the key to the good performance in the course.

In Chapter 1 I also address one of the potential issues with some of the research on peer effects in education. Many of the papers on the subject use cumulative GPA or some other average grade as an outcome. To illustrate the difference between peer effects on average vs. individual course outcomes, I use the grades for Managerial Finance class and supplement this data with the grades in a qualitative, group project-based course called Leading People in Organizations. These two courses are quite different, both in terms of the content and in terms of evaluations, allowing me to approximate a student's average grade in a program. There is no

[1] Because of a different structure of the course and limited availability of grades data I use these grades as a secondary outcome to illustrate that peer effects may be heterogeneous across different classes.

reason to believe that peers will have the same effects on different courses since they require different skills and knowledge, and I show that focusing on the average grade may lead to false conclusions about the absence of peer effects. This is a simple observation, but an important point to consider in any research that finds lack of peer effects when looking at an average grade as an outcome.

The natural next step of peer effects investigation is to see whether there are any team allocation rules that could potentially improve the learning process and outcomes for the students. Using the findings from the first chapter, I test several rules for team allocations informed by the previous research or existing program rules. I find that division of students by admission GPA category results in the highest improvement of the average grade and none of the groups of students experience drops in their projected grades. This research is subject to several caveats. First, dividing students into homogenous groups may be perceived as unfair, especially if the division is done by previous academic achievements. Second, the purpose of the business school may not be to only maximise students' academic achievements, but also to expose them to different peers. According to several business school websites, this provides students with the experience of dealing with different types of people, including improving their cultural intelligence, which is crucial in the modern diverse workforce environment. The counterpoint to this is that often potential employers request the grades in key courses as a part of application package. Thus, it is in students' best interests to achieve the best grade and best academic outcome as possible. The third caveat, is that the grades in the business programs are often "bell-curved", and the grades are brought to the same mean every year. Thus, even with the different group assignment, we may not observe a change in mean grades. However, assuming that the grades reflect the level of knowledge acquired by students, the simulation exercise then shows that students will benefit from improved subject knowledge, even if it does not come through as an increase of final grades.

The third chapter of this thesis, "Comparison of the Two Methods of Social Network Data Collection", directly compares the recognition and recollection methods of collecting the social network data. Often, when investigating peer effects and, in general, social networks, researchers collect data on the networks using surveys. There are two main ways of acquiring the social network information: recollection or recognition questions. In a recollection question, respondents are asked to name a set number of their friends or peers. In a recognition question, respondents are presented with a list of potential peers, and they are asked to pick the names from the list. Aside from the constraints on the completion time or availability of a suitable peer list requirements, it is not clear whether one method is better than the other in terms of obtaining an accurate measure of the network. In the survey I ran among the MBA student I included both types of the questions, which allows me to compare and contrast the resulting networks. Using a method adapted from Comola and Fafchamps (2017), where I explicitly model misreporting probabilities, I am able to estimate that size of the actual network (since either of the questions is likely to capture only a part of connections). To estimate the model I make two assumptions. First, I assume that students only report the links that are indeed there and second, I assume that link reports are independent across the respondents. I find that under the assumption of underreporting the size of the network may represent only two thirds of the size of an actual network. I conclude that there are several crucial differences in the results of the two questions. While neither method is error-free, there are some considerations a researcher may take into account when deciding on a question to ask. I also discuss some simple validation options that may be included in the survey.

Chapter 1

Peer Effects in an MBA Program

1.1 Introduction

Peers play an important role in any educational process. In the setting of an MBA program peers may be helpful or disruptive, they may explain certain concepts better than an instructor or provide personal experiences that make a subject more interesting or understandable. They may make studying for tests easy, or they may needlessly complicate it by creating conflict. Understanding the process of students affecting each other through interactions in class or during small study team meetings is the first step to figuring out a better way of allocating students across sections, tutorials, or any other groups. Despite the growing body of literature on the peer effects in education, there is still a lack of consensus on the importance 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 interacting with their peers.

Using unique data I collected at a leading Canadian MBA program, I analyze peer effects in small, administratively assigned groups called learning teams. There are several features of my data that I can exploit and that differentiate this paper from previous literature. First, I benefit from the exogenous, stratified random assignment of students into small teams. This provides me with the plausibly exogenous variation that helps me identify causal peer effects. Second, I obtained a rich administrative dataset consisting of students' demographic characteristics and 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. I use the grade in Managerial Finance class as the primary outcome. This class is a mandatory core course that is taken in the first semester upon entering the program. It is one of the more quantitatively heavy courses and does not contain any explicit group project. This allows me to see a clearer picture of how peers affect individual outcomes, without worrying about potential "free-rider" problems that are common if the same grade is given to all team members. Grades in this class are also often requested by potential employers as a part of an application package, making students motivated to perform well.

My results indicate that peers do have an effect on students' grades in the Managerial Finance course. First of all, I find that a high proportion of peers with STEM degrees has a negative effect on student's grade. Second, there is some evidence that students assigned to teams with low GPA peers perform better in the finance course. Because of my dataset's nature, I can explore the heterogeneities in the peer effects, particularly how different types of students are affected by their peers. I find that peer effects are heterogeneous across students of different ability levels. Academically weaker students benefit from having a high fraction of low admission GPA peers in their group. In comparison, stronger students have higher grades if they are in a team with peers in the top quartile of the admission GPA distribution. Meanwhile, a 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 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. I find that students assigned to groups with top GMAT peers spend more time studying with their team.

Second, I consider the non-cognitive characteristics of students and whether those could explain the results. I discover that GMAT scores are negatively correlated with the "Agreeableness" score from the personality questionnaire. Using the answers to the question about the roles students take during group study, I find that students with the STEM 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 a suboptimal study atmosphere in the group. While they may encourage their teammates to spend time studying with the team, this study time does not appear to be effective and does not help students achieve better grades. Similarly, students with STEM backgrounds like to engage in arguments over the case points. While this behaviour may be useful for the study process in moderation, having many team members who enjoy arguing may create a hostile environment. Given 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 may be the key to a 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 some common-sense rules deemed appropriate by the administration. The main goal is to create diverse teams that would expose students to various peers and create a fair and equal opportunity learning environment. The findings of my paper will help improve the allocation rules: one clear implication is that mixing students of different abilities 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 the students' personalities and communication styles. Students may need to be instructed on effective group work strategies; for example, they should be warned against "steamrolling" over their teammates and taught how to deal with difficult groupmates without letting them affect the study process.

One of the advantages of looking at peer effects among MBA students is that the learning process in the MBA program is designed to mimic the work environment these students will encounter once they graduate. In particular, this MBA program heavily relies on the use of cases for the teaching process, meaning that students learn how to tackle problems and analyze issues as a group. This also means that my findings are potentially transferable to any work environment where employees work in groups or teams. The results of this paper could provide important insights into the possible improvements in team dynamics and, ultimately, team productivity.

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. To illustrate the difference between the peer effects on average vs. individual course outcomes, I use the grades for Managerial Finance class and supplement this data with the grades in a qualitative, group project-based course called Leading People in Organizations. These two courses are complete opposites, both in terms of the content and evaluations, allowing me to approximate a student's average grade in a program. There is no reason to believe that peers will have the same effects on different courses since they require different skills and knowledge. I show that focusing on the average grade may lead to false conclusions about the absence of peer effects. This is a simple observation, but an important issue to consider in any research that finds a lack of peer effects when looking at an 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.

1.2 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.[1] 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.

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

An 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. Using 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 a higher proportion of female students positively affects the academic achievement outcomes of all students. However, the effect of a 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 Oosterbeek and van Ewijk (2014). The authors run an experiment at the University of Amsterdam's 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

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

are randomly divided into squadrons of 30 people each. Authors first look at the historical data to estimate 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 a lack of positive effect of high ability peers in the treatment groups. The authors explain 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 a 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 low ability students benefit from being in the groups with similar level students, while high ability students are not affected by the switch from the mixed ability to similar ability groups. They also indicate that lower ability students tend to be more involved in the study process in the tracked groups.

One of the more recent papers on the subject of peer effects in education, Feld and Zolitz (2017) discovers that peer effects appear to be channelled through the changes in group interaction rather than, for example, a teacher’s effort. Authors find that in a 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.

My paper contributes to the literature on the peer effects in education by confirming the results found in above-mentioned research - that grouping similar students together may be beneficial for their academic achievement. In addition, I use the results from the "Big Five" evaluation to find evidence that can be supportive of the hypothesis that students' academic results might be affected by the group communication rather than simple characteristics of the peers.

Another area where peer effects play an important role is in the workplace, and especially the workplace with a team environment. One of the features of the MBA program is that students who enter it come from a variety of academic backgrounds (although they obviously have a common interest in advancing their managerial knowledge). Thus, the learning teams that are created among these students have a close similarity to the teams in a work environment. The students are expected to work on a variety of projects together, resolve conflicts on their own and overall, exhibit professionalism when dealing with their teammates.

The findings from the literature on peer effects at the workplace are also mixed. Guryan, Kroft, and Notowidigdo (2009) exploits the random assignment of golf players to four-player teams to investigate the presence of peer effects in a golf tournament. They find no evidence that higher ability players have an effect on their teammates and suggest a few possible explanations for their findings. Chan, Li, and Pierce (2013) take advantage of being able to observe salespeople in a departments store in a variety of incentive schemes. In particular, they consider individual and team performance-based commission and conclude that different incentive schemes prone people to respond differently and peer effects are a crucial factor to consider in creating incentive schemes and allocating teams in a workplace. Bandiera, Barankay, and Rasul (2013) show that team-based incentives affect both individual effort and team composition. In particular, the introduction of team incentives results in workers choosing to form teams with other workers of similar ability rather than their friends. This, in turn, impacts the productivity of the firm. Mas and Moretti (2009) examine the high-frequency data from a supermarket chain. They note that cashiers of higher ability have a strong positive effect on their peers in close proximity.

1.3 Data

1.3.1 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 for the first 6 months of the program. Professors teaching in two sections generally differ; however, the syllabus and the material covered is the same. The data covers six cohorts of students who entered the program in 2011-2016. The data is available for one section for the year 2011 and for both sections for 2012-2016, which results in a 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 STEM background; the rest have humanities or social science (other than economics) degrees. The average GPA grade from the previous degree is 77%, and the average GMAT score is 660 (out of 800) points. The summary statistics are presented in Table 1.1. 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.

Table 1.1: 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%
STEM 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

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 the MBA program is teaching with the use of "cases". A case describes a real or hypothetical firm that 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. For the main part of my analysis I focus on the written grade component. 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. The final exam, on the other 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 a detailed analysis of the issues and make a recommendation. The class contribution is recorded in every class by a Teaching Assistant.[2] Students are given a grade of 3 for a significant, meaningful contribution; grade of 2 for an average insight; and a grade of 1 for a quick comment or a definition. Students may have multiple contributions 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 a high contribution if there are several students willing to answer a question. The final grades are bell-curved with a mean of 80% and a standard deviation of 7. Students are told in advance about the bell-curving process.

In Section 6 I use a proxy for an average program grade to illustrate the importance of picking a correct outcome for the analysis of peer effects. To create this proxy, I use the grades in Managerial Finance and Leading People in Organization (LPO) courses. The latter is a very qualitative course, where students learn effective techniques for leading and managing employees in an organization. The grade for this course consists of participation and group project components. The course runs in the first and second semesters, so for consistency, I use the mid-point grade, which is calculated at the end of the first semester of the program. While some students find LPO an interesting and important course, it appears to me that most students do not treat it with the same rigour as other, more traditional courses (e.g. Finance, Accounting, Marketing). So, LPO is very different from finance, making it a good grade to use in the construction of the program average proxy.

I divide students into three groups according to their previous degrees: commerce/economics, STEM and “other”, which includes mostly students with arts and humanities degrees, as well as a handful of students with a degree in social sciences other than Economics. There are two reasons for this separation. First and foremost, these are the 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 STEM backgrounds should be able to master the concepts faster than students who may

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

need a refresher in math.

1.3.2 Learning Teams

After being divided into sections, students are assigned to learning teams by the administrative staff. The teams are assigned based on their observable characteristics. 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 previous years' student experience, 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.[3] While the rest of the criteria are important, the data suggests a variation in the number of STEM major students or the number of international students across groups. The reason for these allocation rules is to ensure fairness and to create a diverse and safe environment. The main purpose of the learning team is to study and prepare for the various classes as a group and complete group assignments for some of the courses.

Students are not allowed to switch their teams. If a 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 3.4 for more information), I discovered that students are mostly working with the assigned teams at the beginning of the program. As time progresses, students get to know more of their peers in the program. They also get much busier (e.g. employment information sessions, interviews, and networking events start near the end of the first semester). Thus, 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 the proximity of seating in a classroom, these effects will still come mostly from the learning team peers.

Students are encouraged by the program administration and the instructors to spend time studying with their learning teams. Each team is assigned a faculty mentor, whose role is to

[3] 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 dropouts usually happen very early in the semester, which should not be disruptive to students' work.

provide guidance and aid in any conflict resolution. There are special meeting rooms reserved for each team for the semester. During the team meetings, students discuss the cases: using the framework they learn in class, they discuss the main issues, thoroughly analyze the case and propose solutions. Each team may have its own style, but the goal is to get ready for the case discussion in class. Occasionally, instructors will give teams specific assignments, for example, to argue for or against a certain case point, so teams have to prepare their arguments and present their points in class.

There are several complicated interactions students may have with their learning team peers. First of all, there may be a direct knowledge transfer. For example, students with a commerce background may be quite familiar with most of the technical material covered in class and may explain it to the teammates who are falling behind. Second, students may be affected by the interactions during team discussions. A positive, cooperative discussion may lead to a better understanding of the material. Since case analysis is a major component of Managerial Finance grade (class participation and final exam are based solely on the case discussion), students' interactions with peers during the team meetings play a crucial role in their preparedness for the class. These channels may be affected by any number of peers' characteristics, so my goal in this paper is to narrow down the characteristics that seem to matter for peer effects and propose potential mechanisms behind why those characteristics matter.

1.3.3 Survey

To gain some insight into the potential mechanisms behind the peer effects, I ran a survey among the three cohorts of MBA students during their second or third months in the program. This corresponded to the approximate midpoint of the Finance course. 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 a student's social network, the 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 the 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 student 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 ten 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. A 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 are presented in Table 1.2. In general, the proportions of female students, international students and the proportions of students with various background degrees correspond to those in the 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 a 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 an 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 teammates 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 the 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

Table 1.2: 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 STEM 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.

of hours studied for Finance; Extroversion is positively and significantly related to the number of hours spent socializing with peers; Agreeableness has a positive relationship with team satisfaction. These correlations provide me with some evidence that the personality characteristics are measured more or less correctly.

1.3.4 Interviews

Finally, 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. The interviews took place towards the end of the semester, when students were already done with the Finance course. 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.[4]

There were three key pieces of information I was able to learn through the interviews. First, students spend the most time studying with their learning teams at the beginning of the pro-

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

gram. As the 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. The second finding is that students do not necessarily prefer studying with friends. Instead, they may choose peers with whom they do not socialize outside of the program but whom they consider being 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.

1.4 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.

$$y_i = \alpha_1 + \alpha_2 X_i + \alpha_3 \bar{X}_{-i} + Year \times Section + \epsilon_i \tag{1.1}$$

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 for the student's learning team peers, not including the student herself (e.g. for a student who has a science degree and is a member of a six-person team that has two other science graduates, the value of the fraction of peers with a STEM degree will be 0.4).[5] 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 the top and bottom 20% of class GMAT distribution.

[5]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.

The results of the regression (1) are presented in Table 1.3. 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 a 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 degrees in STEM fields get higher grades on the written component of the 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. Female students do worse than male students on average.

In terms of peer effects, there are several interesting findings. First of all, a higher proportion of STEM peers is negatively correlated with the Managerial Finance written grade. For illustration, substituting one peer with a STEM background for one with a commerce background may increase a student's grade in a written component of the Finance class by 1%. This is curious, given that students with STEM 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 the 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 the 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 benefit from having high ability peers, but it is unusual to see that low GPA students may also be helpful, on average. I discuss this result in more detail in the next section, when I show that this peer effect is heterogeneous across students of various abilities.

Now, consider the results of regression (1) when the outcome is class participation grade, presented in the second column of Table 1.3. 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 the student's willingness to participate in class, not necessarily the student's ability or even preparedness. In addition, instructors do cold-call on students who have not participated in a while and tend to choose those with lower participation if several students wish to contribute to class discussion. To look at a clearer picture of peer effects, I focus on the written component

Table 1.3: OLS regression on the components of the Managerial Finance(MF) grade

	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 STEM	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 STEM 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. LT - Learning Team
Year $\times$ Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016, N=661
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

of the total grade for the rest of this paper. This outcome gives me results that are less muddled by a student's own non-cognitive characteristics (willingness to participate in class, in this case) and the instructor's management of class discussion. I do include the results of the regression on the participation grade in the Appendix.

1.4.1 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 the class. [6] [7]

The results of these regressions are presented in the tables below (Tables 1.4-1.8). I find 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 STEM peers, as well as the positive effects of high proportions of bottom Admission GPA peers. Looking at the results in Table 1.4, we see that the negative effect of STEM 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 in value with the increase in GPA.

Peers with low admission GPA scores are beneficial for students of the same ability levels. We can also now see that the 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 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 1.4 provides us with some interesting findings and some intuition regarding the potential mechanisms behind the peer effects. First, I find that the peer effects

[6] 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 the class, not the whole sample. It is 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 of percent across cohorts.

[7] 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.

Table 1.4: OLS regression on Finance written grade: by terciles of admission GPA distribution

	(1) Written Grade - All	(2) Written Grade - Bottom GPA	(3) Written Grade - Middle GPA	(4) Written Grade - Top GPA
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 STEM	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 STEM 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. LT - Learning Team
Year × Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016. N=661.
*** p<0.01, ** p<0.05, * p<0.1

are heterogeneous, with students benefiting from having similar ability peers in their teams. And second, the negative effect of STEM 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 to 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 STEM peers may be explained using similar logic. The stereotypical image of a STEM 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 a 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. The GMAT can be taken multiple times until a student is satisfied with their score - so it is possible that the GMAT may be measuring a different type of ability or even some other characteristic (e.g. grit, motivation).

Table 1.5 shows the results of regression (1) when the sample is split by GMAT tercile. STEM peers have a negative effect on Managerial Finance grades for students in the bottom and middle terciles of the GMAT score distribution. The 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, the 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 heterogeneous 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, in-

Table 1.5: OLS regression on Finance written grade: by the terciles of GMAT score distribution

	(1) Written Grade - All	(2) Written Grade - Bottom GMAT	(3) Written Grade - Middle GMAT	(4) Written Grade - Top GMAT
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 STEM	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 STEM 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. LT - Learning Team
Year × Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016. N=661.
*** p<0.01, ** p<0.05, * p<0.1

ternational/domestic students and students with different degrees. Interestingly, even their own characteristics have different effects on the written component of Finance grade for female/male students (Table 1.6). For example, while all students with STEM degrees perform better in finance than students with other degrees, this effect is stronger and statistically significant for male students. On the other hand, domestic female students have a 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 vary. Most notably, STEM 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 1.7 describes the results of regression (1) on international and domestic students. Once again, even the relationship between their 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 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 than 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 STEM 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. A 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 1.8). It seems that students with commerce/economics background are the ones who are significantly negatively affected by STEM peers. Other groups of students are also harmed by the high fraction of STEM 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 the 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 starkest result is that students of similar ability levels (measured by the previous degree GPA) benefit from being assigned to the

Table 1.6: OLS regression on Finance grade components for male and female students

	(1) Written Grade - Female	(2) Written Grade - Male
Admission GPA	0.338***	0.103**
	(0.0776)	(0.0521)
GMAT score	0.0299***	0.0299***
	(0.0109)	(0.00693)
Degree related to commerce/economics	5.402***	5.512***
	(1.363)	(1.408)
Degree in STEM	1.220	2.502*
	(1.545)	(1.391)
Domestic Student	4.554***	2.269***
	(1.113)	(0.735)
Fraction of LT Peers with Commerce/Economics degree	-5.244	-1.429
	(4.559)	(2.740)
Fraction of LT Peers with STEM degree	-8.770**	-3.047
	(3.802)	(2.551)
Fraction if LT peers who are domestic students	0.117	-0.697
	(3.172)	(2.329)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.307	-2.446
	(3.525)	(1.696)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	3.491	2.102
	(2.779)	(1.740)
Fraction of LT peers in the top 20% of Adm. GPA distribution	1.846	1.310
	(2.658)	(2.020)
Fraction of LT peers in the top 20% of GMAT distribution	-3.348	-1.551
	(3.115)	(1.932)
Constant	32.45***	49.69***
	(8.726)	(6.978)
Observations	181	480
R-squared	0.307	0.140
F test model	6.237	4.006

Standard errors are clustered at the learning team level.LT - Learning Team
Year × Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016. N=661.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1.7: OLS regression on Finance grade components for International and Domestic students

	(1) Written Grade - Canadian/PR	(2) Written Grade - Int'l
Admission GPA	0.225***	0.00727
	(0.0571)	(0.0740)
GMAT score	0.0250***	0.0401***
	(0.00628)	(0.0111)
Degree related to commerce/economics	4.680*** (0.906)	6.617* (3.420)
Degree in STEM	1.746*	2.929
	(0.924)	(3.577)
Female	-1.487**	-3.252***
	(0.688)	(1.175)
Fraction of LT Peers with Commerce/Economics degree	-6.491** (2.905)	6.827* (3.835)
Fraction of LT Peers with STEM degree	-8.707*** (2.816)	5.623 (3.735)
Fraction if LT peers who are domestic students	-0.00957 (2.117)	-3.146 (3.202)
Fraction of LT peers in the bottom 20% of GMAT distribution	-2.587 (1.862)	-0.730 (2.848)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	3.543** (1.639)	-1.572 (2.434)
Fraction of LT peers in the top 20% of Adm. GPA distribution	0.979 (2.052)	0.587 (3.097)
Fraction of LT peers in the top 20% of GMAT distribution	-1.685 (1.893)	-4.749** (2.297)
Constant	49.94***	47.93***
	(6.171)	(9.756)
Observations	470	191
R-squared	0.182	0.251
F test model	6.932	2.487

Standard errors are clustered at the learning team level. LT - Learning Team
Year × Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016. N=661.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: OLS regression on Finance grade components for students with different undergraduate degrees

	(1) Written Grade - All	(2) Written Grade - Commerce/Econ	(3) Written Grade - STEM	(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 STEM	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 STEM 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.LT - Learning Team
Year × Section fixed effects are included in the regression.
Data source: business school administrative dataset 2011-2016. N=661.
*** p<0.01, ** p<0.05, * p<0.1

same teams. On the other hand, some of the findings are still not very intuitive. Why do STEM peers have such a 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 a 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. Since I do control both for personal and team characteristics in my regressions, this problem should be mostly alleviated.

Similarly, there are some student attributes that are correlated. For example, international students are more likely to have a higher admission GPA, and STEM students tend to have higher GMAT scores. I do not think that these correlations nullify my findings of the existence of peer effects, but the effects of the individual characteristics 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, Table 1.16.

1.5 Empirical Strategy and Results - Survey Data

I assume that peers might influence the outcomes of their classmates 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 a 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 the other 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 of 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 abilities.

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

1.5.1 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:

$$s_i^j = a_0 + a_1 X_i + a_2 \bar{X}_{peers} + Year \times Section_i + \epsilon_i \tag{1.2}$$

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

Although, it is important to note that by construction of the groups, students with the highest fraction of 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 1.17 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 not be 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.

1.5.2 Personality traits

When working with other people, be it on a research project or on a class assignment, the personalities 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,

Table 1.9: OLS on the Number of hours studied alone and with the learning team, survey data

	(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 with	0.759	-0.940
STEM degree	(2.335)	(1.436)
Fraction of LT peers who are	3.044*	0.154
domestic students	(1.563)	(0.907)
Fraction of LT Peers with	3.727	-1.144
Commerce/Economics degree	(2.392)	(1.401)
Fraction of LT peers in the bottom	1.622	1.015
20% of Adm. GPA distribution	(1.293)	(0.797)
Fraction of LT peers in the bottom	0.232	0.0965
20% of GMAT distribution	(1.609)	(0.778)
Fraction of LT peers in the top	1.188	1.442
20% of Adm. GPA distribution	(1.507)	(0.948)
Fraction of LT peers in the top	-0.206	2.644***
20% of GMAT distribution	(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. LT - Learning Team
Data source: survey data. N=191.
*** p<0.01, ** p<0.05, * p<0.1

the mechanism that is usually assumed is that peers may aid students in studying by explicitly helping with the classwork or alternatively hinder student's success by being disruptive or distracting.

In the context of this paper, peer personality characteristics could shed light on the puzzles in the results discussed above. To address them, I turn to the results of the survey question aimed at evaluating students' Big Five personality traits: extroversion, conscientiousness, agreeableness, emotional stability and openness to new experiences. The final score (out of 14) for each of these characteristics reflects how well each characteristic applies to a student. For example, a score of 9 in extroversion would imply that the student is more extroverted than introverted.

To illustrate the correlations between personality characteristics and observable characteristics, I run the OLS regressions with personality characteristics scores as outcomes and observable characteristics as independent variables. The results of the regressions can be seen in Table 1.10.

First, admission GPA is positively related to the conscientiousness score, which is in line with the findings from previous literature as well as common-sense expectations, providing some reassurance that the measures of personality characteristics were more or less accurate. Interestingly, GMAT score is not related to conscientiousness, meaning that having a high GPA and scoring well on GMAT may not necessarily require the same skills, which may explain why the correlation between these two measures of ability is not as high as some might expect. [8]

Coming back to the puzzle I encountered in previous sections, a 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 with. 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 longer hours, but not necessarily increase their productivity or knowledge.

As a side note, 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

[8] 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 the other hand, is a measure of knowledge, aptitude, and motivation.

Table 1.10: Regressions with personality characteristic scores as outcomes (survey data)

	(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	-0.170	-1.017**	-0.295	-1.189*	-0.490
Background	(0.621)	(0.504)	(0.457)	(0.696)	(0.436)
STEM	-0.904	-0.218	-0.167	-0.0901	-0.0990
Background	(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)
Domestic	0.205	-1.329***	0.689**	0.711	-1.038***
Student	(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
Data source: survey data. N=191.
*** p<0.01, ** p<0.05, * p<0.1

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.

1.5.3 Roles on the Team and Team Dynamics

The number of hours students spend studying together may only tell us 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 the 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 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 points 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 1.11, I present the results of logit regressions, where the outcome is the indicator variable of whether or not a student behaves in a certain way during the group meetings, to illustrate the correlation between behaviours and observable characteristics. It shows that different types of students have different behaviour styles during group meetings. Female students prefer to ask questions, male students prefer to lead, international students share their work experience, and STEM students like to play "devil's advocate". The results may shed some light on the curious negative effect of STEM students on their peers' finance grade. It appears that students with a STEM 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, STEM 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 ideas 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 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 answer.[9]

Table 1.11: Regressions with most common student behaviour during a group discussion as an outcome (survey data).

	(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	0.167	-0.0543	0.147	-0.137	-0.0982	-0.0937
Background	(0.120)	(0.121)	(0.110)	(0.115)	(0.0905)	(0.109)
STEM	-0.0251	-0.158	0.279**	-0.104	-0.0931	0.0260
Background	(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)
Domestic	0.0771	0.170**	-0.0670	-0.244***	0.0356	-0.139*
Student	(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
Data source: survey data. N=154.
*** p<0.01, ** p<0.05, * p<0.1

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

[9] Unfortunately, since I do not have the survey data for all group members, nor can I make any reasonable assumptions about distributions of personality characteristics in the class, I am not able to directly and definitively estimate the effect of the peers who are argumentative and/or enjoy playing "devil's advocate". If I limit my sample to those students for whom I have enough group observations to perform such an analysis, I am left with 25 observations. I did run the regression on these 25 observations, and indeed, the negative effect of STEM peers disappears if I control for the peers who enjoy playing "devil's advocate".

1.6 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 on the average grade may miss crucial details. It is common 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. This lack of motivation will be reflected both in the individual outcomes as well as the effect of these students on their peers.

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 of the course 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 the 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.[10] I obtained the LPO grades for two cohorts.

Table 1.12 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. For ease of comparison, I limit the sample to the two cohorts for which I have LPO grades. 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 a degree in commerce get higher grades than students with other degrees. There are also some peer effects: negative effects of the high fraction of STEM peers and peers with top GMAT scores. For the two cohorts, there is also a positive effect 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.

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

Table 1.12: OLS on the Managerial Finance, LPO and Average grades as outcomes.

	(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*** (0.866)	-2.367*** (0.624)	0.855 (0.627)
Degree in STEM	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* (1.656)	-3.513 (2.858)	-3.317* (1.723)
Fraction of LT Peers with STEM degree	-6.319*** (1.573)	-0.194 (2.904)	-3.256* (1.714)
Fraction if LT peers who are domestic students	-1.511 (1.298)	1.458 (2.096)	-0.0264 (1.379)
Fraction of LT peers in the bottom 20% of Adm. GPA distribution	1.366 (1.269)	-1.131 (1.973)	0.118 (1.369)
Fraction of LT peers in the top 20% of Adm. GPA distribution	4.628** (1.738)	-3.907 (2.520)	0.361 (1.897)
Fraction of LT peers in the bottom 20% of GMAT distribution	-1.513 (1.770)	-1.157 (1.853)	-1.335 (1.454)
Fraction of LT peers in the top 20% of GMAT distribution	-4.631*** (1.447)	1.259 (1.888)	-1.686 (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.
LT - Learning Team; LPO - Leading People in Organizations; MF - Managerial Finance.
Year and Section fixed effects are included in the regression.
Data source: administrative dataset 2014-2015. N=280.
*** p<0.01, ** p<0.05, * p<0.1

Now, column 3 in Table 1.12 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 coefficients of the characteristics 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 change 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. In the case of this MBA program, a high proportion of students is highly motivated to achieve a high grade in Finance course, while at the same time, most students do not perceive the LPO course as crucial to their future career. In addition, since courses (or even separate course components) are graded differently, this may further muddle the potential peer effects findings if we look at the average grade. For example, courses with heavy group work components may be subject to the "free-rider" problem; participation components may be heavily affected by students' own personality characteristics as well as instructor's preferences for cold-calling or picking students with lower participation grades. The main point is that we might miss the peer effects on the individual courses if we look at the average GPA, and even if peers matter for one course but not others, that may give us an opportunity to improve students' academic performance in some courses while not affecting the others.

1.7 Conclusion

Peer effects need to be taken into consideration when we divide students into groups, sections, and classes. Even though this research question has been given considerable attention, it is still not clear if peer effects exist, how strong and important they are, and why might certain types of students affect each other. In addition, certain types of professional educational programs, such as MBA, may provide us with important insights into how peers may affect each other's performance not only in an academic setting but also in a work environment. In this paper, I showed the existence and magnitude of peer effects in small exogenously assigned groups in an MBA program. I find that students' grades are affected by their peers, and not all students are affected equally. Some important peer effects include the negative effect of STEM peers and the possible positive effect of very low and very high GPA peers. I also find evidence for heterogeneous peer effects, in particular, the possible benefits of grouping students of similar ability together. In addition, I document the heterogeneity of peer effects across different components of the same course. Using the unique survey data collected among the three cohorts of MBA students, I found some 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, STEM 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 exist.

Findings of this paper support some of the previous conclusions found in the literature: people affect each other differently, and a pleasant psychological atmosphere in a group matters. While students' cognitive ability might play a role in how good of a peer they might be, their personality and the way they conduct themselves during the group discussions may be more important. The heterogeneous peer effects also show us that there should be a way to allocate students across teams that is beneficial for some, if not all of them. I understand that the administrations of academic programs may have different objectives in mind when it comes to dividing students into teams. Currently, the most popular explanation for the assignment rules is creating a diverse environment for students, in which they can communicate and learn from students from a variety of academic and cultural backgrounds. This goal may be an important one, and it is difficult to measure how successful these teams are in terms of teaching students about diversity. However, I would encourage programs to look more seriously into students' personality characteristics and their communication styles and making more explicit rules based on those rather than just observables. To my knowledge, some of such assessments are often already being done as a part of career services for students; thus, the only thing that might be required is to incorporate the results of such assessments into the team allocation process. The findings of this paper may also be used in the workplace when dividing workers into teams or groups. Similarly to the education setting, employers may need to be mindful of the psychological atmosphere in the workplace and how it might affect productivity.

1.8 Appendix

1.8.1 Interview Results

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.

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.

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.

1.8.2 Additional Tables

Table 1.13: Correlations between personal characteristics

	(1) Admission GPA	(2) GMAT	(3) Female	(4) Domestic Student	(5) Commerce/Econ	(6) STEM
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 STEM	0.08	0.25	-0.22	-0.20	-0.79	1.00

Table 1.14: OLS on the MF grades accounting for hours studied

	(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)
STEM 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 STEM 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)
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
LT - Learning Team

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Chapter 2

Testing team allocation rules

2.1 Introduction

Almost all academic settings require students to be divided into groups: sections, classes, tutorials, study groups, or project teams. Often this assignment is done randomly (e.g., class/tutorial sections) or by students choosing their group (e.g., class project team). However, in many programs, little consideration is given to how students might affect each other's academic outcomes. In the previous chapter, I showed that in the context of an MBA program where students are assigned to small study groups, peer effects exist, and some are significant. Moreover, some of these peer effects are heterogeneous across different types of students. Most prominently, students with different admission GPA scores are positively affected when grouped with peers of similar ability levels. Male and female students, domestic and international students and students with different academic backgrounds are also affected differently by different peers. An important question then is whether we can improve students' academic outcomes by strategically allocating them to groups with peers who are projected to have a positive influence on student's academic outcomes.

In this chapter, I use data from a leading Canadian MBA program where students are allocated to small learning teams by the administration - the same dataset used in Chapter 1. The main outcome of interest is a grade in a Managerial Finance class. This class is one of the core components of the program and runs in the first semester. Managerial finance is a required course, and students tend to take it seriously because many prospective employers request the grades in this course as a part of an application package.

One of the major benefits of using data from an MBA program is that it is designed to simulate workplace interactions. Students are asked to analyze "cases" in small teams, and they are strongly encouraged to deal with any conflicts or issues by themselves. Also, MBA students tend to have work experience, and most of them are going back into the corporate world after the program. Thus, the findings of this research could potentially be applied not only in an academic setting but also to improve the formation of teams and improve productivity in the workplace.

In this paper, I answer the question of whether there is a way to allocate students across teams in a manner that would benefit (or at least not hurt) all students. I take as given the peer effects found in the previous paper, and I run a variety of simulations, modifying the way students are allocated across teams. I calculate the projected grades and compare them with realized grades to see whether there might be an improvement.

Because of the complicated and heterogeneous nature of peer effects and because each student possesses more than one characteristic, I adjust the estimation of peer effects to include a number of cross-terms that appeared significant in previous findings. I then use the estimated results in the simulations to create the distributions of grades under different allocation rules. The proposed ways of dividing students across teams are mainly motivated by the findings of my previous paper and the existing allocation rules that the program uses. To compare the results, I calculate the mean, standard deviation and also visually assess the distributions of the grades. To ensure that any increase in average grade does not come from increasing grades for one subgroup of students at the expense of another, I report the simulated and realized grades for each subgroup of students.

For the purposes of this paper, student achievement is measured by their grades in the Managerial Finance course. The main finding is that homogeneous within-group assignment rules are optimal. As expected, dividing students into teams based on their admission GPA (creating homogeneous groups) results in an increase in the average grade. In addition, separating male and female students and international and domestic students also results in an increase in average grades in finance class. It also appears that almost all types of students benefit from more homogeneous group assignments and no students experience detrimental effects from these types of assignment rules. In Chapter 1, I suggest that one of the mechanisms behind the peer effects could be the way different types of students shape the psychological atmosphere in the group. In this case, more homogeneous groups may have a more comfortable discussion environment for students, allowing them to contribute their ideas, ask questions without worrying about their peers. Note that it does not mean that peers of certain backgrounds actually behave negatively towards other students, but rather that if a student perceives her peers to be smarter, more knowledgeable, more confident than her, it may affect the way this student behaves in the team, and thus affect her learning and performance.

According to the administration of the business school, one of the reasons for heterogeneous group assignment rules is to expose students to a variety of peers, which will allow them to learn how to interact with colleagues in the increasingly diverse corporate environments.

Therefore, maximization of the current grades may not be the main objective of the MBA program, and there may be other long-term benefits of grouping different students together. However, given that the grade performance in class (in particular finance and other specialization classes) is often used as one of the hiring criteria, I argue that students should be given an opportunity to achieve the best results they can. The goal of learning through interaction with various peers could be achieved in other, less technical classes or through participation in case competitions and other extracurricular activities.

This paper is organized as follows. The next section describes a selection of relevant literature. Section 3 discusses at length the data used for this paper; Section 4 describes the methods and procedures I used in running the simulations. Section 5 shows the results and provides some discussion of possible policy changes. Section 6 concludes.

2.2 Literature Review

The question of efficient allocation of students across teams arises naturally in any research paper that looks at peer effects in education. Chapter 1 provides a more detailed literature review of papers related to the research on peer effects in an MBA program. Below I present a few papers that attempt to either form groups in the quasi-experimental setting or calculate the predicted outcomes given their findings on peer effects.

One of the well-known works on the subject, Carell et al. (2013), uses their findings regarding peer effects in Air Force Academy to create sections of cadets. The authors' goal was to capture the positive effect of high ability peers on lower ability peers by grouping them together. They find, however, that in the experimental sections, these effects did not realize. The authors posit that this may be because students form subgroups within the sections, befriending peers of similar ability, thus eliminating the possible positive spillovers from interactions with higher ability peers. Due to the small size of the groups in the MBA program used in my research, the issue of forming subgroups should not be critical. Thus, running even a simulation exercise should show the improvements in the outcomes depending on the group composition. Booij et al. (2015) use data from an experiment where they manipulate the composition of tutorial groups according to students' ability levels. They find that low ability students benefit from being in the groups with similar level students, while high ability students are not affected by the switch from the mixed ability to similar ability groups. They also indicate that lower ability students tend to be more involved in the study process in the tracked groups. These findings echo the results of Chapter 1, which showed that students benefit from being grouped in teams with similar ability peers. Similarly, another paper on peer effects, Feld and Zölitz (2017) discovers that peer effects appear to be channelled through the changes in group interaction rather than teacher's effort, for example. Authors find that in a German university, where students are divided into sections of 16 students each, students allocated to sections with high ability students benefit. However, they note that this effect is heterogeneous. Low ability students are harmed by high ability peers, while high ability peers benefit from being grouped. Overall, based on the previous research, it appears that homogeneous team allocations may result in better outcomes for students. However, observable characteristics of students are often correlated, and a composite effect of a group member that possesses a number of characteristics is not clear. Therefore, it is interesting to run a simulation and see how different allocation rules will affect grades.

Aside from the academic context, teams are extensively used in a variety of workplaces: governments, consulting agencies, research centres, and virtually any other private sector establishment. As previously mentioned, using the data from an MBA program provides us with insights into how teams might operate not only in the education settings but also in the workplace. Peer effects have been established in previous research on teams at the workplace (Chan et al. (2013), Bandiera et al. (2013), Mas and Moretti (2009)), although there is still no unanimous conclusion about the existence and importance of peer effects (Guryan et al. (2009)). We may not be able to apply all the lessons learned from the MBA program directly to the workplace. However, since the MBA program is designed to mimic a workplace, and MBA students tend to be more mature, with some work experience, this research still might provide some insights into better ways of assigning teams in a variety of work environments.

2.3 Data

2.3.1 Program and Course Description

The dataset used in this paper is constructed using 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. Administrators divide students 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 cover six cohorts of students who entered the program in 2011-2016. The data are available for one section for the year 2011 and for both sections for 2012-2016, which results in a total of 611 observations.

The administrative data on the students of the MBA program include 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

Table 2.1: Summary Statistics

	2011	2012	2013	2014	2015	2016
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%
STEM 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

experience and the industry in which the work experience has been acquired, mother tongue and immigration status. Approximately a third of the 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 a business or economics-related degree; a significant portion (about 30%) have a STEM (mostly engineering or hard science) background; the rest have humanities or social science (other than economics) degrees. The average GPA grade from their previous degree is 77%, and the average GMAT score is 660 (out of 800) points. The summary statistics are presented in Table 2.1. 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 the 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. Managerial Finance is a required course for all students in the program, and it runs in the first semester. Using the first-semester course ensures that students are most likely to engage with their teams since they have not had a chance to form meaningful connections outside of their group or a class yet.[1] The final grade for the Managerial Finance course consists of the weighted average grade for the written assignments (midterm test 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. The final exam, on the other hand, consists of an analysis

[1] This is confirmed by the students who were interviewed.

of a case study. It requires students to read a case describing a problem that a company is facing, provide a detailed analysis of the issues and make a recommendation. The class contribution is recorded in every class by a Teaching Assistant.[2] Students are given a grade of 3 for a significant, meaningful contribution; grade of 2 for an average insight; and a grade of 1 for a quick comment or a definition. Students may have multiple contributions per class, although the instructor somewhat mediates it: he may cold-call on a student with a low contribution level or pick a student with less contribution over the one with a high contribution if there are several students willing to answer a question. The final grades are bell-curved with a 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 degrees: commerce/economics, STEM and others, which includes mostly students with arts and humanities degrees, as well as a handful of students with a degree in social sciences other than Economics. There are two reasons for this separation. First and foremost, these are the main educational 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. This assumption is supported by the fact that students with STEM backgrounds tend to have higher grades in the Managerial Finance course than other students.

2.3.2 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.[3] While the rest of the criteria are important, the data suggests that there is a variation in the number of STEM major students or the number of international students across groups. The reason for these allocation rules is to ensure fairness and to create a diverse and safe environment. The main purpose of the

[2] Starting from 2015 the instructor records the contribution grade

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

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 typically not allowed to switch their teams. If a 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 interviews with some of the students, I discovered that students are mostly working with their assigned teams at the beginning of the 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 any peer effects arise from the proximity of seating in a classroom, these effects will still come mostly from the learning team members.

Students are encouraged by the program administration and by the instructors to spend time studying with their learning teams. Each team is assigned a faculty mentor, whose role is to provide guidance as well as to aid in any conflict resolution. There are special meeting rooms reserved for each team for the semester. During the team meetings, students discuss the cases: using the framework they learned in class, they discuss the main issues, thoroughly analyze the case and propose solutions. Each team may have its own style, but the goal is to get ready for the case discussion in class. Occasionally, instructors will give teams specific assignments, for example, to argue for or against a certain case point, so teams have to prepare their arguments and present their points in class.

There are some complicated interactions students may have with their learning team peers. First of all, there may be a direct knowledge transfer. For example, students with a commerce background may be quite familiar with most of the technical material covered in class and may be able to explain it to the teammates who are falling behind. Second, students may be affected by the interactions during team discussions. A positive, cooperative discussion may lead to a better understanding of the material. Since case analysis is a major component of Managerial Finance grade (class participation and final exam are based solely on the case discussion), students' interactions with peers during the team meetings play a crucial role in their preparedness for class. In Chapter 1, I find that one of the important channels is the psychological atmosphere in the group, which may be achieved by grouping similar students together.

2.3.3 Role of the Business School

The goal of business schools is not just to provide students with knowledge but also to introduce them to the way a workplace operates and give them an opportunity to practice their networking and interpersonal skills. This additional goal brings complexity to the analysis of peer effects in the context of the MBA program. On the one hand, the current team allocation rules are put in place to mimic the diverse environment of a modern workplace. The current motivation for diverse learning teams is based on some branches of management literature which find that diverse teams are beneficial for the work and productivity of teams (Williams and O'Reilly (1998), van Knippenberg et al. (2013)). On the other hand, this allocation may potentially be detrimental to students' knowledge accumulation since students benefit from being grouped with similar peers, according to the findings of Chapter 1. The knowledge students get in their courses is important since they will need it to be able to contribute to their future workplace, and grades are often requested by the employers during the hiring process.[4]

It is up to business schools' administration to determine which goal takes priority. It is also important to note that peer effects do not fully determine a student's grade; they simply may affect it. In the sections that follow, I attempt to find an allocation rule that would incorporate both - peer effects and the considerations of the group.

2.4 Procedure

The necessary condition for the existence of a Pareto-improving allocation is that peer effects are not linear-in-means. Otherwise, shuffling students across units will simply result in the improvement of grades for some at the expense of others. In Chapter 1, I find that peer effects are heterogeneous across a variety of students' characteristics: ability, previous undergraduate degree, gender and immigration status. Since each student possesses more than one of these characteristics and thus may have competing or enhancing peer effects, I estimate the peer effects using a number of relevant cross-terms.

The first step was to get the appropriate coefficients to use in the simulation. To acquire these coefficients, I ran a regression on the written component of managerial finance class grade among the original sample of MBA students. Since the previous paper established the heterogeneous nature of peer effects among MBA students, I specify a regression equation that

[4]According to students, certain employers and industries, such as finance or consulting, will not even consider an application from a student whose grade is lower than a specified cut-off.

accounts for all appropriate cross-terms. It is important to keep in mind, though, that the full set of cross-terms is quite large, and the sample size consists of 611 observations. Thus, to improve the estimation precision, I re-estimate the equation including only the cross-terms that were shown to be important to various groups of students in the previous chapter.

To be precise, I run the following regression:

$$y_i = \alpha_1 + \alpha_2 X_i + \alpha_3 \bar{X}_{-i} + \alpha_3 X_i \times \bar{X}_{-i} + Year \times Section + \epsilon_i \tag{2.1}$$

Where y_i is a grade (written component) 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 for the student's learning team peers, not including the student herself. For example, for a student who has a science degree and is a member of a six-person team that has two other science graduates, the value of the fraction of peers with a STEM degree will be 0.4.[5] In order to control for peers' ability levels, I generate four variables: a fraction of learning team peers in the top 20% of class admission GPA distribution, a 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 the top and bottom 20% of class GMAT distribution.[6] To control for the potential differences across cohorts and instructors, I include $Year\ X\ Section$ fixed effects in the regression.

As discussed above, I also control for a variety of cross-terms to account for the heterogeneous effects of peers on different types of students. I focus on the interactions that have been shown to be significant in predicting grades in the previous chapter. I re-estimate the regression above to account for these cross-terms, collect the coefficients and use them in the simulations below.

I create ten rules motivated by my previous findings and existing program rules. Since students are assigned to teams based on certain observable characteristics, I want to see how modifying these rules might affect the grades.

- Rule 1: The first intuitive way of allocating students is to draw six students for each group randomly. I repeat this exercise 100 times and calculate the statistics described above.

Given that I find heterogeneous peer effects across different types of students, the next

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

[6] Note that the top and bottom 20% for both ability measures are defined on the class level, rather than the overall sample or the percentile results of the GMAT. I.e. given the distribution of the scores in the incoming class, I calculate what fraction of student's learning team peers are in the top or bottom 20%

several ways of team allocation account for these heterogeneities. From chapter 1, I know that students who are assigned to the groups with peers of a similar admission GPA perform better in the Finance class. Thus, I expect that rules that create such groups should create higher average predicted grades. Note that GMAT score and immigration status are correlated with admission GPA. Domestic students tend to have lower admission GPA due to the higher competition among international students and overall selection into the MBA program. It is not clear from the previous findings how the rules based on other characteristics, such as gender or undergraduate degree, would perform. Thus, I test the following group allocation methods:

- Rule 2: Group students by admission GPA, keeping them as homogeneous in terms of GPA as possible.
- Rule 3: Group students by GMAT scores, keeping them as homogeneous in terms of GMAT as possible.
- Rule 4: Group students by gender: separating male and female students.
- Rule 5 and 6: Create heterogeneous teams in terms of admission GPA or GMAT, putting together students with the lowest and highest scores.
- Rule 7: Create groups by undergraduate degree.
- Rule 8: Create groups sorted by immigration status.

Because the number of students in each category is not necessarily divisible by six, there will be one or two mixed groups for each rule, but it should not have a great effect on the average outcome.

The current set of rules that is in place in the program is based on administrators' experience and their goal of "evening out the playing field" for the students and improve students' experience. While it may not explicitly take into consideration the peer effects, there is still merit to how these teams are assigned. The process is done partially by the computer, but partially by hand, with administrators looking over the teams and evening out the number of female students, ensuring that no teams consist of students with the same degrees or only international students. Thus, the next set of rules takes as given the current allocation of students across teams but tweaks it in small ways.

- Rule 9: Switch one randomly selected person in a team for another randomly selected student from a different team. Similar to the random group allocation, but taking existing groups as a base.

- Rule 10: Order teams in terms of average admission GPA. Take the lowest GPA team and the highest GPA team, and switch the second top student in the high GPA team with the bottom student from the low GPA team, repeat with the rest of the teams. This method should result in evening out the average team GPA, again taking the existing groups as a baseline.

2.5 Results and Discussion

Since I have already established the existence of peer effects and showed that these effects are heterogeneous across groups in chapter 1, I was expecting to be able to find students' allocation rules that would improve the finance grades. However, because the effect of any given student is not one-dimensional, finding the best group allocation is not a trivial process. For example, I previously found that peers with STEM degrees may have a negative effect on their peers, but I also found that peers with high admission GPAs may have a positive effect on the grade. So, if a STEM student also has a high admission GPA, that may reduce the negative peer degree effect.

One of the most prominent results in the previous chapter is that students with similar levels of admission GPA benefit from being grouped. So any team allocation that involved splitting students by GPA or by some correlated measure should improve students' grades.

Once again, I compare the grade distributions on two metrics: mean and standard deviation. In Tables 2.4-2.5 I also present the histograms for the visual representation of the grade distribution. Since personal characteristics play the most important role in grade formation, modifying group composition only changes the grade marginally, but it is important to keep in mind that for the given grade distribution change in the mean of 1% constitutes a change statistically significant at 1% significance level. Tables 2.2 and 2.3 present the results of the simulations.

Table 2.2: Predicted grades in Managerial Finance according to the simulated group assignments. Part 1.

			Rule 1		Rule 2		Rule 3		Rule 4	
	Real Avg. Grade	St. Err.	**Random**	St. Err.	**Degree**	St. Err.	**Gender**	St. Err.	**Immig. status**	St. Err.
Commerce	81.5	0.39	81.3	0.15	83.5***	0.14	83.2***	0.14	83.4***	0.15
STEM	79.4	0.36	79.1	0.15	80.3**	0.18	81.1***	0.14	81.8***	0.18
Other	76.2	0.36	76.3	0.31	81.0***	0.37	78.1**	0.28	78.2**	0.31
Male	80.6	0.38	80.3	0.13	82.2***	0.13	82.1***	0.12	82.7***	0.14
Female	78.7	0.38	78.6	0.23	80.9***	0.26	81.1***	0.23	81.0***	0.24
Domestic	80.7	0.39	80.3	0.14	82.2***	0.14	82.2***	0.13	82.2***	0.13
International	78.7	0.35	78.8	0.18	81.0***	0.23	81.0***	0.20	82.3***	0.28
BotGPA	78.3	0.39	78.5	0.24	80.3***	0.29	80.2**	0.22	80.6***	0.24
MedGPA	80.9	0.36	80.2*	0.15	82.2***	0.15	82.1***	0.14	82.2***	0.15
TopGPA	79.7	0.40	80.3	0.26	82.6***	0.27	82.8***	0.23	84.2***	0.28
BotGMAT	78.1	0.41	77.9	0.26	79.9**	0.30	80.2***	0.26	80.3***	0.28
MedGMAT	80.0	0.36	79.9	0.13	82.0***	0.15	81.9***	0.13	82.3***	0.15
TopGMAT	82.0	0.37	81.5	0.23	83.3**	0.24	83.2*	0.22	83.7***	0.24
All	80.1	0.38	80.6	0.12	81.9***	0.12	81.9***	0.11	82.2***	0.12

Stars indicate the statistical significance of differences of the means *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.3: Predicted grades in Managerial Finance according to the simulated group assignments. Part 2.

			Rule 5				Rule 6				Rule 7		Rule 8	
	Real Avg. Grade	St. Err.	**Hom. GPA**	St. Err.	**Het. GPA**	St. Err.	**Hom. GMAT**	St. Err.	**Het. GMAT**	St. Err.	**Switch 1**	St. Err.	**Switch 2**	St. Err.
Commerce	81.5	0.39	84.5***	0.18	82.6***	2.66	82.8***	0.16	83.1***	0.15	82.2*	0.15	81.1	0.14
STEM	79.4	0.36	83.2***	0.24	80.4***	2.30	80.5***	0.15	80.6***	0.14	80.2*	0.15	79.1	0.13
Other	76.2	0.36	79.1***	0.36	77.6	2.58	77.5	0.32	77.7*	0.32	77.1	0.33	76.1	0.28
Male	80.6	0.38	83.9***	0.17	81.6***	2.77	81.7***	0.13	81.9***	0.13	81.3**	0.13	80.2	0.12
Female	78.7	0.38	82.3***	0.30	80.0**	3.07	80.3***	0.28	80.4***	0.24	79.6	0.23	78.6	0.22
Domestic	80.6	0.39	83.3***	0.16	81.7***	3.05	81.7***	0.15	82.0***	0.14	81.2*	0.14	80.1	0.13
International	78.7	0.35	83.8***	0.35	80.0***	2.21	80.3***	0.22	80.4***	0.19	79.8**	0.20	78.9	0.19
BotGPA	78.3	0.39	82.6***	0.27	79.6**	2.81	79.6**	0.24	80.1***	0.26	79.5*	0.25	78.3	0.21
MedGPA	80.9	0.36	82.0***	0.14	81.8***	2.83	81.7**	0.15	82.0***	0.15	81.1	0.15	80.1**	0.14
TopGPA	79.7	0.40	88.3***	0.28	81.0*	2.75	82.1***	0.30	81.8***	0.27	81.5***	0.27	80.4	0.23
BotGMAT	78.1	0.41	81.1***	0.31	79.3*	3.01	78.7	0.26	79.8**	0.27	78.9	0.27	77.3	0.23
MedGMAT	80.0	0.36	83.5***	0.18	81.3***	2.66	82.1***	0.15	81.5***	0.14	80.8**	0.14	80.2	0.13
TopGMAT	82.0	0.37	85.3***	0.32	82.6	2.83	81.6	0.26	83.2*	0.25	82.5	0.23	80.6**	0.21
All	80.1	0.38	**83.4*** **	0.15	81.2***	2.95	81.3***	0.12	81.5***	0.12	80.0	0.13	80.5	0.12

Stars indicate the statistical significance of differences of the means *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Switch 1: Switch lowest with second highest ; Switch 2: Switch random

The first rule - random assignment of students to teams - results in similar grades as the actual sample. However, the average grades of most groups of students decrease - only international students, students with social science and humanities degrees, students in the bottom and top terciles of GPA distributions see an (insignificant) increase in their finance grades. This finding is interesting because it appears that the current rules for group selection are not an improvement on a random assignment of students across teams.

One of the common questions in the economics of education literature is whether or not separating students by ability level helps them achieve better results. On the flip side, does pairing strong and weak students together have the potential to improve weak students' grades while not negatively affecting strong students' outcomes? To address these questions, I test several ability-based group assignments: by admission GPA and by the GMAT scores. First, I created groups that are homogeneous in terms of ability (measured by GPA or GMAT). Second, I created groups where top students were paired with bottom students in such a way that the student with the highest GPA was in the group with the student with the lowest GPA, the student with second-highest GPA was in the team with the student with second-lowest GPA etc.

Separating students by GPA has a positive effect on the finance grades for all students. Students in all GPA terciles see an increase in their grades, with top GPA students benefiting the most (average increase of 9%), followed by the bottom GPA students with a 4% average increase in grades. I have previously shown that students benefit from having peers of similar ability present in their teams. Therefore, this finding is not surprising but important nonetheless. Splitting students into teams by pairing top students with bottoms students also results in a slightly higher average grade. However, the increase is much smaller, and the standard errors are much higher in this scenario. Thus, it appears that splitting students by GPA might be a better way of allocating students across teams.

It is often assumed that GMAT scores are highly correlated with students' GPA. However, in the data used in this paper, this correlation is quite modest at 0.19 (see Table 2.6 for correlations between characteristics). There could be a few reasons for this low correlation. Since students take the GMAT after already realizing their undergraduate GPA, the weaker students may spend more time preparing for the test to improve their chances of getting into a prestigious program. Additionally, students with STEM degrees receive higher GMAT scores. However, students with these backgrounds may come into the program with a lower undergraduate GPA. When it comes to team assignment rules, grouping students by GMAT performs slightly better than the benchmark; however, the average grade of top GMAT students drops. Mixing GMAT scores in the team result in similar outcomes. Thus, the GMAT score is probably not the best tool to take into consideration when assigning students to teams.

Aside from ability, a common question is whether separating students by sex would result in improvement in outcomes. Under the assignment rule by sex, the average grade is increased. In particular, though, female students benefit slightly more than male students from this assignment. In the programs with many international students, it is important to look at the distribution of domestic vs. international students in the groups. When I test the homogeneous assignments by immigration status, I find that again, both types of students benefit from it, but International students see a higher increase in average Managerial Finance grade. Note, however, that there is a positive correlation between the international student status and admission GPA; thus, the gains in the average grade could be attributed to the effects of sorting students by GPA.

So, interestingly, it is the students who may be perceived as vulnerable in a male-dominated, Canadian commerce program benefit from the homogeneous group assignment: female students, international students and lower ability (lower admission GPA) students. In chapter 1, I suggest that students perform better if they are comfortable in their teams, and they may feel more comfortable in teams with similar students. Thus, the results from various homogeneous rules assignments again support the idea that grouping students by certain observable characteristics may be beneficial to them.

For the final group of students' assignment rules, I take the actual teams as given and introduce some minor tweaks. First, I took one random student from each team and placed them in a different team. The results are similar to those from the random student assignment to groups, with a very modest increase of an average grade. The second rule I test uses the following procedure. I order teams in terms of the average student admission GPA. Then, I take the team with the highest average admission GPA and pick the student with the second-highest GPA. I also take the team with the lowest average GPA and pick the student with the lowest admission GPA in that group. Then I switch these students I picked. I want to test if "evening out" the average admission GPA would help all students. However, what I find is that the average finance grade decreases, and interestingly, the bottom admission GPA students now get slightly lower grades. Again, this shows that there might be a benefit in grouping students by ability.

Thus, after performing a number of different simulations, the main conclusion is that grouping students by the ability level (measured by their undergraduate GPA score) might provide the best way of allocating students. This finding echoes conclusions from previous research papers on the subject that also find that allocating similar students to the same groups results in better outcomes (Hoxby (2005), Carrell et al. (2013)).

One note of these findings is that students' grades are bell-curved. Thus, any improvement we see in these simulations would not be translated into an increase in final grades - de facto, the average will always be 80%. However, if we assume that the grades show improvement in

Table 2.4: Histograms of the simulated grades. Blue, thin, solid line - real average. Red, thick, dashed line - average simulated grade

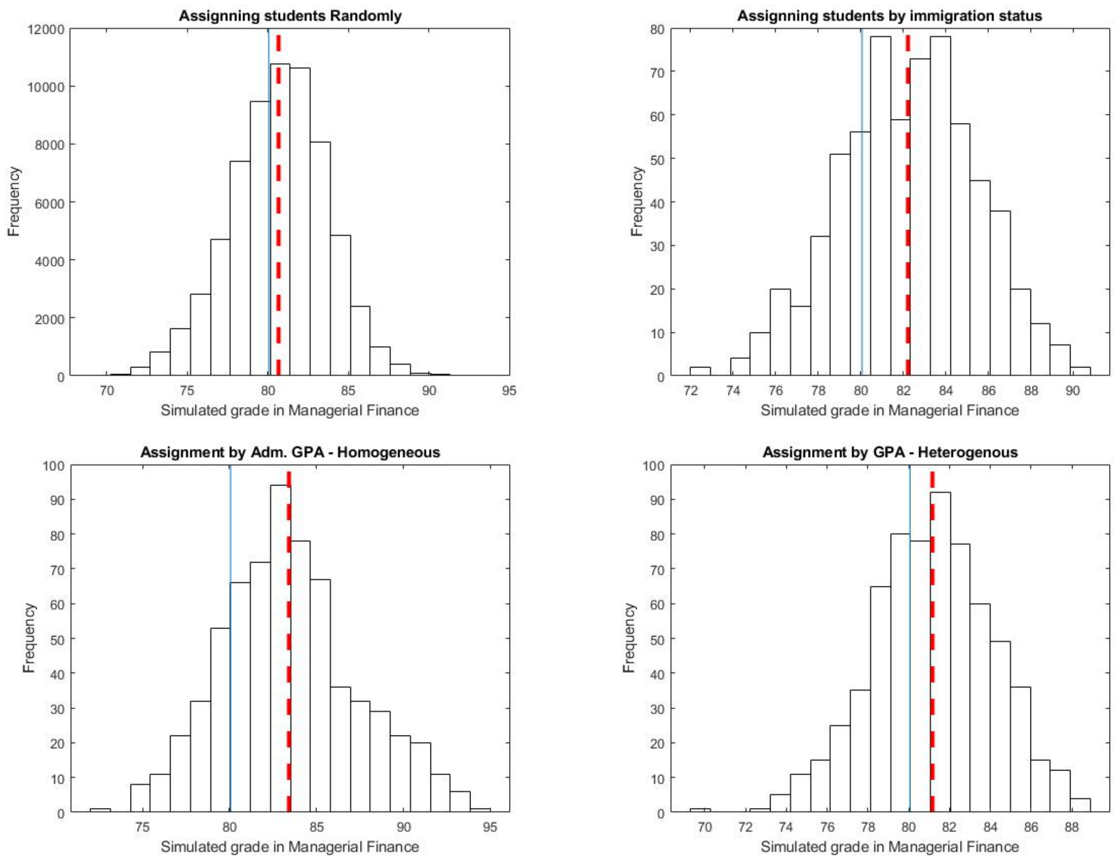
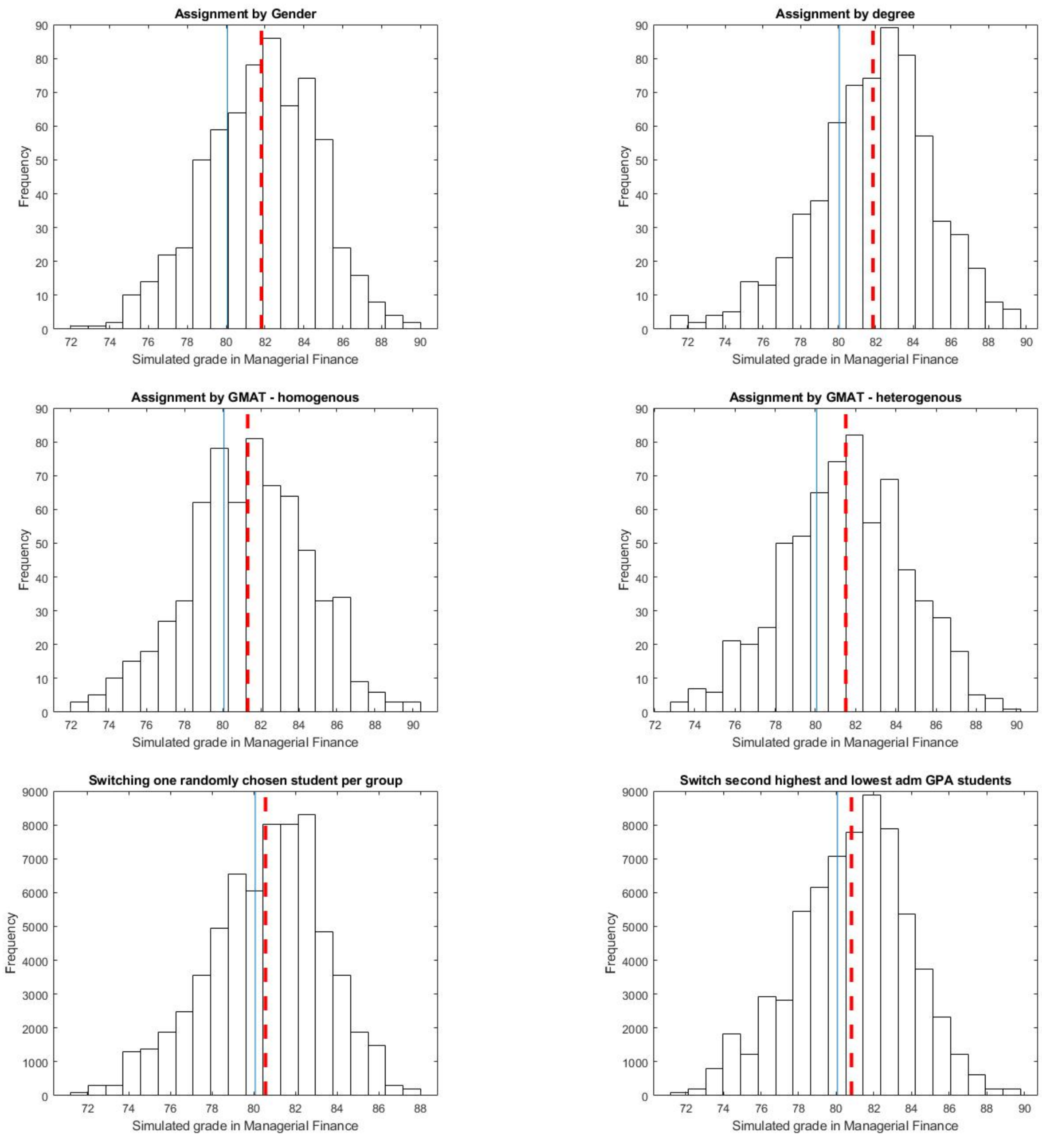


Table 2.5: Histograms of the simulated grades. Blue line - real average. Red line - average simulated grade



knowledge and understanding of the subject, then we can say that shifting to more homogeneous groups may improve students' understanding of the course.

As noted in the introduction, the goal of the MBA program is to prepare students for working in a modern, diverse environment. The focus on diversity is based on the branch of management literature, that finds that diverse teams perform better in the work environment. The program of interest in this paper has certain policies in place that encourage students to learn how to deal with conflict and resolve issues that arise when working in teams. For example, students are not allowed to switch teams. In case of a conflict, they are asked to resolve it, and if there are further issues, to seek council with faculty mentor or administration of the program. It is difficult to estimate the long-term effects of these lessons, and it is possible that those are important for developing students' soft skills. However, again, I argue that students' level of knowledge on the subject is also important in their future careers, and the evidence suggests that peers may have an effect on the level of knowledge (as measured by the simulated grades). Thus, being mindful of how peers affect each other's academic outcomes is crucial in assigning students across teams, and there needs to be a balance between creating a positive academic learning environment and creating opportunities for students to practice their teamwork and conflict resolution skills.

I do foresee that separating students by their GPA or any other characteristic may not be a popular policy among the program administrators, as on the surface, it appears to favour top students. Recall that fairness is the main criterion of any allocation process. However, I suggest that program administration can treat bottom GPA students as another criterion group, making it necessary to group 2 or 3 bottom GPA peers in a group. This assignment process would be similar to what I present above as a "heterogeneous GPA" assignment rule, which still results in higher grades for all students. Thus, the low GPA students will have a "buddy" they can study with, capturing the positive effect of being in a group with similar ability students. At the same time, this will also allow top GPA students to be grouped with similar peers. Another fringe benefit of such allocation will be the likely pairing of top GMAT students with top GPA peers. Recall that top GMAT students have a negative effect on all types of peers, but allocating them to groups with stronger peers will "level the playing field" for the lower ability MBA candidates. Alternatively, or in addition to this, administrators may want to design a workshop, teaching students how to operate in diverse environment, providing them with tools for effective communication. They may focus both on reminding students to be respectful, but also to encourage students to speak up and participate even if they may feel somewhat uncomfortable. This method has the potential to improve the team study process and, as a result, improve all students' performance.

2.6 Conclusion

Allocating students to groups is often done either randomly or according to a set of rules that appear "fair". However, very little is done to confirm that these rules are indeed beneficial to the student or if there is any other way to put students into groups that would result in an enhanced experience. Using a novel dataset from a Canadian MBA program where students are administratively allocated to small teams, I tested a variety of potential allocation rules. I take the coefficients from an OLS regression on the actual finance grades and apply them to the sample of students who have been allocated to teams in new ways. I account for the heterogeneity of peer effects by including several cross-terms in the regression.

While most rules do not result in a significant change of the average Managerial Finance grade, there are some that stand out. Most of all, students benefit from being assigned to the teams with peers of similar ability levels when the ability level is measured by the admission GPA. Interestingly, grouping students by GMAT scores does not result in the same grade improvement. This presents an interesting challenge for future research, as more work needs to be done to pin down the exact mechanism of these peer effects.

I suggest that perhaps the best way to allocate students to teams would be to make sure that there are at least 2-3 students from the bottom 20% of the GPA distribution in a team. This rule would give the bottom GPA students similar peers and simultaneously benefit the top GPA students as well.

2.7 Appendix

Table 2.6: Correlations between personal characteristics

	(1) Admission GPA	(2) GMAT	(3) Female	(4) Domestic Student	(5) Commerce/Econ	(6) STEM
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 STEM	0.08	0.25	-0.22	-0.20	-0.79	1.00

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Chapter 3

Comparison of the Two Methods of Social Network Data Collection

3.1 Introduction

The research on peer effect often requires collecting data on peer groups and social networks. Sometimes, peer groups are exogenously assigned, such as in the MBA program setting used in the previous two chapters. In other cases, a researcher must collect appropriate data describing the social network of the participants, which then can be used to analyze the potential peer effects. There are two main ways of collecting social network data: use of recollection or recognition questions. A recollection question asks participants to list the names of their friends (with or without a limit on the number of friends mentioned). A recognition question asks them to pick names of friends (or colleagues, connections, people they socialize with) from a given list. While in certain situations, a time limit or research ethics concerns dictate the use of one or another question, often a researcher has a choice.

There are some intuitive ways of comparing these two methods; for example, a recognition question is likely to result in more links being mentioned than a recollection question (provided a sufficient roster size), and a recollection question will probably result in less random errors and respondents identifying their "better" friends. [1] Often, the answers of two people responding to the survey do not align: person A may indicate person B as a connection, but person B does not include person A in their response. Researchers usually make one of two assumptions to deal with these discordant answers. Underreporting assumes that respondents may forget the link, but if they do indicate it, then the link is truly there. Overreporting assumes that the respondent may indicate the link that is not truly there, and thus only the links

[1] Because the respondents are actively writing down the names, they are more likely to indicate real links and also are more likely to remember the names of those peers with whom they have a stronger connection.

which are reported by both parties should be included in the network. However, there may be useful information in these discordant answers, and using it may allow us to estimate a correct network.

Researchers pick one method of network data collection over the other largely on an ad hoc basis. This paper, however, provides insight into how these questions compare by directly contrasting the resulting networks, investigating potential sources of reporting errors and by analyzing the discordant answers. In the first part of the paper, I present the description of the network data collected by the recollection and recognition methods among the MBA students. I then perform checks on the accuracy of the data, investigate the sources of potential errors in reporting, and suggest some way of checking the validity of the answers by using other survey questions. In the second part of the paper, I adopt the methodology described in Comola and Fafchamps (2017) and use the discordant answers to estimate the probability of the reporting errors as well as the proportion of true links in the networks. I then use this measure to directly compare the accuracy of the network data collected by each of the two questions.

3.2 Literature Review

3.2.1 Network data collection methods

To my knowledge, no paper in the economics literature performs a direct comparison of recollection and recognition questions, and there is a limited number of research papers in sociology that look at these two methods. Most of the sociology literature on comparing the recall and recognition methods of social network data collection focuses on documenting the resulting networks' differences. A related branch of literature investigates the problem of "forgetting" some of the ties when using the recall method. It uses recognition as a tool to check how many peers were forgotten, under the assumption that recognition question results in a correct network. Brewer (2000) provides a good survey of papers on the subject, focusing mostly on the issue of forgetting. However, since it is closely related to the measurement issue, a few papers in his review apply to the broader question of network measurement. He concludes that forgetting of peers in a free recall question provides a significant source of measurement error.

Hlebec (1993) runs an experiment among 12 members and advisors of the University of Ljubljana's student government. She collects the social network data during an interview by asking students to name peers they talk to most often, go to for advice and who comes to them for advice. Then she presented participants with a roster and asked them to answer the same questions but now picking peers from a list. She compared the results according to the size of the network and the stability of naming. She showed that both methods result in a similar network, but the recognition question gives a larger number of ties for the question "whom do you talk to most often". Brewer and Webster (1999), in their study of 127 students in a residence of an Australian university, first ask students to name peers they talk to and then to ask them to pick names from a roster. They compare the responses and find that students forget to name 20% of their peers on average. Ferligoj and Hlebec (1999) evaluate ways of collecting data on a social support network. Their study collected social support relationship data among third-year students in a high school in Ljubljana using recognition and recollection questions. In the recognition question, respondents were presented with a list of all students and were asked to indicate their connections and estimate the strength of each link. In the recollection question, respondents were asked to name their friends. The results show that the recognition question resulted in a higher number and weaker ties than the recollection question.

There is very little research that focuses on comparing these methods in terms of the resulting network's accuracy. Brewer (2000) quotes two of these. Bernard et al. (1982) take the records of e-mail messages between 57 scientists. The participants were interviewed periodically over five months and asked with whom they correspond via e-mail. Their responses were compared to the e-mail records, and the authors found that 66% of communications were forgotten. In a different study, Freeman et al. (1987) observed university seminar series participants. When these participants were asked to name who was present at a colloquium a few days after each session, many were forgotten (exact number not specified). Both of these studies ask respondents to recall potentially minor interactions that occurred over a considerable time. The prevalence of forgotten links is not surprising in this case.

To sum up, the sociology literature concludes that any social network data collection method will result in a flawed network. However, it is interesting to quantify the errors in these networks and use that measure to compare the two ways of network data collection.

3.2.2 Missing links and discordant answers

While in some cases it may be enough to have knowledge of the characteristics of a subset of person's peers, in other situations, the knowledge of true network is important. For example, Conley, Mehta, Stinebrickner, and Stinebrickner (2018) show that students may be affected by peers who they are not directly connected to, highlighting the importance of understanding of social networks for peer effects research. The standard approach to the network data analysis in the literature is to use either the report of the link by one of the people or by a combination of the two reports (Conley and Udry (2010), Stinebrickner et al. (2010)). Depending on the nature of the social network, researchers may use the maximum or the minimum report. There is usually a non-trivial proportion of discordant answers when one respondent reports a link while their counterpart does not (Fafchamps and Lund; Bramoulle et al. 2009). For example, in the dataset studied in this paper, the proportion of the discordant links varies depending on the survey question, but, on average, around 60% of the reported links are discordant. While researchers incorporate the discordant answers in their analysis by making certain assumptions, the fact that the answers are discordant is usually not used. Comola and Fafchamps (2017) propose an estimator that takes into account the discordant answers, which I discuss in more detail in the later section. Using the data on gifts given and received in rural Tanzania, they suggest that the network generated using the maximum report method only captures two-thirds of the existing links. In this paper, I use the Comola and Fafchamps procedure and calculate the probabilities of the "true" links existing between the MBA students. Since I have two ways of measuring the social network (recall and recognition), I can compare the accuracy of the network data collected via these two methods. The proportion of forgotten links for each social network data collection method provides an additional measure by which I can compare them.

3.3 Basic statistics of the survey responses

The data used in this research comes from the MBA program at a Canadian university.[2] Each year, the program admits approximately 100 students, and the class is divided into two sections. Usually, the instructors teaching the sections are different, but the courses, curriculum and material covered are the same. Students in each section are divided into learning teams: small groups used for preparing for classes, group assignments and occasional in-class work. Learning teams switch three times in one year. Students are assigned to these teams based on their observable characteristics: gender, previous degree, immigration status and admission GPA. The strongest criterion is gender: teams have either two women or none. There is variation across teams for other criteria. Most students starting the MBA program are not familiar with each other: they come from different countries, universities and professional backgrounds. The MBA program is time-intensive and is separated from other graduate programs (both in terms of a campus location and general set up). Thus, students form new links and mainly with each other when they enrol in the program.

I begin by summarizing the basic statistics of the survey responses. Over three years, 376 students were enrolled in the program and 276 completed the survey. One of the main issues for collecting the social network data was obtaining the ethics board's permission to include students' roster into the survey for the recognition question. Since I were not permitted to include the full list of enrolled students to maintain their privacy, only the names of those who

[2]Chapter 1 and Chapter 2 describe the data in more detail

gave their permission were listed. Out of 376 students, 284 gave their permission to include their names on the list. Most of those were the students who agreed to fill out the survey. However, some did not participate in the survey but allowed us to include their names. There were also cases where students decided to participate in the survey at the last moment, and thus their name was not included in the roster, but they filled out a survey. Table 3.1 summarizes the basic statistics of the survey responses.

Table 3.1: Basic statistics of the respondents

	2014	2015	2016
Total number of students enrolled	103	130	143
Number of students responded to the survey	78	98	100
Number of students included in the roster	80	97	107

Table 3.2 summarizes the number of peers named or picked for the two types of questions. Note that in 2014 the roster of students for the recognition question only included students from the same section (i.e. students in section 1 only had students from section 1 in their recognition question roster), thus limiting respondents in the number of possible reported links. The recognition question consisted of three parts and asked students to identify peers they talked to, whom they go to for school-related advice, and those they socialize with. I include the survey in the appendix. The recollection question asked students to name up to 7 friends.

For the recollection question, most students named seven friends, filling all the possible slots. While it could indicate that perhaps students should have been asked to name more than seven friends, I saw that survey respondents were making an effort to fill out all seven names during classroom observations. Some continued with the survey and then came back to complete the list. By construction, the recollection question results in a more sparse network and a lower number of connections. However, the recollection question may result in respondents mentioning the links that are "stronger" because students may be more likely to recall their closer friends first. This could be useful, depending on the research question at hand.

The highest number of links was found for the "talk to" recognition question. This was expected since this is the weakest of all conditions. If I look at the intersection of all three recognition questions, I see that the number of peers mentioned across all three categories is around 5-6. Given that those are likely to be students' closest connections in the class (they talk to, socialize with and go for the school advice to these people), it again supports the idea that limiting the number of friends to 7 in the recall question is a reasonable assumption.

Students may differ in the way they answer the social network questions on the survey. To see whether there are any apparent differences across different types of students, Tables 3.3-3.5 summarize the number of peers picked for recollection and recognition questions based

Table 3.2: Average number of peers picked

	2014	2015	2016
Recollection	5.75	6.34	6.21
Recognition – Talk	26.30	45.07	40.54
Recognition – School Advice	7.62	8.80	10.67
Recognition – Socialize	13.72	27.57	21.20
Recognition – Talk, School and Socialize	4.86	5.82	5.58

on the students' characteristics: gender, previous degree and immigration status. There are no significant differences across the students' responses. Some interesting stylized facts that emerge are that commerce students seem to be less likely to go to someone for school-related advice - which could be expected, given that they are probably most familiar with the program as is. Domestic students may be connected to more peers (they talk to more students in general, and they socialize more as well) than international students. Results vary somewhat from year to year. Again, recall that in 2014 a lower number of students were available in the roster for the recognition question.

Table 3.3: Number of indicated peers by respondent type - 2014

	Women	Men	Commerce	STEM	Other	CAN	Imm
Recollection	6.94	6.80	6.60	6.79	7.00	6.85	6.78
Recognition – Talk	27.77	27.80	31.60	26.21	28.17	28.54	23.44
Recognition – School Advice	9.41	7.32	5.90	7.66	9.14	7.50	10.22
Recognition - Socialize	14.29	15.27	14.70	15.03	15.10	14.90	15.56
Recognition – Talk, School and Socialize	6.59	5.05	4.60	5.07	6.41	5.33	6.33

Table 3.4: Number of indicated peers by respondent type - 2015

	Women	Men	Commerce	STEM	Other	CAN	Imm
Recollection	6.42	6.29	6.42	6.09	6.92	6.50	6.20
Recognition – Talk	45.77	44.52	44.14	44.00	50.582	51.24	39.67
Recognition – School Advice	8.42	9.05	9.14	9.26	7.17	8.63	9.04
Recognition - Socialize	22.19	30.10	24.47	28.49	36.17	33.66	22.70
Recognition – Talk, School and Socialize	5.27	6.10	6.69	5.43	4.67	6.74	5.11

3.4 Characteristics of picked peers

It is often hypothesized that people form links with those similar to them: in demographic characteristics, background, interests, etc. Table 3.6-3.8 show the average proportions of friends of

Table 3.5: Number of indicated peers by respondent type - 2016

	Women	Men	Commerce	STEM	Other	CAN	Imm
Recollection	6.41	6.15	6.22	6.21	6.20	6.02	6.62
Recognition – Talk	38.91	41.07	38.95	40.32	45.07	40.41	40.83
Recognition – School Advice	9.64	11.00	8.95	10.68	14.87	10.67	10.66
Recognition - Socialize	20.23	21.51	20.89	17.68	30.87	23.67	16.00
Rec.– Talk, School and Socialize	4.45	5.94	4.46	5.26	9.13	6.57	3.48

different characteristics for each type of student to perform a basic check of this hypothesis. The statistics are based on the recollection question, where I asked students to name up to 7 friends. Overall, it appears that students tend to be friends with peers of similar educational backgrounds, gender and immigration status. For example, in 2014, on average, 50% of female students' friends were also female while only 22% of male students' friends were female; 43% of friends of students from Commerce/Economics background had the same type of degree; and domestic students had mainly Canadian friends - 95% of the total number of friends.

Table 3.6: Avg. proportion of different friend types by respondent characteristics (based on recollection question) 2014

	Female friends	Commerce degree friends	STEM friends	Canadian friends
Men	0.22	0.22	0.49	0.91
Women	0.50	0.21	0.41	0.86
Commerce	0.31	0.43	0.43	0.88
STEM	0.28	0.21	0.56	0.94
Other	0.32	0.13	0.36	0.84
Canadian	0.31	0.23	0.48	0.95
Int student	0.27	0.16	0.37	0.61

Table 3.7: Avg. proportion of different friend types by respondent characteristics (based on recollection question) 2015

	Female friends	Commerce degree friends	STEM friends	Canadian friends
Men	0.18	0.40	0.33	0.44
Women	0.46	0.34	0.34	0.40
Commerce	0.27	0.36	0.29	0.47
STEM	0.27	0.36	0.40	0.38
Other	0.26	0.49	0.31	0.49
Canadian	0.28	0.44	0.29	0.61
Int student	0.26	0.33	0.37	0.28

Table 3.8: Avg. proportion of different friend types by respondent characteristics (based on recollection question) 2016

	Female friends	Commerce degree friends	STEM friends	Canadian friends
Men	0.14	0.39	0.35	0.68
Women	0.38	0.39	0.30	0.65
Commerce	0.21	0.43	0.26	0.69
STEM	0.19	0.34	0.42	0.59
Other	0.18	0.41	0.32	0.81
Canadian	0.21	0.43	0.31	0.76
Int student	0.18	0.31	0.40	0.47

3.5 Intersections of different peer types

Given my dataset, I can look at the intersections of various networks. Some of these networks are established by students, and I can measure them via survey. However, the learning team membership is defined by the administration, and since students are required to work with their teams on projects, sit next to each other in class and are encouraged to study together, I have a reason to believe that the students assigned to the same team are connected.

There are two ways that I can check the validity of the network that results from the recognition question. First, learning team members are likely to talk to each other. Therefore, conditional on teammates being a part of the roster, a student should indicate a connection with them for at least the "talked to them" category. Second, since the recollection question asks to name friends, students should also pick the same students from the list (conditional on their name being included), at least for the "talked to" and/or "socialize with" questions.

The results show that most students do say that they talk to all or at least some of their learning team peers. But, learning teammates are rarely named as friends. This is not very surprising since it is likely that friendships form not simply "by proximity" but due to some other factors and characteristics.

3.5.1 All peers

I first look at the intersection of different networks for all students. Specifically, I look at how many of their learning team peers respondents also pick for the "talk to" question. Figure 3.1 shows the histogram of the results. I also see how many peers that the respondent named as friends in a recollection question they talk to (according to the recognition question). Figure 3.2 shows the results of this intersection. Figures 3.3 through 3.7 show the intersections of various networks. While there is a definite spike at 100% for the intersections between various network

Figure 3.1: Fraction of Learning Team peers respondent also picked in "talk to" recognition question

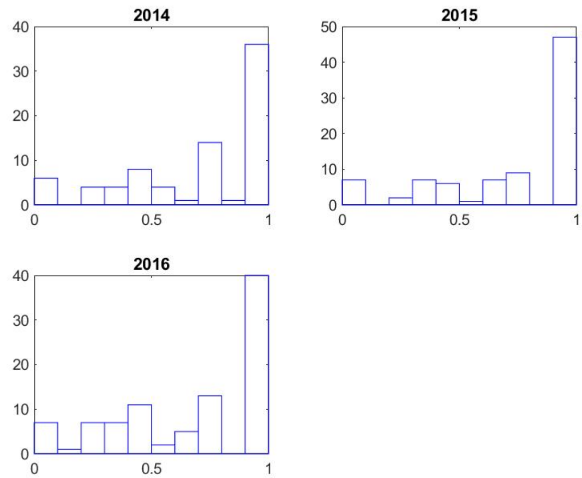
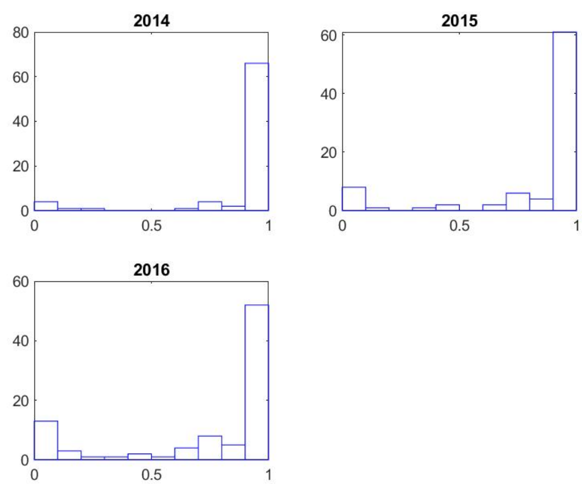


Figure 3.2: Fraction of peers respondent named in recollection question and picked in "talk to" recognition question



questions in the survey – which I expected – there is still variation. Of particular interest are values of zero – meaning that a student indicated the link for one type of network and not another. However, I expect that if students socialize, they are probably talking to each other; if they are friends, then they socialize or at least talk. Thus, the values of zero are potential errors and require further investigation.

When it comes to asking for school-related advice, I think that this link does not necessarily indicate friendship or socializing. People may ask each other for help in class and not often talk outside of that interaction. Thus, I omit this type of network for the rest of the paper.

Figure 3.3: Fraction of peers respondent named in recollection question who are also in his Learning Team

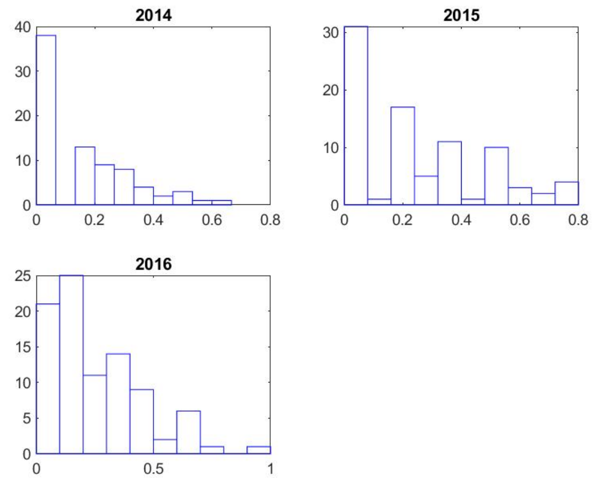
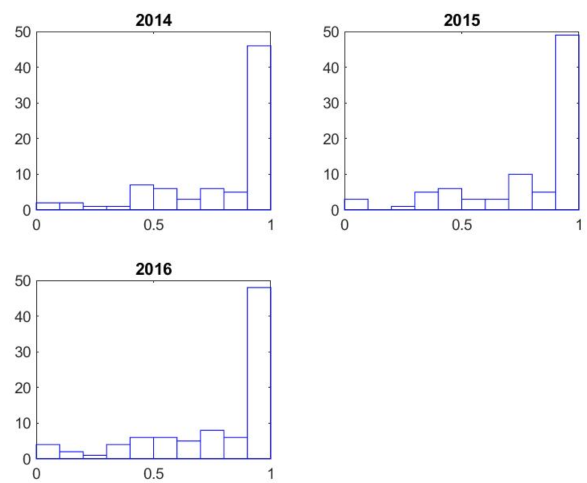


Figure 3.4: Fraction of peers respondent named in recollection question and picked in "socialize with" recognition question



3.5.2 Symmetric links

Not all friends named in the recollection question may be equally close, and not all people communicate with their friends with the same frequency and intensity. This section shows the proportion of "forgotten" links when I limit the adjacency matrix for recollection question to symmetric links only. Limiting the students' friends to only those who named them as a friend should provide us with stronger links and result in fewer errors.

Figures 3.8 and 3.9 illustrate the results of this exercise. They show an improvement in the quality of the responses, with the vast majority of students reporting talking or socializing with

Figure 3.5: Fraction of peers respondent picked in "talk to" and "socialize with" recognition questions

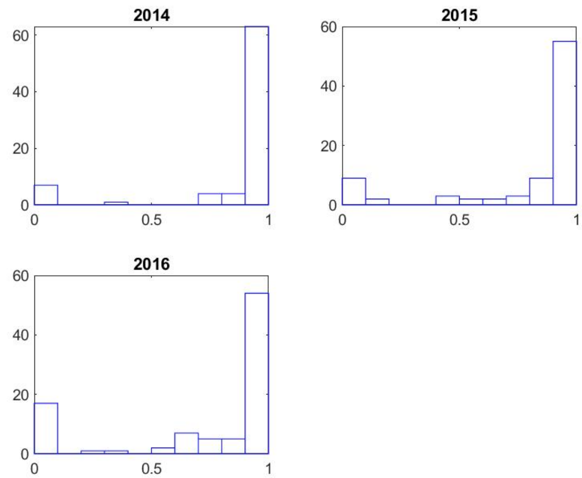
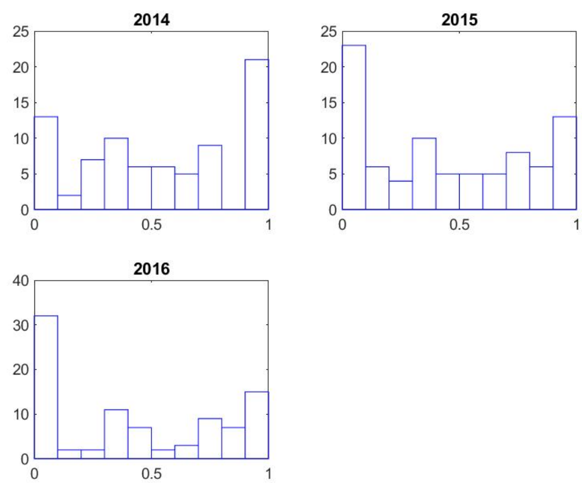


Figure 3.6: Intersection of recollection and all three recognition questions



the peers they named in the recollection question. However, discrepancies still exist.

3.5.3 Top three friends

Finally, most students filled out the recollection question with exactly seven names. It appears that either the respondents interpreted the mention of number seven as a requirement or that students have more than seven friends. Thus, asking them to name only seven was binding[3].

[3]From observing the students during survey completion, it appears that the first option is likely correct. Students filled out a few names and then took some time to remember more and complete the answer to the recollection question.

Figure 3.7: Intersection of recollection and two recognition questions (“talk to” and “socialize with”)

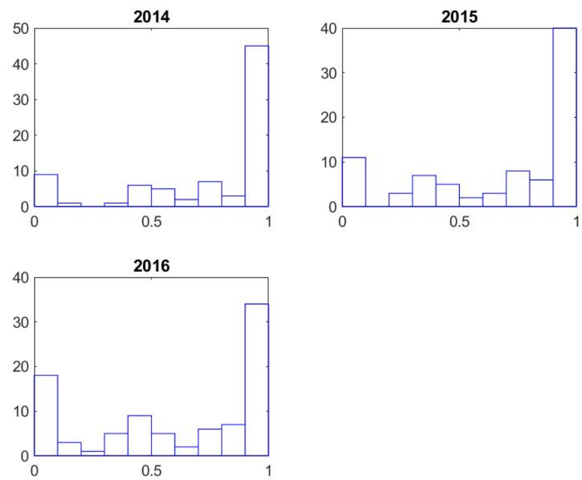
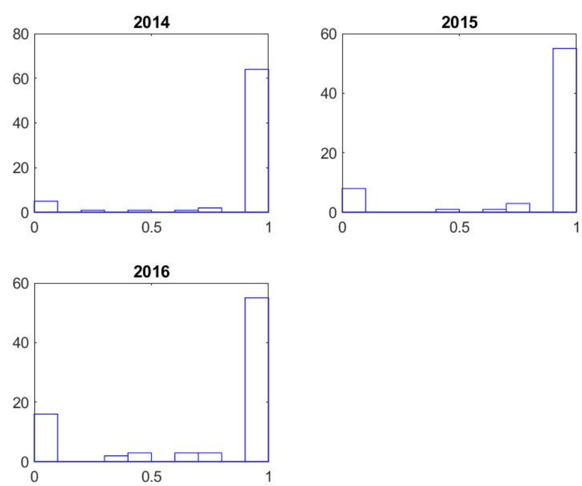


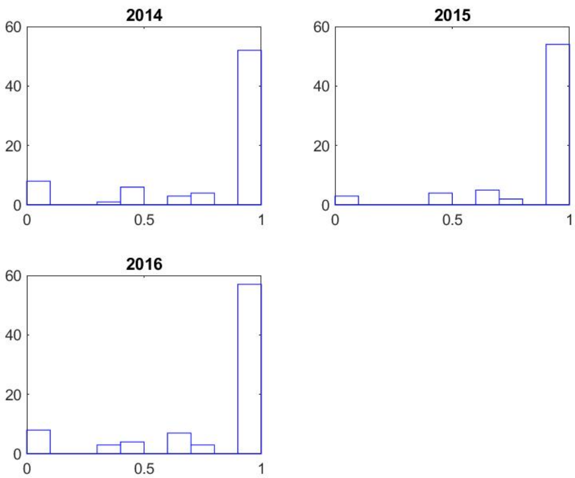
Figure 3.8: Fraction of peers respondent named in recollection question and picked in “talk to” recognition question (limited to symmetric links)



One option to strengthen the network is to limit the adjacency matrix for the recollection question to the top 3 friends. In this case, the assumption is that students first remember the closest peers, the ones they talk and socialize with most frequently.

Figures 3.10 and 3.11 show the proportion of peers that respondents named in the recollection question and talk to or socialize with. Similar to the previous exercise, there is a clear improvement in the results. Indeed, in 2014, a few students reported no intersections between those they consider friends and those they talk to, but the rest of the respondents say that they talk to all of their top three friends.

Figure 3.9: Fraction of peers respondent named in recollection question and “socialize with” recognition question (limited to symmetric links)



The observed misalignments are likely due to the reporting errors, and neither of the intuitive ways eliminates them. The following section investigates the potential sources of the errors and provides some potential ways of improving the results.

Figure 3.10: Fraction of peers respondent named in recollection question and picked in “talk to” recognition question (limited to top 3 friends)

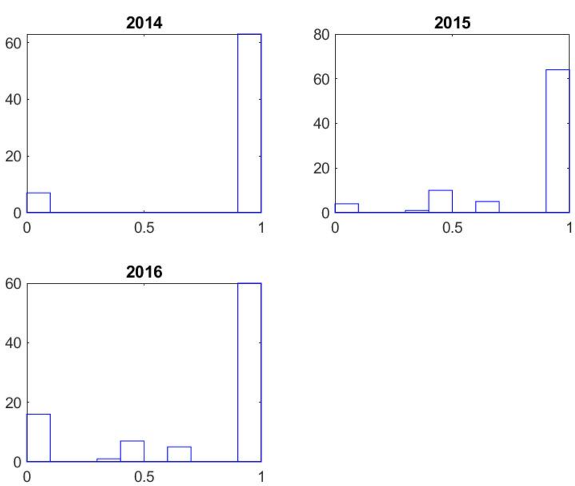
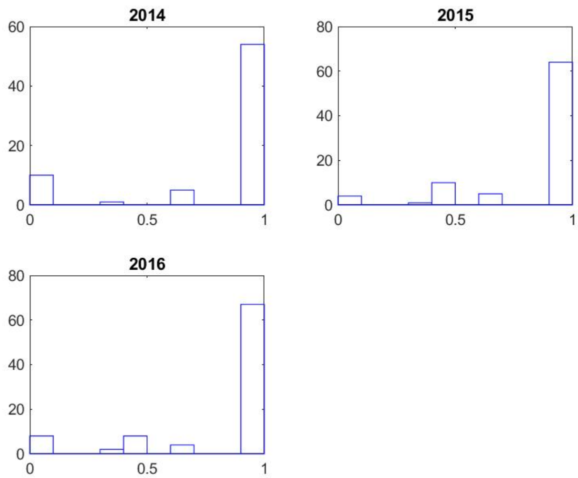


Figure 3.11: Fraction of peers respondent named in recollection question and "socialize with" recognition question (limited to top 3 friends)



3.6 Investigation of possible error sources

Even after limiting the adjacency matrices to include only the top-ranked or mutual connection friends, some respondents "forget" to indicate the connections [4]. Some of the possible reasons behind the missing connections are careless survey completion, misunderstanding of the survey instructions or random errors

The first type of error can potentially be uncovered and corrected by looking at students' responses to other survey questions. To investigate the potential reasons for the missed connections, I performed the following exercise. I looked specifically at the intersection of students named in the recollection question and those picked from the list for the "talk" question. I assume that if a respondent considers someone to be a friend, they probably talk to each other regularly. In particular, I focused on zeros: cases where none of the friends named in the recollection question were picked from the list for the recognition question, even though they were included in the roster.

Some of the potential indicators for the careless survey completion that I discovered are as follows:

- Low number of friends named or picked from the list.
- Very low or very high estimated hours spent studying with the learning team or alone.
- Answers of "zero" for a few of the questions.

[4] It is unlikely that students omit names of friends on purpose – the survey is anonymous, and they do not gain or lose anything from naming or not naming any given peer. Thus, I assume that there is no "strategic" reason for forgetting a link.

- Repetitive numbers, for example: "Study with the team: 3 hours", "Study alone" 3 hours, "Study with the team for all classes" 3 hours, "Study alone for all classes" 3 hours.

- In some cases, the number of hours studied for a previous degree seemed unusually low (2-5 hours a week).

One thing to note is that in 2015 and 2016, the survey was longer than in 2014. First, demographic questions were added to the survey and second, the roster included participants from both sections as opposed to the respondent's section only in 2014. The length of the survey could have contributed to the high number of zeros in 2015 and 2016.

After looking at the answers, the best potential ways to prevent the errors are to exclude respondents who name or pick a very low number of peers and carefully examine those who tend to respond with the same number to the study hours questions. Those who write down an unusually high or unusually low number of hours studied should also be considered potential error sources. Limiting the length of the survey may provide more accurate results. Unfortunately, due to the low sample size of these erroneous entries, I cannot conduct a more in-depth analysis.

Another error source could be a misunderstanding of the question (either due to an honest miscommunication or lack of attention and general carelessness). During the survey delivery process, a few students asked whether they could pick the same person for all three of the recognition questions' columns. In this case, the researchers would answer the student's question and announce to the rest of the students that they can pick the same person in more than one category. However, it is possible that some respondents did not pay attention to the announcement or left before the researchers made the announcement. So, another way to check for errors is to see whether there is an intersection between the list of peers students picked in part A of the recognition question ("pick peers you talked to") and part C of the recognition question ("pick peers you socialize with"). Part B's answer was omitted because it asked for peers the respondent goes to for school advice. Students do not need to socialize with peers who help them with school, and they may not have regular communication with these peers either. However, it is expected that if two students socialize outside of the classroom, they probably are also talking to each other quite often. To make this assumption as conservative as possible, I focus on the students who did not have any intersection between the responses to these two parts of the question.

The results are quite interesting. In 2014, all four participants who did not indicate that they talked to any of the peers they named as friends also had a zero intersection between parts A and C of the recognition question. At the same time, they did pick names out of the list for all three parts of the question. That is, while they picked names for each of the lists, they seem to have avoided picking the same name for more than one column. Four out of 8 respondents in 2015 and 10 out of 13 in 2016 had zero intersection between named friends and peers they talk to and peers they talk to and socialize with. It appears that limiting my analysis to only students who have reasonable intersections between parts A and C of the recognition question would eliminate most of the reporting errors. It seems that the errors occur partly due to a misunderstanding of the instructions and partially due to carelessness. The tables in the appendix (Tables 3.11-3.16) illustrate the error sources. It may be a reasonable assumption that students who made this error are linked to all of the peers they indicated, but the true nature of the link is now muddled (for example, if they picked someone with whom they socialize but do not talk to, what does that mean?).

Overall, the comparison of the two survey data collection methods shows that the resulting network from either of the questions may have flaws and errors. In the recollection question, the limit of the potential responses may limit the size of the network. The recognition questions are prone to the "forgetting" the links issue. This is true even if I restrict my analysis to only the top three named friends or only symmetric links. However, the inclusion of an additional recognition question may provide a checking tool. By looking at the intersection of the responses, I may establish which students did not understand the question correctly or perhaps were careless in the survey completion. Cross-validation using different questions aimed at the same subject is a common way of checking the survey results in psychology. Adding just one more field for the recognition question may provide such a validation mechanism and should not be too costly in terms of the time spent on the survey. Ensuring the participants understand the instructions is also important.

The survey for this study has been done on paper, and it was difficult to customize to a particular respondent. However, in many other situations, an online format may be used. In this case, it may be possible to create checks by giving additional questions to some fraction of the respondents. This check may be implemented randomly or based on the provided answers to the earlier questions. In the discussion above, I mentioned some potential indicators of careless survey completion or errors, mainly based on the survey's other responses. In the section below, I discuss discordant answers and estimate the probability of forgetting an existing link depending on personal characteristics. This probability also may help us "flag" respondents who are more likely to make mistakes or more likely to forget the links, and thus should be subject to additional questions.

3.7 Discordant responses analysis

One of the common assumptions in social network data collection is that if one of the respondents reported a link, but the other did not, then a link exists - i.e. the assumption of underreporting.[5] Under this assumption, if person j reported the link, but the person i did not, that means that person i forgot about (or chose not to report) this connection. Then, by looking at the connections where a person i has reported the link ij and the ones where person i did not report the link ij, but person j did, I can estimate the probability of person i forgot the link conditional on his or her characteristics. I can also estimate the probability of the true link existing between any i and j. I estimate these probabilities using the method used in Comola and Fafchamps (2017). The probability of forgetting the links could serve as one of the metrics by which I can compare the two social network data collection methods. Depending on the intended purpose of using the network data, a researcher can then decide which approach results in the network that would be more aligned with the research question requirements.

3.7.1 Estimation

To estimate the effect of the discordant links on the reported social network, I use the method described by Comola and Fafchamps (2017). Suppose that the true link between students is given by τ_{ij}. My objective then is to estimate the following regression:

$$Pr(\tau_{ij} = 1) = \lambda(\beta_\tau X^{ij}) \tag{3.1}$$

Where X^{ij} is the vector of joint characteristics of students i and j and λ is the logit function. Suppose that the reports of the links are represented by the adjacency matrix R, where R_i^{ij} is a report of person i of the link ij, and R_j^{ij} is the report of person j of the same link. For readability, I will denote these as R_i and R_j. In theory, if $\tau_{ij} = 1$, I should observe $R_i = R_j = 1$. However, in reality, the reports of the links often do not match, and discordant answers are common. The data generation process then is:

[5] The overreporting assumption is less common but could be applicable in certain situations. Under the overreporting assumption, I assume that a link does not exist unless both respondents report it.

$$\begin{aligned}
Pr(R_i = 1, R_j = 1) = & \quad Pr(\tau = 1, R_i = 1, R_j = 1) + Pr(\tau = 0, R_i = 1, R_j = 1) \\
= & \quad Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|R_i = 1, \tau = 1) \\
& +Pr(\tau = 0) * Pr(R_i = 1|\tau = 0) * Pr(R_j = 1|R_i = 1, \tau = 0)
\end{aligned}$$

$$\begin{aligned}
Pr(R_i = 0, R_j = 1) = & \quad Pr(\tau = 1, R_i = 0, R_j = 1) + Pr(\tau = 0, R_i = 0, R_j = 1) \\
= & \quad Pr(\tau = 1) * Pr(R_i = 0|\tau = 1) * Pr(R_j = 1|R_i = 0, \tau = 1) \\
& +Pr(\tau = 0) * Pr(R_i = 0|\tau = 0) * Pr(R_j = 1|R_i = 0, \tau = 0)
\end{aligned}$$

$$\begin{aligned}
Pr(R_i = 1, R_j = 0) = & \quad Pr(\tau = 1, R_i = 1, R_j = 0) + Pr(\tau = 0, R_i = 1, R_j = 0) \\
= & \quad Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 0|R_i = 1, \tau = 1) \\
& +Pr(\tau = 0) * Pr(R_i = 1|\tau = 0) * Pr(R_j = 0|R_i = 1, \tau = 0)
\end{aligned}$$

$$Pr(R_i = 0, R_j = 0) = \quad 1 - Pr(R_i = 1, R_j = 1) - Pr(R_i = 0, R_j = 1) - Pr(R_i = 1, R_j = 0)$$

The above system of four equations has seven unknowns. Thus, to perform the estimations, I make the following simplifying assumptions.

Assumption 1: under-reporting. For simplicity I assume that the students report only the links that are truly there. I.e. $Pr(R = 1|\tau = 0) = 0$. Depending on the context of the social network this assumption may be more or less reasonable. For the network of students who explicitly named their friends (recollection question in the survey), this assumption is likely true. It is likely that students only write down the names of those students who they are indeed connected to. On the other hand, the assumption of under-reporting may be stronger for the recognition question. It is possible that students erroneously check the boxes across the names of the students they do not really talk to or socialize with.[6] Under the under-reporting assumption it is possible that the respondents report no link while the link is truly there. I now re-write the data generating process as follows:

[6] I am working on exploring the implications of modifying this assumption to assume some probability of a mistake, i.e. a probability that a respondent erroneously indicated someone as a friend even though they are not.

$$\begin{aligned}Pr(R_i = 1, R_j = 1) &= Pr(\tau = 1, R_i = 1, R_j = 1)\\ &= Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|R_i = 1, \tau = 1)\end{aligned}$$

$$\begin{aligned}Pr(R_i = 0, R_j = 1) &= Pr(\tau = 1, R_i = 0, R_j = 1)\\ &= Pr(\tau = 1) * Pr(R_i = 0|\tau = 1) * Pr(R_j = 1|R_i = 0, \tau = 1)\end{aligned}$$

$$\begin{aligned}Pr(R_i = 1, R_j = 0) &= Pr(\tau = 1, R_i = 1, R_j = 0)\\ &= Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 0|R_i = 1, \tau = 1)\end{aligned}$$

$$\begin{aligned}Pr(R_i = 0, R_j = 0) = 1 &- Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|R_i = 1, \tau = 1)\\ &- Pr(\tau = 1) * Pr(R_i = 0|\tau = 1) * Pr(R_j = 1|R_i = 0, \tau = 1)\\ &- Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 0|R_i = 1, \tau = 1)\end{aligned}$$

Assumption 2: Reports made by person i and person j are independent of each other. Comola and Fafchamps (2017) in their paper formally show why imposing assumptions about the correlation between reports is necessary. In short, without imposing this type of assumption, the system of equations above is not identified. While it is possible to assume some correlation across the responses, I believe that the assumption of independence is most reasonable in the case of MBA data used in this paper and makes for the easiest estimation. First, there is no reason or possibility for students to collude in their answers to the survey question. That is, if person i named person j as a friend, it should not affect the probability of person j to name person i as a friend. In addition, students were supervised while completing their surveys and thus they would not be able to know who named them as a friend. Thus, I can rewrite the above system of equations as follows:

$$\begin{aligned}Pr(R_i = 1, R_j = 1) &= Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|\tau = 1)\\ Pr(R_i = 0, R_j = 1) &= Pr(\tau = 1) * Pr(R_i = 0|\tau = 1) * Pr(R_j = 1|\tau = 1)\\ Pr(R_i = 1, R_j = 0) &= Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 0|\tau = 1)\\ Pr(R_i = 0, R_j = 0) &= 1 - Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|\tau = 1)\\ &\quad - Pr(\tau = 1) * Pr(R_i = 0|\tau = 1) * Pr(R_j = 1|\tau = 1)\\ &\quad - Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 0|\tau = 1)\end{aligned}$$

I can represent the above system of equations in terms of three unknown probabilities, $Pr(\tau = 1)$, $Pr(R_i = 1|\tau = 1)$ and $Pr(R_j = 1|\tau = 1)$:

$$Pr(R_i = 1, R_j = 1) = Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|\tau = 1) \tag{3.2}$$

$$Pr(R_i = 0, R_j = 1) = Pr(\tau = 1) * (1 - Pr(R_i = 1|\tau = 1)) * Pr(R_j = 1|\tau = 1) \tag{3.3}$$

$$Pr(R_i = 1, R_j = 0) = Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * (1 - Pr(R_j = 1|\tau = 1)) \tag{3.4}$$

$$\begin{aligned} Pr(R_i = 0, R_j = 0) = 1 &- Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|\tau = 1) \\ &- Pr(\tau = 1) * (1 - Pr(R_i = 1|\tau = 1)) * Pr(R_j = 1|\tau = 1) \\ &- Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * (1 - Pr(R_j = 1|\tau = 1)) \end{aligned} \tag{3.5}$$

I assume that the probabilities $Pr(\tau = 1)$, $Pr(R_i = 1|\tau = 1)$ and $Pr(R_j = 1|\tau = 1)$ can be represented as the logit functions of the following forms:

$$Pr(\tau = 1) = \lambda(\beta_\tau X^{ij}) \tag{3.6}$$

$$Pr(R_i = 1|\tau = 1) = \lambda(\beta X^i) \tag{3.7}$$

$$Pr(R_j = 1|\tau = 1) = \lambda(\beta X^j) \tag{3.8}$$

In contrast with the data used by Comola and Fafchamps (givers and receivers of transfers in rural Tanzania), the students in the MBA social network data do not have distinct roles. I.e. students i and j are equivalent conditional on their characteristics and none of them have strategic or other reasons to report or withhold information on certain links. Thus, I expect the coefficients β from the estimation of $Pr(R_i = 1|\tau = 1)$ and $Pr(R_j = 1|\tau = 1)$ to be equivalent. I also assume that the existence of a true link depends on the joint characteristics of the students. In contrast, reporting a link conditional on the link existing depends on the respondent's characteristics. Student j's characteristics do not affect the probability of student i reporting a link, conditional on the link truly being there.

Together, equations (3.2) -(3.8) describe the likelihood function. The results of the MLE estimation are presented below in Table 3.9. The reports of the links may be correlated on the respondent level. Thus, the standard errors are adjusted (clustered two ways) using the method by Cameron and Miller (2015).

The results support previous findings that students tend to form links with similar peers. Indeed, students of the same gender, domestic students and international students are more likely to have a connection. For the recognition question, having a similar, high admission GPA (>73%) predicts the existence of a true link. Interestingly, students who score high on extraversion characteristic form links with other extraverts. Students with "other" degrees (social science, humanities, arts) tend to talk and socialize with each other, but they do not

Table 3.9: Results of MLE estimation. Estimated probability of a true link existing and estimated probability of reporting a link conditional on the true link existing

	Recollection Question		Recognition (talk to)		Recognition (socialize)	
	$Pr(\tau = 1)$	$Pr(R = 1\|\tau = 1)$	$Pr(\tau = 1)$	$Pr(R = 1\|\tau = 1)$	$Pr(\tau = 1)$	$Pr(R = 1\|\tau = 1)$
Both same sex	0.633***		0.442***		0.511***	
	(0.086)		(0.097)		(0.08)	
Both STEM	-0.0424		-0.0710		0.0220	
	(0.067)		(0.141)		(0.124)	
Both Commerce	-0.0447		0.0372		-0.145	
	(0.088)		(0.157)		(0.134)	
Both other degrees	0.0434		0.437*		0.474***	
	(0.103)		(0.292)		(0.210)	
Both domestic students	0.512***		0.804***		1.010***	
	(0.108)		(0.170)		(0.143)	
Both international students	0.447***		0.257**		0.273**	
	(0.120)		(0.142)		(0.153)	
Both extraverts	0.227***		0.831***		0.437***	
	(0.072)		(0.172)		(0.144)	
Both have high GPA	0.0584		0.700***		0.353***	
	(0.024)		(0.21)		(0.153)	
Both have low GPA	0.171		0.129		0.0883	
	(0.214)		(0.335)		(0.209)	
Female		0.0926		0.0932		0.0714
		(0.1963)		(0.11)		(0.127)
Commerce degree		0.293*		-0.001		0.258**
		(0.203)		(0.105)		(0.139)
STEM		-0.185		-0.0783		-0.0433
		(0.168)		(0.114)		(0.144)
Domestic student		0.275*		0.106		0.132
		(0.171)		(0.114)		(0.138)
Adm. GPA		0.0146*		-0.00120		-0.00158
		(0.011)		(0.006)		(0.008)
Constant	-2.668***	-1.195*	1.087***	1.203***	-0.694***	0.417
	(0.129)	(0.907)	(0.240)	(0.472)	(0.191)	(0.595)
Year FE	YES	YES	YES	YES	YES	YES
Observations	16,296	16,296	14,438	14,438	14,438	14,438

Standard errors in parentheses. Standard errors are clustered two-ways on the respondent level
Data source: survey data 2014-2016.
$***p < 0.01, **p < 0.05, *p < 0.1$

necessarily form friendships. When it comes to the probability of reporting a link, students with commerce degrees and domestic students tend to report links more accurately, and they are less likely to forget the existing links. Students with high admission GPA are more likely to report links accurately in the recollection question but do as well as others on the recognition question. Using the results from Table 3.9, I calculated the estimated proportion of true links for each network. I then compare it to the measure of links under the underreporting assumption (taking the maximum of the reports of R_i and R_j). The results are in Table 3.10. The results show that the maximum report's network only captures around 70% of the true links. This is in line with Comola and Fafchamps (2017) findings, who find that only about two-thirds of all links are reported in their data. The recognition question, which asked students to identify who they talk to, performed the best, capturing about 79% of the links (under the maximum report rule). The recollection question performed the worst under this metric, reflecting only 64% of the links.

Table 3.10: Estimated proportions of true links vs. maximum reported links

	Recollection question	Recognition question (talk)	Recognition question (socialize)
Predicted links (MLE)	0.22	0.91	0.69
Maximum report	0.14	0.72	0.47

3.7.2 Reporting probabilities

The second part of the estimation shows how the probability of reporting (or forgetting) links varies with the characteristics. The results are not quite the same across different network measures, yet there are similarities. For example, domestic students seem to report links more reliably in all cases. Students with commerce degree backgrounds are more likely to report links in the recollection question and the recognition question asking about socializing. Female students appear to have significantly more accurate responses to the recognition question about talking to their peers. However, there is a positive (albeit not statistically significant) relationship between gender (female) and reporting probabilities for all questions. Finally, students with higher admission GPA scores provide more accurate responses to the recollection question, but GPA does not matter for the recognition question. The histograms of the estimated probabilities of reporting a link (conditional on a true link existing) are presented below.

There could be several potential implications for these findings for both the analysis of the data and the methods of survey data collection. First, if I know who is more likely to provide an accurate response to the questions, I may be able to assign a higher weight to their answers when constructing an adjacency matrix. For example, I can make an assumption that all links reported by certain types of students are correct, while the links reported by other students have a probability of being erroneous. Depending on the intended use of the data, this may help us determine a more accurate network structure and/or make better assumptions.

Figure 3.12: Predicted probability of reporting a link (conditional on true link existing) - Recollection

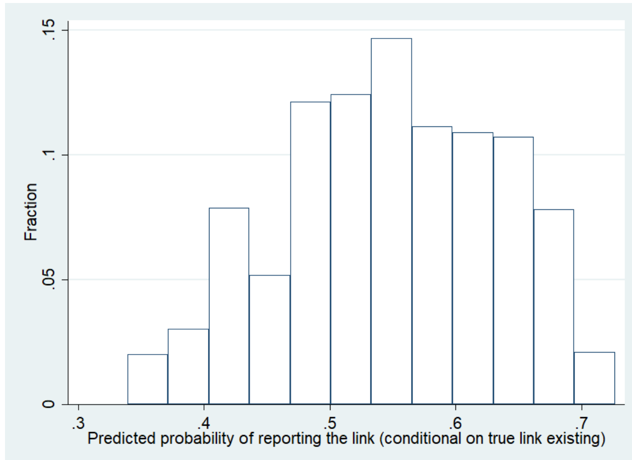
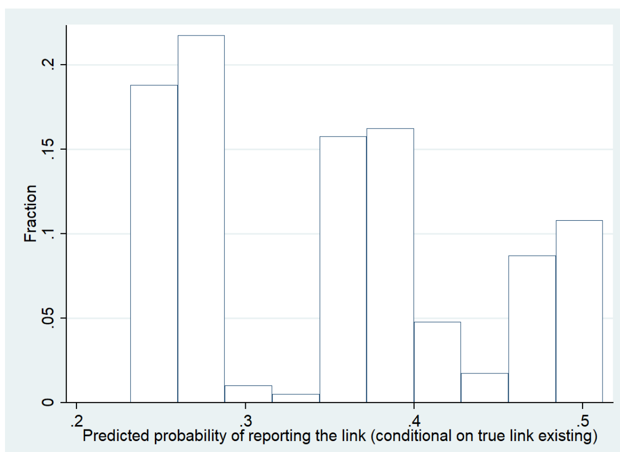
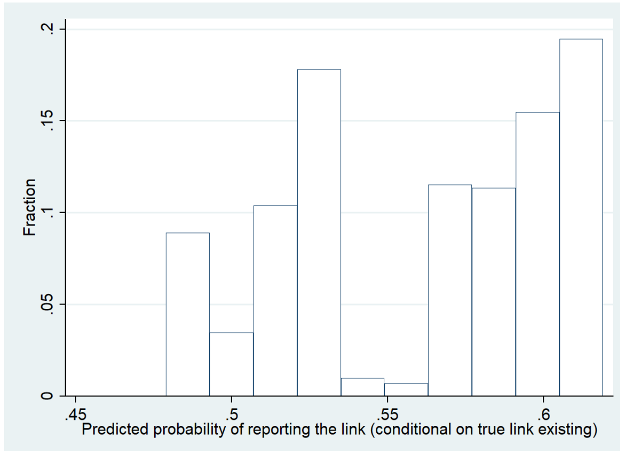


Figure 3.13: Predicted probability of reporting a link (conditional on true link existing) - Recognition (Talk)



Second, there are possible improvements in how I collect the survey network data if I can identify the types of respondents who are likely to make mistakes. These respondents may be asked to answer the network question again, or asked to check their answers or asked clarifying questions about the nature of their relationship with those whom they indicated as friends. For example, if a person is identified as someone with a higher probability of making errors, she may be asked "Who are your five friends?", and then as a follow-up question: "How many times a week/month do you speak to [Friend 1]". This will allow the respondent (or the researchers) to catch the potential mistakes either during the survey completion or analysis.

Figure 3.14: Predicted probability of reporting a link (conditional on true link existing) - Recognition (Socialize)



3.8 Conclusion

This paper provides some descriptive statistics of the MBA students' network and gives a few critical considerations for the choices of the social network collection questions in a survey, and gives some direction for dealing with misreported links and discordant answers.

By applying Comola and Fafchamps (2017) method to discordant links, I show that the recollection question fails to capture approximately half of the true network. The recognition questions do somewhat better by missing only 30-40% of the true links. However, recognition questions may be more prone to errors due to the respondents' carelessness and misunderstanding of the task. I suggest some ways of recognizing potential error sources, one of which involves using two recognition questions that are likely to result in overlapping networks (for example, people who also socialize likely talk to each other). The recollection question is also likely to capture stronger links, although it depends on the question's wording. Depending on the network's intended use, a researcher may choose the appropriate way of collecting social network data.

My estimations also show the type of students who are less likely to forget to report the links. It would be interesting to see if these findings hold in other social network datasets. Suppose I can predict the type of respondent who is likely to give correct answers. In that case, I may be able to create more strategic ways of collecting social network data by considering the respondents' characteristics.

3.9 Appendix

3.9.1 Additional tables - Descriptive results

Table 3.11: 2014 - survey answers summary - no intersection between named friends and peers student talks to

IDs	25	51	53	79
# of friends named	6	7	7	7
# of friends talks to	7	26	25	4
# of questions answered with non-zero	8	8	8	6
# of hours studying alone - finance	10	3	3	5
# of hours studying with LT - finance	6	1	3	0
# of hours studying alone - total	60	15	15	20
# of hours studying with LT - total	12	5	15	8

Table 3.12: 2015 - survey answers summary - no intersection between named friends and peers student talks to

ID	10	36	43	57	72	82	94	98
# of friends named	7	7	7	5	7	7	5	7
# of friends talks to	13	50	39	32	48	22	32	29
# of questions answered with non-zero	10	5	10	9	10	9	10	10
# of hours spent studying alone - finance	2	0	10	6	3	4	5	6
# of hours spent studying with LT - finance	2	1	5	1	4	2	2	6
# of hours spent studying alone - total	35	0	55	24	10	12	20	20
# of hours studying with LT - total	6	3	10	5	5	4	5	8

Table 3.13: 2016 - survey answers summary - no intersection between named friends and peers student talks to

ID	2	14	18	24	36	43	49	61	63	66	99	101	107
# of friends named	7	7	2	4	7	7	7	7	6	5	6	7	6
# of friends talks to	16	27	36	11	67	76	38	4	14	9	28	41	0
# of questions answered with non-zero	10	9	7	10	8	10	10	8	10	10	10	10	10
# of hours spent studying alone - finance	4	5	4	6	8.5	3	8	3	10	10	2	10	12
# of hours spent studying with LT - finance	1	2	0	1	0	3	5	8	15	0.5	2	2	6
# of hours spent studying alone - total	16	20	4	20	65	38	12	25	10	30	8	20	30
# of hours studying with LT - total	4	5	0	10	2.5	7	12	20	10	5	8	10	10

Table 3.14: Intersection of Parts A and C (Talk and Socialize) of the recognition question - 2014

IDs	16	25	51	53	62	74	79
Number of peers named in A	27	7	26	25	14	12	4
Number of peers named in C	6	5	7	8	19	10	6
Number of peers named in B	0	7	2	8	2	3	4

Table 3.15: Intersection of Parts A and C (Talk and Socialize) of the recognition question - 2015

IDs	1	10	19	57	72	82	84
Number of peers named in A	0	13	21	32	48	22	25
Number of peers named in C	0	0	10	17	26	53	1
Number of peers named in B	0	3	5	5	4	21	4

Table 3.16: Intersection of Parts A and C (Talk and Socialize) of the recognition question - 2016

IDs	2	4	13	14	24	38	43	49	53	61	66	80	99	101
Number of peers named in A	16	30	8	27	11	35	76	38	26	4	9	23	28	41
Number of peers named in C	22	10	1	30	36	16	16	32	2	22	10	9	23	32
Number of peers named in B	12	27	0	6	10	0	15	5	5	2	5	0	0	4

3.9.2 Relaxing the assumption of no overreporting

The assumption of underreporting is most reasonable for the recollection question. Indeed, it is highly unlikely that a respondent puts down the name of a peer they are not connected to. However, in the case of recognition questions, a mistake can easily be made when a respondent checks off a name on the roster by mistake or carelessness. Thus, I test the sensitivity of the results to relaxing the assumption of underreporting. I consider three cases: the probability of reporting a link that is not there is 10%, 5% and 20%, to see how it affects the resulting estimated network size for roster questions. I maintain the independence assumption for this exercise.

I rewrite the equations (2)-(5) in the following manner:

$$
\begin{aligned}
Pr(R_i = 1, R_j = 1) = &\ Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * Pr(R_j = 1|\tau = 1) \\
&+ (1 - Pr(\tau = 1)) * Pr(R_i = 1|\tau = 0) * Pr(R_j = 1|\tau = 0) \\
Pr(R_i = 0, R_j = 1) = &\ Pr(\tau = 1) * (1 - Pr(R_i = 1|\tau = 1)) * Pr(R_j = 1|\tau = 1) \\
&+ (1 - Pr(\tau = 1)) * (1 - Pr(R_i = 1|\tau = 0)) * Pr(R_j = 1|\tau = 0) \\
Pr(R_i = 1, R_j = 0) = &\ Pr(\tau = 1) * Pr(R_i = 1|\tau = 1) * (1 - Pr(R_j = 1|\tau = 1)) \\
&+ (1 - Pr(\tau = 1)) * Pr(R_i = 1|\tau = 0) * (1 - Pr(R_j = 1|\tau = 0)) \\
Pr(R_i = 0, R_j = 0) = &\ 1 - Pr(R_i = 1, R_j = 1) - Pr(R_i = 0, R_j = 1) - Pr(R_i = 1, R_j = 0)
\end{aligned}
$$

I assume the values of 0.05, 0.1 and 0.2 for $Pr(R = 1|\tau = 0)$, and see how these assumptions affect the estimations. The resulting network sizes are presented in the table below.

Table 3.17: Results of relaxing the underreporting assumption

Recognition question - Talk

Probability of an error	0%	5%	10%	20%
Estimated network	0.91	0.9	0.88	0.83
Max Report	0.72	0.72	0.72	0.72

Recognition question - Socialize

Probability of an error	0%	5%	10%	20%
Estimated network	0.69	0.64	0.58	0.53
Max Report 0.47	0.47	0.47	0.47	0.47

The results show that the estimated network size is somewhat responsive to the assumptions on the probability of erroneously picking a non-connection as a connection. The "socialize" recognition question seems to be somewhat more sensitive. However, even at a 20% probability of making a mistake, the size of the estimated network is larger than the maximum report. Thus, for the maximum report network to be accurate, I need to assume that students mistakenly pick peers out of the list with a higher than a 20% probability. It appears that in the absence of a strategic reason for students to pick connections that are not truly there, this error rate is unreasonably high. However, this exercise provides us with a range of possible network sizes under some reasonable assumptions of the error rate.

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Western Research

Research Ethics

Western University Health Science Research Ethics Board
NMREB Delegated Initial Approval Notice

Principal Investigator: Timothy Conley
Department & Institution: Social Science\Economics,

NMREB File Number: 105218
Study Title: Peer Effects in the Classroom Setting
Sponsor:

NMREB Initial Approval Date: June 13, 2014
NMREB Expiry Date: September 30, 2015

Documents Approved and/or Received for Information:

Document Name	Comments	Version Date
Other	References	2014/04/02
Western University Protocol		2014/06/09
Instruments		2014/06/12
Revised Letter of Information & Consent		2014/06/12

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the above named study, as of the HSREB Initial Approval Date noted above.

NMREB approval for this study remains valid until the NMREB Expiry Date noted above, conditional to timely submission and acceptance of HSREB Continuing Ethics Review.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

[redacted]

Ethics Officer, on behalf of Riley Hinson, NMREB Chair

Ethics Officer to Contact for Further Information

✓ Erika Basile ebasile@uwo.ca	___ Grace Kelly grace.kelly@uwo.ca	___ Mina Mekhail mmekhail@uwo.ca	___ Vikki Tran vikki.tran@uwo.ca

This is an official document. Please retain the original in your files.

Western University, Research, Support Services Bldg., Rm. 5150
London, ON, Canada N6A 3K7 t. 519.661.3036 f. 519.850.2466 www.uwo.ca/research/services/ethics

Western Research

Research Ethics

Western University Health Science Research Ethics Board
NMREB Annual Continuing Ethics Approval Notice

Date: May 04, 2015
Principal Investigator: Timothy Conley
Department & Institution: Social Science\Economics,

NMREB File Number: 105218
Study Title: Peer Effects in the Classroom Setting
Sponsor:

NMREB Renewal Due Date & NMREB Expiry Date:
Renewal Due -2016/05/31
Expiry Date -2016/06/13

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed the Continuing Ethics Review (CER) form and is re-issuing approval for the above noted study.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), Part 4 of the Natural Health Product Regulations, the Ontario Freedom of Information and Protection of Privacy Act (FIPPA, 1990), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

[redacted]

Ethics Officer, on behalf of Prof. Riley Hinson, NMREB Chair

Ethics Officer to Contact for Further Information

____ Erika Basile ebasile@uwo.ca	✓ Grace Kelly grace.kelly@uwo.ca	___Mina Mekhail mmekhail@uwo.ca	___Vikki Tran vikki.tran@uwo.ca

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Western Research

Research Ethics

Western University Non-Medical Research Ethics Board

NMREB Annual Continuing Ethics Approval Notice

Date: June 13, 2016
Principal Investigator: Timothy Conley
Department & Institution: Social Science\Economics,

NMREB File Number: 105218
Study Title: Peer Effects in the Classroom Setting

NMREB Renewal Due Date & NMREB Expiry Date:
Renewal Due -2017/05/31
Expiry Date -2017/06/13

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed the Continuing Ethics Review (CER) form and is re-issuing approval for the above noted study.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), Part 4 of the Natural Health Product Regulations, the Ontario Freedom of Information and Protection of Privacy Act (FIPPA, 1990), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

[redacted]

Ethics Officer, on behalf of Dr. Riley Hinson, NMREB Chair

Ethics Officer: Erika Basile ___ Katelyn Harris___ Nicole Kaniki ___ Grace Kelly ✓ Vikki Tran ___ Karen Gopaul ___

Western University, Research, Support Services Bldg., Rm. 5150
London, ON, Canada N6G 1G9 t. 519.661.3036 f. 519.850.2466 www.uwo.ca/research/ethics

Date: 17 May 2018

To: Timothy Conley

Project ID: 105218

Study Title: Peer Effects in the Classroom Setting

Application Type: Continuing Ethics Review (CER) Form

Review Type: Delegated

Meeting Date: June 1, 2018

Date Approval Issued: 17/May/2018

REB Approval Expiry Date: 13/Jun/2019

Dear Timothy Conley,

The Western University Research Ethics Board has reviewed the application. This study, including all currently approved documents, has been re-approved until the expiry date noted above.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Daniel Wyzynski, Research Ethics Coordinator, on behalf of Prof. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Date: 6 June 2019

To: Timothy Conley

Project ID: 105218

Study Title: Peer Effects in the Classroom Setting

Application Type: Continuing Ethics Review (CER) Form

Review Type: Delegated

Meeting Date: 05/Jul/2019

Date Approval Issued: 06/Jun/2019

REB Approval Expiry Date: 13/Jun/2020

Dear Timothy Conley,

The Western University Non-Medical Research Ethics Board has reviewed this application. This study, including all currently approved documents, has been re-approved until the expiry date noted above.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Daniel Wyzynski, Research Ethics Coordinator, on behalf of Prof. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Western Research

Date: 9 June 2020

To: Timothy Conley

Project ID: 105218

Study Title: Peer Effects in the Classroom Setting

Application Type: Study Closure Form

Review Type: Delegated

Date Acknowledgement Issued: 09/Jun/2020

Dear Timothy Conley,

The Western University Research Ethics Board has reviewed the application, and the closure of this study is acknowledged. The REB file on this study is now officially closed.

Thank you for using the Western Research Ethics Manager System (WREM).

Sincerely,

The Office of Human Research Ethics

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Study ID_____

Survey

Background Information

Gender (circle) M F

GMAT score ____________

What was the average <u>percentage</u> GPA score from your previous undergraduate degree? ___________%

What is the major of your undergraduate degree? ____

How much work experience do you have? ____ years ____months

What industry do you have work experience in? ____

Where you born in Canada? Yes No

If not, how many years ago did you arrive in Canada?_____

What is your mother tongue_____________________

Please rank the following subjects according to your interests (1 being the most interesting to you, 5 being the least interesting):
__Finance
__Marketing
__HR/Organizational Behaviour
__Accounting
__ Strategy

Q1 Please write down the names of **up to 7 friends** you have in this program

1. ____
2. ____
3. ____
4. ____
5. ____
6. ____
7. ____

Q2 Even though you do not know for sure, you may have certain beliefs about your performance in the Managerial Finance course. In your opinion, what is the probability that your grade in the Finance course will be (recall that the sum of the probabilities should be 100%):

Grade	**Probability**
0-50%	
51-60%	

Study ID_____

60-70%	
70-80%	
80-90%	
90-100%	

Q3 How many hours a week (approximately) do you spend studying for the Managerial Finance course (outside of class time)?
By myself _____hours With my Module 1 Learning Team _____hours

Q4 How many hours a week (approximately) do you spend studying for the Leading People and Organizations course (outside of class time)?
By myself _____hours With my Module 1 Learning Team _____hours

Q5 How many hours a week (approximately) do you spend studying for **all your courses** (outside of class time)?
By myself _____ hours With my Module 1 Learning Team _____hours

Q6 Finish the sentence by picking one or more options (if you pick more than one, please rank them in order of frequency, 1 being "most often"):
"During the meeting with my Learning Team, most often I:
___ Explain concepts to other students
___ Lead the discussion of the case
___ Use my work experience to illustrate the concepts covered in class or mentioned in the case
___ Play "devil's advocate" by arguing various case points with my colleagues
___ Prefer to listen to my team members rather than actively participate in the discussion
___ Ask my teammates to explain to me concepts covered in class."

Q7 How many hours a week (approximately) did you spend studying while completing your previous degree (outside of class time)?
______hours a week

Q8 How many hours a week (approximately) do you spend socializing with your peers from the MBA program (go to bars, restaurants, concerts, events, playing sports, etc.)?
______hours a week

Q9 How satisfied are you with your Learning Team (Module 1)? Please circle the appropriate answer:
Very Unsatisfied Unsatisfied Neither satisfied or unsatisfied Satisfied Very Satisfied

Q10 Given a chance, would you like to switch your Learning Team (Module 1)? Please circle the appropriate answer:
Yes No

Q11 Here is a number of traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which *you agree or disagree with that statement*. You should rate

Study ID_____

the extent to which the pair of traits applies to you, even if one trait applies more strongly than the other.

Disagree Strongly	Disagree Moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
1	**2**	**3**	**4**	**5**	**6**	**7**

I see myself as:

1. ______ Extraverted, enthusiastic
2. ______ Critical, inflexible
3. ______ Dependable, self-disciplined
4. ______ Anxious, easily upset
5. ______ Open to new experiences, imaginative
6. ______ Reserved, quiet
7. ______ Sympathetic, warm
8. ______ Disorganized, careless
9. ______ Calm, emotionally stable
10. ______ Traditional, uncreative

Q12 For each of the students on the following list, please indicate by circling the number in the appropriate cell whether or not:

- You have had a conversation with him/her within the last 2 weeks. By conversation I mean an interaction with some content. (e.g. simply greeting someone does not count as a conversation).
- You ever go to him/her for schoolwork related advice (e.g. questions about concepts covered in class, help with assignments or preparation for exams)
- You socialize with him/her outside of the school (e.g. attend parties together, go to bars, concerts, events, play sports etc.)

Had a conversation within the last 2 weeks	Ask for school related advice	Socialize outside of school	Names (Section 1)
1	1	1	Name
2	2	2	Name
…	…	…	…
N	N	N	Name

ZINAIDA FOLTIN

EDUCATION	**University of Western Ontario** Ph.D. Economics	London, ON, Canada (Expected: 2021)
	University of Western Ontario M.A. Economics	London, ON, Canada 2013
	McMaster University MBA, focus in Finance and Strategic Business Valuation	Hamilton, ON, Canada 2010
	McMaster University B.Comm. (Honours) Commerce	Hamilton, ON, Canada 2009

DISSERTATION **Peer Effects in Education**
Committee Members: Timothy Conley (Supervisor), Todd Stinebrickner, and David Rivers

RESEARCH AREAS Economics of Education, Applied Microeconomics, Social Networks

TEACHING INTERESTS Microeconomics, Macroeconomics, Econometrics, Economics of Education, Corporate Finance

JOB MARKET PAPER **"Peer effects in MBA Program,"** Job Market Paper, September 2017

RESEARCH PAPERS

- **"Peer Effects in Small Teams: Testing Team Allocation Rules,"** Working Paper, September 2017
- **"On Methodology of Social Network Data Collection: Comparison of Two Common Methods (With Tim Conley) ,"** Working Paper, September 2019

WORK EXPERIENCE

- **Research Associate**
  Social Research and Demonstration Corporation, Ottawa, ON — April 2018 - Present

TEACHING EXPERIENCE

Course Instructor:

King's University College (UWO)
- MOS 3310 - Introduction to Corporate Finance — Winter 2015

Teaching Assistantships:

The University of Western Ontario
- Economics 9601A/9602B - Microeconomics I & II (Graduate) — Fall 2013 - Winter 2014
- Economics 1021A/1022B - Principles of Economics — Fall 2012 - Winter 2013

McMaster University
- COMM 4FE3 - Options and Futures — Fall 2009
- COMM 4SA3 - International Business — Winter 2010

PRESENTATIONS **Conference Presentations:**
The 51st Annual Conference of the Canadian Economic Association, Antigonish — 2017
UM-MSU-UWO Labo(u)r Day, East Lansing — 2016

REFEREEING Journal of Development Economics

RESEARCH ASSISTANTSHIPS	**University of Western Ontario:**	
	Research assistant to Professor Timothy Conley	2014-2016
	McMaster University:	
	Research assistant to Professor Narat Charupat	Winter 2010
AWARDS AND DISTINCTIONS	**University of Western Ontario**	
	Joseph-Armand Bombardier Canada Graduate Scholarship *Focus: Peer Effects in MBA program*	2015-2018
	Lindau Nobel Meetings in Economics *Participant*	2017
	Doctoral Excellence Research Award	2016-2017
	Ontario Graduate Scholarship *Declined in lieu of larger scholarship.*	2015-2016
	Ontario Graduate Scholarship	2014-2015
	Western Graduate Research Scholarship	2012-2016
	McMaster University	
	DeGroote Graduate Scholarship	2009
	Queen Elizabeth II Aiming for the Top Scholarship	2004 - 2008
	City of Hamilton Economic Development Scholarship	2005
	University (Senate) Scholarship	2005
	Deans Honours List	2005, 2006, 2010