Competing for Talent: Firms, Managers and Social Networks

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Abstract

We use a randomized experiment to demonstrate the value of social networks for firms competing for talented young managers. In our experimental setting, firms are connected to prospective managers through their former employees. The connections are exogenous due to the random assignment of individuals into classrooms and small study groups as they complete an MBA. Using measures of managerial talent, we document that social connections double the probability a firm hires a high-ability manager, while decreasing the probability of hiring a low-ability manager. We show that managers hired through social connections have longer job tenures, and relate our evidence to the role of former employees in providing referrals and supplying information, leading to better labor market matches.

Keywords: Managerial Labor Market, Social Networks, Experimental Setting, Random Assignment, Human Capital

JEL Classification Codes: G34, M12, M51, J24

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"The talent wars begin even before (MBA) classes do."

Wall Street Journal,[1] October 7, 2017

1 Introduction

Highly productive human capital is concentrated across a selected set of highly-valued firms (Abowd et al., 2005). As of October 2017, among the ten US firms with the largest market capitalization, the five oldest had an average value of \$2.6 million dollars per employee, while the five youngest had an average value of \$10.8 million dollars per employee,[2] suggesting that returns to (skilled) human capital are increasingly more important for firm value, particularly for top growth firms. Consistent with this view, recent work shows that firms with more productive human capital have higher market-to-book ratios, higher growth rates, and lower cost of capital (Belo et al., 2017; İmrohoroğlu and Tüzel, 2014). However, as the supply of human capital is limited, potential employers must compete to hire and retain a talented workforce (Gabaix and Landier, 2008a; Terviö, 2008). In this environment, understanding how firms acquire the most productive employees is akin to understanding the sources of their value.

This paper provides micro-level evidence that social networks improve a firm's access to the managerial labor market. Specifically, by using multiple measures of managerial talent, we document that a firm connected to a high-ability young manager through former employees is more likely to hire that manager than a firm that has no social connections with the manager. We focus on social networks as (i) prior evidence underlines the important role of social networks in corporate policies (Shue, 2013), investment decisions (Ahern et al., 2014; Cohen et al., 2010), mergers and acquisitions (Cai and Sevilir, 2012; Schmidt, 2015), and the cost of capital (Engelberg et al., 2012; Faccio, 2006; Haselmann et al., 2017; Karolyi, 2014), and (ii) social networks play a central role for low-skilled workers in finding and securing a job

[1] On "Another Thing Amazon Is Disrupting: Business-School Recruiting", October 7, 2017.

[2] The five oldest firms among the non-financial firms are Berkshire Hathaway, Johnson & Johnson, Exxonmobil, Walmart, and Chevron, while the five youngest are Apple, Google, Microsoft, Amazon, and Facebook.

(Granovetter, 1995; Holzer, 1988).[3]

In this paper, we analyze the labor market for a sample of Master of Business Administration (MBA) graduates. Each year, firms compete to hire new MBA graduates for managerial positions.[4] By focusing on MBA graduates, we are able to clearly identify a population of managerial job applicants. Since the set of firms hiring newly graduated MBA students is highly concentrated, we can simultaneously identify a population of potential employers hiring managers each year.[5] The combined result is a unique setting to study both supply and demand in the managerial labor market.

Given that the majority of MBA students have prior work experience,[6] recruiting firms are connected to managerial job applicants through former employees enrolled in the same MBA program. Firms may exploit these social networks when competing for the most talented managers, but former workers may lack strong incentives to help firms, and may instead make referrals for nepotistic reasons, decreasing firm productivity (Goldberg, 1982; Kramarz and Skans, 2014; Kramarz and Thesmar, 2013).[7] In this paper we test (i) whether a firm connected to a young manager through a former employee is more likely to hire that manager, (ii) whether this effect is larger for high-talent managers (relative to low-talent managers), and (iii) whether managers hired through social connections have longer job tenures.

A primary identification issue concerns the endogeneity of social networks: individuals often choose to interact with peers who have similar unobservable characteristics, and peer groups often experience common unobservable shocks (Manski, 1993). In our setting, this

[3]The labor economics literature also shows that referred applicants often earn higher wages (Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2011), suggesting that social networks have a positive effect on firms' productivity.

[4]MBA graduates are likely to become managers shortly after graduation. Confirming this prediction, we show that approximately 80% of the MBA graduates in our sample reach a middle manager position within 5 years of graduation. To produce this statistic, we defined a middle-manager as an employee whose job title includes one of the following words: 'manager', 'director', 'executive', or 'president'.

[5]In our sample, ten firms hire nearly 25% of the graduating students.

[6]The average student in our sample has five years of work experience prior to beginning the MBA program

[7]It is unclear whether former employees can help firms identify talent. Economists have argued that social networks make referrals due to direct compensation (Beaman and Magruder, 2012; Heath, 2017) or indirect incentive mechanisms (Pallais and Sands, 2016); as a result, the literature has traditionally focused on current employees as the primary source of referrals.

endogeneity is particularly problematic as former employees are likely to choose to interact with prospective employees of a given firm. Fortunately, the Master of Business Administration (MBA) program at Indiana University (IU) provides us with a unique experimental setting. At IU, every entering MBA student is randomly assigned to a cohort and a team in their first year in the program. Students in the same cohort (each composing approximately fifty individuals) take the core MBA classes together; students in the same team (each composing five individuals) are assigned to work together on course projects and a large case study at the end of the first semester.[8] We consider a student to be connected to a firm if a former employee of that firm belongs to his or her cohort (or team). Given that students do not choose their cohorts or teams, some students will be more connected to a given firm for reasons exogenous to their ability, effort, or interests.

Testing our hypotheses requires analyzing each manager's career path before and after his or her involvement with former employees. We obtain detailed individual-level employment records from a large online business networking service. From this online platform, we observe employment history (job title, location, start and end dates, firm name) and education (school, major, year of graduation). We then merge this data with information about cohort and team assignments, admissions information, and class performance for each graduate, obtained from the MBA office at Indiana University. Finally, we use the online networking service to collect detailed information for each employer in the sample. Our sample includes a total of 2,109 MBA students graduating between 1999 and 2013.

To study the sorting of managers into firms, we need to identify a set of employers who receive job applications across the full distribution of managerial talent. Therefore, we focus our analysis on the set of high-skill firms that employ graduates of the top-ranked U.S. MBA programs.[9] Specifically, we consider only employers that hire at least five managers from top-ranked MBA programs —Harvard University, the University of Chicago, and Stanford

[8]Depending on the year, an MBA class at IU has approximately 200 students.

[9]This selection process produces an additional benefit as it focuses the analysis on a set of firms that strongly depend on young managerial talent to create value.

University— during our sample period.[10] Forty-nine employers, or about 20 percent all firms that hire IU students, fit this definition, including McKinsey & Company, Deloitte, Apple, Microsoft, Goldman Sachs, Google, and Procter & Gamble.[11] For each potential employer in the sample, we need to observe whether a given student (i) entered that particular firm and (ii) has a cohort (team) member previously employed at the particular firm. As such, we build a dataset that maps all possible employer-student combinations.

The likelihood that a given firm hires a given Indiana University MBA graduate is 1.2 percent; having a cohort connection to the given student through a former employee increases the likelihood of employment by 0.6 percentage points, a 50 percent increase relative to the mean. If the connection is formed through interactions with a team member, this likelihood increases by 2.0 percentage points, a two-fold increase relative to the mean, suggesting that tighter connections between former employees and prospective managers lead to an even higher likelihood that the firm hires the connected manager.[12] We also estimate the effect of connections with former employees on the likelihood of employment three and five years after graduation, and confirm employers with a connection to a manager still have an edge over employers without a connection. While the statistical significance falls slightly, these results suggest that social connections induce permanent effects in the allocation of young managers to employers.

Given the causal evidence that a connection to a former employee increases the likelihood of employment, we next examine whether these connections help attract the best managers and potentially avoid bad ones. To measure managerial talent, we introduce two separate measures, based on first-semester course grades and a quantitative exam taken as part of the MBA application process, respectively.[13] While neither grades nor exam scores are perfect

[10]These three programs cover three separate geographic regions and place among the top five programs according to multiple MBA rankings.

[11]The complete list of high-skill firms is presented in Table 6.

[12]We similarly confirm that network effects are largest when the former employed had a long tenure with the employer.

[13]Recent papers have explored more direct measures of worker productivity (Brown et al., 2016; Burks et al., 2015; Pallais and Sands, 2016); however, these papers are only able to focus on a single firm or industry. In comparison, our measures allow us to follow all workers, regardless of firm of industry.

measures of managerial talent, we offer evidence that they are reasonable proxies. During the first semester, all students take core courses in Marketing, Finance, Strategy, Accounting, and Operations.[14] MBA core grades will proxy for an individual's managerial skills in these core disciplines.[15] Entrance exam scores are a primary input into MBA rankings, and are used to proxy for more general verbal and quantitative skills.

We find strong evidence that social networks help firms attract more talented managers. High-talent managers connected to a firm through a cohort member are 1.5 percentage points more likely to join that firm, more than doubling the rate of entry relative to the mean. If the connection is established through a team member, this likelihood increases to 4.0 percentage points, a four-fold increase relative to the mean. In contrast, social networks have a negative (or no impact, depending on the specification) on the hiring of low-talent managers, despite that 25 percent of low-talent students still join high-skill firms at graduation. The results hold whether we define talent based on grades during the MBA program or entrance exam scores. We also confirm our results using alternative network definitions based on gender and race, which have been previously used in the referral literature as workhorses to define labor and social networks (Bandiera et al., 2009; Bertrand et al., 2000; Dustmann et al., 2015).[16]

Thus far, we identify the role of social networks only indirectly, by following employment outcomes for connected and unconnected firms. We next develop more direct evidence that networks increase public information in the labor market. First, we confirm that connections will lead to improved firm-employee matches. We estimate that students joining a firm through networks remain employed with the firm for eleven months longer than uncon-

[14] A recent literature has confirmed the value of these general managerial skills over more firm- or industry-specific knowledge (Custódio et al., 2013; Frydman, 2005; Murphy and Zabojnik, 2007).

[15] Anedoctal evidence provided by the MBA office suggests that core courses are relevant to employers in assessing students' managerial skills. Students report that they are often asked about their grades in the core courses during the interviewing process.

[16] These social networks are no longer exogenous, and the observed network effects may be attributable to managers with similar characteristics joining the same firms. However, we still find that high-talent managers are more likely to benefit from a social network than low-talent managers. Dividing managers based on the two talent measures, we again find evidence that more talented managers are significantly more likely to enter the firm due to a connection; in comparison, networks can actually decrease the likelihood of a less talented manager entering a firm.

nected students, an increase of 20 percentage points relative to the mean. Second, to directly confirm the relevance of social networks for hiring outcomes, we conduct a survey by contacting directly treated managers in our sample. We ask them two questions to infer (i) whether they obtained their post-MBA job by receiving a referral from a fellow cohort member, and (ii) whether a cohort member provided relevant information about the high-skill firm, influencing their decision to join that firm. The results show that both channels are relevant for hiring outcomes, though access to private information about the firm is more prevalent.

We conclude by rejecting alternative explanations of our results. First, we confirm that connections to a given firm do not increase the likelihood of employment at other high-skill firms, even within the same industry. Second, we incorporate information on intended major (prior to peer interaction) and actual major at the time of graduation. Except for students switching majors to study entrepreneurship, we find no evidence that MBAs change their majors due to their connections. Third, by analyzing first semester grades, we find no evidence that team members impact classroom outcomes.

Our results have significant implications outside the particular experimental setting. First, as students in our setting will routinely interact with peers outside their team or cohort, our estimates are only a lower bound on the value of social networks for young managers. The results then highlight how policies promoting interaction between managers can ultimately impact the allocation of managerial talent across firms. Second, the firms in our sample are well-known to the prospective managers in our sample and have developed screening mechanisms given the size of the MBA labor market. If social networks have large effects in our setting, one can only infer that they might assume an even greater role for other firms with weaker screening processes and less public information available to prospective workers.

2 Literature Review

This paper helps advance the literature that studies: (i) the determinants of young managers' career outcomes and how they sort into firms; (ii) social networks' effect on firm productivity;

and (iii) the causal identification of peer effects on labor outcomes due to random assignment.

First, we expand the literature on social networks to the managerial labor market. The finance literature has long acknowledged the implications of managerial talent for firm value (Benmelech and Frydman, 2015; Bertrand, 2009; Malmendier and Tate, 2009), leading researchers to question how managers select and sort into firms (Gabaix and Landier, 2008b; Terviö, 2008). To understand these dynamics, recent research has evaluated the drivers of young managers' careers, including stock market conditions (Oyer, 2008) or individual firms' stock returns (Bhole and Oyer, 2014), gender (Bertrand et al., 2010), risk aversion and optimism (Kaniel et al., 2010; Sapienza et al., 2009), university ranking (Arcidiacono et al., 2008; Zimmerman, 2016), and previous industry experience (Kuhnen and Oyer, 2016).[17] Most closely, Kuhnen (2017) illustrates that candidates search for work with greater intensity if they have low ability or worse outside options, are looking for more valuable jobs, or are applying to employers with more vacancies. Our work contributes to this literature by showing how social networks (i) help young managers advance in their careers, and (ii) explain how young mangers sort into firms.

Second, we add to a recent literature detailing the benefits of social networks to firms.[18] Researchers suggest that referrals have the potential to increase labor market efficiency by providing new information previously unknown to the firm (Beaman and Magruder, 2012; Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2015; Heath, 2017; Pallais and Sands, 2016).[19] By studying the role of social networks within the managerial labor market and introducing unique measures of managerial talent, we analyze a setting with significant implications for firm value as employers benefit from social networks by hiring more talented

[17] In addition, recent research has offered suggestive evidence that business school networks may help support entrepreneurial partnerships between workers (Cai et al., 2015).

[18] More broadly, this literature examines the impact of social networks on labor outcomes using employee-employer linked data. Researchers have evaluated how workers benefit from networks arising through residential neighborhoods (Bayer et al., 2008; Dustmann et al., 2015; Hellerstein and Neumark, 2008), previous employment (Cingano and Rosolia, 2012; Glitz, 2013, 2014; Saygin et al., 2014), or minority communities (Dustmann et al., 2015; Giuliano et al., 2009).

[19] In addition, other papers have suggested that referrals are made for nepotistic reasons and potentially hurt firm productivity (Kramarz and Skans, 2014; Kramarz and Thesmar, 2013).

managers.

Lastly, we expand the social networks and labor outcomes literature using an experimental setting that exploits random assignment. A common criticism of social networks research is that results may be driven by exogenous sources of variations in networks since unobservable differences are likely correlated with both social interactions and the outcome variable (Hellerstein et al., 2015).[20] To solve identification concerns, we build on a second literature that estimates peer effects through random assignment (Ahern et al., 2014; Lerner and Malmendier, 2013; Shue, 2013). While Shue (2013) studies how CEO/CFO peers impact firm policies, Ahern et al. (2014) focuses instead on measures of altruism and trust. Our paper is more similar to Lerner and Malmendier (2013) who consider a separate employment outcome, entrepreneurship at graduation.[21] In comparison to this literature, we apply the identification to study the long-term outcomes of all students. To our knowledge, the only prior paper on random assignment and long-term labor outcomes is Laschever (2009), who in a very different setting considers how involuntarily-formed social networks among World War I draftees affect reported employment in the 1930 Census.[22]

3 Data

The contribution of this paper stems jointly from the random assignment of MBA students, data on long-term career outcomes at the individual level, and measures of managerial talent. We first discuss and summarize our unique data sources: (i) the Indiana University Kelley

[20] As discussed in Sacerdote (2014), there is a wide range of attempts to overcome identification concerns, including (i) exogenous movements of people, such as court-ordered desegregation of schools and hurricane refugees (Billings and Deming, 2014; Imberman et al., 2012), (ii) random variation across cohorts due to gender or race (Hoxby, 2000), and (iii) discontinuities due to test score cut-offs (Abdulkadiroğlu et al., 2014; Jackson, 2013). Although these studies can offer large datasets, they cannot easily identify peers that interact closely with each other.

[21] A related line of research relies on random assignment of dormmates and roommates to examine their influence on short-term test scores (Carrell et al., 2009; Lyle, 2009; Sacerdote, 2001; Zimmerman, 2003).

[22] However, Laschever (2009) breaks down social groups into large blocks of a hundred individuals, can only observe whether the individual is employed, and has a single employment observation over ten years after the end of the war. We differ by narrowly defining social groups with five or less individuals, observing each individual's employer and industry, and including the full employment history of each manager.

School of Business MBA Program and (ii) a large online business networking service that provides us employment history and firm-level data.

3.1 Data Sources

Kelley School of Business MBA Program. All entering Full-Time MBA students are assigned to one of three or four cohorts of approximately 50 students. Members of a cohort take the first semester classes together. In addition, students are assigned to a team within the cohort, composed of roughly five students. Members of a team compete in two different case competitions that compose part of their final grades for the semester. In addition, teams work together on group homework assignments.

The assignment process for the Kelley School of Business MBA Program attempts to maximize diversity across both cohorts and teams and is similar to the method used at Harvard Business School (discussed in Shue (2013)) and the University of Michigan (discussed in Ahern et al. (2014).[23] Students entering prior to 2009 were assigned to their cohort/team by maximizing diversity across four characteristics: gender, race (for domestic students), citizenship (classified as US or International), and undergraduate major. While the system is electronic, staff members are also allowed to make manual corrections to achieve balance.

Starting in 2009, with the advent of a new admissions director, IU's measures of diversity changed. The new system split students by application status (US domestic, International, or US underrepresented minorities), country of citizenship, gender, GMAT (generally defined as under 600, 600-690, and 700 and above), Keirsey Personality Type (Guardians, Artisans, Idealists, Rationals), and undergraduate major (defined as business studies, STEM disciplines, and all other subjects). In addition, special considerations were taken into account on rare occasions, usually requiring that two students in a relationship not be placed in the same cohort. Students are unable to switch cohorts/teams once the semester starts; however, stu-

[23] For instance, according to Ahern et al. (2014), the University of Michigan MBA Program maximizes diversity within sections by equally weighting six dimensions: gender, ethnicity, citizenship, undergraduate institution, employer, and dual-degree status. A similar randomization is used by Harvard Business School.

dents may be able to switch prior to the semester if the class time conflicts with childcare or a medical engagement.

Our data has three clear advantages over similar datasets. First, while past studies are only able to randomize across larger classrooms (Hoxby, 2000; Shue, 2013), we also include information at the team level (4-5 students), allowing for a much finer measure of peer relationships. Second, we note that students are not sorted based on their intended MBA major or future employment goals. This is a particular benefit of the data: as discussed in Chetty et al. (2011), randomizing based on majors/employment goals will generate little variation across teams and cohorts. Third, the data includes the intended major of each applicant prior to entering the MBA. By merging this information with data on students' eventual majors, we can identify the effect of peer effects on short-term career interests.

Measures of Managerial Talent. We collect two measures of managerial talent: scores from a quantitative MBA entrance exam, and MBA classroom performance. Our classroom performance measure is based on two arguments. First, recent evidence suggests that shareholders value managers with an MBA education. A line of literature documents that stocks react more positively when a newly-appointed manager has higher educational credentials, and that such managers receive higher compensation (Bhagat et al., 2010; Falato et al., 2015). This preference is unsurprising given that managers with MBAs have superior performance to peers without an MBA (Chevalier and Ellison, 1997; King et al., 2016). Second, an MBA education is likely valuable across the firms and industries in our sample. Classroom performance is measured using grades from the first semester of the MBA. In the first semester, all MBA students are enrolled in the Core Curriculum. Though the exact nature of the Core Curriculum has changed over the years, the courses cover eight topics taught by eight different faculty members: Critical Thinking, Economics, Finance, Accounting, Marketing, Operations, Quantitative Analysis, and Strategic Management. A recent literature has confirmed the value of these general managerial skills over more firm- or industry-specific knowledge

(Custódio et al., 2013; Frydman, 2005; Murphy and Zabojnik, 2007).

In addition to MBA performance, we follow the economic literature (Hensvik and Skans, 2016) and also measure talent based on students' scores on a quantitative MBA entrance exam. We support this measure by noting that firms pay significantly higher wages to managers with higher-ranked MBA degrees (Arcidiacono et al., 2008). Given that MBA rankings depend both directly and indirectly on the average exam scores of the entering MBA students, MBA programs have incentives to base admissions decisions on entrance exam scores;[24] as a result, managers have significant wage incentives to score as high as possible to earn a spot in a highly-ranked MBA program.

Finally, we collect admissions data, including personal characteristics (citizenship, gender, ethnicity, etc.), undergrad GPA, and intended MBA major. We merge this admissions data with the team and cohort information and our measures of managerial talent.

Online Business Networking Service. Without additional data sources, prior research on peer effects is often limited to short-term outcomes. To observe career outcomes over several years we instead rely on a large online social network for both workers and firms. We match each Kelley MBA graduate to his/her user profile on this online platform, which includes self-reported employment and education data. We then collect additional information about each employer, including the location and industry of the firm. All data is publicly available and is obtained through web searches and then parsed into a panel dataset.[25]

Our unique dataset has a number of advantages over alternative sources. First, employer-employee linked data from the U.S. Census Longitudinal Employer-Household Dynamics does not include employee names or educational histories (Graham et al., 2013; Jacobson et al., 1993); as a result, it is not possible to identify our graduates at the individual level. Second, data on individual employees at public firms has been used extensively in the finance literature (Gompers et al., 2003; Jensen and Murphy, 1990; Weisbach, 1988); however, this data

[24]For instance, in the 2018 MBA rankings, over 16% of the ranking is based on the mean entrance exam scores.

[25]For a more detailed description of the data, we refer readers to Hacamo and Kleiner (2016).

focuses only on top executives and excludes all information for employees at private firms.

Data Cleaning. We manually match each MBA graduate to his or her online profile by first and last name, MBA degree, and year of graduation (if available in the profile). We do not require an exact match on first name since a high fraction of managers use nicknames (this is especially true of international managers); similarly, we do not necessarily require a strict last name match since a fraction of managers (especially female managers) have changed their last names since graduation. We drop any graduates without online profiles. To confirm that our matches are correct, we first require that each online profile refers to an MBA from the Kelley School of Business. In addition, we drop cases where the profiles list incorrect graduation years.[26] Finally, for a portion of the sample (from graduating class 2004 to 2013), we have admissions data that includes undergraduate school. For this subsample, we also confirm that the undergraduate school from the admissions data matches the data from the online profile.

3.2 Classification

Employers. Employers hiring MBA graduates vary widely in size, location, and firm longevity. Given that we observe only graduates' ultimate employers, rather than the entire set of job applications submitted by each student, we have a large number of potential employer-manager combinations. To constrain the data sample, we focus our analysis on a subset of potential employers. Specifically, we limit the dataset to employers that receive applications from even the most talented Indiana University MBA graduates.

To identify employers that hire from Indiana University, we require that at least one graduate in a given year enters the firm directly following graduation. To identify the set of employers that receive applications from the most talented job applicants, we introduce employment data for MBA students graduating from top-ranked MBA programs during the period 2001-

[26] In a robustness check, we exclude all individuals whose online profiles do not include entering/graduation dates, and our results do not change.

2013.[27] We incorporate data from Harvard Business School, University of Chicago Booth School of Business, and Stanford University Graduate School of Business in order to include universities across the East Coast, Midwest, and West Coast.[28] We then include only firms that employed at least five managers at graduation from each one of these three MBA programs during the time sample. We label these employers high-skill firms. We introduce the set of high-skill firms in our sample in Table 6. We identify a total of 49 high-skill firms across a wide range of industries.

In unreported results, we examine alternative definitions of high-skill firms by changing the cutoff of number of students. Our estimations in the results section hold over these alternative definitions of high-skill firms. We also confirm these set of firms correlates over time and across the top three schools. First, we find that employment outcomes are correlated over time: the number of graduates from each program entering a given firm is highly persistent over years. Second, we find that the employment outcomes are correlated across universities: the number of graduates entering a given firm from one school is highly predictive of the number of graduates entering from a different school. This correlation over time and the cross-section suggests that the list of high-skill firms is relatively robust to alternative specifications.

3.3 Data Summary

Manager Demographics. Our initial sample includes MBA students graduating between 1999 and 2013, comprising 2,843 students. First, we exclude students without an online networking profile. Second, due to our focus on the set of high-skill firms, we exclude the subset of students with prior experience in a high-skill firm for the regression analysis, decreasing

[27]In the appendix, we introduce a simple revealed-preference model detailing how firms that consistently hire any students from top-ranked MBA programs can hire even the most talented Indiana University graduates.

[28]These are often considered the three highest-ranked MBA programs in the US. For example, in the 2017 *US News* MBA rankings, the Harvard MBA is ranked first, the Chicago MBA is second, and the Stanford MBA is fourth. In the 2017 *Bloomberg* MBA rankings, the Harvard MBA is ranked first, the Stanford MBA is second, and the Chicago MBA is fourth. Rankings in previous years are similar.

the sample by 16%.[29] Our final data sample include 2,109 students as presented in Panel A of Table 1. We estimate that 63% are male, 25% are international, and 16% are U.S. minorities. The average quantitative entrance exam score is 43 out of 60 and 23% of students received an overall A grade in the first semester of the MBA.[30] Approximately 15% of students in the sample graduated from a top U.S undergraduate institution.[31] Upon graduation, finance is the most common major, with half of the student body graduating with a first or second major in finance. Marketing is the second most common major (44%), followed by strategy (15%), management (10%), entrepreneurship (8%), and operations (7%).

We also summarize the characteristics of each team and cohort in the sample. As discussed earlier, cohorts and teams are assigned based on several criteria. Students are randomly assigned to one of four cohorts during the early years of our sample period, and to one of three cohorts starting with the 2006 graduating class. Then, students are randomly assigned into a 4-5 member team within each cohort, resulting in a total of fourty to fifty teams per graduating class. From the original admissions data, we note that team size ranges between 4 and 5 students, with an average of 4.5 students.

Missing Graduates. We are able to match nearly 95% of MBA graduates to their online profiles. We highlight the match details in Figure 1. For each MBA graduation year, we split managers into three categories (Domestic White, Domestic Minority, and International) and plot the match percent for each category. There are three primary takeaways from the results. First, we have a similar match rate for white and international managers, both over 95%. However, the match rate for minorities is slightly lower at 93%. Second, in unreported results,

[29] The estimation results hold when we include managers with prior employment experience at a high-skill firm, as only 19% of students return to a former employer following graduation.

[30] First, we note that we have only 1,625 observations of the quantitative exam score as we are missing exam scores for the graduating classes of 1999-2002. Second, we are missing first semester MBA grades for the graduating classes of 1999-2002. We instead proxy for classroom performance by identifying students that graduated from the MBA program with Honors. We assign students graduating with Honors an A letter grade, and all other students a B letter grade.

[31] We identify top undergraduate institutions using the 2016 U.S. News and World Report Best Colleges Ranking. In our analysis, a top institution is any institution defined as (i) a top twenty overall university, (ii) a top ten liberal arts college, (iii) a top five public university, or (iv) a top five undergraduate business school.

we find little difference between male and female students within each category. Third, the match rate does not rise over time.

Given that we are missing 5% of the managers in our sample, one potential concern is that results might be biased if graduates with online profiles have different skills/interests compared to graduates without such profiles. In unreported results, we find no evidence that manager skill (defined as MBA entrance exam scores or Undergrad GPA) predicts our ability to match a graduate to his/her online profile. Similarly, the managers' career interests (determined by intended major upon admission) are insignificant.

Middle-manager Titles. To confirm that students reach middle-managers status, we identify key words in job titles used in managers' résumés. In Figure 2, we show that within five years of graduation, the majority of IU MBA graduates obtain middle-manager status. We define middle-manager status as encompassing six managerial titles: (1) Manager, (2) Director, (3) President or Vice-President, (4) Executive, (5) Partner, and (6) Principal. The likelihood of obtaining a middle-manager title increases with time since graduation. At graduation, fewer than 50% of workers have a manager title; this percentage increases to approximately 55% in year one, nearly 70% in year three, and nearly 80% in year five. While the majority of titles include the word "Manager", we confirm a significant and rising fraction of higher-level titles over the five-year period. For example, by year five, 10% of workers hold Director-level jobs, and over 5% of job titles include the word "President" or "Vice-President". These results help confirm that the individuals in our sample are indeed potential middle-managers that oversee a subset of other employees and firm projects.

Employer Characteristics. We summarize employer characteristics in Table 3, including only firms hiring multiple IU MBA graduates in the same graduation year. Our analysis focuses on the set of 49 high-skill firms. These firms employ an average of 13.6 graduates from the Kelley MBA Program during the sample. In addition, 71% are classified as distant firms, with headquarters at least 750 miles from Bloomington, Indiana.[32] These firms are concentrated in the financial (33%), technology (12%) and consulting (14%) industries. For comparison, we also include summary statistics for the 274 less-skill hiring firms. Less-skill firms employ fewer managers on average (5.1 graduates during the sample period) and are geographically closer to the Indiana University campus. Also, less-skill firms are less likely to belong to the finance, technology, and consulting sectors.

4 Methodology

First, we develop an empirical framework that allows us to identify the impact of social networks on employers in the sample. Second, we summarize the data necessary for the regression analysis.

4.1 Regression Framework

To identify whether social networks have a causal effect on employers competing for managers, we must first address the endogeneity associated with the formation of such networks. In our analysis, a worker has a connection to a firm if she knows a former employee of that firm. However, worker connections are potentially driven by particular skillsets, current and past decisions, and networking efforts (Hellerstein et al., 2015; Manski, 1993). Thus, to estimate plausible causal effects of former employees' networks, we rely on the forced assignment into cohorts and teams introduced by the MBA office at Indiana University.[33] Importantly, as the forced assignment does not depend on students' pre-MBA experience, the set of connections is exogenous to the job applicant. Since only 16% of the entering class has experience in any high-skill firm, a student only has a 12% (0.8%) change of being connected to a given high-skill firm through her cohort (team).

[32] We choose 750 miles to distinguish between firms headquartered in the Midwest and firms headquartered on the coast.

[33] Students in the same cohort take the core MBA classes together, while students in the same team are assigned to work together on course projects and a large case study at the end of the semester.

We test whether an employer with a connection to an applicant (student at graduation) has a higher likelihood of hiring that applicant. As each employer has a wide range of potential applicants, we implement this test by forming all possible pairs between all managers and firms in our sample. Specifically, we evaluate whether a firm i is more likely to hire applicant j if any cohort members (or team members, in robustness tests) of manager j worked at firm i prior to entering the MBA program. We estimate the following linear probability regression model:

$$Employment_{i,j} = \alpha_C + \beta_C \times Connection_{i,j} + FirmYearControls + \varepsilon_{ij}, \tag{1}$$

where $Employment_{i,j}$, the dependent variable of interest, is a binary variable that takes a value of one when firm i hires applicant j. The key independent variable is $Connection_{i,j}$, a binary variable denoting whether any cohort (or team) member of manager j had previous employment experience with firm i. We test the hypothesis that $\beta_C > 0$, which implies that former employees support the firm's recruitment process.

To assess whether social networks lead firms to hire more talented managers, we estimate the following linear probability model:

$$\begin{aligned} Y_{i,j} = Employment_{i,j} &= \alpha_C + \beta_I \times Connection_{i,j} \times Talent_i \\ &+ \beta_T \times Talent_i + \beta_C \times Connection_{i,j} \\ &+ FirmYearControls + \varepsilon_{ij}, \end{aligned} \tag{2}$$

and compare the coefficient estimates for β_I and β_C. In this framework, β_C reflects the value of a connection to a non-talented manager, while β_I represents the additional value of a connection to a talented manager. If firms recruit more talented managers through social networks, $\beta_I > \beta_C$. If $\beta_C < 0$, social networks help firms avoid low-talented managers.

Our analysis needs to evaluate how cohort (team) assignment impacts employment outcomes relative to other managers in the same graduation class, but in a separate cohort. If the likelihood of entering a given firm were equal across all firms, then we could simply include a fixed effect for each graduating class. However, the likelihood of entering a given firm differs significantly over the cross-section of employers: certain firms regularly hire five or more managers each year, while other firms rarely hire even one manager. Therefore, we consider two potential control variables. In the first specification, we estimate the number of managers that enter each firm in a given year. We then include a fixed effect based on this number of managers that enter the firm that particular year. In the second specification, we include a firm-year fixed effect directly into the regression. Both specifications control for the likelihood that a given manager enters a firm in a given year. In addition, as students are assigned to cohorts and teams based on specifiic characteristics, we control for demographic differences across gender, race, and nationality. Finally, to control for the correlation of errors, we depend on two-way clustering at the firm level and the worker level.[34]

4.2 Regression Dataset

The regression requires an observation for each firm i, manager j pair. Therefore, we create a matrix from the 2,109 students in the sample and 49 employers in the sample, creating a total of 103,341 observations. To limit the number of null observations, we drop any firm i, manager j pair if no student from the given graduating class entered the firm following graduation. The end result is an average of 12.2 possible firm outcomes for each student in the sample.

We create this dataset and present several summary statistics in Table 4. The complete dataset contains 25,755 observations; in 20,840 observations, we also have data on intended major of the student and the quantitative exam score. For a given firm, the likelihood a manager enters the firm is 1.2%, and the likelihood that a manager has a cohort (team) member with prior experience at the firm is 12% (0.8%).

[34] In additional robustness tests, we also cluster errors at the cohort level.

5 Results

First, we evaluate the impact of social networks on the allocation of an average manager across high-skill firms. Second, we examine how social networks affect the allocation of the most talented managers in our sample. Third, we present evidence that allows us to reject alternative explanations of the results, and offer suggestive evidence on the economic mechanism behind our results by introducing a survey administered to managers in our treated sample.

5.1 Do Social Networks Affect the Allocation of Young Managers to Firms?

In Table 5, we incorporate cohort connections to evaluate the role of social networks in the allocation of managers to firms. Panel A reports the estimates of a linear probability model, while Panel B presents the estimates of a probit model. In both panels, Columns (1), (3), (5), and (7) include a fixed effect for the number of managers entering the given firm in a given year, while Columns (2), (4), (6), and (8) include a firm-year pair fixed effect. We rely on the interactions established at the cohort level to estimate the effect of social connections. In Panel A, Columns (1) and (2) focus on employment directly after graduation. We estimate that the likelihood that a firm hires a connected manager is 0.6 percentage points higher than the likelihood that it hires an unconnected manager, representing a 50% relative increase (the likelihood that a firm hires an unconnected manager is 1.2%). Columns (3) through (8) evaluate employment one, three, and five years after graduation. We estimate that networks are strongest at graduation. Five years after graduation, the effects attenuate but still exist, suggesting that social networks might have a permanent effect on the allocation of young managers.

Since the likelihood of a manager being employed at a given firm is only 1.2%, the dependent variable takes a non-zero value for only a small subset of the data. One might thus be concerned with the fitness of a linear probability model for this analysis. Therefore, we introduce a probit regression model in Panel B. Though the coefficients cannot be directly compared with the linear results in Panel A, we document statistical significance across the five years following MBA graduation, confirming that the network results estimated with the linear probability model do not depend on the particular empirical specification.

We next examine whether the coefficients depend on the strength of the relationship between manager and former employee. Recall that cohorts are composed of roughly fifty students that take the courses together in the first semester. While teams are also subject to forced assignment, they are smaller (four to five members) and members of the same team have to work on course assignments together in addition to a case competition at the end of the first semester. According to our hypothesis, the close interactions between students working in the same team should result in a stronger connection and therefore a higher coefficient.

The results outlined in Table 10 confirm that team connections increase the likelihood of employment relative to cohort-based connections. In Column (1) and (2) we confirm a team member connection increases the likelihood of entering a given firm by a full two percentage points; this coefficient is significantly larger than the estimate of 0.6 percentage points when we define the network at the cohort level. As students also routinely interact with peers outside their team, our estimate is still only a lower bound on the value of social networks for these young managers.

Controlling for Manager Characteristics. While the MBA office at IU aims to randomly assign students into cohorts, it must also balance a few key student characteristics, as we outlined in the data section. Technically, social connections are only random after controlling for the variables used in the assignment process. As such, one could be concerned that the estimates presented above are biased due to correlations between the outcome, explanatory, and assignment variables. To demonstrate that this is not an issue, we report in Table 6 the regression from Table 5 with controls for gender, nationality, and race—the main variables that the MBA office aims to balance across cohorts. For the purposes of the regression, nationality is broken into seven categories (US, India, China, South Korea, Japan, Taiwan, and Other) as all other nations compose less than one percent of the full manager sample. Race is defined only for domestic managers: Asian, Black, Hispanic, White, Other, and International. Other includes multiracial, Native American, and Pacific Islander, which each comprise less than one percent of the sample.

After controlling for personal characteristics, social networks affect the probability that a manager is allocated to a firm at graduation by 0.6 percentage points. Given that the likelihood of entering a given firm is 1.2%, this translates into a relative increase of 50%, similar to the effects reported in Table 5. Overall, our results are not driven by cohort sorting due to manager personal characteristics.

Placebo Networks. Individuals enter the MBA program with experience in firms that other graduates are likely to join. Since everyone needs to be assigned to a cohort, it is possible that our results may arise in a mechanical manner. To rule out this possibility, we report in Table 7 the results of a model in which we reassign each student to a placebo cohort in the same graduation year, making no other change to the cohort. Using the placebo cohort, we test whether these false networks have any impact on student employment outcomes. Our results show that a placebo cohort member has no impact on student employment outcomes. We take the lack of results as evidence that cohorts are in fact acting as social networks and impacting employment outcomes.

Strong and Weak Connections. Our results do not account for the length of the relationships between former employees and employers. However, the effects of social networks should be more prevalent when the relationship between the former employee and the employer is especially long-lasting. Longer-tenured employees carry more valuable information for firms and prospective managers. Therefore, we split the sample based on the number of years for which a connection was employed at the hiring firm. In our sample, the median tenure at a high-skill firm prior to the MBA is three years. We define a connection as strong if the worker was previously employed at the firm of interest for at least three years, and as weak if the worker was employed there for less than three years. We re-estimate the baseline model using these two different explanatory variables, and report the estimates in Table 8. A strong connection increases the likelihood of entering a given firm by 1.3 percentage points, effectively doubling the probability of employment, relative to the mean. In contrast, we find no evidence that weak connections have any impact on employment outcomes. The results confirm that the role of former employees depends on the strength of their underlying relationships with the hiring firms.

5.2 Do Social Networks Affect the Allocation of the most *Talented* Managers?

Thus far, our results confirm that social networks affect the allocation of an average manager. While these results highlight an impact on the applicant, the actual value to the firm is less clear. To evaluate whether firms benefit from social networks in our setting, we examine whether they are more likely to hire talented managers (and potentially less likely to hire low-talent managers) through social networks. Specifically, we incorporate two measures of managerial talent: (i) the quantitative entrance exam score (required by Indiana University) and (ii) grades in the MBA core courses[35] that students need to take in the first semester of the program (all students take the same curriculum in the first year). We split the entrance exam scores into quartiles and the course number grades into three groups based on letter grades (A, B, or C). We then estimate the linear probability model outlined in equation (2).

Table 9 reports the estimated coefficients. We focus on employment within one year of graduating from the MBA program. First, we find evidence that social networks may negatively impact the likelihood that a low-talent manager enters the firm. In contrast, cohort connections improve the likelihood that a firm hires a high-talent manager. We estimate that, for students receiving an A average in the first semester core courses, social networks increase the likelihood of being hired by a given connected firm by 1.5 percentage points.[36] We esti-

[35] Core coursework includes disciplines such as finance, strategy, accounting, and marketing. In the Data section, we discuss in detail the fitness of these courses in evaluating managerial ability.

[36] As mentioned before, we are missing first semester MBA grades for the graduating classes of 1999-2002. We instead proxy for classroom performance by identifying students that graduated from the MBA program with Honors. We assign students graduating with Honors an A letter grade, and all other students a B letter grade. In unreported results, we exclude the graduating classes of 1999-2002 from the regression and confirm the estimates

mate a similar value of 1.6 percentage points for students in the top quartile of entrance exam scores.[37]

These results shed light on how social networks might affect firms' competition for talent. Assuming that a talented manager receives offers from two firms, and building on our results, she is more likely to join a connected firm than an unconnected firm. This conclusion stems from a careful analysis of the interpretation of β_I in the regression model (2):

$$\begin{aligned}\beta_I &= (\overline{Y}^{talent}_{conn} - \overline{Y}^{no-talent}_{conn}) - (\overline{Y}^{talent}_{no-conn} - \overline{Y}^{no-talent}_{no-conn}) \\ &= (\overline{Y}^{talent}_{conn} - \overline{Y}^{talent}_{no-conn}) - (\overline{Y}^{no-talent}_{conn} - \overline{Y}^{no-talent}_{no-conn})\end{aligned}$$

Since Table 9 implies that $\overline{Y}^{no-talent}_{conn} - \overline{Y}^{no-talent}_{no-conn}$ is not statistically different from zero, we can interpret β_I as the difference in probability that a talented manager joins a firm that she is connected to relative to a firm that she is not connected to. Social networks help firms compete for talent because prospective managers can access information on the quality of the match through their connections to the firm. Below, we reinforce this view by drawing on the results of a direct survey that we administered to treated managers in our sample.

Our frameworks assumes both that (i) all graduates have opportunities to join a high-skill firm and (ii) talented graduates are more likely to be hired by high-skill firms. We test both assumptions in our setting. In Table 12, we evaluate the relationship between talent and employment at a high-skill firm. We measure talent based on core course grades. Sub-column (i) includes no other controls, Sub-column (ii) includes year fixed effects, and Sub-column (iii) includes year fixed effects and student controls for gender, race, and ethnicity. First, we confirm that roughly twenty-five percent of low-talent students enter a high-skill firm upon graduation. Second, we find strong evidence that high-ability students are more likely to enter high-skill firms. Specifically, in the model that includes year fixed effects and

are similar.

[37] We note that we have only 20,878 observations of the quantitative exam score as we are missing exam scores for the graduating classes of 1999-2002.

controls for student characteristics, we find that a high-talent student is more likely to join a high-skill firm by nine percentage points relative to a low-talent student.

We next return to the team setting in Table 10 to confirm that tightly-defined networks leads to (i) a greater likelihood of hiring a high-talent manager and (ii) an even lower likelihood of hiring a low-talent manager. In Column (3) - (6) we evaluate the team effects across the talent distribution. Among low-talent managers (talent measured in both classroom performance and entrance exam scores), interaction with a team member significantly decreases the likelihood of entering a given firm by a full percentage point. However, for managers with high classroom performance, team members increase the likelihood of employment at the firm by 4.1 percentage points; for managers with high exam scores, team members increase employment by 6 percentage points.

Alternative Network Definitions. To provide further evidence to support our results, we introduce two alternative measures of networks based on gender or race. These measures of networks have been previously used in the labor literature as workhorses to define social networks (Bandiera et al., 2009; Bertrand et al., 2000; Dustmann et al., 2015). Both networks are endogenous as managers of the same gender/race may have similar preferences or abilities, increasing the likelihood of entering the same firm. In this instance, we are not identifying a network effect, but rather a "similarity" effect. However, this would not necessarily explain a cross-sectional result where talented managers in the same network are more likely to enter a firm while less talented managers are less likely to enter the same firm.

We present the results with these alternative measures of networks in Table 11. For the purposes of the regression, we follow the earlier framework to race (Asian, Black, Hispanic, White, and Other). In Panel A, we first evaluate the impact of a gender network (i.e., a manager is connected to the firm by a former employee of the same gender). According to Columns (1) and (2), a gender-based connection increases a high-talent manager's likelihood of entering a given firm by 0.7-1.8 percentage points. Meanwhile, these same connections decrease the likelihood of entering a given firm by 0.5 percentage points for low-talent managers. Second, in Panel B, we study a race-based network, and again find significant heterogeneity based on worker talent. In Columns (1)-(2), we estimate that individuals with high exam scores are 0.8-0.9 percentage points more likely to enter the firm when a connection exists. In Columns (3)-(4) we show that students in the top quartile of entrance exams with a connection are 1.6-1.9 percentage points more likely to join the firm following graduation. In comparison, race-based connections negatively impact the employment of low-ability students by roughly 0.6 percentage points. These results help confirm our cohort-level analysis: regardless of our definition of network, we find that social networks positively (negatively) affect the employment outcomes of high-talent (low-talent) managers.

5.3 Rejecting Alternative Mechanisms

Our paper evaluates how social networks impact a firm's ability to recruit talented managers. The purpose of this section is to attempt to isolate the particular channel that results in firms hiring more talented managers.

First, we examine whether managers improve interviewing skills by learning from peers. In this instance, a connection to a particular high-skill firm may increase the likelihood of employment at all other high-skill firms in the same industry. Second, we test whether peer interactions impact managers' career interests. If peers are more likely to switch career tracks due to peer interaction, this could increase the likelihood of entering the peer's prior firm. Third, we estimate the impact of peer networks on classroom performance. If strong team members help their peers receive better course grades, then these peers will also be more likely to enter a high-skill firm. Fourth, we investigate the informational role that social networks might hold for firms and prospective managers. Firms might obtain referrals from social networks, while prospective employees might obtain private information about firms. We survey a sample of fifty treated managers in our sample to identify whether these mechanisms were relevant in helping them find and secure a job at graduation.

Job Application and Interviewing Skills. Managers may depend on peers to gain information about the job application and interviewing process. In this setting, connections to one high-skill firm may increase the likelihood of employment across all high-skill firms; as a result, connections to former employees benefit all firms (not only the former employer). To test this scenario, we evaluate whether a connection to a high-skill firm in one industry increases the likelihood of employment at the other high-skill firms in the same industry.

We present the results in Table 13. We create a new dataset that maps every manager to five possible industries of employment, resulting in 10,823. We define a Cohort-Industry Connection as the number of cohort members with prior experience at any high-skill firm in a given industry. In Column (i), we estimate the average likelihood that a student takes a job in a given industry; in Columns (ii) and (iii), we estimate the effect of entering the specific industry as a function of the number of former employees in the cohort who had experience in that industry. In Column (ii), we include fixed effects for the number of hires in each year, and in Column (iii), we include firm-year fixed effects. Across both specifications, we estimate that a connection actually leads to a decline in the likelihood of employment within the industry. We take these results as evidence that managers are not learning about the job application and interviewing process through networks.

Classroom Learning. To test whether peers influence classroom performance outcomes, we require a new framework. Following the traditional approach in the literature, we estimate these peer effects using a linear-in-means model Graham (2008); Manski (1993).

To assess whether peers can affect classroom outcomes in our setting, we estimate the following model:

$$Grade_i^t = \alpha + \beta \times High\ Grade\ Team_{-i}^t + \delta^t + controls_i^t + \varepsilon_i^t \tag{3}$$

The dependent variable in this model, $Grade_i^t$, is a discrete variable that takes a value of one when worker i receives an C letter grade or lower in the first semester courses, a value of 2 when the worker receives a B letter grade, and a value of 3 when the worker receives an A letter grade. $High\ Grade\ Team$ is a binary variable to indicate whether a student has at least one team member receiving an A letter grade. We control for the year of entry into the MBA program, δ^t, in case the student population and the job market differ over time. We also control for individual characteristics including gender, citizenship, and race. We run a similar test evaluating the impact of a $High\ Skill\ Team$ (defined as a team with a student previously employed at a high-skill firm) on classroom performance.

Note our focus on team networks rather than cohort networks in this analysis. The distinction is largely due to the size of the respective groups. Since cohorts are roughly fifty students on average, every cohort includes students from every grade distribution. As a result, we have no variation across cohorts. However, given that teams are composed of four to five members, only a portion of teams will include students with an A letter grade in the first semester. We can use this variation to identify peer effects at the team level.

In Table 14 we report the impact of team members on individual first semester course grades. In Column (1) we document no significant correlation between having a high-grade team member and a student's grades after controlling for the year of graduation. In Column (2) we control for entrance exam score, while in Column (3) we also include controls for race, nationality, and gender. Again, we establish no correlation. In Table 14, Columns (4) - (6) we examine how students with experience in high-skill firms impact the classroom performance of other team members. Across all three specifications, having teammates with experience in high-skill firms is correlated with a slightly lower grade, though the relationship is not statistically significant at the 10% level. Overall, we find no evidence that an individual's grades or prior work experience impact the course grades of other team members. As a result, we conclude that the effects of social networks documented above are unlikely to be driven by improved classroom performance.

Career Interests. We next estimate the effect of peers on career interests by estimating the following model:

$$Major_{i,y}^{t} = \alpha + \beta \times Major\ Team_{-i,y}^{t} + \delta^{t} + controls_{i}^{t} + \varepsilon_{i}^{t} \tag{4}$$

The dependent variable, $Major_{i,y}^{t}$ is a binary variable that takes a positive value when worker i graduating in year t chooses to major in subject y. The key independent variable is $Major\ Team$, a binary variable which is positive when at least one of a worker's team members intends to major in subject y. We control for the year of entry into the MBA program, δ^{t}, in case the student population and the job market differ over time. When evaluating major choice, we are able to control for the student's intended major. Importantly, the intended major is chosen at the time of application to the MBA program, prior to any interaction with team members. By controlling for intended major, we are explicitly testing for changes in major choice due to team members.

We identify six primary majors in our data sample: Entrepreneurship, Finance, Management, Marketing, Strategy, and Operations. We test the impact of team members on major choice in Table 15, splitting the results into two panels, and establish three results. First, a student is three percent more likely to major in Entrepreneurship if a team member intends to major in this subject.[38] Interestingly, a change in career interest towards entrepreneurship would move students away from existing and established firms, such as high-skill firms in our sample. Second, a student is actually eight percent less likely to major in Strategy if a team member intends to major in this subject. Lastly, for all other majors, there is no correlation between students' majors and those of their team members. With the exception of Entrepreneurship, we find no evidence that students are more likely to switch to a team member's intended major, suggesting that peers have no impact on academic focus.

[38] In subsequent work Hacamo and Kleiner (2017) study this effect in detail to understand the positive and negative effects that peers might have on entrepreneurship outcomes.

5.4 The Flow of Information Through Networks

Thus far, we do not take a stance on the flow of private information. Economic theory suggests social networks between job applicants and firms can provide information in two directions. In the standard framework, workers learn about job opportunities (Calvo-Armengol and Jackson, 2004); in an alternative framework, firms learn about the ability of workers (Montgomery, 1991). We next offer evidence that social networks lead to better labor market matches, and evaluate whether peers transfer information about the employer to the applicant or information about the applicant to the employer.

Indirect Evidence of Information Flow. First, we offer indirect evidence that agents are learning through networks. Specifically, we illustrate that information leads to improved matching between applicants and employers. Similar to the prior literature (Dustmann et al., 2015), we estimate mismatch as the time until job turnover.

We present our results in Table 16. We include only students entering high-skill firms following graduation from the MBA, leading to 557 total observations. In our analysis we include year fixed effects as students are only randomly assigned within a graduating class. We also control for the number of students with prior experience at the particular employer in that year. In addition, in Column (iv) we add controls for student characteristics including gender, nationality, and race, in case job tenure differs across demographics.

According the first two columns, we estimate that networks increase the likelihood a student remains at the firm by 0.82-0.93 years, depending on the specification. Given that the mean student stay at the first job for 4.6 years following graduation, our results imply that networks increase tenure by 20 percentage points relative to the mean. One concern with this analysis is that the variable job tenure is potentially bounded as workers may remain in the first job after MBA graduation up to 2017. Therefore, we consider two alternate definitions of tenure: we winsorize tenure at ten years (i.e. all workers employed with a firm over ten years will be counted as ten years) or winsorize the variable at five years. Across all specifications, we confirm that connections to the firm lead to longer job tenure. The results suggest that networks lead to better matches in the labor market.

Direct Evidence of Information Flow. Next, to offer direct evidence that information is flowing between agents, we survey a subset of the managers in our sample. Specifically, we survey managers who (i) entered a high-skill firm following graduation and (ii) were connected to a cohort member with prior experience in the same firm. In total, we contacted ninety-two managers and received replies from approximately fifty managers. We asked two questions in our survey:

- "Did you receive a referral for your employer XXX from a cohort-member previously employed at the firm?".
- "Did you receive advice/opinions about your employer XXX from a cohort-member previously employed at the firm?"

We find evidence of both mechanisms at work, though information primarily flows to the applicant (rather than to the firm). First, 6.3% of the respondents indicate they received a referral from a peer in their cohort. In comparison, 36% of the respondents learned about the firm from a cohort member, while another 8% stated that may have learned about the firm from a cohort member.

6 Conclusion

This paper confirms the value of social networks for firms competing for managerial talent. Relying on the random assignment of MBA students into teams and cohorts, we can precisely isolate peer effects on prospective employers. By incorporating MBA admissions data with online profiles, we are able to follow individual managers over their careers and measure their talent.

Our results stress the value of social networks in helping firms acquire talented human capital. In our setting, social networks are key to the diffusion of information to employers and prospective employees. By focusing on talented young managers, we zero in on a set of workers that can have a large impact on firm value; by examining high-skill firms, we study a set of firms that highly depend on the acquisition of talent. If social networks have large effects in this setting, one can only infer that they assume an even larger role for other firms, which are likely to have weaker screening processes and less public information available to prospective employees.

More broadly, our research sheds light on (i) the sorting of managers into firms and (ii) the value of former employees to a firm. On the first point, a recent literature has shown that selection of managers into firms might be a function of search efforts (Kuhnen, 2017) or economic conditions at graduation (Oyer, 2008; Schoar and Zuo, 2011). This paper shows that social networks help explain how (talented) managers sort into firms. On the second point, prior research has shown the value of current employees in recruiting talented workers (Beaman and Magruder, 2012). We extend this literature by confirming a similar role for former employees; this extension is not trivial given the lack of direct incentives for this latter group.

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Appendix

Revealed-Preference Model

In this paper, we analyze the set of high-skill firms to limit our analysis to firms receiving applications from even the most talented managers in the sample. To define the set high-skill firms, we now develop a simple revealed preference argument: The intuition for the model is quite simple: the firm's with the greatest human capital employ the most preferred employees. Given our focus on managers with MBAs, we define the set of preferred employees as all managers that graduate from the highest-ranked MBA programs.

We can forumlate this argument in a theoretical framework based on Avery et al. (2012). For simplicity, assume that the desirability of any job follows an extreme value distribution. We denote desirability of employment in firm i as θ_i and order desirability as: $\theta_1 > \theta_2 > \theta_3 ...$ for $i = 1, 2, ...n$ possible employment outcomes. Then we can readily define the utility of Kelley student j from employment at firm i using: $u_{ij} = \theta_i + \varepsilon_{ij}$. We can think of θ_i as incorporating both average wages, as well as non-wage benefits such as quality of life, location, and future career opportunities at firm i. Finally, we define F_j as the set of offers available to student j with the understanding that students will not face the same set of available job offers.

We then make two additional assumptions in our analysis. First, we assume graduates from a top MBA program have access to the full set of job opportunities available to managers from the Indiana University MBA. Second, graduates from the Kelley MBA Program have the same employment preferences as managers at the top MBA programs. This first assumption is violated if the low ability managers from a top MBA are not able to enter firms available to a high ability Indiana University manager. For instance, it might be possible that firms located in Indiana might prefer a high ability Indiana University graduate to a low ability manager from a top MBA program. In this case we may falsely identify a firm as highly preferred. If the second assumption is violated, then we are failing to identify firms that are actually highly preferred. In the regressions, this works against us; thus, we can think of this classification as conservative.

Under the first assumption, managers from top MBA programs will only enter firms above a cut-off θ_m. Under the second assumption, Kelley MBA managers will prefer firms above the cut-off θ_m. Therefore, we can identify high and low human-capital employers in the sample by identifying the set of firms that regularly employ managers from high-ranked MBA programs.

Table 1: Summary Statistics of Students

This table reports the summary statistics for MBA students in our sample. The summary statistics for students are based on admissions information, student majors upon graduation, and cohort/team demographics. We note the smaller number of observations on the Entrance Exam Grade variable due to data limitations as described in the data section.

	N	Mean	Std
Graduation Year	2109	2006.4	4.25
Entrepreneur Major	2109	0.081	0.27
Finance Major	2109	0.50	0.50
Marketing Major	2109	0.44	0.50
Management Major	2109	0.10	0.30
Operation Major	2109	0.066	0.25
Strategy Major	2109	0.15	0.36
Top Undergraduate Institution	2109	0.15	0.36
Team Size	2109	3.22	0.95
Cohort Size	2109	45.6	8.95
Entrepreneur Team Member	2109	0.45	0.50
Finance Team Member	2109	0.38	0.48
Marketing Team Member	2109	0.36	0.48
Management Team Member	2109	0.22	0.41
Operation Team Member	2109	0.11	0.31
Strategy Team Member	2109	0.057	0.23
Male	2109	0.63	0.48
International	2109	0.25	0.43
Racial Minority	2109	0.16	0.37
Entrance Exam Grade	1625	42.8	5.44
Grade Level	2109	2.16	0.52
High Grade Level	2109	0.23	0.42
Team Member with High Grade Level	2109	0.32	0.47

Table 2: List of High-Skill Firms in the Sample

This table presents a list of the firms denoted high-skill firms in our sample. We identify high-skill firms as any firm that hired at least five students from high-ranking MBA programs during 1999-2013 immediately after MBA graduation. The high-ranking MBA programs in our sample are: Harvard University, Stanford University, and University of Chicago.

List of High-Skill Firms	
A.T. Kearney	Hewlett Packard Enterprise
Abbott	IBM
Accenture	J.P. Morgan
Alcatel-Lucent	Johnson & Johnson
Amazon	Lehman Brothers
American Express	McKinsey & Company
Apple	Medtronic
Baird	Merrill Lynch
Barclays	Microsoft
Booz Allen Hamilton	Morgan Stanley
Boston Scientific	Oracle
Capital One	PepsiCo
Cisco	Procter & Gamble
Citi	PwC
Credit Suisse	Sears Holdings Corporation
Danaher Corporation	Target
Dell	The Dow Chemical Company
Deloitte	The Walt Disney Company
Deutsche Bank	UBS
Diamond Management & Technology	Unilever
GE	Wells Fargo
General Mills	William Blair
Goldman Sachs	Yahoo
Google	eBay
HSBC	

Table 3: Summary Statistics of Firms

This table reports the summary statistics for firms in our sample. Panel A reports the firm characteristics for high-skill firms, while Panel B reports the same firm characteristics for less-skill firms. We classify firms into high- and low-skill based on the methodology presented in the data section.

Panel A: High-Skill Firm Characteristics

	N	Mean	Std
Num of IU Students Employed	49	13.6	14.1
Distant Firm	49	0.71	0.46
Banking Industry	49	0.31	0.47
Tech Industry	49	0.24	0.43
Consulting Industry	49	0.12	0.33

Panel B: Less-Skill Firm Characteristics

	N	Mean	Std
Num of IU Students Employed	274	5.11	5.75
Distant Firm	274	0.46	0.50
Banking Industry	274	0.15	0.36
Tech Industry	274	0.095	0.29
Consulting Industry	274	0.033	0.18

Table 4: Summary Statistics of Student-Firm Pairs

This table reports the summary statistics for all possible student-*high-skill firm* pairs. Cohort-Firm Connection is as a binary variable that takes a value of one when a firm previously employed a student in that particular cohort. Gender-Firm Connection is a binary variable equal to one when a firm previously employed a student in the same gender, similarly for race.

	N	Mean	Std
Employed upon Graduation	25755	0.012	0.11
Cohort-Firm Connection	25755	0.12	0.33
Team-Firm Connection	25755	0.0078	0.088
Gender-Firm Connection	25755	0.31	0.65
Race-Firm Connection	25755	0.18	0.50

Table 5: Network Effect

This table presents the baseline network regression results. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. We define the network at the cohort-level and define Cohort-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in that particular cohort. In Panel A we include all workers in the sample. In Panel B, we include the complete sample, but use a probit regression rather than a linear regression. Initial Employment focuses on employment initially after MBA graduation, while One (Three, Five) Year focuses on employment at year one (three, five). Sub-columns (i) include a fixed effect for the number of students entering the firm in the year of graduation, while sub-columns (ii) interacts a graduation year fixed effect with a firm fixed effect. . We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

Panel A: Network Effects for All Workers

	Initial Employment		One Year		Three Years		Five Years	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.005**	0.007**	0.006***	0.006*	0.005**	0.004	0.005**	0.004
	(2.50)	(2.10)	(2.67)	(1.87)	(2.41)	(1.32)	(2.24)	(1.42)
Firm Hires FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	25755	25755	25755	25755	25755	25755	25755	25755
R-squared	.011	.013	.01	.014	.0077	.014	.0036	.012

Panel B: Network Effects for Workers under Probit Regression

	Initial Employment		One Year		Three Years		Five Year	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
main								
Cohort-Firm Connection	0.146***	0.205**	0.166***	0.168**	0.176***	0.109	0.185***	0.136
	(2.85)	(2.31)	(3.16)	(1.99)	(3.02)	(1.13)	(2.93)	(1.33)
Firm Hires FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	25755	20539	25755	19886	25755	16633	25755	14978

Table 6: Network Effect with Student Controls

This table presents the baseline network regression results including student controls. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. Controls include fixed effects for gender, nationality, and race. We define the network at the cohort-level and define Cohort-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in that particular cohort. Sub-columns (i) include a fixed effect for the number of students entering the firm in the year of graduation, while sub-columns (ii) interacts a graduation year fixed effect with a firm fixed effect. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

	No Controls		Gender		Nationality		Race	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.006***	0.006*	0.006***	0.006*	0.006***	0.006*	0.006***	0.006*
	(2.67)	(1.87)	(2.67)	(1.88)	(2.74)	(1.90)	(2.72)	(1.89)
Firm Hires FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Gender FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	No	No	No	No	Yes	Yes	Yes	Yes
Race FE	No	No	No	No	No	No	Yes	Yes
N	25755	25755	25755	25755	25755	25755	25755	25755
R-squared	.01	.014	.01	.014	.011	.014	.011	.014

Table 7: Placebo Network Effect

This table presents the network regression results where students are assigned to a placebo cohort. To create a placebo network, we theoretically assign each student to a cohort different from his/her actual cohort, keeping cohorts the same otherwise. The regression then evaluates the impact of the placebo network on the given firm hiring the given manager. The dependent variable is a binary variable that takes a value of one when the student is employed at the given firm. We define the network at the cohort-level and define Cohort-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in that placebo cohort. Sub-columns (i) include a fixed effect for the number of students entering the firm in the year of graduation, while sub-columns (ii) interacts a graduation year fixed effect with a firm fixed effect. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

	Initial Employment		One Year		Three Years		Five Years	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.000	-0.001	0.000	-0.003	0.001	-0.002	0.000	-0.002
	(0.24)	(-0.33)	(0.07)	(-1.17)	(0.39)	(-1.16)	(0.27)	(-1.04)
Firm Hires FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	25755	25755	25755	25755	25755	25755	25755	25755
R-squared	.011	.012	.01	.013	.0074	.014	.0033	.012

Table 8: Heterogeneous Network Effects

This table presents the network regression results by connection strength. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. We split the sample by the strength of the connection to the given firm. Specifically, a Strong Cohort-Firm Connection is a binary variable equal to one if the firm previously employed a student in that particular cohort for more than three years. A Weak Cohort-Firm Connection is a binary variable equal to one if the firm previously employed a student in that particular cohort for one to three years. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

	Strong Connection		Weak Connection	
	(i)	(ii)	(i)	(ii)
Strong Cohort-Firm Connection	0.012***	0.014**		
	(3.29)	(2.35)		
Weak Cohort-Firm Connection			-0.001	-0.001
			(-0.57)	(-0.43)
Firm Hires FE	Yes	Yes	Yes	Yes
Firm X Year FE	No	No	No	No
N	25755	25755	25755	25755
R-squared	.011	.014	.01	.013

Table 9: Network Effect across the Student Talent Distribution

This table presents the network regression results by student talent. All regressions include the direct effects but we do not report them in the table due to space concerns. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. We define the network at the cohort-level and define Cohort-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in that particular cohort. We introduce two measures of talent. The first two columns define talent according to first semester grades on core coursework, and we split the scores by letter grade (A, B, or C/D). The last two columns define talent according to the score on a quantitative MBA entrance exam, and we split the scores into quartiles. Columns (i) include a fixed effect for the number of students entering the firm in the year of graduation, while Columns (ii) interacts a graduation year fixed effect with a firm fixed effect. We note the smaller number of observations under the entrance exam regressions due to data limitations. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

	MBA Grades		Entrance Exam	
	(i)	(ii)	(i)	(ii)
MBA Grade Level=3 X Cohort-Firm Connection	0.015*	0.015*		
	(1.88)	(1.67)		
MBA Grade Level=2 X Cohort-Firm Connection	0.012**	0.010*		
	(1.99)	(1.67)		
Entrance Exam Score=4 X Cohort-Firm Connection			0.016*	0.016*
			(1.77)	(1.74)
Entrance Exam Score=3 X Cohort-Firm Connection			0.005	0.005
			(0.85)	(0.80)
Entrance Exam Score=2 X Cohort-Firm Connection			0.005	0.005
			(0.74)	(0.76)
Cohort-Firm Connection	-0.006	-0.005	-0.002	0.001
	(-1.36)	(-0.98)	(-0.51)	(0.12)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
Gender FE	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
N	25755	25755	20878	20878
R-squared	.011	.014	.0084	.0093

Table 10: Network Effect across the Student Talent Distribution: Team Results

This table presents the network regression results by student talent. All regressions include the direct effects but we do not report them in the table due to space concerns. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. We define the network at the team-level and define Team-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in that particular team. We introduce two measures of talent. The first two columns exclude the talent measures.The next two columns define talent according to first semester grades and we split the scores by letter grade (A, B, or C/D). The last two columns define talent according to the score on a quantitative MBA entrance exam, and we split the scores into quartiles. Sub-columns (i) include a fixed effect for the number of students entering the firm in the year of graduation, while sub-columns (ii) interacts a graduation year fixed effect with a firm fixed effect. We note the smaller number of observations under the entrance exam regressions due to data limitations as described in the data section. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

	Baseline		MBA Grades		Entrance Exam	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
MBA Grade Level=3 X Team-Firm Connection			0.042*	0.041*		
			(1.67)	(1.64)		
MBA Grade Level=2 X Team-Firm Connection			0.032*	0.028*		
			(1.86)	(1.66)		
Entrance Exam Score=4 X Team-Firm Connection					0.061	0.063
					(1.47)	(1.50)
Entrance Exam Score=3 X Team-Firm Connection					0.049*	0.049
					(1.64)	(1.63)
Entrance Exam Score=2 X Team-Firm Connection					0.035	0.036
					(1.17)	(1.14)
Team-Firm Connection	0.021*	0.020	-0.010***	-0.009***	-0.015***	-0.016***
	(1.72)	(1.56)	(-2.68)	(-3.26)	(-7.78)	(-8.05)
Firm Hires FE	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25755	25755	25755	25755	20878	20878
R-squared	.011	.014	.011	.014	.0078	.01

Table 11: Alternate Network Effects across the Student Talent Distribution

This table presents the network regression results by student talent and using alternate definitions of networks. All regressions include the direct effects but we do not report them in the table due to space concerns. The dependent variable is a binary variable that takes a value of one when the given firm hires the given manager. Panel A defines the network at the gender-level and define Gender-Firm Connection as a binary variable that takes a value of one when the firm previously employed a student in the same gender. Panel B defines the network at the race-level. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We use two-way clustering at both the worker- and the firm-level.

Panel A: Network Based on Gender

	Grades		Exam	
	(i)	(ii)"	(i)	(ii)"
MBA Grade Level=3 X Gender-Firm Connection	0.007**	0.006		
	(1.98)	(1.52)		
MBA Grade Level=2 X Gender-Firm Connection	0.007**	0.007**		
	(2.42)	(2.07)		
Entrance Exam Score=4 X Gender-Firm Connection			0.017**	0.018**
			(2.15)	(2.11)
Entrance Exam Score=3 X Gender-Firm Connection			0.004*	0.004*
			(1.85)	(1.69)
Entrance Exam Score=2 X Gender-Firm Connection			-0.000	-0.002
			(-0.17)	(-0.89)
Gender-Firm Connection	-0.005*	-0.003	-0.002	-0.001
	(-1.96)	(-1.22)	(-1.46)	(-0.24)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
Gender FE	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
N	25755	25755	20878	20878
R-squared	.011	.014	.0087	.011

Panel B: Network Based on Race

	Grades		Exam	
	(i)	(ii)"	(i)	(ii)"
MBA Grade Level=3 X Race-Firm Connection	0.006***	0.006**		
	(2.61)	(2.12)		
MBA Grade Level=2 X Race-Firm Connection	0.008***	0.007***		
	(3.24)	(2.65)		
Entrance Exam Score=4 X Race-Firm Connection			0.016***	0.019***
			(3.09)	(3.05)
Entrance Exam Score=3 X Race-Firm Connection			0.001	0.002
			(0.35)	(0.57)
Entrance Exam Score=2 X Race-Firm Connection			-0.000	-0.002
			(-0.16)	(-0.53)
Race-Firm Connection	-0.006***	-0.008***	-0.002	-0.006**
	(-2.76)	(-2.59)	(-0.86)	(-2.49)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
Gender FE	Yes	Yes	Yes	Yes
Nationality FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
N	25755	25755	20878	20878
R-squared	.011	.014	.0078	.011

Table 12: High Screening Effect

This table presents the high screening regression results. The regression evaluates the correlation between MBA classroom performance and employment at a high-skill firm following MBA Graduation. We include only students not previously employed at these firms prior to entering the MBA. Talent is defined according to first semester grades and we split the scores by letter grade (A, B, or C/D). Column (i) includes no control variables, Column (ii) includes year fixed effects, and Column (iii) includes year fixed effects and control variables for student characteristics, namely, gender, race and nationality. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster the coefficients at the team level.

	MBA Grades		
	(i)	(ii)	(iiii)
MBA Grade Level=3	0.074*	0.073*	0.091**
	(1.91)	(1.77)	(2.10)
MBA Grade Level=2	0.083**	0.071*	0.083**
	(2.39)	(1.94)	(2.15)
Constant	0.193***	0.291***	0.264***
	(5.90)	(4.55)	(3.07)
Year FE	No	Yes	Yes
Student Controls	No	No	Yes
N	2109	2109	2109
R-squared	.0021	.013	.023

Table 13: Industry Knowledge Effect

This table presents the industry knowledge regression results. The regression evaluates how connections to a given industry impacts employment in the industry. Cohort-Industry Connection is defined as the number of cohort members previously employed at high-skill firms within the industry. The outcome variable is a binary variable that takes a value of one when the worker is employed at a high-skill firm within the industry following the MBA, but not the same firm as the cohort members. Column (i) includes only a constant. Column (ii) include a fixed effect for the number of students entering the firm in the year of graduation, while Column (iii) includes a fixed effect that interacts a graduation year fixed effect with a firm fixed effect. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We two-way cluster the coefficients at both the worker level and the industry level.

	Employment within Industry		
	(i)	(ii)	(iii)
Cohort-Industry Connection		-0.007***	-0.013***
		(-4.44)	(-9.75)
Constant	0.022***	0.004***	0.000
	(7.14)	(3.29)	(0.00)
Firm Hires FE	No	Yes	No
Firm X Year FE	No	No	Yes
N	10823	10823	10823
R-squared	-2.2e-16	.013	.019

Table 14: Learning Effect

This table presents the learning regression results. The regression evaluates how first semester MBA grades are impacted by team member grades. The outcome variable is Grade Level, defined as a discrete variable that takes a value of one when the student receives an C or lower overall for the first semester, a value of two when the student receives a B, and a value of 3 when the student receives an A. For Columns (1)-(3) the independent variable is Team Member with High Grade Level defined as a binary variable that takes a value of one when at least one student in the team receives an A letter grade. For Columns (4)-(6) the independent variable is High-Skill Firm Team, a binary variable that takes a value of one when at least one team member has prior experience in any high-skill firm. Columns (1) and (4) includes graduation year fixed effects. Column (2) and (5) includes year fixed effects and controls for scores on the quantitative entrance exam. Columns (3) and (6) also includes controls for student race, nationality, and gender. We note the smaller observation in Columns(iii) due to data limitations. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster the results at the team-level.

	High Grade Team			High-Skilled Firm Team		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Team Member with High Grade Level	0.028	0.038	0.024			
	(0.70)	(1.01)	(0.65)			
Team Member with High-Skilled Firm Experience				-0.010	-0.007	-0.038
				(-0.39)	(-0.30)	(-1.36)
Entrance Exam Level=4			0.474***			0.476***
			(9.35)			(9.37)
Entrance Exam Level=3			0.297***			0.299***
			(8.77)			(8.90)
Entrance Exam Level=2			0.133***			0.134***
			(3.83)			(3.88)
Constant	2.075***	2.030***	1.404***	2.076***	2.035***	1.405***
	(75.98)	(33.23)	(25.59)	(75.80)	(33.43)	(25.51)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	No	Yes	Yes	No	Yes	Yes
Race FE	No	Yes	Yes	No	Yes	Yes
Gender FE	No	Yes	Yes	No	Yes	Yes
N	2109	2109	1625	2109	2109	1625
R-squared	.13	.19	.27	.13	.19	.27

Table 15: Major Switching Effect

This table presents the major switching regression results. The regression evaluates how a student's choice of academic major is impacted by team members. The outcome variable is a binary variable that takes a value of one when the students choice to major in the particular discipline. In Panel A, in Columns (1) and (2), the major is Entrepreneurship, in Columns (3) and (4), the major is Finance, and in Columns (5) and (6) the major is Marketing. In Panel B, in Columns (1) and (2) the major is Management, in Columns (3) and (14) the major in Operations, and in Columns (5) and (6) the major is Strategy. The dependent variable is a binary variable that takes a value of one when a team member intended to major in that particular discipline at the time of application to the MBA program. All regressions control for whether the students intended to major in the particular discipline at the time of application to the MBA program. Columns (1), (3), and (5) control for year fixed-effects, and columns (2), (4), and (6) add student controls. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster results at the team level.

Panel A: Entrepreneurship, Finance, and Marketing Major

	Entrepreneurship		Finance		Marketing	
Entrepreneur Team Member	0.030**	0.031**				
	(1.99)	(2.06)				
Finance Team Member			0.017	0.010		
			(0.75)	(0.43)		
Marketing Team Member					0.000	0.008
					(0.02)	(0.36)
Intended Entrepreneur Major	0.153***	0.152***				
	(7.87)	(7.82)				
Intended Finance Major			0.431***	0.416***		
			(18.05)	(16.88)		
Intended Marketing Major					0.524***	0.507***
					(22.80)	(20.44)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	No	Yes	No	Yes
N	1625	1625	1625	1625	1625	1625
R-squared	.073	.091	.15	.22	.21	.22

Panel B: Management, Operations, and Strategy Major

	Management		Operations		Strategy	
Management Team Member	-0.015	-0.016				
	(-0.71)	(-0.79)				
Operation Team Member			-0.002	-0.002		
			(-0.13)	(-0.13)		
Strategy Team Member					-0.080***	-0.076**
					(-2.60)	(-2.35)
Intended Management Major	0.051*	0.062**				
	(1.86)	(2.27)				
Intended Operation Major			0.301***	0.301***		
			(6.63)	(6.55)		
Intended Strategy Major					0.153***	0.147**
					(2.71)	(2.56)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	No	Yes	No	Yes
N	1625	1625	1625	1625	1625	1625
R-squared	.026	.038	.094	.11	.037	.064

Table 16: Network Effect on Tenure

This table presents the effect of networks on job tenure. The outcome variable is the number of years the student is employed at their first job following MBA graduation. Given that job tenure is bounded in our sample (as some workers may still be employed with the firm as of 2017) we consider three possible definitions of tenure: uncensored, censored above ten years (we winsorize the data at ten years), and censored above five years. Column (i) includes no controls, Column (ii) controls for the number of students entering the firm in the given year, Column (iii) also includes year fixed effects, and Column (iv) also includes student demographic controls. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster results at the team level.

	Uncensored		Censored at 10 Years		Censored at 5 Years	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.808*	0.914**	0.840**	0.918**	0.437**	0.458**
	(1.82)	(2.02)	(2.33)	(2.50)	(2.24)	(2.30)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Hires FE	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	No	Yes	No	Yes	No	Yes
Race FE	No	Yes	No	Yes	No	Yes
Gender FE	No	Yes	No	Yes	No	Yes
N	557	557	557	557	557	557
R-squared	.12	.16	.11	.15	.069	.11

Figure 1: Profile Match Demographic by Citizenship and and Race

This figure provides a plot of the percentage of Indiana University admissions data matched to an online business networking profile. We plot the match rate across the MBA graduation year between 2003 and 2013. We also split individuals into three groups: (i) international students, (ii) US racial minority students, and (iii) US white students.

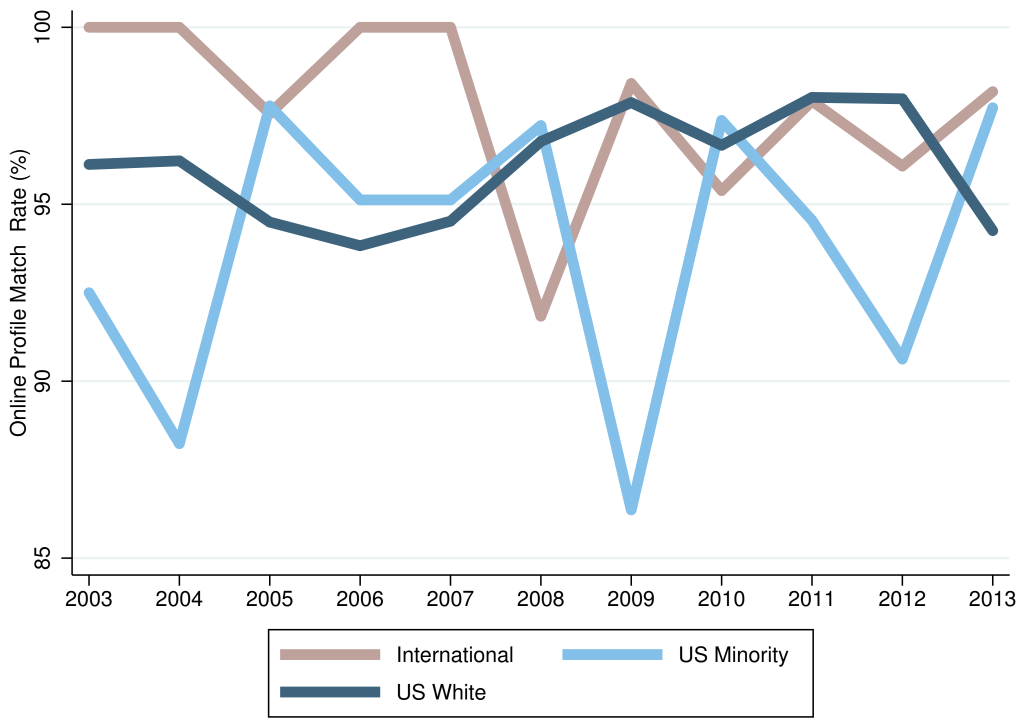

Figure 2: Composition of Managerial Job Titles Across MBA Careers.
This figure plots the breakdown of professional titles among Indiana University MBA students. We plot titles at the time of MBA graduation, as well as one, three, and five years following graduation. The plot on the left includes the title *Manager, Director, President*, *Executive, Partner, and Principal*, while the plot on the right exludes the *Manager* title.