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Former Employees and the Recruitment of Talented Managers

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Abstract

We use a randomized experiment to show that former employees remain a key asset for firms recruiting managerial talent. In our experimental setting, prospective managers interact with former employees of prestigious firms while completing the MBA program at Indiana University. The connections between managers and former employees are exogenous due to the random assignment of individuals into classrooms and study groups. First, we confirm that managers connected to a firm through its former employees are significantly more likely to join that firm. Second, using multiple measures of managerial ability, we document a direct benefit to hiring firms, which are consistently able to hire *high-ability* (vs. *low-ability*) managers. Third, we show that firms benefit because former employees (i) provide direct referrals to firms and (ii) supply information about the firm to talented peers. Our results document a new channel that helps explain how talented managers sort into firms.

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1 Introduction

Most professionals work for several firms throughout their careers; as a result, most firms are connected to large networks of former employees.[1] Surprisingly, firms known for making significant investments in human capital (e.g., Google Inc, McKinsey & Company, General Electric) have shorter-than-average job tenures, and, consequently, are connected to particularly large networks of highly skilled employees. While the turnover rates at these firms are often intentional, driven by their organizational structures (e.g., up-or-out policies or incentives to pursue entrepreneurial endeavors), it is largely unknown how firms benefit from access to networks of their former employees. Given that the majority of jobs are filled through informal networks (Granovetter, 1995; Holzer, 1988), former employees might plausibly help firms in the acquisition of productive human capital.

Former employees may contribute to the hiring process by providing referrals to firms or supplying private information to prospective workers. Economists have argued that referrals are driven by 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. In contrast, 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). Alternatively, firms may benefit from former employee networks—regardless of the incentives—if former employees selectively choose to interact with more talented peers (Carrell et al., 2013; Montgomery, 1991). Whether former employees help firms in the recruitment of talented workers is then an empirical question.

In this paper we evaluate recruitment in the managerial labor markets. Our setting is motivated by the large impact of manager talent on a firm's value (Benmelech and Frydman, 2015; Bertrand et al., 2003; Malmendier and Tate, 2005, 2008). While prior research has shown

[1] For example, in the US, the median number of years that wage and salary workers have been with their current employer was just 4.2 years in January 2016 (U.S. Bureau of Labor, 2016)

that selection of mangers into firms might be a function of search efforts (Kuhnen, 2017), and economic conditions at labor market entry (Oyer, 2008; Schoar and Zuo, 2017), we instead focus on the role of social networks. Assuming better workers are connected to more talented managerial applicants (Montgomery, 1991), social networks will especially benefit firms endowed with high human capital. Our paper therefore offers a new channel to explain the persistent nature of human capital allocation across firms.

To conduct our study, we require a sample of prospective managers in a setting in which they randomly connect with former employees of outside firms. To meet these requirements, we use a sample of graduates from the Master of Business Administration (MBA) program at Indiana University (IU).There are three primary benefits to this empirical setting. First, eighty percent of IU's MBA graduates reach a middle-level manager position within 5 years of graduation.[2] Second, a large proportion of workers enter an MBA program with the goal of switching careers; only 19% of the individuals in our sample return to their prior place of employment following graduation. Therefore, one can view our sample as a set of job seekers. Third, individuals in our sample have an average of five years of work experience pre-MBA.

The MBA program at IU also provides a unique experimental setting since students are randomly assigned to a cohort and a team.[3] Students in the same cohort take the core MBA classes together, while students on the same team are assigned to work together on course projects and a large case study at the end of the first semester. 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 than others for reasons exogenous to their ability, effort, or interests. We then test (i) whether a manager (student at graduation) with a connection to a firm has a higher likelihood of joining that firm, and (ii) whether the effects are larger for high-talent managers.

[2]To produce this statistic, we defined a middle-level manager as an employee whose job title includes one of the following words: 'manager', 'director', 'executive', or 'president'.

[3]A cohort has an average of approximately 50 students, while a team has 5 students on average. Depending on the year, an MBA class at IU has between 200 to 300 students.

Testing our hypothesis requires analyzing each manager's career path before and after his or her involvement with former employees of high-skill firms. 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 and admissions information for each graduate, obtained from the MBA office at Indiana University. Finally, we collect detailed information for each employer in the sample from the online networking service.[4] Our sample includes a total of 1,499 MBA students graduating between 2003 and 2013.[5]

We focus our analysis on a set of employers in high demand among MBA graduates, as these firms have access to the full pool of managerial talent. To identify this set of highly-demanded employers, which we refer to as *prestigious firms*, we rely on a simple revealed preference model to find and rank employers in the market. Prestigious firms are firms that regularly recruit the most skilled managers, [6], defined as students graduating from the top-ranked MBA programs in the U.S.—Harvard University, the University of Chicago, and Stanford University.[7] As such, a prestigious firm is one that hires at least 5 managers from each of these highly ranked schools during our sample period. According to this definition, there

[4]The mean firm hired 6.6 IU MBA graduates during the time sample. Nearly 50% of firms have headquarters at least 500 miles from Indiana University and approximately 50% of firms were started after 1950. The data shows that about a quarter of the firms are in the financial industry, 15% are in professional services (including consulting), and 12% are in the information technology sector. Upon graduation from the MBA program, a manager?s probability of entering a given firm is 1%. Finally, for the average firm in the sample, 10% of cohorts (0.5% of teams) include a graduate with prior experience at that firm.

[5]We estimate that 75% are male, 27% are international, and 17% are U.S. minorities. Fifteen percent have graduated from a top US undergraduate institution. Students in our sample have about five years of work experience. Finance and marketing are the two most common majors, chosen by 49% and 47% of the students in the sample (counting both primary and secondary majors). Not surprisingly, we document significant persistence in the labor market: 85% (43%) of managers are employed at the same firm one year (five years) after graduation. Finally, we confirm that workers in our sample are indeed middle-level managers: nearly 80% have a managerial title five years after graduation, with 10% at the level of Director/Vice-President/President.

[6]Firms that have more skilled employees are more desired by job-seekers due to productivity spillovers stemming from the agglomeration of talent (Acemoglu and Angrist, 2000; Lucas, 1988; Moretti, 2004), despite paying similar wages as firms that have a smaller fraction of skilled labor.

[7]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.

are forty-nine prestigious firms, including McKinsey & Company, Deloitte, Apple, Microsoft, Goldman Sachs, Google, and Procter & Gamble. Among all of the firms that hire IU students, approximately 20% are defined as prestigious.[8]

An average Indiana University MBA graduate has a 1.2% probability of joining a given prestigious firm, and by having a connection to that prestigious firm through a former employee increases the likelihood of obtaining a job there by 0.6%, a 50% increase relative to the mean. After including managers' personal characteristics, this network effect decreases only slightly, to 0.5%. We also estimate the effect of connections with former employees on the likelihood of still being employed at a firm three and five years after graduation. We find that managers with a connection still have an edge over managers without a connection several years after graduation. Even though the statistical significance falls slightly, this evidence suggests that managers without a connection take several years to attenuate the advantage of having a connection to a former employee of a prestigious firm.

Given the causal evidence that a connection to a former employee of a prestigious firm improves managerial employment outcomes, we next examine how these network effects impact hiring firms. We test whether former employees predominantly help more talented applicants by introducing two measures of talent based on first semester course grades and a quantitative exam taken as part of the MBA application process.[9] While neither grades nor exam scores are perfect measures of managerial talent, they are reasonable proxies. During the first semester, all students take core courses in Marketing, Finance, Strategy, Accounting, and Operations.[10] MBA grades will proxy for an individual's managerial skills in these core disciplines.

[8]The complete list of prestigious firms is presented in Table 6. To confirm that managers are better off at these firms, we estimate that the salary and benefits in the first year of employment (after the MBA program) are 19-27% higher in these firms relative to other employers. In general, these firms are larger, have more distant headquarters, and are more likely to be in the financial, professional services, and technology sectors. The managers in our sample entering these prestigious firms are more likely to remain there after one year (93%) and five years (47%).

[9]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

[10]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).

We find strong evidence that networks of former employees benefit the firm. Surprisingly, these networks have no impact on the employment outcomes of low-talent managers; however, high-talent managers connected to a former employee of a prestigious firm are 1.4% - 1.6% more likely to join that firm, more than doubling the rate of entry relative to the mean. The results hold whether we define talent based on grades during the MBA program or entrance exam scores. We confirm our results using alternative network definitions based on gender, nationality, and race, which have been previously used in the referral literature as a workhorse to define labor and social networks (Bandiera et al., 2009; Bertrand et al., 2000; Dustmann et al., 2015).[11]

Former employees might support firms' recruitment efforts by providing referrals and alleviating asymmetry of information, or, alternatively, supplying private information about the firm to prospective managers and improving the matching process. To isolate the channel through which former employees help prestigious firms, we conducted a survey by contacting directly treated managers in our sample. We asked them two questions to infer (1) whether they obtained their post-MBA job by receiving a referral from a fellow cohort member, and (2) whether a cohort member provided relevant information about the prestigious firm, influencing their outcome of joining the firm. The results show that both channels are relevant, even though access to private information about the firm is more prevalent. Former employees disseminate information about past employers that is relevant to prospective managers. This information channel only helps talented managers because individuals are likely to sort into networks based on ability (Carrell et al., 2013; Montgomery, 1991).

We conclude by testing alternative explanations of our results. First, we confirm that networks do not increase the likelihood of employment at other prestigious firms, even within the same industry. Second, we incorporate information on intended major (primary to peer

[11] 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 prestigious firm due to a connection; in comparison, networks can actually decrease the likelihood of a less talented manager entering the firm.

interaction) and actual major at the time of graduation. Except for entrepreneurship, we find no evidence that students change their major focus due to their connections. Third, by using information on first semester grades, we find no evidence that team members impact classroom outcomes.

2 Literature Review

This paper helps advance the literature that studies: (i) how networks affect hiring outcomes and firm productivity; (ii) causal identification of peer effects due to random assignment; and (iii) the determinants of career outcomes of middle-level managers.

A first literature determines the value of networks on labor outcomes using employee-employer linked data. These networks are developed 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). To the best of our knowledge, only Oyer and Schaefer (2007) uses past education, illustrating that law partners hire graduates from their own alma mater. The concern with this line of work is that results may be driven by exogenous sources of variations in networks since unobservable differences are likely correlated with sorting into a network and correlated with the outcome variable (Hellerstein et al., 2015).[12]

This literature has led to a related research agenda that studies the benefit of social networks to firms. Researchers suggest referrals have the potential to increase labor market efficiency by providing new information 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,

[12] As discussed in Sacerdote (2014), there is a wide range of attempts to overcome identification concerns including (i) exogenous movements of people including court-ordered desregregration of school 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.

2016).[13] We differ from this literature by focusing on skilled labor and expanding our analysis across firms and industries. Second, we are the first to examine exogenous network connections . Third, by surveying the managers in our sample we actually find evidence against the referral hypothesis.

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; however, they depend on a survey of graduating students and so are unable to document long-term effects. A related line of research relies on random assignment of dormmates and roommates to influence short-term test scores (Carrell et al., 2009; Lyle, 2009; Sacerdote, 2001; Zimmerman, 2003). In comparison to this literature, we apply the identification to study 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 consider how involuntary-formed social networks among World War I draftees affect reported employment in the 1930 Census.[14]

By bringing together these two literatures we contribute to the research evaluating the drivers of middle-level manager careers including stock market conditions (Oyer, 2008) or individual firm 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). Most closely, (Kuhnen, 2017) illustrates that candidates search with greater intensity if they have low ability or worse outside options, are looking for more valuable jobs, or more firms

[13]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).

[14]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 the firm and industry, and including the full employment history of each manager.

have vacancies. Last, recent research has offered suggestive evidence that business school networks may help support entrepreneurial partnerships between workers (Cai et al., 2015). We distinguish ourselves from this literature by incorporating a new mechanism, the role of former employees on firm recruitment opportunities.

3 Data

The contribution of this paper comes jointly from the random assignment of MBA students and data on long-term career outcomes at the individual level. We first discuss and summarize our unique data sources: (i) the Indiana University Kelley 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 classwork 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 composes part of their final grades for the semester. In addition, teams work together in 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 at Harvard Business School (discussed in Shue (2013)) and the University of Michigan (discussed in Ahern et al. (2014).[15] Students entering prior to 2009 were assigned to their cohort/team by maximizing diversity across five characteristics: gender, race (for domestic students), citizenship

[15] 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.

(classified as US or International), and undergraduate major. While the system is electronic, staff are also allowed to make manual corrections to achieve balance.

Starting in 2009, and with the advent of a new admissions director, the measures of diversity switched. 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 everything else). In addition, there are rare cases of special considerations, usually requiring that two students in a relationship are not placed in the same cohort. Students are unable to switch cohorts/teams once the semester starts; however, students may be able to switch prior to the semester if the class time conflicts with child care or a medical engagement.

This 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 peers. 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 eventual major, 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 stock returns react more positively when an appointed manager has higher educational credentials, while the manager receives a higher compensation (Bhagat et al., 2010; Falato et al., 2015). This preference is unsurprising given managers with MBAs have superior performance to peers without an MBA (Chevalier and Ellison, 1997; King et al., 2016). Second, the 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 the scores of 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 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;[16] 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

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

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.[17]

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

Data Cleaning. We drop any graduates without an online profile. We manually match each MBA graduate to the 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 a nickname (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 name since graduation. To confirm we have a correct match we first require that the online profile refers to an MBA from the Kelley School of Business. In addition, we drop cases where the profiles lists incorrect graduation years.[18] 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.

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

[18] In a robustness check, we exclude all individuals where the online profile does not include entering/graduating dates, and our results do not change.

3.2 Classification

Prestigious Firm. A prestigious firm is identified using employment data of MBA students graduating from top-ranked MBA programs during 1999-2013. Specifically, 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. These are considered among several rankings as the three highest-ranked MBA programs in the US.[19] We then define a prestigious firm as any firm that employed at least five managers at graduation from each one of these three MBA programs during the time sample.

We introduce the set of prestigious firms in the sample in Table 6. We identify a total of 49 prestigious firms across a wide range of industries. In unreported results, we examine the employment outcomes of MBA graduates from top MBA programs. First, we find that employment outcomes are correlated over time: the number of graduates entering a given firm is highly persistent over years. Second, we find 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 prestigious firms is relatively robust to alternative specifications.

High-Ranking Undergraduate Institution. We next identify a top undergraduate institution 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. To be included as graduating from a top business school, managers needed to explicitly graduate from the business school according to their major.

[19]For example, in the 2017 *US News* MBA rankings, the Harvard MBA is first, the Chicago MBA is second, and the Stanford MBA is fourth place. In the 2017 *Bloomberg* MBA rankings, the Harvard MBA is first, the Stanford MBA is second, and the Chicago MBA is fourth place. Rankings in previous years are similar.

3.3 Data Summary

Manager Demographics. Our sample includes a total of 2,109 MBA students graduating between 1999 and 2013 as presented in Panel A of Table 1. We estimate 75% are male, 27% are international, and 17% are U.S. minorities. The average quantitative entrance exam score is 43 and the average first semester MBA grade is 84%. Approximately, 15% have graduated from a top U.S undergraduate institution and students apply with about five years of worker experience. 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 (9%), and operations (7%).

We also summarize the characteristics of each team and cohort under assignment. As discussed earlier, cohorts and teams are assigned based on several criteria. Students are randomly assigned to one of four cohorts during the early graduation years, and one of three cohorts starting with the 2006 graduating class. From there, students are then randomly assigned into one of 4-5 teams within each cohort, making a total of fifteen or sixteen teams per graduating class. From the original admissions data, we note that the average team size is 4.5 students, and is between 4 and 5 students for each graduating class. After cleaning the data, and average team size has 3.2 students and an average cohort has 45.6 students.

Missing Graduates. We are able to match nearly 95% of MBA graduates to their online profile. We highlight the match details in Figure 1. For each MBA graduation year, we split managers into three categories (Domestic White, Domestic Minority, and Internatinal) 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, we find little difference between male and females of the same group. Third, the match rate is not higher during the more recent years.

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

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

Employer Characteristics. We summarize the firm characteristics in Panel B and C of Table 3. Given our focus on networks, we include only firms where multiple managers in the same graduation year entered the firm. We include a total of 311 firms in the sample, split into 49 prestigious firms and 262 non-prestigious firms. First, prestigious firms employ a total of 13.6 graduates from the Kelley MBA Program during the sample. In addition, 50% are classified as distant firms with a headquarters at least 750 miles from Bloomington, Indiana. Turning to the remainder of the sample, we establish that non-prestigious firms employ fewer managers (5.1 graduates during the time period). Second, they are geographically closer to the Indiana

University campus. Third, we offer a complete measure of the industry breakdown of firms in Figure 3. We split each of the 311 firms in the sample by two-digit NAICS code. We find that prestigious firms are more likely to belong to the financial industry (33% compared to 18%), information industry (12% compared to 5%) and professional services (14% compared to 8%).

4 Methodology

We develop a simple methodology to evaluate the value of former employee's networks. First, we explore a simple theoretical model to confirm that firms hiring consistently from high-ranking MBA programs are high human capital firms. Second, we develop the empirical framework that allows us to isolate the effect that former employees have on prospective managers. Third, we summarize the data necessary for the regression analysis.

4.1 Theory

We choose to focus our analysis on the set of human capital intensive firms, hereacter referenced as *prestigious employers*. First, these firms are especially dependent on recruiting managerial talent and exposed to human capital risk. Second, former employees of these firms may be especially likely to sort into sub-groups with talented peers. To test our hypothesis, we need to define the set human capital intensive firms. Therefore, we develop a simple revealed preference argument: the firm's with the greatest human capital employ the most preferred employees. To complete this argument, we instead need a way to define the set of 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.

4.2 Regression Framework

To identify whether networks of former employees have a causal effect on employment outcomes of middle-level managers, we need to address the endogeneity associated with the formation of networks. We define that 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 random assignment into cohorts and teams introduced by the MBA office at Indiana University.[20] This forced assignment allows us to exploit a setting in which the set of connections is exogenous to the job seeker.

We test if a job seeker (student at graduation) with a connection to a prestigious firm has a higher likelihood of joining that firm. Given each manager has a wide range of potential employers, we implement this test by forming all possible pairs between all managers and firms in our sample. Given our focus on the set prestigious firms, we restrict the sample exclusively to managers without prior experience in a prestigious firm.

Specifically, we evaluate whether a manager i joins firm j if any cohort members (or team members in robustness tests) of manager i worked at firm j prior to entering the MBA program; and 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 $Employment_{i,j}$ is the dependent variable of interest, a binary variable that takes a value of one when manager i enters employment with firm j. The key independent variable is $Connection_{i,j}$ a binary variable denoting if any cohort (or team) member of manager i had previous employment experience with firm j. We test the hypothesis that $\beta_C > 0$, which implies that cohort members provide private information in the employer recruitment process.

Our analysis needs to evaluate how cohort assignment impacts employment outcomes relative to other managers in the same graduation class, but in a separate cohort. If the likelihood to enter a given firm was equal across all firms, then we can simply include a fixed effect for each graduating class. However, the likelihood of entering a given firm differs signifi-

[20] 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.

cantly over the cross-section of employers: certain firms regularly hire five or more managers each year, while other firms rarely hire one manager. Therefore we consider two potential controls 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 the 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 managers enter that firm in that given year. Finally, to control for the correlation of errors, we depend on two-way clustering at the firm level and the worker level.[21]

We make two concessions. First, our data is limited in that we are not able to observe the set of job applications submitted by each MBA manager. Instead, we can only observe the actual employment outcome. To limit the number of firm-manager observations, we instead consider the sample of firms that have employed at least two MBA managers and employed at least one manager from the same graduation year. Second, we are not able to explicitly identify the set of firms that offer employment to each manager, but instead only the offer the manager ultimately accepts. Assuming managers depend on multiple cohort members when searching for jobs, we will only understate the value of the network process.

4.3 Regression Dataset

The regression requires an observation for each manager i , firm j pair. We create this dataset and present several summary statistics in Table 4. We discuss the results for all firms in Panel A. The likelihood manager i is employed at firm j is 1.1% at graduation from the MBA program. In addition, for a given firm, 9.9% of managers have a cohort member with prior employment experience and 0.5% have a team member with prior employment experience. Conditional in entering the firm at graduation, 85% of managers remain employed at the firm after one year and 43% after five years. In Panel B, we conduct a similar analysis exclusively on prestigious firms. For a given firm, the likelihood a managers enters the firm is 1.2%,

[21] In additional robustness tests we also cluster errors at the cohort-level.

while 15% (0.8%) of managers have a cohort (team) member with prior experience at the firm. Conditional on entering the firm, managers are more likely to remain in a prestigious firm compared to a non-prestigious one.

5 Results

First, we evaluate the the impact of former employees on the employment outcomes of other cohort members, focusing specifically on prestigious firms. Second, we examine how this result depends on the talent of the particular cohort member. Third, we identify the primary firm characteristics that drive our estimates. Fourth, we reject alternative explanations of the results.

5.1 Manager Results

In Table 5 we evaluate the role of former employees on prestigious firm recruitment. Panel A reports the estimates for all managers, while Panel B focuses on managers with no experience in a prestigious firm prior to the MBA program. 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) instead include a firm-year pair fixed effect. In Panel A, Columns (1) and (2) focus on employment directly after graduation. We estimate that access to a cohort member with prior firm experience increase the probability of entering the firm by 0.6%. Given the likelihood of entering a given firm is 1.2%, this translates to relative increase of 50%. 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, suggesting that managers without connections to former employees of prestigious firms eventually obtain a job at these firms.

Panel B reports similar statistics to Panel A, but control for manager characteristics by including fixed effects for gender, nationality, and race. The concern is that managers may not be randomly assigned to cohorts. In this instance, managers may be more likely to enter a given firm not due to connection in the cohort, but rather sorting due to observable personal characteristics.[22] 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 included only for domestic managers and is defined as: Asian, Black,Hispanic, White, and Other. Other includes multiracial, Native American, and Pacific Islander, which all compose under one percent of the sample.

Even after controling for personal characteristics, access to a cohort member with prior firm experience increase the probability of entering the firm by 0.4% to 0.6% at graduation. Given the likelihood of entering a given firm is 1.2% for these students, this translates to a relative increase of 33% to 50%. The results are also stronger across all other years, and barely dissipate over time. Five years after graduation, a manager with a connection to a firm through the MBA cohort is still 40% more likely (relative to the mean) to be employed in that same firm. Overall, our results do not appear to be driven by cohort sorting due to manager personal characteristics.

Finally, in Panel C we alter the linear regression framework. We note that the likelihood a manager is employed at a given firm is only 1.2%. As a result, the dependent variable in the specification takes a positive value for only a small sample of the data. Therefore, we next introduce a probit regression framework. Though the coefficients can not be directly compared with the linear results in Panel A and B, we document statistical significance across the five years following MBA graduation. We confirm the network results do not depend on the particular empirical specification.

The results help confirm prior studies that detail the role of informal networks in employment outcomes (Granovetter, 1995; Holzer, 1988). The size of the coefficient is striking

[22]In unreported results, we directly confirm that personal characteristics are uncorrelated with the likelihood of a cohort-based connection to a prestigious firm. This holds for both the full sample of managers and the subsample without experience in a prior prestigious firm.

given that each graduating class includes only three cohorts. As managers will routinely interact with peers outside the cohort, our estimate is only a lower bound on the value of social networks for middle managers.

Given that employment is highly persistent at the skill-intensive firms (93% remain after the first year and 47% remain by the fifth year), these networks have long-run career implications. While we cannot place a monetary value of the former employee (due to a lack of data in earnings at the individual level), we can document a higher starting salary among Kelley MBA graduates in the industries with a high concentration of prestigious firms. Specifically, we use data from the initial employment statistics for the Kelley MBA class of 2000. The data is based on annual exit survey of Kelley MBA graduates. We focus on the class of 2000 since survey responses after 2000 have no information on base salary and bonuses by industry. We focus on two industries, finance and consulting, due to their prevalence among the set of firms: in our sample 33% of prestigious firms are in the financial industry (compared to 19% of the other firms in the sample), while 12% of these firms are in the professional services industry (compared to less than 8% of the other firms in the sample).

We find that graduates hired by consulting firms had the highest base salary of all other industries at over $91,000 (for comparison the closest industry is $77,603). Alternatively, while Investment Banking has a similar base salary to other industries, graduates can expect a significantly higher signing and guaranteed bonus. In particular, 78% of graduates receive a guaranteed bonus (after the signing bonus) with a mean value of nearly $32,000. In comparison, only a quarter of other industries offer a guaranteed bonus and the mean value is less than half at $15,000. Overall, we find a 19% higher salary for consulting and a 27% higher salary for investment banking, compared to outside options for MBA graduates.

Managers with Weak Signaling Ability. Our results highlight the role of former employees on recruitment efforts. In this setting, former employees should have an especially large affect on managers who do not have stronger networks. Therefore, we next show that managers with otherwise weaker networks especially benefit from interaction with former employees. We focus on employment one year after graduation; however, the results hold across the five years sample period.

We identify two sets of managers with weak quality signals. First, we focus on high-ranking undergraduate institutions, given prior evidence that 10-20% of CEOs have an undergraduate degree from one of just seven colleges (Cook et al., 1993). Second, we exclusively analyze the network effects for U.S. racial minority/international managers. We use race/nationality as a measure of available outside opportunities following the theoretic argument of Montgomery (1991) and the empirical estimates of Marsden (1988).

In Panel A of Table 7, we estimate a cohort connection increases employment by 0.8% for managers that graduate from lower-ranked undergraduate universities. For international and minority managers, we estimate that a cohort-based connections increases the likelihood of employment in the firm by 0.9% to 1.1%. The results illustrate that social networks are especially valuable for workers with otherwise weaker networks and help confirm a prior theoretical literature on heterogeneous network effects (Galenianos, 2014).

Strong and Weak Connections. Thus far the results do not distinguish based on the relationship between the former employee and the employer. Therefore, we next split the sample based on the number of years a connection was employed at the firm. In our sample, the average tenure at a prestigious firm prior to the MBA is three years. Therefore, we define a connection as strong if the worker was previously employed at the firm for at least three years, while a weak connection is a worker employed for less than three years at the firm of interest.

We present that Panel B of Table 7. We estimate that a strong connection increases the likelihood of entering a given firm by 1.2-1.4%, effectively doubling the rate of employment. In contrast, we find no evidence that weak connections have any impact on employment outcomes. The results confirm that the role of former employees depend on the strength of the underlying relationships.

Distinguishing the Flow of information. We next examine the flow of information in our empirical setting. Economic theory suggests a social network 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); however, in an alternative framework, firms instead learn about the ability of workers (Montgomery, 1991).

With the current dataset, it is difficult to identify whether peers transfer information about the employer to the applicant, or the information about the applicant to the employer. We instead survey a subsample of the managers in our sample. Specifically, we survey the sample of managers that (i) entered a prestigious firm following upon graduation and (2) was connected to to cohort member with prior experience in the same firm. In total, we contacted ninety-two managers and received replies from approximately forty managers.

We asked two questions in our survey. In the first question, "Did you received a referral for your employer XXX from a cohort-member previously employed at the firm?". In the second question, "Did you receive advice/opinions about your employer XXX from a cohort-member previously employed at the firm?". We find limited evidence that managers act as referrals in the sample: only 6.3% of the responses indicate they recieved a referral from a peer in their cohort. In comparison, 36% of the responses say they learned about the firm from a cohort member, while another 8% responses saying they "maybe" learned about the firm from a cohort member. In other words, peers are 6-7 times more likely to transmit information to a job applicant than a prior employer.

We note these results differ from past research highlighting the role of referrals. One key difference is that while past researchers focus on the role of current employees, we focus on former employers. This distinction is important as current employees may receive incentives for referrals: a monetary bonus Beaman and Magruder (2012), earnings partially correlated with the new worker's productivity (Heath, 2017), or more generally, a better relationship with the firm (Pallais and Sands, 2016). However, in our analysis, less than twenty percent of the workers in our sample return to their prior employee after graduating from the MBA program; for prestigious firms, this number decreases to only thirteen percent. As a result, there are likely limited benefits to referring a cohort manager.

5.2 Talent Results

Thus far, our result confirm that a former employee has a positive effect on the likelihood a cohort-member enters the firm. While these results highlight an impact on the recruiting firm, the actual value to the firm is less clear. As discussed earlier, theoretical worker argues talented employees will develop networks with other talented individuals, benefiting the firm (Montgomery, 1991). In our own setting, this suggests former employees at prestigious intensive firms may form homogenous subgroups with high-talent managers (Carrell et al., 2013).

To test this possibility, we evaluate how former employees impact employment outcomes across the managerial talent pool. Specifically, we incorporate two measures of managerial talent: (i) the quantitative entrance exam score (required by Indiana University) and (ii) MBA courses grades in the first semester of the program (when all students take the same curriculum). We split the entrance exam scores into quartiles and the course number grades into three group sets based on letter grades (A, B, or C).

We present the results in Table 8. We focus on employment within one year of graduating the MBA program. First, we find no evidence that a former employee impacts the likelihood a low talent manager enters the firm. However, the connection does improve the chances of entering a given firm for more talented managers. We estimate that for students in the top quartile of exam scores, a cohort member increases the rate of employment by 1.8%. We estimate a similar value of 1.4% for students receiving an A in the first semester courses. Overall, low-talent managers are unaffected by former employees, while high-talent managers benefit.

Team Networks. For further evidence that managers sort into subgroups based on talent, we test whether the same heterogeneous effects that we document with cohorts exist within members of the same team. At Indiana University, teams are also subject to forced assignment, but 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.

In Table 9, we repeat the same estimation that we report in Table 8, but instead of using cohort connections, we use team connections. The independent variable is a binary variable equal to one when a team member of manager i is a former employee of firm j. The results outlined in Table 9 confirm the findings documented in Table 8. In Column (1) and (2) we first confirm a team member connection increases the likelihood of entering a given firm by 2%. Note the coefficient is significantly larger than the estimate of 0.6% when we define the network at the cohort level. However, given teams are roughly five students (compared to 50 students in a cohort), we should expect a stronger relationship between members, resulting in a larger coefficient.

Next in Column (3) - (6) we evaluate the team effects across the talent distribution. We estimate that for low-talent managers (talent measured in both classroom performance and entrance exam scores), interaction with a former employee slightly decreases the likelihood of entering a given firm. However, we estimate a positive effect for high-talent individuals. For managers with high classroom performance, former employees increase the likelihood of employment at the firm by 3.4%; for managers with high exam scores, former employees increase employment by 5-6%. Again, the large magnitudes are not surprising as managers have numerous interactions through group projects and homework assignments. We note that due to the small sample size, these coefficients are only significant at the 20% level; however, the results help confirm that network are exclusively valuable to higher-performing managers.

Alternative Network Definitions. To provide further evidence to our results, we introduce three alternative measures of networks based on: (i) gender, (ii) race, or (iii) nationality. These measures of networks have been previously used in the labor literature as a workhorse to define social networks (Bandiera et al., 2009; Bertrand et al., 2000; Dustmann et al., 2015). We note that all three networks are endogenous: if managers in the same (gender/race/nationality) have similar preferences or abilities, then they are also more likely to enter the same firms. 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 the firm and less talented managers are less likely to enter the firm.

We present the results with these alternative measures of network in Table 10. For the purposes of the regression, we follow the earlier framework to define nationality (US, India, China, South Korea, Japan, Taiwan, and Other) and 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 the Column (1) and (2), a gender-based connection increases a high-talent manager's employment rate by 0.8%-1.8% more likely to enter a given firm if connected to the firm by another manager of the same gender. In Panel B, we examine the role of a nationality-based network. Managers in the top quartile of entrance exams are 1% to 1.2% more likely to enter a given firm when connected to the firm through a peer of the same nationality. In comparison, former employees either have no effect on low-talent managers, or actually negatively affect employment outcomes. Finally, in Panel C, we study a race-based network, and again find significant heterogeneity based on worker talent. In Column (1)-(2) we estimate that individuals with high exam scores are 08-0.9% more likely to enter the firm when also connected. In Columns (3)-(4) we show that students in the top quartile of entrance exams with a cohort connection to a prestigious firm are 1.6-1.9% more likely to enter a prestigious firm. These results help confirm our cohort-level analysis: regardless of our definition of network, we find that former employees only affect the employment outcomes of high-talent managers.

Screening Ability. The results document that former employees impact the employment outcomes of other cohort members, specifically high-talent cohort members. We argue this result is mostly due to sorting within the cohort: former employees of prestigious firms interact predominantly with more talented students. An alternate explanation is that our measures of managerial talent are actually directly observable to prestigious firms due to sufficient screening technologies. In this instance, networks may influence all cohort members, but only the talented managers are actually hired by the firm. As a result, former employees will have little effect on improving the firm's acquisition of talent.

To reject this explanation, we evaluate the relationship between talent and employment at a prestigious firm in Table 13. In Columns (1)-(3) we measure talent based on grades, while in Columns (4)-(6) we measure talent by entrance exam score. In Columns (i) we include no other controls, in Columns (ii) we include year fixed effects, and in Columns (iii) we include year fixed effects and student controls for gender, race, and ethnicity.

We find strong evidence that less talented students have access to jobs in prestigious firms. First, without any controls, we find no significant relationship between classroom performance in the MBA and employment at a prestigious firm. Specifically, 27.4% of students with a C average are employed in a prestigious firm following graduation; this number increases 6% (2.6%) for B-level (A-level students), though neither estimates are statistically-significant. The results are relatively unchanged by including year fixed effects. By including both year fixed effects and controlling for student characteristics we now find evidence that A/B students are 12% more likely to take a position in a prestigious firm. Using entrance exam scores as a measure of talent, we actually find a negative relationship between talent and employment at a prestigious firm. This result holds across all three specifications. Overall, we find no evidence that only talented managers gain employment at prestigious firms.

5.3 Results across All Firms

Firm Characteristics. We next evaluate the firm characteristics that are associated with social networks. We begin by distinguishing between our sample of employers into prestigious and non-prestigious firms. In Panel B of Table 11, we estimate no network effect for non-prestigious firms; however, networks increase the likelihood of employment in a given prestigious firm by 0.6%.

We focus on prestigious firms as a proxy for firms with high demand for human capital. However, it is likely that other firms will also depend on the recruitment efforts of prior employees. As an alternative proxy for a firm's dependency on informal hiring networks we use geographic distance. We make the assumption that job applicants have less information about geographically distant firms and may instead depend more on informal social networks. Specifically, we define a distant firm as any firm with a headquarters more than 750 miles from the university. Under this distance, a distant employer is any employer located on West Coast of the United States or has an international headquarters. We present the results in Columns (3) and (4) of Panel B. We continue to define a network at the cohort-level and include graduation year fixed effects in the analysis. In Column (3) we find no evidence that private information about geographically-close firms impacts employment outcomes. However, in Column (4), we establish that a connection to a geographically distant firm increases the probability of employment by 0.3%, a 30% relative increase. Overall, geographic distance impacts the value of private information to a job applicant.

Talent Results using Distant Firms. Based on the results above, social networks are especially valuable to an employer when the firm is geographically distant. Given this result, we next confirm that these distant firms also benefit from manager social networks. In Table 12 we again use MBA entrance exams scores and first semester grades as a measure of talent. In all specifications, we estimate that networks have no impact on the employment of low-talent managers. However, the value of the networks increases to roughly 0.8% for managers with a B letter grade and 1.3% for managers with an A letter grade. Similarly, in Columns (3) and (4) we determine that managers with the highest entrance exam scores are 1.3% more likely to enter a given firm. The results confirm that the talent results are not particular to the set of prestigious employers in our sample.

5.4 Identifying Mechanisms.

Our paper evaluates the value of the former employee base as a recruiting asset for prestigious firms. To identify the role of former employees, we exploit the random assignment of students to MBA classrooms: peers in each classroom have unique employment histories and as a result, private information about potential employers. In line with our assumptions, we find that social networks impact recruiting outcomes for firms. The purpose of this section is to attempt to isolate the particular channel that results in firms hiring more talented managers.

First, we examine if managers improve applying and interviewing skills by learning from peers. In this instance, a connection to a particular prestigious firm may increase the likelihood of employment at all other prestigious firms. Second, we test if peer interactions impact the career interests of managers. If peers are more likely to switch career tracks due to peer interaction, then this could increase the likelihood of also entering the peer's prior firm. Third, we estimate the impact of peer networks on classroom performance. If peers receive better course grades due to the benefits of good team member, then they will be more likely to enter a prestigious firm.

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 a prestigious firm may increase the likelihood of employment across all prestigious firms; as a result, former employees benefit all firms (not only the former employer). To test this scenario, we evaluate whether a connection to a prestigious firm in one industry increases the likelihood of employment at the other prestigious firms in the same industry.

We present the results in Table 14. We define a Cohort-Industry Connection as the number of cohort members with prior experience at any prestigious firm in a given industry. In Columns (1) and (2) we estimate the value of a industry connection for all workers; while in Columns (3) and (4) we include only workers without prior experience in a prestigious firm. In Columns (1) and (3) we include fixed effects for the number of hires in each year, while in Columns (2) and (4) we include firm-year fixed effects. Across all four specifications , we estimate that a connection actually leads to a decrease 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 these that 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 generate large sample size, we include all managers in the sample, even those with prior experience in a prestigiuous firm. We note that the results do not depend on the particular dataset.

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

$$Grade_i^t = \alpha + \beta \times High\ Grade\ Team_{-i}^t + \delta^t + controls_i^t + \varepsilon_i^t \quad (2)$$

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 recieves a B letter grade, and a value of 3 when the worker recieves a C letter grade. $High\ Grade\ Team$ is a binary variable for an individual that has at least one team member receiving an A letter grade. We control for the year of entering the MBA program, δ^t, in case the student population and the job market differ over time. We control for individual characteristics including gender, citizenship, race, and work experience as teams are assigned based on these student characteristics.

Note our focus on team networks rather than cohort networks. The distinction is largely due to the size of the respective groups. Since cohorts are roughly forty students on average, every cohort includes students from every major and every grade distribution. As a result, we have no variation across cohorts based on these variables. However, given teams are composed of four to five members, an average team does not include a student from every single major. Similarly, 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 15 we first evaluate 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 15, Columns (4) - (6) we alternatively examine how students with experience in prestigious firms impact the classroom performance of other team members. Across all three specifications, participating in a prestigious firm team 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 on 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:

$$Major_{i,y}^{t} = \alpha + \beta \times Major\ Team_{-i,y}^{t} + \delta^{t} + controls_{i}^{t} + \varepsilon_{i}^{t} \tag{3}$$

The dependent variable, $Major_{i,y}^{t}$ is a binary variable that takes a positive value when the worker i graduating in year t chooses to major in subject y. The key independent variable is $Major\ Team$, which is defined as a binary variable when at least one team member intends to major in subject y. We control for the year of entering 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 intended major of the student. Importantly, the intended major is chosen at the time of application to the MBA program and therefore 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. Historically, entrepreneurship has been denoted as both "Entrepreneurship & Corporation Innovation" and "New Ventures & Business Development"; Operations uses the terms "Supply chain & Operations" and "Operations and Systems Management". We confirm significant differences between intended and major at graduation. First, a large fraction of students intend to major in entrepreneurship and this fraction has generally increased over time (from about 20% to over 50% in more recent classes); yet, the fraction of actual entrepreneurship majors has stayed roughly constant at 15%. Second, we note that both marketing and finance attract many more students than initially intend to enter the major. Third, both operations and strategy has seen periods with minimal intended majors and a small fraction of actual majors.

We test the impact of team members on major choice in Table 16. We split the results into Panel A and B. In Panel A, Columns (1) and (2) focus on Entrepreneurship, Columns (3) and (4) focus on Finance, and Marketing is Columns (5) and (6). In Panel B, Management is Columns (1) and (2), Operations is Columns (3) and (4) and Strategy is Columns (9) and (10). We establish two results. First, a student is three percent more likely to major in Entrepreneurship if a team member intends to major in the area. Second, a student is actually eight percent less likely to major in Strategy if a team member intends to major in the area. In all other majors, there is no correlation. With the exception of Entrepreneurship, we find no evidence that students are more likely to switch to a team members intended major, suggesting that peers are not impacting the focus of other students.

6 Conclusion

This paper estimates the role of former employees on mangagerial recruitment. Relying on the random assignment of MBA students into teams and cohorts, we can precisely isolate peer effects on prospective managers, and by incorporating both MBA admissions data with online profiles, we are able to follow individual managers over their careers. The results highlight how social networks are important to explain how talented managers sort into firms.

Beyond improving our understanding of the value of former employees, these findings have implications for prospective MBA students and programs. For prospective managers, these results support the value of attending a top business school in order to access peer networks. For business schools, these results document that students with strong prior employment experiences offer an externality to the rest of the student population, implying that admissions policies should place a particular emphasis on applicant's prior employment. For the wider public, these results confirm the value of policies that promote network development, especially for workers with otherwise weak networks.

Finally, our results add to our understanding of the middle-level manager labor market. We believe that MBA programs offer an unique opportunity to examine the managerial labor market; with the framework and data developed in this paper, we plan to continue this line of study in the near future.

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Table 1: Summary Statistics of Students

This table reports the summary statistics for students in our sample. The summary statistics for students are based on admissions information, student majors upon graduation, and cohort/team demographics.

	N	Mean	Std
Graduation Year	1497	2008.3	3.35
Male	1497	0.75	0.43
International	1497	0.27	0.44
Racial Minority	1497	0.17	0.38
High Grade Level	1497	0.27	0.44
Entrance Exam Grade	1497	42.9	5.44
Top Undergraduate Institution	1497	0.14	0.35
Work Experience (Months)	1497	56.3	28.2
Entrepreneur Major	1497	0.091	0.29
Finance Major	1497	0.50	0.50
Marketing Major	1497	0.45	0.50
Management Major	1497	0.11	0.32
Operation Major	1497	0.071	0.26
Strategy Major	1497	0.16	0.36
Team Size	1497	3.31	0.95
Cohort Size	1497	47.3	9.41
Team Member with High Grade Level	1497	0.45	0.50
Entrepreneur Team Member	1497	0.60	0.49
Finance Team Member	1497	0.50	0.50
Marketing Team Member	1497	0.46	0.50
Management Team Member	1497	0.31	0.46
Operation Team Member	1497	0.16	0.36
Strategy Team Member	1497	0.064	0.25

Table 2: List of prestigious Firms in the Sample

This table presents a list of the firms denoted prestigious in our sample. We identify prestigious 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 Business School, Stanford University Graduate School of Business, and University of Chicago Graduate School of Business.

List of Prestigious 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 prestigious firms, while Panel B reports the same firm characteristics for less-prestigious firms.

Panel A: Prestigious 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 Prestigious 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-firm pairs. Panel A summarizes the characteristics of all student-firm pairs. Panel B summarizes the characteristics of the pairs between students and prestigious firms. 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 as a binary variable equal to one when a firm previously employed a student in the same gender. Similarly for Nationality and Race.

Panel A: Student and Firm Characteristics

	N	Mean	Std
Employed upon Graduation	91452	0.010	0.10
Cohort-Firm Connection	91452	0.081	0.27
Team-Firm Connection	91452	0.0051	0.071
Gender-Firm Connection	76835	0.19	0.54
Nationality-Firm Connection	76835	0.16	0.53
Race-Firm Connection	76835	0.10	0.40

Panel B: Student and prestigious Firm Characteristics

	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	20857	0.29	0.63
Nationality-Firm Connection	20857	0.26	0.65
Race-Firm Connection	20857	0.15	0.45

Table 5: Network Effect

This table presents the baseline network regression results. The regression evaluates the impact of an exogenous network on employment in a prestigious firm. The dependent variable is a binary variable that takes a value of one when the student is employed at a particular 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 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). 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. prestigious firms are defined as all firm that employed at least five MBA students from (1) Harvard Business School, (2) Stanford Graduate School of Business, or (3) University of Chicago Booth School of Business immediately following graduation during the years 1999-2013. 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 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 regression evaluates the impact of an exogenous network on employment in a prestigious firm. Controls include fixed effects for gender, nationality, race, and entrance exam quartiles. The dependent variable is a binary variable that takes a value of one when the student is employed at a particular firm one year following graduation. 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. 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. Prestigious firms are defined as all firm that employed at least five MBA students from (1) Harvard Business School, (2) Stanford Graduate School of Business, or (3) University of Chicago Booth School of Business immediately following graduation during the years 1999-2013. 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 firm level.

	No Controls		Gender		Nationality		Race		Exam	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.004*	0.006*	0.004*	0.006*	0.004*	0.006*	0.004*	0.006*	0.004*	0.006*
	(1.71)	(1.71)	(1.72)	(1.73)	(1.74)	(1.75)	(1.72)	(1.73)	(1.75)	(1.73)
Firm Hires FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Gender FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Entrance Exam Fe	No	No	No	No	No	No	No	No	Yes	Yes
N	20840	20840	20840	20840	20840	20840	20840	20840	20840	20840
R-squared	.0071	.0081	.0073	.0083	.0074	.0083	.0078	.0088	.008	.009

Table 7: Heterogeneous Network Effects

This table presents theheterogeneous network regression results across prestigious firms . The regression evaluates the impact of an exogenous network on student employment at MBA graduation. We focus exclusively on the set of firms defined as prestigious. In Panel A, we focus on the sample of workers with otherwise weak signaling mechanisms. Columns (1) and (2) focus on students that did not graduate from a top-ranked undergraduate institution. The last two columns include only international and racial minority students. 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. In Panel B, we split the sample by the strength of the connection to the given firm. Specifically, a Strong Cohort-Firm Connection is defined as the number of cohort members with at least three years experience at the given firm prior to the MBA. A Weak Cohort-Firm Connection is the number of cohort members with less than three years experience at the firm prior to the MBA.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 firm level.

Panel A: Network Effects for Workers with Weak Signaling Mechanisms

	Low-Ranked Undergrad		Racial Minority/International	
	(i)	(ii)	(i)	(ii)
Cohort-Firm Connection	0.008***	0.008*	0.011***	0.009*
	(3.06)	(1.95)	(2.85)	(1.91)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	21820	21820	9118	9118
R-squared	.011	.016	.0064	.021

Panel B: Network Effects for Workers with Strong Connections

	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 8: Network Effect across the Student Talent Distribution

This table presents the network regression results across prestigious firms by student talent. The regression evaluates the heterogeneous impact of an exogenous network on student employment by student talent measures. We focus exclusively on employment in a prestigious 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 particular cohort. We introduce two measures of talent. The first 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. 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 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 firm level.

	MBA Grades		Entrance Exam	
	(i)	(ii)	(i)	(ii)
MBA Grade Level=3 X Cohort-Firm Connection	0.014*	0.014*		
	(1.77)	(1.77)		
MBA Grade Level=2 X Cohort-Firm Connection	0.007	0.007		
	(1.21)	(1.21)		
Entrance Exam Score=4 X Cohort-Firm Connection			0.016*	0.016*
			(1.74)	(1.70)
Entrance Exam Score=3 X Cohort-Firm Connection			0.005	0.005
			(0.86)	(0.81)
Entrance Exam Score=2 X Cohort-Firm Connection			0.005	0.005
			(0.79)	(0.80)
Cohort-Firm Connection	-0.004	-0.002	-0.002	0.000
	(-0.98)	(-0.45)	(-0.53)	(0.11)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	19417	19417	20878	20878
R-squared	.0073	.0082	.0078	.0087

Table 9: Network Effect across the Student Talent Distribution: Team Results

This table presents the network regression results across prestigious firms by student talent. The regression evaluates the heterogeneous impact of an exogenous network on student employment by student talent measures. We use all firms in the sample for this estimation. 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 define talent according to the score on a quantitative MBA entrance exam, and we split the scores into quartiles. The last two columns define talent according to first semester grades and we split the scores by letter grade (A, B, or C/D). Columns (i) have no fixed effects, Columns (ii) include graduation year fixed effects. 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 firm level.

	Baseline		MBA Grades		Entrance Exam	
	(i)	(ii)	(i)	(ii)	(i)	(ii)
MBA Grade Level=3 X Team-Firm Connection			0.034	0.034		
			(1.30)	(1.30)		
MBA Grade Level=2 X Team-Firm Connection			0.034	0.032		
			(1.64)	(1.52)		
Entrance Exam Score=4 X Team-Firm Connection					0.060	0.061
					(1.45)	(1.47)
Entrance Exam Score=3 X Team-Firm Connection					0.049	0.048
					(1.62)	(1.61)
Entrance Exam Score=2 X Team-Firm Connection					0.035	0.036
					(1.17)	(1.14)
Team-Firm Connection	0.021*	0.020	-0.009***	-0.009***	-0.015***	-0.016***
	(1.72)	(1.56)	(-2.84)	(-3.41)	(-8.18)	(-8.12)
Firm Hires FE	Yes	No	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes	No	Yes
N	25755	25755	19417	19417	20878	20878
R-squared	.01	.014	.0069	.0095	.0073	.0099

Table 10: Alternate Network Effects across the Student Talent Distribution

This table presents the network regression results across prestigious firms by student talent and using alternate definitions of networks. The regression evaluates the heterogeneous impact of an exogenous network on student employment by student talent measures. We focus exclusively on employment in a prestigious firm. 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. Panel C defines the network at the nationality-level. The Base Column estimates the impact of having a connection to the firm. 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 firm level.

Panel A: Network Based on Gender

	Grades			
	(i)	(ii)"	(i)	(ii)"
MBA Grade Level=3 X Gender-Firm Connection	0.008**	0.007		
	(2.13)	(1.58)		
MBA Grade Level=2 X Gender-Firm Connection	0.008***	0.008**		
	(2.71)	(2.40)		
Entrance Exam Score=4 X Gender-Firm Connection			0.017**	0.018**
			(2.20)	(2.16)
Entrance Exam Score=3 X Gender-Firm Connection			0.004*	0.004*
			(1.94)	(1.79)
Entrance Exam Score=2 X Gender-Firm Connection			-0.000	-0.002
			(-0.08)	(-0.77)
Gender-Firm Connection	-0.005**	-0.004	-0.003	-0.002
	(-2.24)	(-1.23)	(-1.61)	(-0.56)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	19417	19417	20840	20840
R-squared	.0068	.0094	.0082	.011

Panel B: Network Based on Nationality

	Grades			
	(i)	(ii)"	(i)	(ii)"
MBA Grade Level=3 X Nationality-Firm Connection	0.002	0.001		
	(0.58)	(0.41)		
MBA Grade Level=2 X Nationality-Firm Connection	0.003	0.003		
	(0.80)	(0.74)		
Entrance Exam Score=4 X Nationality-Firm Connection			0.010**	0.012**
			(2.38)	(2.40)
Entrance Exam Score=3 X Nationality-Firm Connection			-0.001	-0.001
			(-0.48)	(-0.29)
Entrance Exam Score=2 X Nationality-Firm Connection			0.000	0.000
			(0.20)	(0.04)
Nationality-Firm Connection	-0.003	-0.007	-0.001	-0.006**
	(-0.83)	(-1.26)	(-0.69)	(-2.09)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	19417	19417	20840	20840
R-squared	.0065	.0094	.007	.0099

Panel C: Network Based on Race

	Grades			
	(i)	(ii)"	(i)	(ii)"
MBA Grade Level=3 X Race-Firm Connection	0.009***	0.008**		
	(2.60)	(2.14)		
MBA Grade Level=2 X Race-Firm Connection	0.009***	0.008***		
	(2.97)	(2.87)		
Entrance Exam Score=4 X Race-Firm Connection			0.016***	0.019***
			(3.16)	(3.06)
Entrance Exam Score=3 X Race-Firm Connection			0.001	0.002
			(0.34)	(0.50)
Entrance Exam Score=2 X Race-Firm Connection			-0.000	-0.002
			(-0.16)	(-0.54)
Race-Firm Connection	-0.007***	-0.008***	-0.002	-0.006**
	(-3.11)	(-3.00)	(-0.91)	(-2.32)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	19417	19417	20840	20840
R-squared	.0066	.0092	.0073	.01

Table 11: Network Effect by Employer Characteristics

This table presents network regression results across all firms (not just prestigious). The regression evaluates the impact of an exogenous network on student employment outcomes. The dependent variable is a binary variable that takes a value of one when the student enters the particular firm. Columns (1) and (2) distinguish firms by the level of human capital, splitting between prestigious and non-prestigious firms. Columns (3) and (4) distinguish firms by geographic distance, split at the 750 mile distance mark. All specifications include a fixed effect for the number of students entering the firm in the year of graduation. 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 firm level.

	Prestige		Distance	
	Non-Prestigious	Prestigious	Close	Distant
Cohort-Firm Connection	0.000	0.003*	-0.001	0.002*
	(0.14)	(1.72)	(-0.92)	(1.81)
Firm X Year FE	Yes	Yes	Yes	Yes
N	91663	36097	68361	59399
R-squared	.004	.0071	.0045	.0057

Table 12: Network Effect across the Student Talent Distribution for Distant Firms

This table presents the network regression results across geographically-distant firms by student talent. The regression evaluates the heterogeneous impact of an exogenous network on student employment by student talent measures. We focus exclusively on employment in a distant firm, defined as any firm with a headquarters at least 750 miles from Indiana University. The first two columns define talent according to the score on a quantitative MBA entrance exam, and we split the scores into quartiles. The last two columns define talent according to first semester grades and we split the scores by letter grade (A, B, or C/D). 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 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 firm level.

	MBA Grades		Entrance Exam	
	(i)	(ii)	(i)	(ii)
MBA Grade Level=3 X Cohort-Firm Connection	0.013**	0.013**		
	(1.98)	(1.98)		
MBA Grade Level=2 X Cohort-Firm Connection	0.008	0.008		
	(1.51)	(1.51)		
Entrance Exam Score=4 X Cohort-Firm Connection			0.013*	0.013*
			(1.84)	(1.84)
Entrance Exam Score=3 X Cohort-Firm Connection			0.001	0.001
			(0.35)	(0.35)
Entrance Exam Score=2 X Cohort-Firm Connection			0.004	0.004
			(0.72)	(0.72)
Cohort-Firm Connection	-0.005	-0.005	-0.001	-0.001
	(-1.28)	(-1.28)	(-0.37)	(-0.37)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	33118	33118	35312	35312
R-squared	.0071	.0071	.0075	.0075

Table 13: High Screening Effect

This table presents the high screening regression results. The regression evaluates the correlation between MBA classroom performance (or entrance exam scores) and employment at a prestigious firm following MBA Graduation. We include only students not previously employed at these firms prior to entering the MBA. We introduce two measures of talent. The first three columns define talent according to first semester grades and we split the scores by letter grade (A, B, or C/D). The last three columns define talent according to the score on a quantitative MBA entrance exam, and we split the scores into quartiles. Columns (i) include no additional controls., Columns (ii) include year fixed effects, and Columns (iii) include year fixed effects and 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 the coefficients at the team level.

	MBA Grades			Entrance Exam		
	(i)	(ii)	(iiii)	(i)	(ii)	(iii)
MBA Grade Level=3	0.056	0.061	0.093**			
	(1.42)	(1.43)	(2.05)			
MBA Grade Level=2	0.063*	0.073**	0.094**			
	(1.76)	(1.98)	(2.42)			
Entrance Exam Score=4				-0.031	-0.029	-0.010
				(-0.95)	(-0.89)	(-0.23)
Entrance Exam Score=3				-0.077***	-0.076***	-0.062*
				(-2.70)	(-2.60)	(-1.93)
Entrance Exam Score=2				-0.065**	-0.063**	-0.056*
				(-2.07)	(-1.99)	(-1.71)
Constant	0.194***	0.137***	0.143	0.293***	0.246***	0.247***
	(5.90)	(2.94)	(1.62)	(13.57)	(7.13)	(2.90)
Year FE	No	Yes	Yes	No	Yes	Yes
Student Controls	No	No	Yes	No	No	Yes
N	1497	1497	1497	1497	1497	1497
R-squared	.0017	.0065	.021	.0054	.0094	.021

Table 14: 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 prestigious firms within the industry. The outcome variable is a binary variable that takes a value of one when the worker is employed at a prestigious firm within the industry following the MBA, but not the same firm as the cohort members. Columns (1) and (2) focus on all workers, while Columns (3) and (4) include only workers without prior experience in a prestigious firm. 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 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.

	All Firms		Prestigious Firms	
	(i)	(ii)	(i)	(ii)
Cohort-Industry Connection	-0.027**	-0.028**	-0.018***	-0.020***
	(-2.41)	(-2.30)	(-6.65)	(-6.04)
Firm Hires FE	Yes	No	Yes	No
Firm X Year FE	No	Yes	No	Yes
N	18975	18975	10823	10823
R-squared	.034	.04	.013	.018

Table 15: 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 prestigious Firm Team, a binary variable that take a value of one when at least one team member has prior experience in any prestigious 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 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					
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Team Member with High Grade Level	0.009	0.001	0.026			
	(0.24)	(0.03)	(0.73)			
Team Member with Prestigious Firm Experience				-0.035	-0.044	-0.036
				(-1.15)	(-1.52)	(-1.22)
Entrance Exam Level=4		0.390***	0.496***		0.392***	0.496***
		(10.07)	(9.26)		(10.14)	(9.25)
Entrance Exam Level=3		0.343***	0.309***		0.344***	0.310***
		(10.11)	(8.66)		(10.20)	(8.77)
Entrance Exam Level=2		0.198***	0.143***		0.198***	0.145***
		(5.46)	(3.95)		(5.48)	(4.01)
Constant	2.290***	2.105***	1.772***	2.304***	2.117***	1.800***
	(54.13)	(48.35)	(17.99)	(57.71)	(49.68)	(18.81)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nationality FE	No	No	Yes	No	No	Yes
Race FE	No	No	Yes	No	No	Yes
Gender FE	No	No	Yes	No	No	Yes
N	1497	1497	1497	1497	1497	1497
R-squared	.15	.22	.29	.15	.22	.29

Table 16: 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 (7) and (8) the major is Management, in Columns (9) and (10) the major in Operations, and in Columns (11) and (12) 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. Columns (2), (4), and (6) also control for whether the students intended to major in the particular discipline at the time of application to the MBA program. 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	0.036**	0.039**				
	(2.27)	(2.42)				
Finance Team Member			0.022	0.017		
			(0.92)	(0.74)		
Marketing Team Member					-0.005	0.002
					(-0.23)	(0.07)
Intended Entrepreneur Major	0.151***	0.150***				
	(7.60)	(7.52)				
Intended Finance Major			0.444***	0.429***		
			(18.50)	(17.48)		
Intended Marketing Major					0.526***	0.513***
					(21.83)	(19.91)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	No	Yes	No	Yes
N	1497	1497	1497	1497	1497	1497
R-squared	.073	.092	.16	.22	.21	.22

Panel B: Management, Operations, and Strategy Major

	Management		Operations		Strategy	
Management Team Member	-0.016	-0.018				
	(-0.78)	(-0.88)				
Operation Team Member			-0.001	-0.001		
			(-0.06)	(-0.08)		
Strategy Team Member					-0.103***	-0.100***
					(-3.04)	(-2.82)
Intended Management Major	0.049*	0.061**				
	(1.75)	(2.20)				
Intended Operation Major			0.304***	0.303***		
			(6.71)	(6.61)		
Intended Strategy Major					0.189***	0.194***
					(2.86)	(2.92)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Student Controls	No	Yes	No	Yes	No	Yes
N	1497	1497	1497	1497	1497	1497
R-squared	.026	.041	.099	.11	.042	.075

Figure 1: Profile Match Demographic by Citizenship and and Race

This figure provides a plot of the percent 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.

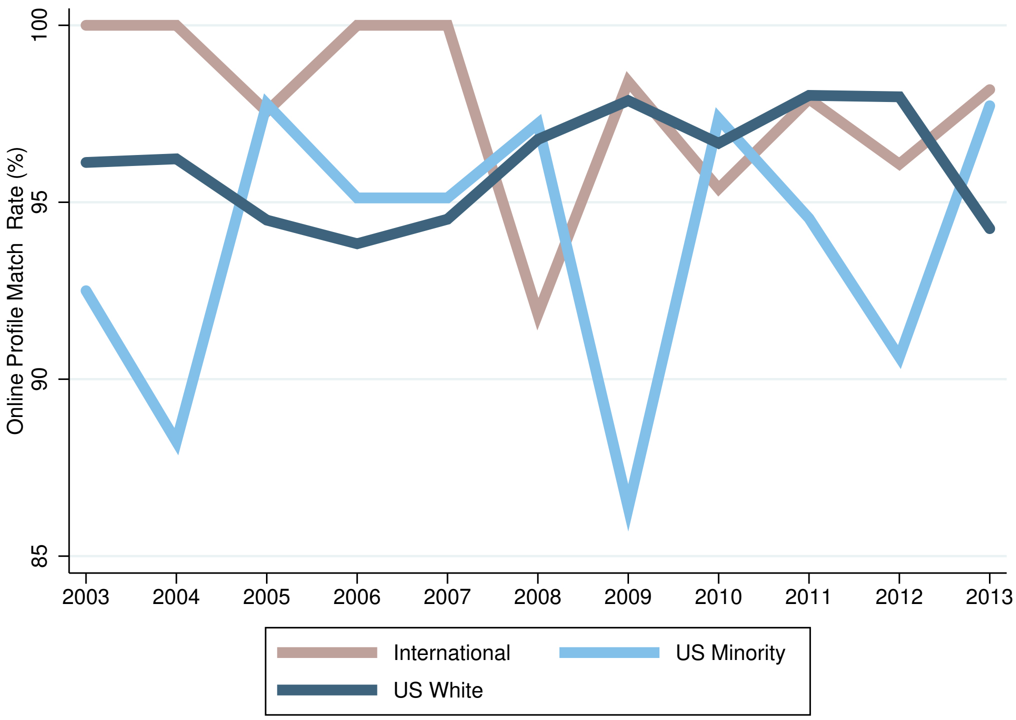

Figure 2: Composition of Managerial Job Titles Across MBA Careers.
This figure plots the breakdown of professional titles among Indiana University MBA students. We plot titles at the time of MBA graduation, as well as one, three, and five years following graduation. The plot on the left includes the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

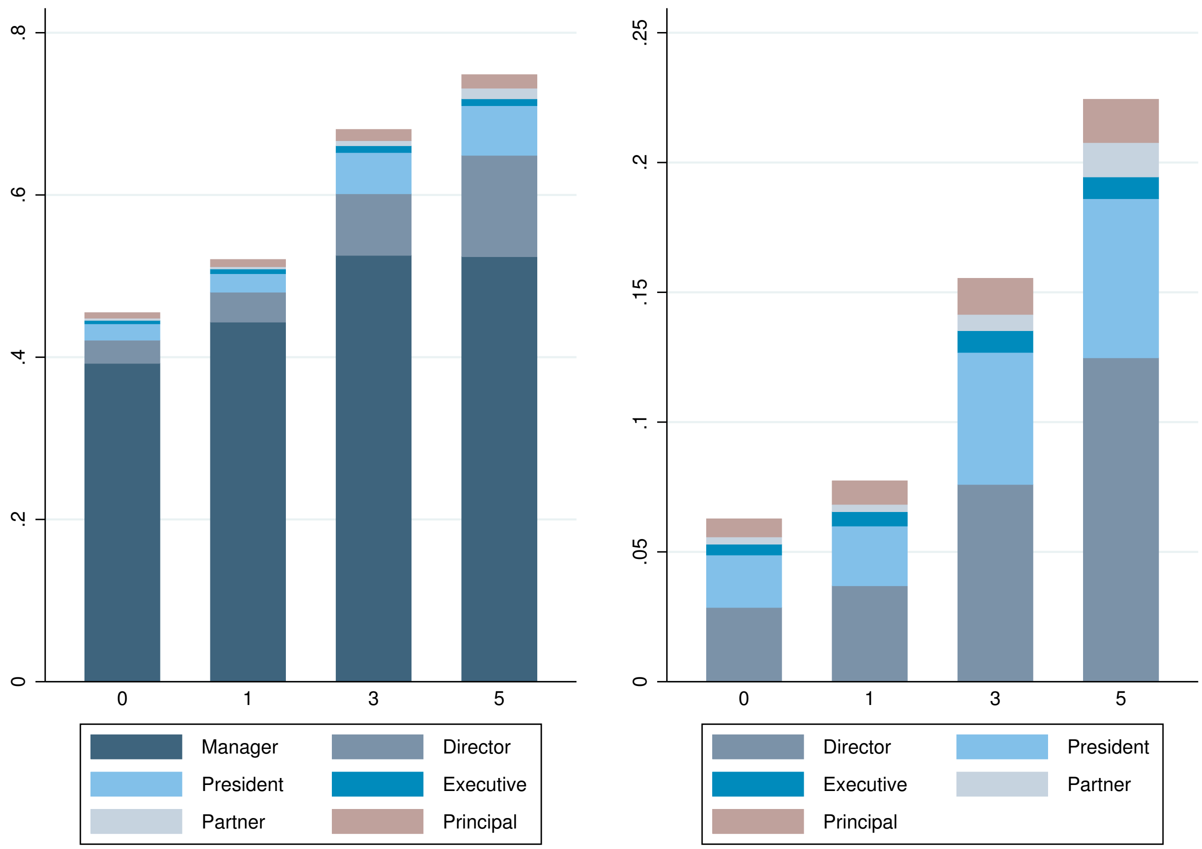

Figure 3: The Industry Composition of MBA Employers

This figure plots the industry classification for all firms in the sample. We split firms into prestigious firms and non-prestigious firms. Industry classification is based on two-digit NAICS codes.