PEER INFLUENCE AND THE CHOICE OF IT CAREERS

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ABSTRACT

The productivity of the Information Technology (IT) and IT enabled Services (ITeS) industry depends critically on the supply of high quality human capital. While existing research has examined the role of education and training on the human capital in this industry, little research informs the role of peer influences on the decision to pursue IT/ITeS careers. Focusing on managerial employees, we examine the influence of peers on the choice to pursue information technology careers in India. Specifically, we analyze data on student networks at a leading business school where students are exogenously assigned to peer groups, and link these to students' choice of post-program careers in the IT industry. Although before the program, students have experience in both IT and non-IT fields, they may switch roles and/or industries after the program. For instance, some may pursue IT roles in non-IT sectors such as retail, whereas others may pursue non-IT roles such as strategy and sales in IT companies. We posit that such career choices may be informed and driven not only by own motivation and ability, but also by the influence of peers. Our findings reveal that being part of a group that includes peers who have worked in IT increases the likelihood of accepting an offer in the IT industry. However, counter-intuitively, we find that if a student has had no IT experience, having IT peers decreases the likelihood of accepting a job in the IT industry. In other words, IT peers discourage non-IT peers from being part of the IT industry.

Key words: Peer Networks, Peer Influence, IT Human Capital, IT Services Industry

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1. Introduction

How does human capital form in the Information Technology (IT) industry? The availability of high quality human capital capable of doing complex knowledge work is an important determinant of the overall returns to scale for labor and the consequent profitability in the ITeS industry (Ang et al. 2002, Mehra et al. 2014). Relatively few studies examine factors that affect the formation of IT human capital, focusing instead on either the productivity improvements of IT human capital, that is, how training and education help hone the productivity of IT human capital (e.g., Bapna et al. 2013, Mehra et al. 2014), or the wage gains commensurate with human capital acquisition (e.g., Mithas and Krishnan 2008, Kim et al. 2014). To a lesser extent, research has also assessed how IT firms acquire human capital; more recently, Tambe and Hitt (2014) examine factors that affect the IT human capital firms have access to, and identify job-hopping of IT workers as one of the critical factors that affects firm productivity.

In addition to studying the effect of formal, on-the-job training and other human-capital investments, research has also sought to understand the effect of peer networks and communities on learning and productivity. For instance, Sacerdote (2001) examines the efficacious effect of peers among undergraduate students;[2] similar effects have also been studied among graduate business students (Shue 2013; Lerner and Malmendier 2015; Jain and Kapoor 2015, Jain and Langer 2015). While this literature examines students' productivity (as measured by outcomes such as GPA), how peer networks may influence students' career choices that subsequently affect the human capital available to firms is relatively understudied. This study aims to systematically examine the role of peer influence as one of the factors that informs IT human capital.

[2] See also Foster (2006); Stinebrickner and Stinebrickner (2006); Carrell, Fullerton, and West (2009).

While models prevalent in research on labor markets assume that individuals have access to all information and make informed decisions, a "fully informed choice could not explain important features of the typical individual's experience in the labor market (Mortensen 1986 p. 850)." We posit that the sphere of peer influence extends beyond mere knowledge acquisition; social connections play an important role in career choice (Marmaros and Sacerdote 2002). Individuals increasingly rely on their social network in job search, lending credence to "*not what you know but whom you know*," (Granovetter 1995). The research strand on social networks in labor markets has focused on how weak connections help job search efforts by enabling more information on new job opportunities available in the labor market, reducing search frictions. In contrast, some recent findings suggest that strong ties are more helpful in job search, whereas weak ties may even hurt (Garg and Telang 2015). While search is an important aspect of labor market research, the influence of peers on career decisions and subsequently on human capital formation has not been studied as extensively. In this study, we examine the influence of peers on the choice to pursue IT careers, particularly for managerial employees in the IT/ITeS industry.

We examine our research question in the context of the Indian IT industry, which has consistently posted double-digit growth figures over the last few years and is expected to account for more than 55% of the global ITeS sourcing industry in the coming years (NASSCOM Report 2015). Specifically, we analyze data on student networks at a leading business school, using exogenously assigned peers, and link these to students' choice of post-program careers in the IT industry. Before pursuing their MBAs, students have undergraduate education and experience in both IT and non-IT domains. However, after the completion of their degrees, they may switch roles and/or industries. For instance, some may pursue IT roles in non-IT sectors such as retail, whereas others may pursue non-IT roles such as strategy and sales in IT companies. We posit that such career choices may be informed and driven not only by own motivation and ability, but also by the influence of peers. In particular, we examine whether IT peers encourage or discourage IT careers.

Lerner and Malmendier (2015) discuss why peers may influence career choices. Because IT peers have worked in the IT industry, they may be regarded as experts about jobs in the IT sector. Interacting closely with such peers may accelerate the learning process about the IT sector. The expert students (ones with experience in the IT industry) can help the novices (those who do not have any IT experience) with the learning in several ways – they may share stories of their own careers, they may explain the ins and outs of the industry, including prospective career paths, salary expectations, and any common pitfalls. Therefore, not only may the novices learn more about a hitherto unknown domain, they may make better decisions based on the expert peers advice (McDonald and Westphal 2003).

Research examining the effect of peer networks may inherently be flawed, posing two major empirical challenges. First, most observational datasets (for example, employee records from IT firms on the demand side or student records from an engineering college on the supply side) contain neither a sufficient mix of individuals from IT and non-IT backgrounds, nor diversity in career outcomes after exposure to peers. Second, not accounting for the role of unobservable peer characteristics in career choice may confound the findings. In most professional settings, employees either choose the teams to work with, or are assigned to peers based on both observed and unobserved factors that influence productivity. In social settings, individuals might choose their own friends based on homophily or other characteristics that increase their receptivity to peer influences. To disentangle the effect of peers on career choices from confounding factors such as network self-selection and simultaneity, we rely on random assignment of peers to the network.

We find that own IT experience is one of the strongest predictors for both getting and accepting a job in the IT sector. We also find that being part of a group that includes peers who have worked in IT increases the likelihood of accepting an offer in the IT industry. However, counter-intuitively, we find that if a student has had no IT experience, having IT peers decreases the likelihood of accepting a job in the IT industry. In other words, IT peers discourage non-IT peers from being part of the IT industry. Our subsample analysis suggests that these findings stem from differences between men and women, women are more susceptible to peer influence than men, who rely on their own work experience in generating and accepting jobs in IT. Our results are robust to various specifications.

While it has long been acknowledged that peers play a critical role in career choices, prior research has examined the strength of peer networks primarily in job search. Moreover, disentangling peer effects from homophily, contagion, and similar confounding factors is necessary to infer causal peer influence. Using micro-level, individual data on human capital variables as well as peer effects and a robust identification strategy, our study is one of the first to shed light on IT human capital formation, not only addressing gaps in existing research but is also of significance to managers and policy makers.

The rest of the paper is organized as follows. We describe the identification issues in Section 2. Section 3 explicates the research setting and discusses the data generation process and summary statistics of the data. We present our analysis and results in Section 4. We discuss the managerial implications and conclude the paper in section 5.

2. IDENTIFICATION

The primary objective of this study is to determine the causal influence of peer characteristics on career choices. In most empirical settings, the estimation of peer effects is an econometric challenge, either due to sampling issues or due to endogenous self-selection into networks.

Consider a typical study utilizing observational data on peer networks. First and foremost, econometricians seldom have access to complete network information; many studies utilize a sub-sample of the network under consideration. Any causal inference that relies on such a sample would be problematic if the sampled nodes are systematically different from the un-sampled nodes, even if sampling is random. It would also be difficult to quantify any network variables for a sub-sample since the complete network is unavailable.

The second and graver concern in research on peer effects is accounting for self-selection into networks (Manski 1993). Individuals may select into networks for various reasons; for instance, these individuals may hope to gain from network association, and those who join a particular network may be different from those who don't. In such a scenario, network membership may be endogenous and eludes identification of network effects. Indeed, as prior research finds, network effects often tend to "vanish" once self-selection into networks is accounted for (Duflo and Saez 2002, 2003, Kremer and Levy 2008). Similarly, individuals may connect with each other because they share common interests or are similar in their attributes. Thus, any outcomes from networks that we detect may actually be attributed to homophily rather than network effects (McPherson et al. 2001, Aral et al. 2009). Finally, network effects may actually be a result of a common shock administered to the network and not the effect of peers on each other (Sacerdote 2001, Kremer and Levy 2008). Controlling for any pre-determined attributes may help alleviate the latter problem (Lerner and Malmendier 2015).

The discussion above highlights why it is difficult to cleanly identify the influence of peer characteristics from endogenous selection, homophily, and other unobserved factors, making causal inference of network effects an elusive problem in empirical research. The next section describes the study design, the research setting, and the data that allows us to overcome the challenges identified above.

3. Research Setting and Data Description

To examine peer influences on career choice, we would need to have access to data in a setting where individuals have a diverse range of prior educational and professional experiences as well as both IT and non-IT job options at the end of the program, allowing us to investigate the full set of outcomes (IT jobs landed, IT jobs accepted as well as the complete matrix of peer influences (influence of IT background students on non-IT students, and vice versa, and so on). Furthermore, to identify the causal effect of peer influence, we would need to have exogenous allocation of individuals to the network.

3.1 Data Source and Research Setting

The source of our data is the flagship post-graduate business program at the Indian School of Business (ISB). Established in 2001, ISB is a large, independent provider of post-graduate management education with a one year, full-time, residential diploma program. The school was founded in academic collaboration with the Wharton School at the University of Pennsylvania, Kellogg School of Management at Northwestern University, and London Business School. ISB incorporates many academic features and policies from its partner institutions.

An application to ISB consists of GMAT scores, essays, letters of recommendation, undergraduate and graduate transcripts, and an interview. Although drawing from a pool of applicants predominantly from India, student characteristics at ISB are comparable with those at a number of leading international business schools. Hence, ISB is arguably similar to a number of major international business schools on observable characteristics such as GMAT and years of work experience.

We study four student cohorts for years graduating in 2008, 2009, 2010, and 2011. In our study period, 2007-08 to 2010-11, classes at ISB were held for 50 weeks without any significant break and were divided into eight terms of six weeks each. In the first four terms, students took a common "core" of 16 non-elective classes covering a range of management topics.[3] In the next four terms, students chose various elective courses that allow them to concentrate in the areas of entrepreneurship, finance, information management, operations, marketing or strategy.

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

[3] The assignment of student study groups to sections, and therefore instructors and class times, is random.
[4] Students do not know the correspondence between the class score and letter grades, which is determined at the end of the term.

possible, regardless of the relative performance of the other members in the study or residential groups.

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

Student assignment, coursework and grade data are supplemented with data from admissions records that contain each student's academic (undergraduate and graduate institutions and associated majors and GMAT scores), professional (sector and firm of employment, employment duration, earnings, and functional role) and demographic backgrounds (year of birth, gender, marital status, and citizenship).

The on-campus placement process at ISB begins at the start of the sixth term, when various prospective employers post job openings on the school's job portal. The typical process includes applications to various posted jobs, a short-listing of candidates, and subsequent interviews with the employers, job offers, and finally, job acceptance. These offers are made with the expectation that the students will join the firm after successful completion of the PGP program. As soon as a student accepts a job, they are taken off the job portal. Our data set includes records from the on-campus placement process; specifically, we have information on the firm that made the job offer as well as the role that was offered to the student. We classify a job offer as an "IT offer" if the job was predominantly in the IT sector and/or involved an IT role. Similarly we include an indicator variable that is 1 if the student accepted the IT offer.

Table 1 summarizes a number of relevant variables in the dataset and Table 2 shows correlation between these variables. Enrolled students have an average of 4.9 years of full time work experience before joining. Consistent with the BusinessWeek data, the mean GMAT score of students in the sample is 709. The top two undergraduate alma maters are Delhi University (15%) and the Indian Institutes of Technology (14% from all campuses). In demographic characteristics, 73% of students are single with an average age of 28.7 years. Twenty six percent of the students are women, and 96% are Indian citizens. The average salary drawn before enrolling at ISB was INR 997,000.[5]

For this study, we want to understand the influence of IT peers, hence we first use a dummy variable *IT_Experience* to indicate whether the student has held jobs in the IT sectior (*IT_Experience* = 1) or not (*IT_Experience* = 0). Our data indicate that 36% of incoming students have worked in the IT industry. We then compute the average number of IT experience in the study and housing (roommate) groups for each student, resulting in variables *IT_Exp_StudyGroup* and *IT_Exp_Roommates*. We describe below the construction of these peer groups

Insert Tables 1 and 2 here

3.2 Peer Group Structure

Our data is particularly suitable for understanding peer influence on career choices. Because we rely on administrative sources, the variables we described previously are objectively and

[5] The average INR to USD exchange rate for year 2011 was around USD $1 = INR 46.06. At the time of writing this paper, USD $1 = INR 66.06.

comprehensibly measured and do not suffer from self-reporting bias, measurement error, or missing data.

A critical criterion for identifying peer effects is random, exogenous assignment of individuals to the network. We now describe how our data meet this criterion, in that students are simultaneously and randomly assigned to multiple, non-overlapping peer groups. Before the academic year begins, the ASA allocates each enrolled student to a study group. This study group is required to collaborate on coursework, particularly any group based projects and assignments. This study group allocation is fixed for the duration of the core terms, however in elective terms, when students can select their own courses, they may choose to be part of a group that may be different than their core term study group.

ASA staff that assigns students to these core study groups has access to only their demographic information. The allocation is based on two consecutive rules: a) each group can have either two women or none, and b) then the assignment is balanced in the number of engineers; each group has either four or five members. These assignment rules resulted in 90 study groups for classes graduating in 2008 and 2009, and 120 groups for classes graduating in 2010 and 2011. Note that the assignment process does not consider either the number of years of prior work experience (whether in IT or otherwise), or any academic attributes such as GMAT scores or undergraduate or graduate degrees from elite universities, which may be correlated with the student abilities. The ASA also does not rely on any unobservable factors such as motivation, choice of major, or potential interaction with peers. Thus, the study group allocation by ASA staff can be regarded as statistically random on unobservable attributes.

ISB’s PGP program is different from those at similar international business schools in that it is completely residential. Students are expected to stay in residential dormitories located on-campus. Students can stay in either studio apartments or share a quad with three other "roommates." These quads have four bedrooms as well as a shared kitchen and living space. Typically those students who want to live with their family members (e.g. spouse and/or kids) or those with special needs choose to live in a studio apartment. For assignment to quads, we note that ISB does not solicit any roommate preferences; hence this assignment is unlikely to result in homophilous groups that may confound peer effects. Instead, the assignment process follows two simple rules – first, each quad can only have members of the same sex, and second, the housing group cannot overlap with the study group. Students remain in their allocated studio or quad for the duration of the academic year. More importantly, for the purpose of this study, these assignments, including choosing to live in a studio or a quad, are not based on any academic attributes or prior industry experience. In our dataset, 1484 out of 1987 students lived in a quad.

The above process results in mutually exclusive study and residential groups that help create the peer groups for each student group in a year.[6] Each student is part of a core study group, and most are connected to their quad peers, and so on till all students in a particular cohort are connected to each other. Figure 1 illustrates this process for a single student; Figures 2-5 in the appendix depict the networks for the years 2007-2008, 2008-2009, 2009-10, and 2010-2011 respectively.

[6] Note that ISB's PGP program is a one-year course; there are no spill overs from previous years, thereby avoiding any concerns of auto-correlation in our dataset.

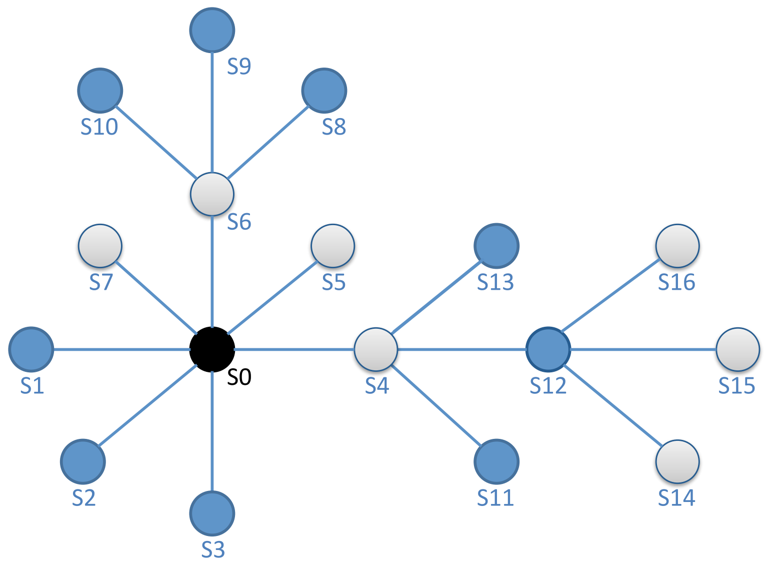

Figure 1: Network Sample

In Figure 1, student S0 is connected to students S1, S2, and S3 through the quad they share, and to students S4, S5, S6, and S7 through their core study group. Further, the students S4 and S6 are in turn connected to their quad peers (S4: S11, S12, and S13; S6: S8, S9, and S10 respectively). In this illustration, student S5 and S7 may choose to stay in a studio apartment and hence may not be part of any residential group, and so on. Therefore, in addition to interacting with peers in their study groups, students may also interact with peers in their residential groups. Lerner and Malmendier (2015) suggest that such peer groups are influential in predicting potential career outcomes. These groups become an integral part of the students' lives at ISB: the students use their peer interactions to not only complete formal coursework but also to reinforce their understanding of various academic endeavors (Jain and Kapoor 2015) as well as career options (Lerner and Malmendier 2015).

Each student is thus exposed to a different set of peers who vary in their academic abilities as well as their prior industry experience. We now examine alternate networks that may affect students' experience during their ISB sojourn.

3.2 Social Connections and Friendships

The network structure we discuss above is useful for ascertaining peer effects only if these peers are influential in career choices. However, social connections need not necessarily form between students who are part of either the study or housing group. Suppose that students have an alternate set of friends on whom they rely on not only for learning and knowledge gains but also for advice on careers. In such a case, the influence of peers described previously, that is, the peer groups to which the student has been randomly assigned by the administrative process, would be negligible (Carrell et al. 2013). To alleviate this concern, we examine whether there is any overlap between the administratively allocated peers and the students' self reported closest friends.

At the end of each academic program, ISB conducts a survey with the graduating students about the efficacy of the program. This survey asks students to name up to five of their closest friends amongst their graduating class. The survey results are not shared with other students, hence we can assume that this question elicits true friendships and indicates the peers who have been most influential for a particular student. We use the results of this survey to create binary friendship cohorts between students '*i*' and '*j*'. We then specify variable $friends_{ijt}$ to indicate whether student '*i*' n ames student '*j*' ≠ '*i*' in cohort '*t*' as a friend (=1) or not (=0). We then regress this variable on a number of explanatory variables that may affect this binary relationship, including being in the same study or housing group. We also include variables that may capture homophily; using shared demographic attributes such as same college, major, gender, citizenship, amongst other controls (See Jain and Langer 2015 for more details).

Table 3 reports the results of this OLS regression and shows that the strongest determinant of friendship between students '*i*' and '*j*' is whether the pair are roommates ($\beta = 0.103$, $p<0.01$) or part of the same study group ($\beta = 0.069$, $p<0.01$). These results suggest that the roommate and study group peers are deemed critical aspects of the students' peer network and can be considered to most influential.

Insert Table 3 here

4. Analysis, Results, and Discussion

To analyze the impact of peer influence on IT human capital formation, we examine two outcomes that are a result of the placement process: *IT_Offer* and *IT_Offer_Accepted*. *IT_Offer* captures whether the student ***gets*** a job offer in the IT sector (*IT_Offer* = 1) or not (*IT_Offer* = 0). Likewise, *IT_Offer_Accepted* denotes whether the student ***accepts*** a job in the IT sector (*IT_Offer_Accepted* = 1) or not (*IT_Offer_Accepted* = 0). We use an OLS specification for each of these models; the results from the probit specification are qualitatively similar. As described previously, we use a dummy variable to indicate prior IT experience (=1 if yes, 0 otherwise), and control for GMAT, prior work experience, gender, marital status, age, core term GPA, and pre-program income. We also use year dummies.

Our network variables include information on IT peers in study and housing groups, and interaction variables for the peer groups with no IT experience dummy (*No_IT_Exp** *IT_Exp_StudyGroup* and *No_IT_Exp***IT_Exp_Roommates* respectively). These interaction variables capture the differential effect of IT peers in study group and IT peers as roommates on those students who did not have any pre program IT experience.

RESULTS

Our results are shown in **Table 4**. Columns 1 and 2 show the estimation results for the outcome *IT_Offer*; column 1 reports the baseline results, and column 2 reports the additional results with the interaction variables. Likewise, columns 3 and 4 show the estimation results for the outcome *IT_Offer_Accepted*.

*Insert **Table 4** here*

Our baseline results (in columns 1 and 3 respectively) indicate that prior familiarity with the IT industry, as captured by the dummy IT experience, is positively and significantly associated with both an IT offer being extended and accepted (*IT_Offer:* $\beta = 0.306$, $p<0.01$; *IT_Offer_Accepted*: $\beta = 0.212$, $p<0.01$). We also find that in the full model for the outcome *IT_Offer_Accepted* (column 4), the coefficient for IT experience of the study group peers is positive and significant ($\beta = 0.176$, $p<0.01$), suggesting that interactions with IT peers have a positive influence on accepting an IT job offer. The coefficients for roommates who have IT experience are positive but not significant in any of the regressions. It is possible that communication with roommates is more social than geared towards career discussions, a finding consistent with that of Jain and Kapoor (2015).[7]

However, our interaction results (columns 2 and 4 respectively) tell a more nuanced story: if a student has had no IT experience, we find the interaction coefficient between the no IT experience dummy and IT experience of study group peers to be negative. This finding is consistent for both the outcome variables: *IT_Offer* ($\beta = -0.279$, $p<0.01$) and *IT_Offer_Accepted* ($\beta = -0.262$, $p<0.01$). The negative interaction coefficient indicates that IT peers discourage their non-IT peers from their choice of careers in the IT industry.

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[7] Jain and Kapoor (2015) find that study group peers are more influential than roommates in predicting students' performance, as measured by their GPA.

ARE MEN OR WOMEN MORE SUSCEPTIBLE TO INFLUENCE?

The results for interaction coefficients described above encourage us to examine whether male and female students differ in their susceptibility to peer influence. Research on social influence suggests that women are more likely to be collaborative in their decision making approach, and hence more susceptible to social influence (Venkatesh and Morris 2000). In contrast, Aral and Walker (2012) suggest that men are more likely to be influential and women are less likely to be susceptible to influence.

We therefore investigate whether men and women are more or less influenced by (knowledgeable) peers when making career choices. We analyze our models for sub-samples of male and female students. Our results are reported in

Table 5. We find that while the interaction coefficients for students with no IT peers and study group IT peers is negative for both men and women, it is only significant for women (Men: *IT_Offer:* $\beta = -0.127$, $p>0.1$; *IT_Offer_Accepted*: $\beta = -0.172$, $p>0.1$, Women: *IT_Offer:* $\beta = -0.449$, $p<0.01$; *IT_Offer_Accepted*: $\beta = -0.479$, $p<0.01$). Thus, our results suggest that female students with no IT experience are influenced more by their IT study group peers in not only generating but also accepting a job offer in the IT sector. In contrast, our results show that own work experience is positive for both men and women, but significant only for men (Men: *IT_Offer:* $\beta = 0.028$, $p<0.05$; *IT_Offer_Accepted*: $\beta = 0.044$, $p<0.01$, Women: *IT_Offer:* $\beta = -0.449$, p< $p>0.1$; *IT_Offer_Accepted*: $\beta = -0.479$, $p>0.1$).

Considering the underrepresentation of women in the IT industry (Ahuja 2002), these results are especially significant. Do these differences in our results for men and women suggest suboptimal decision-making? The influx of women in managerial roles in the IT industry should be encouraged, and hence our results shed a light on possible interventions that may be helpful.

*Insert

Table 5Table 6 here*

FALSIFICATION CHECK:

While our dataset utilizes random allocation of students to various peer groups, it is possible that our results are merely a result of either perfunctory correlations in the data or unobservable factors in the data that vary between peer groups. To test the robustness of our model, we conduct a falsification check in which we randomly shuffle the peer groups. If the peer groups are truly influential, the coefficients obtained from the variables of the shuffled network groups should be smaller in magnitude as well as statistically insignificant.

We report the results of the regressions using the shuffled groups in **Table 6**. While own IT experience continues to be a significant factor for both outcomes, the coefficients for the variables capturing IT experience in peer groups as well as from any of their interactions are insignificant. This lends credence to our assertion that our data and model are able to identify the influence of peer groups on both *IT_Offer* and *IT_Offer*_Accepted and that our findings are not a result of mechanical correlations or other factors that influence our outcome variables.

*Insert **Table 6** here*

5. CONCLUSION

Our study contributes primarily to the literature on human capital in the IT industry (e.g., Bapna et al. 2013, Mehra et al. 2013, Tambe and Hitt 2014, Mithas and Krishnan 2008). This literature has examined the role of human capital investments in improving employee and firm level performance in the IT industry, or the IT labor pool from which firms recruit. However, the scarcity of relevant data has precluded our understanding of the motivations an individual has to enter the industry in the first place. Our paper is amongst the first to examine this dynamic, and the first to rigorously analyze the role of peers in influencing the choice of IT careers. In particular, we find that IT peers in general increase the likelihood of an individual's pursuit of a career in IT, but also these very peers discourage individuals with no exposure to IT industry. It is possible that students with IT experience who foray into a B-school may not have had positive experiences with the IT industry, and hence they dissuade their non-IT peers from IT careers. We find this effect to be stronger for women than men, and may call for policy interventions to encourage more women to join managerial ranks in the IT industry.

While researchers have addressed the value of effective management on firm productivity in emerging economies (Bloom et al. 2013), as well as the role of peer influences on academic outcomes among business school students (Jain and Kapoor 2014, Jain and Langer 2015), little is known about how managers in emerging economies choose their occupations and industries. Ours is among the first papers in the literature on occupational choice among managers in emerging economies, and we hope to stimulate more discussion on this in the future.

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Appendix: Tables and Figures

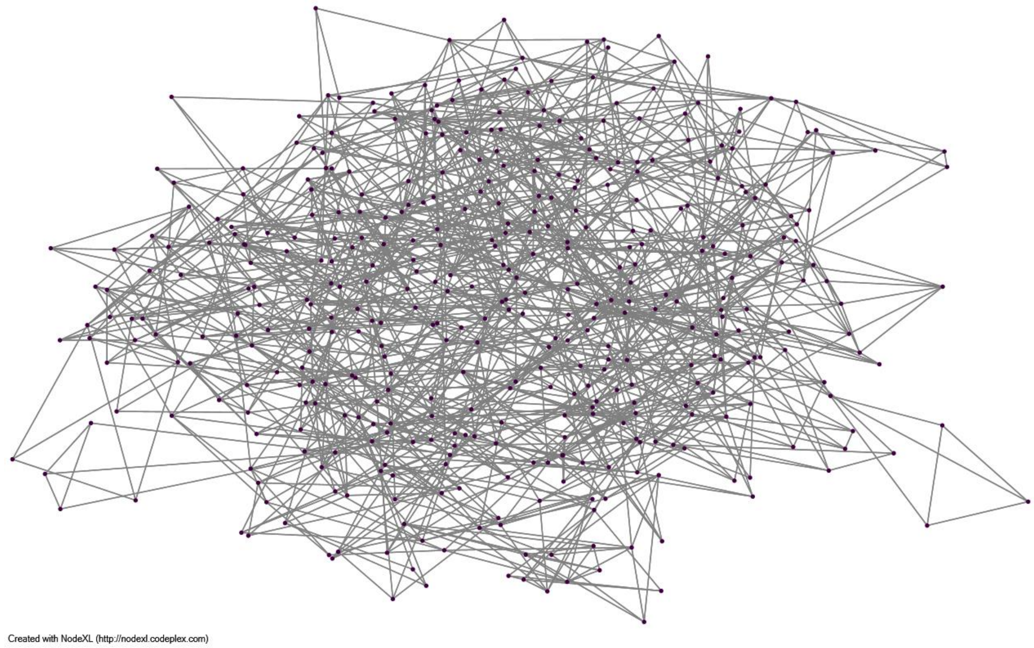

Figure 2: Network for Student Cohort in Year 2007-2008

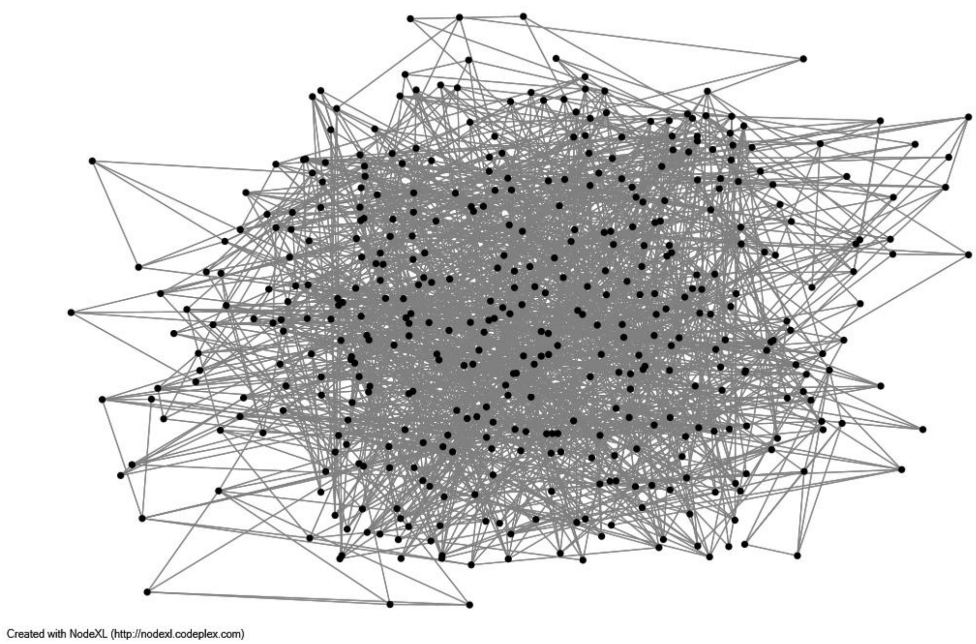

Figure 3: Network for Student Cohort in Year 2008-2009

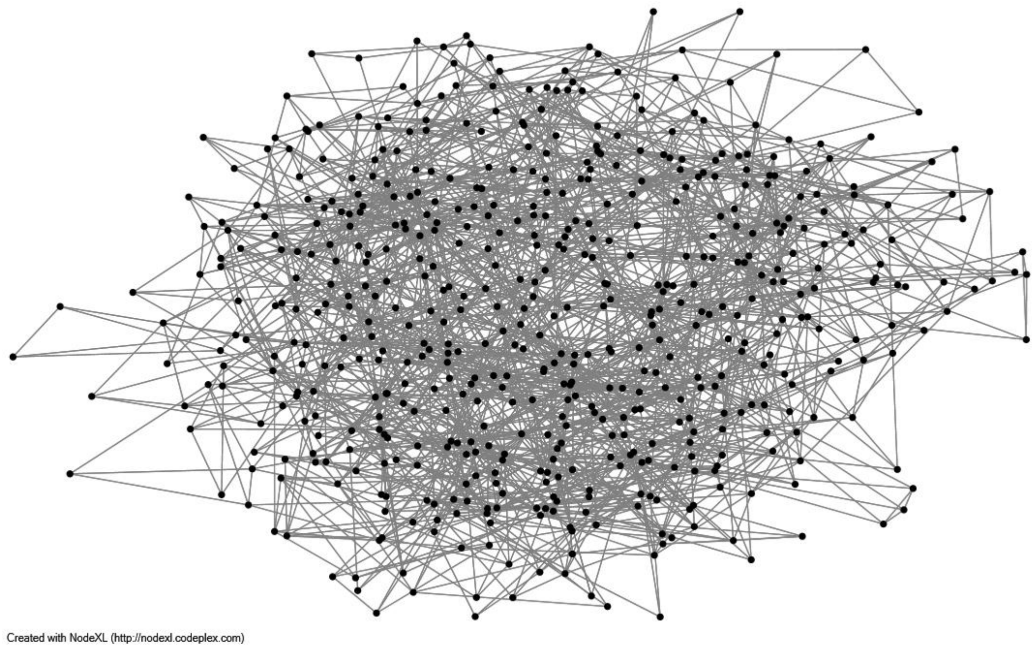

Figure 4: Network for Student Cohort in Year 2009-2010

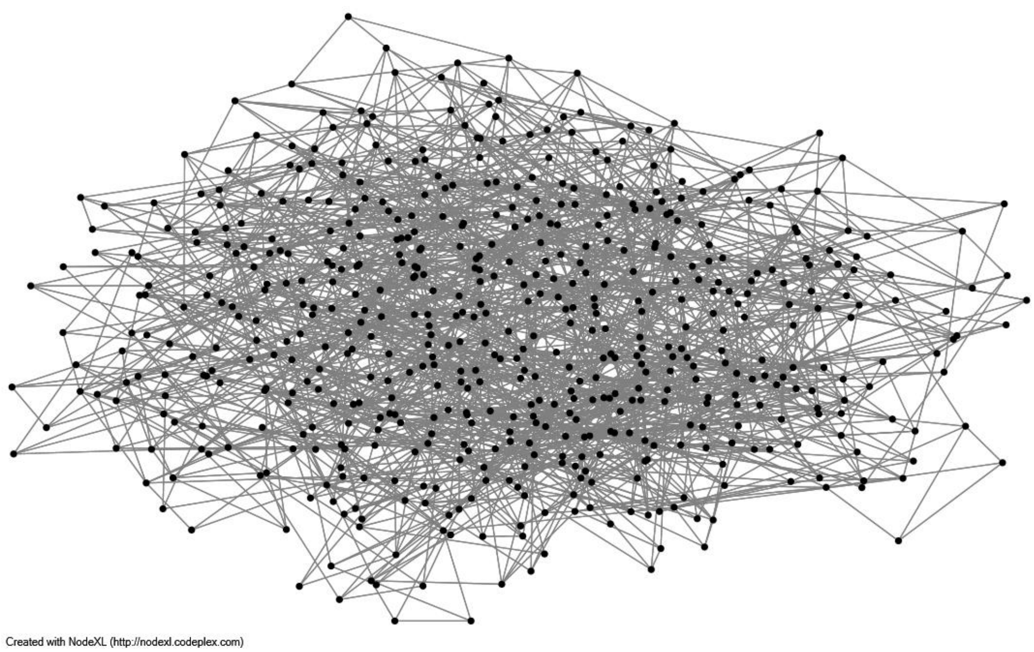

Figure 5: Network for Student Cohort in Year 2010-2011

Table 1: Summary Statistics

Variable	Mean	Std. Dev.
GMAT	709.10	40.18
Work experience (years)	4.86	2.22
Female (=1 if female, =0 if male)	0.26	0.44
Single(=1 if single, =0 otherwise)	0.73	0.45
Citizen of India	0.96	0.20
Pre-program earnings (INR)	997152.40	1195588.00
Age (years)	28.71	2.78
IT experience	0.36	0.48
IT experience (study group)	0.36	0.24
IT experience (roommates)	0.35	0.32
IT offer	0.25	0.43
IT offer accepted	0.27	0.44
Observations	1998	

Table 2: Correlation Between Variables

		1	2	3	4	5	6	7	8	9	10	11
1	GMAT											
2	Work experience (years)	-0.102										
3	Female	-0.167	-0.179									
4	Single	0.033	-0.379	-0.087								
5	Citizen of India	0.143	0.034	-0.030	-0.001							
6	Pre-program earnings	0.030	0.078	-0.010	-0.026	-0.030						
7	Age	-0.106	0.800	-0.174	-0.448	-0.025	0.081					
8	IT experience	0.220	0.091	-0.024	-0.031	0.037	0.069	0.042				
9	IT experience (study group)	-0.063	0.035	0.026	0.001	-0.057	-0.048	0.020	-0.070			
10	IT experience (roommates)	0.017	0.056	-0.001	-0.077	0.025	0.077	0.035	0.195	0.037		
11	IT offer	0.066	0.152	-0.037	-0.080	-0.048	0.031	0.115	0.367	-0.028	0.109	
12	IT offer accepted	0.065	0.144	-0.036	-0.066	-0.064	0.034	0.104	0.352	-0.008	0.086	0.897

Table 3: Determinants of Friendship

	Coefficient	**Std Error**
Study group	**0.070*** **	**(0.00113)**
Roommate	**0.103*** **	**(0.00145)**
Student Village (SV)	0.001***	(0.000207)
Section	0.009***	(0.000279)
Both have masters	0.0007	(0.000515)
Same college	0.003***	(0.000351)
Same major	-0.00007	(0.000194)
Same function	0.0009***	(0.00026)
Difference in GMAT scores	-0.00008	(0.000097)
Difference in experience	-0.0001	(0.00014)
Difference in income	-0.0002*	(0.0001)
Both single	0.00056**	(0.00021)
Both female	0.00063	(0.00036)
Difference in age	-0.0006***	(0.0001)
Both Indian citizens	-0.0001	(0.0004)
Observations	626112	
R-squared	0.018	

Notes: *** $p < 0.01$,** $p < 0.05$,* $p < 0.10$. Standard errors in parentheses. Source: ISB survey and administrative records.

Table 4: Effect of IT Peers on Probability of IT Offer and the Probability of Accepting the IT Offer

	IT offer		**IT offer accepted**	
	(1)	(2)	(3)	(4)
IT experience	**0.306***	**0.225***	**0.298***	**0.212***
	(0.0260)	**(0.0519)**	**(0.0275)**	**(0.0540)**
IT experience (study group)	-0.0493	0.0901	0.0144	**0.176**
	(0.0505)	(0.0837)	(0.0534)	**(0.0855)**
IT experience (roommates)	0.0251	0.0360	0.0286	0.0236
	(0.0382)	(0.0606)	(0.0409)	(0.0632)
No IT experience * Study group IT experience		**-0.217**		**-0.262**
		(0.104)		**(0.108)**
No IT experience * Roommates IT experience		-0.0186		0.00549
		(0.0778)		(0.0823)
GMAT	0.000418	0.000417	0.000130	0.000113
	(0.000333)	(0.000333)	(0.000351)	(0.000351)
Work experience (years)	**0.0281**	**0.0279**	**0.0376***	**0.0377***
	(0.0120)	**(0.0119)**	**(0.0130)**	**(0.0130)**
Pre-program earnings	-1.18e-08	-1.22e-08	-6.06e-09	-7.02e-09
	(9.64e-09)	(9.64e-09)	(1.04e-08)	(1.04e-08)
Demographic controls and year fixed effects	Yes	Yes	Yes	Yes
Observations	1217		1028	

Note: Columns 1 and 3 show the estimation coefficients for the OLS regression for outcomes a) IT job offer being made to a particular student and b) an IT job offer being accepted. Columns 2 and 4 also incorporate the interaction effects for those students with no IT experience and study group and roommates IT experience. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses. Source: ISB administrative records.

Table 5: Sub-sample analysis for men versus women

	IT offer		IT offer accepted	
	Male	**Female**	**Male**	**Female**
IT experience	**0.264******	0.148	**0.271******	0.0729
	(0.0611)	(0.101)	**(0.0652)**	(0.101)
IT experience (study group)	0.0332	0.258	0.130	0.284
	(0.0949)	(0.178)	(0.0984)	(0.179)
IT experience (roommates)	0.104	-0.157	0.0280	0.0351
	(0.0709)	(0.121)	(0.0748)	(0.125)
No IT experience * Study group IT experience	-0.127	**-0.449****	-0.172	**-0.479****
	(0.120)	**(0.213)**	(0.128)	**(0.214)**
No IT experience * Roommates IT experience	-0.0861	0.151	0.00996	-0.0389
	(0.0929)	(0.148)	(0.100)	(0.152)
GMAT	0.000393	0.000359	0.000249	-0.000113
	(0.000428)	(0.000538)	(0.000467)	(0.000538)
Work experience (years)	**0.0280****	0.0337	**0.0437******	0.0177
	(0.0137)	(0.0252)	**(0.0153)**	(0.0258)
Pre-program earnings	-3.04e-08*	-3.45e-09	-3.46e-08	-5.62e-10
	(1.74e-08)	(1.19e-08)	(2.33e-08)	(1.16e-08)
Demographic controls and year fixed effects	Yes	Yes	Yes	Yes
Observations	859	358	714	314

Notes: *** $p < 0.01$,** $p < 0.05$,* $p < 0.10$. Standard errors in parentheses. Source: ISB administrative records.

Table 6: Shuffled networks

	IT offer		IT offer accepted	
	(1)	(2)	(3)	(4)
IT experience	**0.312*** **	**0.270*** **	**0.309*** **	**0.282*** **
	(0.0304)	**(0.0499)**	**(0.0322)**	**(0.0526)**
IT experience (study group)	-0.0127	-0.0100	0.0297	0.0494
	(0.0577)	(0.0650)	(0.0613)	(0.0694)
IT experience (roommates)	0.0118	0.0222	0.00436	-0.0208
	(0.0438)	(0.0505)	(0.0464)	(0.0536)
No IT experience * Study group IT experience		-0.108		-0.0833
		(0.0823)		(0.0876)
No IT experience * Roommates IT experience		0.0318		0.0652
		(0.0666)		(0.0718)
GMAT	-0.0000228	0.000421	-0.000196	-0.0000472
	(0.000408)	(0.000468)	(0.000440)	(0.000502)
Work experience (years)	0.00804	0.0260	0.0121	0.0342*
	(0.0128)	(0.0162)	(0.0138)	(0.0176)
Pre-program earnings	-5.68e-09	-6.55e-09	-4.82e-09	-5.76e-09
	(1.02e-08)	(1.10e-08)	(1.05e-08)	(1.13e-08)
Demographic controls and year fixed effects	Yes	Yes	Yes	Yes
Observations	1217		1028	

Notes: ∗∗∗ $p < 0.01$,∗∗ $p < 0.05$,∗ $p < 0.10$. Standard errors in parentheses. Source: ISB administrative records.