Friends with (Wage) Benefits: Random Assignment of MBA Peers and Reallocation to the Financial Industry

Isaac Hacamo and Kristoph Kleiner*

Indiana University, Kelley School of Business

April 29th, 2016

Abstract

We study one channel that links peer effects to lifetime earnings: workers can more easily transfer industries with peer support, resulting in long-term wage benefits even after the interaction declines. By incorporating a random assignment of MBA students into small-sized teams matched with employee-employer linked data, we first document that individuals in the same team are more likely to work in the same industry after graduation; yet the results are exclusively driven by the financial sector. We estimate that having a peer in the financial industry increases the chance a low-wage-industry worker can transfer to the financial industry by 5%. The results are strongest when (i) a worker intends to enter the industry after MBA graduation and (ii) during high industry growth. Interestingly, peer effects are inexistent during recession times. At a lower-bound, having a peer in the financial industry increases five-year compensation by \$8,192 for all students and \$40,964 for intended finance majors. Overall, professional networking plays a valuable role in the allocation of MBA graduates to the financial sector, and more broadly explains how past peer networks affect lifetime earnings.

*Department of Finance, Indiana University, 1309 East 10th Street, Bloomington, IN 47405. Email: KleinerK@Indiana.edu.
We thank Nandini Gupta for helpful comments.

1 Introduction

Economists have long been interested the determinants of life time earnings, especially in the characteristics of high-wage workers [Abowd et al., 1999]. Because of the abnormal wage growth in the financial industry in the last decades [Philippon and Reshef, 2012], recent research has starting to document the characteristics of workers in finance [Célérier and Vallée, 2015, Bohm et al., 2015]. Yet, little is known on how workers move into high-wage industries, particularly how peers might affect this transition. In this paper, we document that peer effects are an important determinant to help workers transition to high-wage industries, particularly the financial industry. Recent research has underlined the importance of peers on life time earnings, by showing that childhood peers impact lifetime earnings Chetty et al. [2011a,b], this paper extends this literature by documenting the compensation value of networking during adulthood. Identifying both the extent and method that peer effects matter is, however, not a simple task. First, unobservable differences across individuals are likely correlated with sorting into a network [Manski, 1993, Hellerstein et al., 2015]. Second, our peers may influence our career paths through several channels: by expanding our interests, serving as a reference/guide to alternative sectors, or advancing our progression within our current line of work. Distinguishing between these theories requires detailed information on both past peer relationships and future employment. Overcoming both obstacles simultaneously—identification concerns and data limitation—has remained a challenge in the literature.

By incorporating a random assignment of MBA students into classrooms and small-sized teams matched with employee-employer linked data, this paper attempts to determine how peer networks affect reallocation of workers into high-wage industries, which might affect worker's lifetime earnings. Our results suggest that peers might impact industry choice early in the career perhaps helping overcome barriers to entry in high-wage industries, where competition for jobs is likely to be large. With the help of their peers, low-wage-industries workers might get a wedge into a high-wage industries, possibly by getting a reference, private industry-specific knowledge, or simply tips on how to perform better in the interview process. In our sample period, we show that both finance and consulting industries exhibit (i) higher initial compensation, (ii) persistent employment, and (iii) swift wage growth. These characteristics make jobs in these industries desirable and competitive. Peers who already work in these industries can then facilitate the entry of outside workers. Even though we bundle consulting and finance as high-wage industries, employment in the financial industry dominates employment in the consulting industry—among Kelley MBAs students who go to high-wage industries upon graduation, 80% go to the financial industry.

At Indiana University Kelley School of Business, MBA graduates are assigned to a particular cohort and a specific team of 4 or 5 students within a cohort. The assignment rule is orthogonal to students' preferences since it is intended to maximize team diversity, especially across demographic dimensions.[1] The cohort takes all first semester coursework together, while teams work together in all group assignments and in a case study competition at the end of the semester. We assume that this close experience during the first semester of graduate school creates on average a stronger bond between two members of the same team, relative to two members of different teams. We first merge this data with admissions data that was collected during the application process (e.g., GMAT scores, GPA from undergraduate studies, intended major, gender, nationality). We then merge this data with detailed employment records from a large online business networking service, including information on both employer (e.g., headquarter location, industry, size, year founded) and employee characteristics (e.g., undergraduate school, current geographic location). This unique assignment mechanism offers the opportunity to causally identify peer networks, while the employee-employer linked data offers a setting to to study long-term employment outcomes.

We first document that peers in the same team are one percent more likely to work in the same industry after graduation. Yet, this result masks a substantial amount of heterogeneity. The break-down by industry shows that the results are driven exclusively by the finance and consulting sectors, with no evidence of peer effects in other industries. Being on the same team increases the relative likelihood two students are employed in these high-wage industries by twenty percent. This heterogeneity suggests that outsiders might need help to transition to a high-wage industry.

To better understand the relationship between peers and industry reallocation, we introduce our baseline regression. We determine that having a team member with past finance or consulting experience increases the probability a graduating student transfers from an outside industry to consulting/finance industry by 5%. Relative to the unconditional probability (13.52%), this is an 40% increase of entering the high-wage industry. Peer effects best predict industry placement in the first two years

[1]Generally, the MBA assignment rule tried to maximize diversity across five characteristics: gender, race (for domestic students), citizenship (classified as US or International), and undergraduate major. Section 3.1 provides a detailed explanation of the two assignment rules that the MBA office at Kelley had during our sample period.

of graduation before decreasing slightly in year three, and disappear in year five. The results cannot be explained by differences across graduating years or among cohorts within the same graduation year. We also find the results hold after controlling for admissions characteristics of the student and demographics of their team. Our results show that peers play a fundamental role helping low-wage worker transitioning to high-wage industries.

To reinforce that we identify network effects, we argue that not all connections are equal. First, peers in high-wage industries are most valuable for students inclined to pursue careers in those areas. Second, graduates are more likely to use a connection when their contact is in good standing with the industry and plans to return after graduation. One advantage of our data is that we observe the intended major of each student prior to entering the MBA and therefore before peers can any influence each other on career plans. First, we find that students intending to major in finance at the time of application are more likely to enter the a high-wage industry if at least one member of their team has prior finance or consulting experience. The results are strongest when both sides intend to major in finance and hold even five years after graduation.

Additionally, the value of peer effects are likely impacted by the business cycle. One theory is that social connections are most useful during periods of heightened unemployment risk. Alternatively, industry distress may also weaken the strength of the network if students formerly working in the industry lose their position and/or their contacts. Furthermore, since our results suggests that peers help the transition to high-wage industries in the years immediately after graduation, it may be that both peers compete for the same jobs. Therefore, we study the value of social networks across graduation years with the underlying assumption that students graduating in 2005-2007 face different finance/consulting prospects unique from the classes of 2008-2010. We find evidence that networks effects are cyclical, with the greatest value during periods of high industry growth.

We next test two alternative explanations of our results. First, we have assumed that transferring to finance/consulting is less of an obstacle when peers already have prior experience; however, this assumes that a student is already planning to join the industry and therefore peers are not altering the area of focus. Yet, using information on intended major (prior to peer interaction) and actual major at the time of graduation, we find little evidence that team members switch majors due to peer effects. While students are likely to switch away from entrepreneurship and towards finance, marketing, and strategy, team members have little impact on this decision. Secondly, we are interested in how former peers impact lifetime earnings, yet it is possible that teams continue to support their members long after graduation. Again, we find no evidence of later referrals, partially due to the observed persistence of workers to stay in the industry chosen upon graduation.

Incorporating the result that participating in a high-wage team increases entry to these industries by five percent, we estimate the value of placing into these teams at $14,373. Additionally, for students planning to major in finance (using an estimate of 25%), this value increases to $71,866. Even after allowing for entrances and exits in/out of these industries, we estimate an additional benefit of $8,192 for all students and $40,964 for students intending to major in finance.

2 Literature Review

This paper builds on two related literatures: (i) identification of peer effects through random assignments and (ii) documenting networks impacts on labor outcomes using employee-employer linked data. By bringing these two areas together we are the first to isolate the long-term effect of peers on career paths and employment.

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, Hellerstein and Neumark, 2008, Dustmann et al., 2011], previous employment [Cingano and Rosolia, 2012, Glitz, 2013, 2014, Saygin et al., 2014], or minority communities [Giuliano et al., 2009, Dustmann et al., 2011][2]. To our knowledge, only Oyer and Schaefer [2007] uses past education, illustrating that law partners hire graduates from their own alma mater. However, due to the use of broadly-defined groups (by neighborhood, past employer, race), this literature is generally unable to distinguish peer effects from informational advantages that arise through networks. We note that [Kramarz and Skans, 2007] overcomes these obstacles using a tightly-defined definition of network (parent-child relations). We view our paper as complementary given survey data finds both family and friends are important in job search (10% of respondents found their last job from immediate family, while 13% report close friends) and their results are driven by low educated youths (as opposed to our focus on highly-educated adults) [Kramarz and Skans, 2007] .

[2]In comparison, other papers include explicit information about whether a new hire was referred by a current employee, including Dustmann et al. [2015], Burks et al. [2015], Brown et al. [2016] and then test the impact of referrals on wages. However, because referrals are not exogenous, these papers cannot causally estimate the impact of social connections on job search.

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]. 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 [Imberman et al., 2012, Billings and Deming, 2014], (ii) random variation across cohorts due to gender or race [Hoxby, 2000], and (iii) discontinuities due to test score cut-offs [Jackson, 2013, Abdulkadiroğlu et al., 2014]. Although these studies can offer large datasets, they cannot easily identify peers that interact closely with each other.

Instead we build on a second literature that estimates peer effects through random assignment, and our identification most closely follows Lerner and Malmendier [2013], Ahern et al. [2014], 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 beginning with Sacerdote [2001], Zimmerman [2003] and more recently Lyle [2009], Carrell et al. [2009]. 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. 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 student.

Finally, a small literature has documented the career drivers of recent MBA graduates, including stock market conditions Oyer [2008] or individual firm stock returns Bhole and Oyer [2014], gender Bertrand et al. [2010], risk aversion and optimism Sapienza et al. [2009], Kaniel et al. [2010], and previous industry experience Kuhnen and Oyer [2015]. Closest to our research, Kuhnen [2011] 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 have vacancies. We distinguish ourselves from this literature in two ways: first, we focus on a separate mechanism, the peer network of recent MBA graduates. Secondly, by relying on a unique dataset, we are able to focus not only on immediate employment outcomes, but also long-term career paths.

3 Empirical Methodology and Data Sources

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. Therefore, we first discuss and summarize our unique data sources from the Indiana University Kelley School of Business MBA Program and a large online business networking service. Secondly, we develop the empirical framework that allows us to isolate peer effects between MBA graduates. Third, we offer preliminary evidence of peer effects using a pairwise comparison among all students within a graduating class.

3.1 Data Sources

Kelley School of Business MBA Program Our measure of proximity is two-fold. First, all entering Full-Time MBA students are assigned to one of three cohorts. Member(s) 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 all group homework assignments. The assignment process at Kelley 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]).[3]

Even though maximizing diversity in teams and cohorts was always the primary goal of the MBA office, they had two assignment systems throughout our sample period. Students entering prior to 2009 were assigned to their cohort/team by maximizing diversity across five characteristics: gender, race (for domestic students), citizenship (classified as US or International), and undergraduate major. In addition, students could explicitly ask to be placed in the afternoon cohort if they had a schedule

[3]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.

conflict being in the morning schedule. The system was electronic, however, staff also made manual assignments 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.

We next match the cohort/team information with data on the student at the time of application. The admissions data includes personal characteristics (citizenship, gender, ethnicity, etc), grades and test information (undergrad GPA and GMAT broken down by section), and intended MBA major and academy. One unique facet of the Kelley MBA Program is an Academy: in addition to a major, students specialize in an Academy, which helps develop professional skills through a combination of activities (consulting projects, corporate visits, industry networking), and meetings with the Academy Director, Career Coach (industry expert and/or recruiter), and Peer Coach (second year MBA student). Students are asked their preferred academy at the time of application; however, they can switch academies into the fall semester.

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. Secondly, 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. [2011a], randomizing based on student characteristics 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 short-term peer effects.

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 website, which includes self-reported employment and education data. We then collect additional information about each employer, including the location and industry of the firm. All data is publicly-available and is obtained and then parsed into a panel dataset.[4]

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 [Jacobson et al., 1993, Graham et al., 2013]; 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 [Weisbach, 1988, Jensen and Murphy, 1990, Gompers et al., 2003]; however, the data focuses only on top executives and excludes all information for employees at private firms. Third, a recent literature that merges educational data with administrative records Chetty et al. [2011a]. However, the administrative records do not include the industry and occupation information necessary for our analysis.

Data Cleaning We drop any students without an online profile with employment history. 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 students use a nickname (this is especially true of International students); similarly, we do not necessarily require a strict last name match since a fraction of students (especially female students) 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 entering/graduating dates and the dates are incorrect [5]. Finally, 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 undergraduate school from the online profile.

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

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

3.2 Identification

We first develop a simple methodology to determine if graduates previously employed in low-wage industries are more likely to enter high wage industries upon graduation due to characteristics of their assigned cohort/team. Following the traditional approach in the literature we estimate these peer effects using a linear-in-means model Manski [1993], Graham [2008].

$$
\begin{aligned}
\text{High-Wage Industry}_i^{t+s} = \alpha + \beta_T \times \text{High-Wage Team}_{-i}^t \\
+ \delta^t + \text{Controls}_i^t + \text{Controls}_{-i}^t + \varepsilon_i^{t+s}
\end{aligned}
$$

We estimate this model on the sample of individuals who had no working experience in high-wage industries prior to the MBA. Our key dependent variable, $High\text{-}Wage\ Industry_i^t$, is a binary variable that takes a positive value when the worker i is employed in a high-wage industry s years after MBA graduation at time t. The key independent variable is $High\text{-}Wage\ Team_{-i}^t$, defined as the number of graduates in team of individual i who were employed in high-wage industries prior to entering the MBA. Therefore, this variable is static for each individual i as we are only interested in experience prior to starting the MBA program.

In addition, we control for individual characteristics and for characteristics of worker i's team members. We are required to control for individual characteristics since many factors will likely impact career outcomes. For our study, individual characteristics include gender, citizenship, race, work experience, gmat (both total score and quant score). For the purposes of the regression, citizenship 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 student sample. Race is included only for domestic students and is defined as: Asian, Black, Hispanic, White, Other, and No Response. Other includes multiracial, Native American, and Pacific Islander, which all compose under one percent of the sample. GMAT Total Score is split into one of four bins: Under 600, 600-649, 650-699, and 700+. These bins are roughly in line with quartiles. Finally, work experience and GMAT Quant Score is broken into quartiles.

In addition, career outcomes might be affected by characteristics of their assigned peers. While we are interested in past work experience in high wage industries, other characteristics might have alternative effects. Therefore, for each individual i we summarize the characteristics of his/her team excluding i. Specifically, for each control variable (gender, citizenship, race, work experience, gmat) we aggregate the number of incidences at the team level (minus i). We also control for the number of team members matched to our online networking service. Finally, we control for the year of entering the MBA program,δ^t, in case of differences if the student population and the job market differ over time. In later regressions, we create a fixed effect for each entering year and cohort ruling out differences among teachers inside the classroom.

3.3 Data Summary

Three Employment Statistics In order for peers to significantly impact lifetime earnings, we need to document three facts: (i) consulting and investment banking offer higher initial compensation than other industries for the Kelley MBA graduates, (ii) entering/exiting these industries is unlikely upon graduation, and (iii) the earnings differential holds throughout the career.

Consulting and Investment Banking offer Higher Initial Salaries than the Alternatives We define a high-wage industry as all firms in financial services and consulting. In Table 1 we present the initial employment statistics for the Kelley MBA class of 2000 (though our data sample technically starts with the class of 1999, we were unable to find full employment records for that year). We find that Consulting has 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, then outside options for MBA graduates[6].

Industry Employment is Persistant Secondly, conditional on entering finance/consulting directly after the MBA, graduates are have a 98.5% probability of remaining in these industries one

[6]While it is possible that other industries have caught up with this income discrepancy, it appears unlikely. According to data from the Bureau of Labor Statistics, national salaries across all industries have grown an average of 2.74%; in comparison, investment banking salaries have grown at the higher rate of 3.95%, while consulting has grown a slightly lower 2.56%.

year later. Yet, only two percent of graduates not entering these industries make the transition within one year.These results continue to hold over the long term; students initially entering these industries have a 76% of remaining three years later and sixty percent after five years. However, a few outside do students begin to bridge the gap as six percent of the rest of the population enter these same industries.

A High Level of Promotion Third, we require that the higher compensation continues to hold past the first year. Due to a lack of data on later compensation, this is difficult to document directly for our MBA graduates population. However, an advantage to focusing on the consulting and banking sectors is the use of universal job titles; we use these titles to illustrate a high degree of promotion within these industries, at least implying high wage growth throughout the career.

In both consulting and investment banking, the majority of newly minted MBA graduates start at the Associate level. In consulting, Associates are promoted to Manager/Officer, while students in finance are promoted to Vice-President. The next promotion is Principal (in consulting) and Senior Vice-President/Director/Principal (in finance). Using these definitions, we document the likelihood of promotion in these industries compared with other potential careers. While the rate of promotion increases over time in all industries, it is especially high in finance/consulting.

Industry Employment Statistics Our sample includes a total of 1,379 students as presented in Table 3; eighty percent have no finance/consulting experience, while 17% are from the finance industry and four percent from consulting. After the MBA we see a slight decline in the number in finance (thirteen percent) and a slight increase in consultants (six percent). These employment statistics are relatively constant even five years after the MBA.

Not surprisingly, employment following the MBA is highly correlated with prior employment. In particular, 29% of the students previously employed in finance return upon graduation and 33% after five years. Similarly, students coming from consulting return 7-8% of the time. Our baseline estimation does not focus on these students as it is clear they can (and have) enter finance/consulting without their team members. Instead, of the remaining students, 9% enter finance and six percent enter consulting; we focus on the factors that allocate these 1,096 students to high-wage industries.

Individual Demographics According to the summary statistics presented in Table 3 we include MBA graduating between 1999 and 2013. We first split the sample based on prior experience with finance and consulting. Focusing on students outside these industries, we estimate 73% are male, 29% are international, and 10% are U.S. minorities. The average GMAT is 652 and students apply with about five years of worker experience. Additionally, 29% of the student intend to major in finance. In comparison, students coming from finance and consulting are more likely to be male (81%), less likely to be international (19%), and more likely to major in finance (63%). These students have similar GMAT scores and have worked for a similar time period.

Finally, we summarize the characteristics of each team 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, the mean team has a total of 2.5 students with a minimum of one student and a max of five students.

Missing Graduates According to Table 3 we are able to match 84% of MBA graduates to their online profile. We highlight the match details in Figure 1. For each MBA graduation year, we split students into three categories (Domestic White, Domestic Minority, and International) and plot the match percent by male/female for each category. There are three primary takeaways from the results. First, we have a similar match rate for white and minority students, 91% and 88%, respectively. However, the match rate for internationals is lower at 70% on average. Secondly, we find little difference between male and females of the same group; for instance domestic white males have a match rate of 91.3% compared to 91.5% for females. Third, match rates are higher for more recent cohorts, particularly for international students. In the lowest graduation year (2004) we have a 51.4% match rate, but this generally increases over time, achieving a maximum of 83% in 2011.

Given we are missing 16% of graduating students, one potential concern is that results might be biased if students with profiles have different skills/interest compared to students without profiles. We investigate this concern in Table 4 by if student skill or student interests predict matching. Given the results in Figure 1 we control for the year of graduation, citizenship, gender, and race. We find no evidence that student (defined as GMAT score, GMAT Quant score, or Undergrad GPA) predict matching ability. Similarly, student interests (determined by intended major upon admission) are generally insignificant. The only variable significant at the 10% level is the entrepreneurial major, suggesting the sample might be slightly biased towards entrepreneurs.

3.4 Preliminary Evidence

Methodology Before the primary results, we develop a simple methodology to determine if graduates share career paths more similar to their peers (defined as graduates in the same graduating class, section, or team) than non-peers. Our method differs from the traditional linear-in-means model as the primary variables of interest are not continuous, rather categorical (such as the particular firm, industry, or location). We follow empirical setup similar to Fracassi [2014], Shue [2013]. Specifically, we incorporate a pairs distance metric to measure whether the distance in outcomes between two peers is less than the distance of non-peers.

$$\begin{aligned}\text{Same Industry}^t_{i,j} = \alpha + \beta_T \times \text{Same Team}^t_{i,j} \\ + \beta_C \times \text{Same Cohort}^t_{i,j} + \delta^t + \varepsilon^t_{ij}\end{aligned}$$

The pairs distance metric considers all possible pairwise comparison between two MBA graduates, designated a i and j who both graduated from the MBA Program in year t. We define $Same\ Industry^t_{i,j}$ as the dependent variable of interest, generally a binary variable that takes a value of one when both graduates work within the same industry (alternatively firm or location) starting in graduation year t. Specifically, we require that at most one individual was employed by the industry prior to the MBA and that the two individuals worked in that industry within ten years of each other. The key independent variable are $Same\ Cohort^t_{i,j}$ and $Same\ Team^t_{i.j}$, also binary variable denoting when two graduates are randomly assigned to the same cohort or team, respectively.

Pairwise Regression We begin with our baseline regressions in Table 5. Controlling only for the year of graduation, we find there is a 19% probability of being in the same industry as another student and that peers in the same cohort have no significant effect on industry choice. However, the probability of being in the same industry as someone from your graduating class increases 1% if you are both in the same team.

We next split the sample into high and low-wage industries. Therefore, the new dependent variable is a binary variable with a value of one when both individuals are employed in the same high wage industry (or same low wage industry). Controlling for the graduation year, we estimate there is a 4% chance that two students enter in the same high-wage industry and a 14% chance they both enter into the same low-wage industry. However, we find no evidence that two students from the same team are more likely to enter into the same low-wage industry. In comparison, two students are 0.8% more likely to enter into the same high-wage industry. Though this may appear small, it implies a relative increase of nearly 20%. The evidence above suggests that peer effects impact career outcomes, and are especially prevalent in high-wage industries. However, the results offer little guidance on how peer effects impact job placements; this is the purpose of the next section.

4 Results

We are now ready to introduce and discuss the results of the paper. We start with our baseline case-determining the role of peers in affecting our industry employment. We next consider how individual/team demographics and the business cycle impact the estimation. Third, we determine that the results are not driven by learning from peers during the MBA program or from referrals later in the career. We conclude by estimating the total impact of peer effects on lifetime earning using a back-of-the-envelope calculation.

4.1 Primary Results

Baseline We present the baseline results in Table 6; without any controls we estimate fourteen percent of students from low-wage industries (outside financial services and consulting) enter these industries directly after graduation; by year five these numbers are only slightly higher at fifteen percent. However, they are over five percent more likely to enter a high-wage industry at graduation when one member of the team has prior experience. The results remain nearly identical and statistically significant at the five percent level even three years later. By year five, we find no evidence that peer effects has an impact on your industry.

We next consider two alternative specifications. First, we note that the results may depend on differences in (i) team size or graduation year. Secondly, even within a graduation year, students may differ by cohort if teachers differ. However, controls for team size, year, and cohort has little effect on the estimate.

We also consider how individual and team demographics affect the value of professional networks. One primary objection to Table 6 is that we do not control for either individual differences or team differences. Therefore, in Table 7 we first include individual controls (columns 1 and 4) as well as both individual and team controls (columns 2 and 5). Note, that since we only have admissions data starting with the class of 2003, we have a significantly smaller sample. Yet, similar to earlier, we estimate that directly after graduation, students previously from low-wage industries are 5-6% more likely to enter a high-wage industry when another team member has that experience.

To put our estimates into perspective, we evaluate the correlation between alternative individual/team characteristics on entering high-wage industries. Starting with individual differences, we see that gender is a primary predictor of moving to high-wage industries; males are six percent more likely to move into consulting/financial services. Next, considering citizenship, we find that Indian students are 22% more likely to enter these industries, while the results are similar for other nationalities. In addition, there are not significant differences across race among U.S. citizens. A unique advantage of the admissions data is information on GMAT and undergraduate GPA. Yet, we find not strong evidence that GMAT (total or just quantitative) predict entry to these industries.

Across Student Population Given the robustness of the results above, it is clear that peer networks impact entry to finance/consulting. However, the effect of these networks likely depends on characteristics of both parties. In particular, we argue that peer effects will differ when one (or both) graduates already plans to enter finance/consulting prior to starting the MBA (and therefore prior to having a team). In general, it is not possible to distinguish the prior intentions of a student. However, one advantage of our data is that we are able to identify not only majors at graduation, but also intended major at the time of application.

Using this distinction in Table 7 we estimate that intending to be a finance major increases the probability of entering a high-wage industry by 7-8%. Given that high-wage careers are defined as financial and consulting industries, the result is unsurprising. More significantly, the results depends on whether the student was a member of a high-wage team. Intended finance majors outside these teams are roughly 4% more likely to enter a high-wage industry; for intended finance majors in high-wage teams, the coefficient increases to 18%. In addition, these same individuals are 13% more likely to be in a high-wage industry even five years after graduation. For comparison, we see no evidence of peer effects for students not planning on a career in finance. Overall, the results suggest that intended finance majors are especially impacted by participating in a high-wage team, with minimal effects on the rest of the graduating class.

Next, we determine if the results differ when the connection also plans to return to finance/consulting. Therefore, we now create a new binary variable that takes a value of one when at least one team member both has prior experience in a high-wage industry and intend to major in finance; again the estimates are larger in this case, though we lose statistical significance. Finally, we illustrate that peer effects are strongest when the students share the intention to major in finance. The estimates suggest that students coming from consulting/finance- and plan to return- are more likely to have stronger professional ties and a positive view of the industry.

Across Time We next evaluate how the networks depend on the economic conditions. Ideally, we can observe these conditions directly at the worker level. However, forced unemployment is often difficult to directly observe in the data for two reasons. First, individuals may attempt to hid unemployment spells by extending dates, self-employment, or including non-work activities including training programs or volunteering. In addition, losing a job from a firing will likely signal poor ability and affect any chance of positive referrals from peers. Therefore we instead focus on differences at the aggregate level over the business cycle. We argue that economic conditions can impact both the quality and the value of peer connections.

First, MBA graduates without experience in finance/consulting may be particularly likely to lean on peer networks during periods of poor job opportunities; in other words, peers with prior experience in high-wage industries may only be necessary when there is a low number of available positions. [7]

Yet, complicating matters is that students with prior experience in finance/consulting are not a homogenous set; they likely differ depending on the business cycle. In particular, students coming from consulting/finance during a recession are more likely to have lost their position, potentially also

[7]Of course this argument rests on the assumption that graduates can easily find employment in these sectors during non-recessionary periods. Yet, due to the competition for these sectors, Kelley MBA graduates might find it difficult to place into finance and consulting in any year. However, we determine that even in the graduating classes of 2008-2010, fifteen percent of students previously from other industries enter finance/consulting.

losing professional ties and a positive view of the industry. Therefore, even if there is an increase in the number of students with prior experience in a class during a recession, the value of each connection is actually lower.

We first test the relative value of peers during economic growth (graduating class of 2005-2007) and economic decline (2008-2010). We estimate only peer effects during the high-growth years with no impact during the later period. In addition, the results are stronger when the team member/individual also intends to major in finance. This is significant since we should expect that low growth in finance/consulting should decrease initial interest in these industries; however, even among workers that intend to major in finance, there is no major peer effect during the recessions years.The results support our argument that ties to the finance/consulting industry are strongest when growth is high. The evidence can be used as evidence that matching efficiency is pro-cyclical [Cheremukhin and Restrepo-Echavarria, 2014, Barnichon and Figura, 2015], potentially due to the value of referrals [Galenianos, 2014].

4.2 Alternative Explanations

Switching Career Plans One potential concern with our analysis is that it is difficult to fully distinguish two explanations. The first possibility is that MBA students switch career plans due to the composition of their team; the second alternative is that graduates use one another for job referrals and information on job openings after obtaining the first job.

Before testing if peers impact career plans, we first document significant differences between intended and major at graduation in Figure 2, highlighting that students do change their focus. We identify six primary majors: 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". First, a large fraction of students intend to major in entrepreneurship and this fraction has generally increased over time (from about 20% to over fifty percent in more recent classes); however, 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 fraction of actual majors. One possible explanation of these results is that peers influence major choices after entering the MBA program.

Next, in Table 10 we determine if low-wage students change majors after exposure to a (i) high-wage team or (ii) finance major team. A student has a finance major team if any other member majors in finance. First, we find no evidence that students decide their major based on their team members. This is true regardless of whether the student intended to major in finance. Next, students in a high wage team are slightly more likely to major in finance; however, the result disappears once controlling for initial major. The result seems driven by students transferring into finance rather than remaining finance majors from the outset. Taken together, we do not find much evidence that team members impact initial career plans.

Late Career Referrals A second explanation of the results is that workers use their peer network to transfer industries years after graduating from the MBA. This appears possible given team members do have an effect on industry even five years after graduation.

However, according to Table 9 we find no evidence that students use their team members as a professional network after their job placement. However, this is not conclusive since team members with experience prior to the MBA are likely less valuable than team members with experience since the MBA. Therefore, we conduct a separate estimation identifying teams where one member is in finance/consulting directly after the MBA. Again, we find not significant effect.The results are not surprising given the persistence of staying in the high-wage industries; 76% (60%) of students entering these sectors remain after three years (five years).

4.3 Economic Impact

The results clearly illustrate that peer networks impact entering finance/consulting industries, yet estimating the full economic impact is made difficult without directly measuring compensation over the career. However, using the Table 1 we estimate a 19% salary increase for consulting and a 27% increase for investment banking above other industries. Using average compensation growth for these industries from 2001-2014, we estimate that investment banking compensation has grown roughly 3.95% a year, consulting at 2.56% a year, and all other industries at 2.74% a year. Taken together, this implies that MBA graduates entering the workforce in 2016 will make \$221,784 in investment banking, \$167,165 in consulting, and \$144,397 in other industries. Assuming graduates stay in these industries, we estimate total 5-years compensation to be $1,200,055, $878,728, and $762,649 for banking, consulting, and other industries respectively. In other words from our back of the envelope calculation, we estimate that entering the banking industry results in $437,405 additional compensation; entering consulting includes an additional $117,078. Finally, under the most recent graduate class we estimate that 22% entered consulting while 25.1% entered finance; using these averages we estimate a mean additional compensation at $287,465 for these students.

Incorporating the result that participating in a high-wage team increases entry to these industries by five percent, we estimate the value of placing into these teams at $14,373. Additionally, for students planning to major in finance (using an estimate of 25%), this value increases to $71,866. Of course, we are making the assumption that graduates entering finance/consulting are never required to exit; similarly, graduates in other fields can never enter these sectors. However, after five years, we estimate that only eight percent of graduates have entered these industries after initially placing elsewhere. In comparison, there is a 65% chance of remaining in finance/consulting if you started there. Therefore, at the lowest bound, we estimate a differential of 57%, which still implies an additional benefit of $8,192 for all students and $40,964 for students intending to major in finance.

5 Conclusion

This paper tests if MBA peers can impact lifetime earnings through industry choice directly after graduation. Relying on the random assignment of MBA students into teams, we can precisely isolate peer effects, and by incorporating both MBA Admissions Data with online profiles on employment history, we are able to follow an individual student over their career. We find that having a team member with prior experience in finance/consulting increases the likelihood of entering these industries by five percent. The estimates are greatest when at least one party intends to major in finance, and during periods of high industry growth. We find little evidence that team members have any effect on major choice, and are unlikely to serve as referrals later in the career. The economic effect is large given the persistence of staying in the same firm/industry.

Despite the simplicity of our simple back-of-the-envelope calculation, there are clear financial incentives to having a a peer with experience in finance/consulting. From a narrow policy perspective, it appears that team formation should incorporate previous employment histories. However, more broadly, the results speak to the role of professional networks on explaining large earnings differentials through the lifetime. While these results are likely unique to a small sample of the population-MBA graduates with valuable employment opportunities— it is particularly valuable to understand the sources of allocation of highly skilled individuals. With the framework and especially data developed in this paper, we plan to continue this path of research to determine where workers decide to work and why.

References

Atila Abdulkadiroğlu, Joshua Angrist, and Parag Pathak. The elite illusion: Achievement effects at boston and new york exam schools. *Econometrica*, 82(1):137–196, 2014.

John M. Abowd, Francis Kramarz, and David N. Margolis. High wage workers and high wage firms. *Econometrica*, 67(2):251–333, 1999. ISSN 1468-0262. doi: 10.1111/1468-0262.00020. URL http://dx.doi.org/10.1111/1468-0262.00020.

Kenneth R Ahern, Ran Duchin, and Tyler Shumway. Peer effects in risk aversion and trust. *Review of Financial Studies*, page hhu042, 2014.

Regis Barnichon and Andrew Figura. Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics*, 7(4):222–249, 2015.

Patrick Bayer, Stephen L Ross, and Giorgio Topa. Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy*, 116(6):1150–1196, 2008.

Marianne Bertrand, Claudia Goldin, and Lawrence F Katz. Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, 2(3):228–255, 2010.

Monica Bhole and Paul Oyer. Do mbas pick winning stocks when choosing their first job? 2014.

Stephen B Billings and David Deming. J., & rockoff, jonah.(2014). school segregation, educational attainment, and crime: Evidence from the end of busing in charlotte-mecklenburg. *The Quarterly Journal of Economics*, 129(1):435–476, 2014.

Michael Bohm, Daniel Metzger, and Per Stromberg. Since you?re so rich, you must be really smart?: Talent and the Finance Wage Premium. (313), November 2015. URL https://ideas.repec.org/p/hhs/rbnkwp/0313.html.

Meta Brown, Elizabeth Setren, Giorgio Topa, et al. Do informal referrals lead to better matches? evidence from a firm's employee referral system. *Journal of Labor Economics*, 34(1):161–209, 2016.

Stephen V Burks, Bo Cowgill, Mitchell Hoffman, and Michael Housman. The value of hiring through employee referrals. *The Quarterly Journal of Economics*, page qjv010, 2015.

Scott E Carrell, Richard L Fullerton, and James E West. Does your cohort matter? measuring peer effects in college achievement. *Journal of Labor Economics*, 27(3), 2009.

Claire Célérier and Boris Vallée. Returns to talent and the finance wage premium. *Available at SSRN 2669468*, 2015.

Anton A Cheremukhin and Paulina Restrepo-Echavarria. The labor wedge as a matching friction. *European Economic Review*, 68:71–92, 2014.

Raj Chetty, John N Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan. How does your kindergarten classroom affect your earnings? evidence from project star*. *The Quarterly journal of economics*, 126(4):1593–1660, 2011a.

Raj Chetty, John N Friedman, and Jonah E Rockoff. The long-term impacts of teachers: Teacher value-added and student outcomes in adulthood. Technical report, National Bureau of Economic Research, 2011b.

Federico Cingano and Alfonso Rosolia. People i know: job search and social networks. *Journal of Labor Economics*, 30(2):291–332, 2012.

Christian Dustmann, Albrecht Glitz, and Uta Schönberg. Referral-based job search networks. 2011.

Christian Dustmann, Albrecht Glitz, Uta Schönberg, and Herbert Brücker. Referral-based job search networks. *The Review of Economic Studies*, page rdv045, 2015.

Cesare Fracassi. Corporate finance policies and social networks. In *AFA 2011 Denver Meetings Paper*, 2014.

Manolis Galenianos. Hiring through referrals. *Journal of Economic Theory*, 152:304–323, 2014.

Laura Giuliano, David I Levine, and Jonathan Leonard. Manager race and the race of new hires. *Journal of Labor Economics*, 27(4):589–631, 2009.

Albrecht Glitz. Coworker networks in the labour market. 2013.

Albrecht Glitz. Ethnic segregation in germany. *Labour Economics*, 29:28–40, 2014.

Paul Gompers, Joy Ishii, and Andrew Metrick. Corporate governance and equity prices. *Quarterly Journal of Economics*, 118(1), 2003.

Bryan S Graham. Identifying social interactions through conditional variance restrictions. *Econometrica*, 76(3):643–660, 2008.

John R Graham, Hyunseob Kim, Si Li, and Jiaping Qiu. Human capital loss in corporate bankruptcy. *Available at SSRN 2276753*, 2013.

Isaac Hacamo and Kristoph Kleiner. Productive labor reallocation through bankruptcy: Evidence from new firm creation. *Working Paper*, 2016.

Judith K Hellerstein and David Neumark. Workplace segregation in the united states: Race, ethnicity, and skill. *The Review of Economics and Statistics*, 90(3):459–477, 2008.

Judith K Hellerstein, Mark J Kutzbach, and David Neumark. Labor market networks and recovery from mass layoffs before, during, and after the great recession. Technical report, National Bureau of Economic Research, 2015.

Caroline Hoxby. Peer effects in the classroom: Learning from gender and race variation. Technical report, National Bureau of Economic Research, 2000.

Scott A Imberman, Adriana D Kugler, and Bruce I Sacerdote. Katrina's children: Evidence on the structure of peer effects from hurricane evacuees. *The American Economic Review*, pages 2048–2082, 2012.

C Kirabo Jackson. Can higher-achieving peers explain the benefits to attending selective schools? evidence from trinidad and tobago. *Journal of Public Economics*, 108:63–77, 2013.

Louis S Jacobson, Robert J LaLonde, and Daniel G Sullivan. Earnings losses of displaced workers. *The American Economic Review*, pages 685–709, 1993.

Michael C Jensen and Kevin J Murphy. Performance pay and top-management incentives. *Journal of political economy*, pages 225–264, 1990.

Ron Kaniel, Cade Massey, and David T Robinson. The importance of being an optimist: Evidence from labor markets. Technical report, National Bureau of Economic Research, 2010.

Francis Kramarz and Oskar Nordström Skans. With a little help from my... parents? family networks and youth labor market entry. Technical report, CREST, mimeo, 2007.

Camelia M Kuhnen. Searching for jobs: Evidence from mba graduates. *Available at SSRN 1563510*, 2011.

Camelia M Kuhnen and Paul Oyer. Exploration for human capital: evidence from the mba labor market. Technical report, National Bureau of Economic Research, 2015.

Ron Laschever. The doughboys network: Social interactions and the employment of world war i veterans. *Available at SSRN 1205543*, 2009.

Josh Lerner and Ulrike Malmendier. With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *Review of Financial Studies*, page hht024, 2013.

David S Lyle. The effects of peer group heterogeneity on the production of human capital at west point. *American Economic Journal: Applied Economics*, pages 69–84, 2009.

Charles F Manski. Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542, 1993.

Paul Oyer. The making of an investment banker: Stock market shocks, career choice, and lifetime income. *The Journal of Finance*, 63(6):2601–2628, 2008.

Paul Oyer and Scott Schaefer. Personnel-economic geography: Evidence from large us law firms. In *2nd Annual Conference on Empirical Legal Studies Paper*, 2007.

Thomas Philippon and Ariell Reshef. Wages and human capital in the u.s. finance industry: 1909?2006*. *The Quarterly Journal of Economics*, 2012. doi: 10.1093/qje/qjs030. URL `http://qje.oxfordjournals.org/content/early/2012/10/09/qje.qjs030.abstract`.

B Sacerdote. Peer effects with random assignment: Results for dartmouth roommates. *Quarterly Journal of Economics*, 116(2):681–704, 2001.

Bruce Sacerdote. Experimental and quasi-experimental analysis of peer effects: two steps forward? *Annu. Rev. Econ.*, 6(1):253–272, 2014.

Paola Sapienza, Luigi Zingales, and Dario Maestripieri. Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences*, 106 (36):15268–15273, 2009.

Perihan Saygin, Andrea Weber, and Michèle Weynandt. Coworkers, networks, and job search outcomes. 2014.

Kelly Shue. Executive networks and firm policies: Evidence from the random assignment of mba peers. *Review of Financial Studies*, 26(6):1401–1442, 2013.

Michael S Weisbach. Outside directors and ceo turnover. *Journal of financial Economics*, 20:431–460, 1988.

David J Zimmerman. Peer effects in academic outcomes: Evidence from a natural experiment. *Review of Economics and Statistics*, 85(1):9–23, 2003.

Table 1: Employment Statistics from the MBA Class of 2000 Immediately after Graduation. We split the sample by industry: Consulting, Investment Banking, and Other. Receive Bonuses is the percentage of students that recieved the signing/guaranteed bonus. The value of the bonus excludes students that did not recieve the bonus.

	Initial Employment Statistics from Class of 2000							
	All Employment		Consulting		Investment Banking		Non-Consulting/Inv Banking	
	Mean	Receive Bonuses	Mean	Receive Bonuses	Mean	Receive Bonuses	Mean	Receive Bonuses
Sample of Population	100%		15%		18%		67%	
Base Salary	$78,664		$91,356		$76,549		$76,391	
Signing Bonus	$15,910	93%	$17,847	91%	$20,306	88%	$14,295	95%
Guaranteed Bonus	$18,607	34%	$18,857	21%	$31,934	78%	$14,971	25%
Average Total Compensation	$113,181		$111,557		$119,327		$93,697	

Table 2: Employment Persistence and Promotion in Finance/Consulting for MBA Graduates. The top panel estimates the likelihood a graduate previously employed in a high-wage industry remains in that industry in the future. Each test is a linear probability regression where the dependent variable is a binary variable that designates whether the graduates are currently working in finance/consulting after graduation. The bottom panel estimates the likelihood a graduate currently employed in a high-wage industry has an executive title. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	Employment in Consulting and Finance Industries							
	Year 0	Year 1	Year 3	Year 5	Year 0	Year 1	Year 3	Year 5
High Wage At MBA Graduation						0.9589***	0.7399***	0.5696***
						(86.5802)	(37.1414)	(25.6588)
High Wage Prior to MBA	0.1684***	0.1899***	0.1970***	0.1808***				
	(6.6125)	(7.1684)	(7.4257)	(7.1066)				
Cons	0.1496***	0.1670***	0.1670***	0.1478***		0.0293***	0.0711***	0.0800***
	(12.9713)	(13.9118)	(13.8940)	(12.8241)		(6.1715)	(8.3173)	(8.3969)
R-squared	0.03	0.04	0.04	0.04		0.84	0.50	0.32
N	1379	1379	1379	1379		1379	1379	1379

	Promotions in the Consulting and Finance Industries							
	Vice-President and Officer				Senior Vice President, Principal, and Director			
	Year 0	Year 1	Year 3	Year 5	Year 0	Year 1	Year 3	Year 5
High Wage Industry	0.0564***	0.0510***	0.0894***	0.1171***	0.0478***	0.0536***	0.0752***	0.0951***
	(4.5113)	(4.0470)	(5.6012)	(6.5301)	(3.3231)	(3.3022)	(3.6415)	(3.6544)
Cons	0.0223***	0.0265***	0.0435***	0.0516***	0.0349***	0.0520***	0.0926***	0.1519***
	(4.0113)	(4.5700)	(5.9059)	(6.5964)	(5.4647)	(6.9661)	(9.7228)	(13.3849)
R-squared	0.02	0.01	0.02	0.03	0.01	0.01	0.01	0.01
N	1285	1341	1344	1341	1285	1341	1344	1341

Table 3: Summary Statistics for the Cleaned Sample. The top panel summarizes employment in the finance/consulting/other industries prior to the MBA, directly at graduation, and five years after graduation. The bottom panel summarizes the admissions data on all students in our sample.

MBA Employment Statistics									
Upon Entering MBA				After Intially Graduating from MBA			Five Years After Graduating from MBA		
Variable	Obs	Mean		Variable	Obs	Mean	Variable	Obs	Mean
Finance	1379	0.168		Finance	1379	0.128	Finance	1379	0.130
Consulting	1379	0.038		Consulting	1379	0.057	Consulting	1379	0.055
Low Wage	1379	0.795		Low Wage	1379	0.815	Low Wage	1379	0.839
			Finance Prior						
				Finance	231	0.294	Finance	231	0.325
				Consulting	231	0.030	Consulting	231	0.034
				Low Wage	231	0.710	Low Wage	231	0.710
			Consult Prior						
				Finance	52	0.115	Finance	52	0.096
				Consulting	52	0.173	Consulting	52	0.096
				Low Wage	52	0.731	Low Wage	52	0.827
			Low Wage Prior						
				Finance	1096	0.093	Finance	1096	0.090
				Consulting	1096	0.057	Consulting	1096	0.057
				Low Wage	1096	0.876	Low Wage	1096	0.867

MBA Demographic Statistics										
	MBA Students with No Finance/Consulting Exp					MBA Students with No Finance/Consulting Exp				
Variable	Obs	Mean	St Dev	Min	Max	Obs	Mean	St Dev	Min	Max
MBA Graduation Year	1094	2007.02	4.15	1999	2013	283	2007.02	3.98	1999	2013
Male	895	0.73	0.44	0	1	236	0.81	0.39	0	1
International	895	0.29	0.45	0	1	236	0.19	0.39	0	1
U.S. Minority	895	0.10	0.30	0	1	236	0.09	0.29	0	1
GMAT	895	652.29	57.08	500	780	236	647.37	52.44	510	770
Quant GMAT	895	43.08	5.65	27	59	236	42.71	5.03	29	51
Work Experience (Months)	895	57.99	28.30	0	228	236	56.50	23.74	0	184
Intended Major in Finance	895	0.29	0.46	0	1	236	0.63	0.48	0	1
Num of Team Members	1096	1.49	1.01	0	4	283	1.50	0.97	0	4
Num of Cohort Members	1096	30.42	9.04	1	45	283	30.20	8.28	12	45
High Wage Team	1096	0.26	0.44	0	1	283	0.30	0.46	0	1

Table 4: Testing if Student Demographics Predict an Online Profile. The dependent variable is a binary variable that take a value of one when the student has an online profile. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	Data Quality Validation Regressions					
GMAT Score	0.0000				0.0001	0.0002
	(0.1607)				(0.5942)	(0.9391)
GMAT Quant Score		-0.0008			-0.0022	-0.0025
		(-0.4130)			(-0.7929)	(-0.9353)
Undergrad GPA			-0.0202			-0.0248
			(-0.8609)			(-1.0448)
Intended Entrepreneur Major				0.0031	0.0031	0.0440*
				(0.1284)	(0.1266)	(1.8105)
Intended Finance Major				0.0054	0.0065	0.0394
				(0.2133)	(0.2576)	(1.5328)
Intended Management Major				0.0151	0.0142	0.0377
				(0.5368)	(0.5046)	(1.2799)
Intended Marketing Major				-0.0135	-0.0144	0.0082
				(-0.5163)	(-0.5476)	(0.3107)
Intended Operations Major				0.0024	0.0032	0.0346
				(0.0517)	(0.0698)	(0.7161)
Intended Strategy Major				-0.0670	-0.0668	-0.0446
				(-1.6128)	(-1.6076)	(-1.0548)
Citizenship FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Year of Graduation FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.5779***	0.8611***	0.6829***	0.5735***	0.6139***	0.6948***
	(4.4318)	(10.1494)	(7.1765)	(10.9241)	(4.5552)	(4.6257)
R-squared	0.09	0.09	0.07	0.09	0.08	0.07
N	1931	1931	1594	1931	1931	1594

Table 5: Pairwise Regression testing the Effect of Being on the Same MBA Team/Cohort on Subsequently Joining the Same Industry after Graduation. Each test is a linear probability regression where the Same Industry variable is a binary variable that designates whether the graduates ever worked in the same industry after graduation. Same Cohort and Same Team are also binary variable that denote the two individuals are in the same team/cohort. The regressions compare all graduates within the same graduation year. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	All Industries			
Same Team		0.0095*	0.0107**	0.0106**
		(1.8673)	(2.0673)	(2.0470)
Same Cohort	-0.0010			-0.0016
	(-0.7691)			(-1.1381)
Constant	0.1856***	0.1848***	0.1473***	0.1856***
	(40.3008)	(40.5622)	(16.2581)	(40.3034)
Year Graduation FE	Yes	Yes	No	Yes
Year-Cohort FE	No	No	Yes	No
R-squared	0.00	0.00	0.01	0.00
N	282619	282619	282619	282619

	High Wage Industries			
Same Team		0.0081***	0.0087***	0.0086***
		(2.5866)	(2.7391)	(2.7180)
Same Cohort	-0.0004			-0.0008
	(-0.4474)			(-0.9474)
Constant	0.0421***	0.0417***	0.0493***	0.0421***
	(14.8378)	(14.8596)	(8.8495)	(14.8412)
Year Graduation FE	Yes	Yes	No	Yes
Year-Cohort FE	No	No	Yes	No
R-squared	0.00	0.00	0.01	0.00
N	282619	282619	282619	282619

	Low Wage Industries			
Same Team		0.0014	0.0020	0.0019
		(0.3313)	(0.4601)	(0.4506)
Same Cohort	-0.0007			-0.0008
	(-0.5956)			(-0.6693)
Constant	0.1435***	0.1431***	0.0979***	0.1435***
	(37.6031)	(37.9021)	(13.0444)	(37.6035)
Year Graduation FE	Yes	Yes	No	Yes
Year-Cohort FE	No	No	Yes	No
R-squared	0.00	0.00	0.00	0.00
N	282619	282619	282619	282619

Table 6: Baseline Regression testing the Employment Effect of Having a Team Member with Prior Employment in Finance/Consulting. Years denote the number of Years after MBA graduation. High Wage Team is a binary variable that denote at least one team member has finance/consulting expeirience prior to the MBA. The top panel has no controls; the middle panel includes graduation year fixed effects and the bottom panel includes cohort fixed effects. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	Employed in High-Wage Industries after MBA			
	Year 0	Year 1	Year 3	Year 5
High Wage Team	0.0544**	0.0543**	0.0543**	0.0053
	(2.2309)	(2.1283)	(2.1283)	(0.2188)
Cons	0.1352***	0.1526***	0.1526***	0.1464***
	(10.7778)	(11.6302)	(11.6302)	(11.7006)
Team Size FE	No	No	No	No
Year FE	No	No	No	No
R-squared	0.00	0.00	0.00	0.00
N	1096	1096	1096	1096

	Year 0	Year 1	Year 3	Year 5
High Wage Team	0.0494*	0.0500*	0.0438	-0.0071
	(1.8536)	(1.7963)	(1.5741)	(-0.2668)
Cons	0.1198*	0.1201*	0.1034	0.0754
	(1.8565)	(1.7802)	(1.5329)	(1.1740)
Team Size FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.01	0.01	0.01	0.01
N	1097	1097	1097	1097

	Year 0	Year 1	Year 3	Year 5
High Wage Team	0.0560**	0.0522*	0.0453	-0.0007
	(2.0288)	(1.8076)	(1.5647)	(-0.0239)
Cons	0.1105	0.1109	0.0580	-0.0035
	(1.1792)	(1.1319)	(0.5905)	(-0.0375)
Team Size FE	Yes	Yes	Yes	Yes
Year Cohort FE	Yes	Yes	Yes	Yes
R-squared	0.03	0.03	0.03	0.03
N	1097	1097	1097	1097

Table 7: Regression Testing the Employment Effect of Having a Team Member with Prior Employment in Finance/Consulting including both Individual and Team Control Variables variables. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	Employed in High-Wage Industries after MBA with Controls					
	No Controls		Individual Controls		Ind/Team Controls	
	0 Y	5 Y	0 Y	5 Y	0 Y	5 Y
High Wage Team	0.0576*	-0.0045	0.0511*	-0.0053	0.0513*	-0.0084
	(1.9344)	(-0.1511)	(1.7218)	(-0.1772)	(1.6519)	(-0.2668)
Constant	0.2124**	0.1796*	0.1218	0.0098	0.0855	-0.0203
	(2.1717)	(1.8232)	(0.9003)	(0.0717)	(0.6111)	(-0.1426)
Year-Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.03	0.02	0.09	0.08	0.10	0.08
N	897	897	897	897	897	897

	Employed in High-Wage Industries after MBA by Intended Major					
	Peer Finance Major		Individual Finance Major		Peer + Individual Finance Major	
	0 Y	5 Y	0 Y	5 Y	0 Y	5 Y
Int Fin ×(High Wage + Finance Team)					0.2194***	0.1953***
					(3.3138)	(2.9057)
Int Fin ×High Wage Team			0.1671***	0.1202**		
			(2.8435)	(2.0083)		
High Wage + Finance Team	0.0826	0.1300**			0.0073	0.0629
	(1.5655)	(2.4337)			(0.1292)	(1.0968)
High Wage Team	-0.0042	-0.0959**	-0.0051	-0.0500	-0.0054	-0.0970**
	(-0.0898)	(-2.0080)	(-0.1416)	(-1.3743)	(-0.1166)	(-2.0489)
Int Finance			0.0368	0.0445	0.0414	0.0393
			(1.0951)	(1.3031)	(1.3154)	(1.2307)
Constant	0.1209	0.1616	0.1027	0.1345	0.1229	0.1629
	(0.8894)	(1.1739)	(0.7627)	(0.9810)	(0.9127)	(1.1919)
Year-Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.11	0.09	0.12	0.10	0.13	0.11
N	897	897	897	897	897	897

Table 8: Regression Testing the Employment Effect of Having a Team Member with Prior Employment in Finance/Consulting over the Business Cycle. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

Employed in High-Wage Industries after MBA over the Business Cycle								
	0 Y		1 Y		3 Y		5 Y	
	05-07	08-10	05-07	08-10	05-07	08-10	05-07	08-10
High Wage Team	0.1966**	0.0309	0.1672**	0.0309	0.1694**	-0.0351	0.0997	-0.0260
	(2.5487)	(0.4912)	(2.1670)	(0.4621)	(2.1174)	(-0.5171)	(1.3737)	(-0.3811)
Constant	-0.2270	-0.4833**	-0.2360	-0.5391**	-0.2018	-0.3141	-0.1669	-0.0580
	(-0.7765)	(-2.2794)	(-0.8068)	(-2.3903)	(-0.6653)	(-1.3717)	(-0.6065)	(-0.2521)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.22	0.26	0.24	0.25	0.18	0.28	0.18	0.18
N	205	258	205	258	205	258	205	258
	0 Y		1 Y		3 Y		5 Y	
	05-07	08-10	05-07	08-10	05-07	08-10	05-07	08-10
High Wage + Finance Team	0.2713**	-0.1753	0.2973**	-0.1595	0.2054*	0.0287	0.2834***	0.0221
	(2.3693)	(-1.5372)	(2.6042)	(-1.3123)	(1.7145)	(0.2318)	(2.6400)	(0.1778)
High Wage Team	0.0464	0.1673	0.0027	0.1550	0.0557	-0.0575	-0.0571	-0.0432
	(0.4691)	(1.5398)	(0.0274)	(1.3389)	(0.5384)	(-0.4871)	(-0.6155)	(-0.3646)
Constant	-0.2683	-0.4717**	-0.2813	-0.5286**	-0.2331	-0.3160	-0.2100	-0.0594
	(-0.9299)	(-2.2308)	(-0.9778)	(-2.3463)	(-0.7719)	(-1.3759)	(-0.7766)	(-0.2577)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.25	0.27	0.27	0.26	0.19	0.28	0.22	0.18
N	205	258	205	258	205	258	205	258
	0 Y		1 Y		3 Y		5 Y	
	05-07	08-10	05-07	08-10	05-07	08-10	05-07	08-10
Int Fin $\times$High Wage Team	0.2916**	0.0918	0.2491*	0.1457	0.0770	0.0605	0.1130	0.1155
	(2.2753)	(0.7672)	(1.9535)	(1.1430)	(0.5702)	(0.4649)	(0.9317)	(0.8840)
High Wage Team	0.0697	0.0058	0.0508	-0.0078	0.1262	-0.0510	0.0385	-0.0559
	(0.7619)	(0.0836)	(0.5576)	(-0.1044)	(1.3105)	(-0.6716)	(0.4452)	(-0.7324)
Intended Finance Major	-0.0054	0.0688	0.0593	0.0391	0.0754	0.0050	0.0933	-0.0237
	(-0.0713)	(1.0715)	(0.7870)	(0.5716)	(0.9448)	(0.0718)	(1.3020)	(-0.3379)
Constant	-0.1773	-0.4933**	-0.2108	-0.5502**	-0.2094	-0.3179	-0.1734	-0.0629
	(-0.6120)	(-2.3339)	(-0.7314)	(-2.4446)	(-0.6865)	(-1.3822)	(-0.6329)	(-0.2727)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.26	0.27	0.28	0.26	0.19	0.28	0.21	0.18
N	205	258	205	258	205	258	205	258

Table 9: Regression Testing the Employment Effect of Having a Team Member with Prior Employment in Finance/Consulting for Graduates that did not Enter these Industries directly after the MBA. T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

	Employed in High-Wage Industries through Late Referrals					
	1 Y	3 Y	5 Y	1 Y	3 Y	5 Y
Int Fin ×High Wage Team				0.0108	-0.0227	0.0161
				(0.3928)	(-0.4983)	(0.3369)
High Wage Team	-0.0091	-0.0108	-0.0349	-0.0132	-0.0054	-0.0398
	(-0.6486)	(-0.4671)	(-1.4356)	(-0.8260)	(-0.2038)	(-1.4339)
Int Finance				0.0269*	0.0309	0.0071
				(1.7805)	(1.2370)	(0.2704)
Constant	-0.0508	-0.1148	-0.0446	-0.0566	-0.1220	-0.0460
	(-0.8294)	(-1.1382)	(-0.4205)	(-0.9248)	(-1.2064)	(-0.4320)
Year-Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.10	0.10	0.13	0.10	0.10
N	757	757	757	757	757	757

	1 Y	3 Y	5 Y	1 Y	3 Y	5 Y
Int Fin ×High Wage Team				-0.0013	0.0417	0.0682
				(-0.0446)	(0.8800)	(1.3660)
High Wage Team	-0.0051	0.0098	0.0251	-0.0063	-0.0042	0.0037
	(-0.3571)	(0.4140)	(1.0072)	(-0.3737)	(-0.1527)	(0.1257)
Int Finance				0.0303**	0.0127	-0.0088
				(1.9979)	(0.5077)	(-0.3344)
Constant	-0.0493	-0.1151	-0.0446	-0.0557	-0.1177	-0.0426
	(-0.8044)	(-1.1404)	(-0.4197)	(-0.9093)	(-1.1648)	(-0.4010)
Year-Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.10	0.10	0.13	0.11	0.10
N	757	757	757	757	757	757

Table 10: Regression Testing the Major Effect of Having a Team Member with Prior Employment in Finance/Consulting (or Intended Finance Major). T-Statistics are included below the coefficient. We use * to denote significance at the 5% level, ** to denote significance at the 1% level, and *** to denote significance at the 0.1% level.

Graduating with Finance Major			
	Intended Finance Major on Team		
Int Fin ×Int Fin Team			0.0921
			(1.1166)
Int Finance Team	0.0088	0.0071	-0.0145
	(0.2364)	(0.2062)	(-0.3658)
Int Finance		0.4477***	0.3960***
		(11.1715)	(6.4730)
Constant	0.0202	0.0327	0.0252
	(0.1073)	(0.1876)	(0.1442)
Controls	Yes	Yes	Yes
R-squared	0.19	0.31	0.31
N	843	843	843
	High Wage Team		
Int Fin ×High Wage Team			-0.0089
			(-0.1072)
High Wage Team	0.0672*	0.0461	0.0480
	(1.6858)	(1.2434)	(1.1622)
Int Finance		0.4451***	0.4481***
		(11.1049)	(9.2400)
Constant	0.3418*	0.3021	0.3012
	(1.7213)	(1.6390)	(1.6308)
Controls	Yes	Yes	Yes
R-squared	0.20	0.31	0.31
N	843	843	843
	High Wage & Intended Finance Major Team		
Int Fin ×(High Wage + Finance Team)			0.0284
			(0.2904)
High Wage + Finance Team	0.0242	0.0053	-0.0018
	(0.3656)	(0.0864)	(-0.0268)
High Wage Team	0.0528	0.0429	0.0432
	(0.9412)	(0.8241)	(0.8290)
Int Finance		0.4450***	0.4393***
		(11.0910)	(9.8324)
Constant	0.3455*	0.3029	0.3018
	(1.7367)	(1.6402)	(1.6329)
Controls	Yes	Yes	Yes
R-squared	0.20	0.31	0.31
N	843	843	843

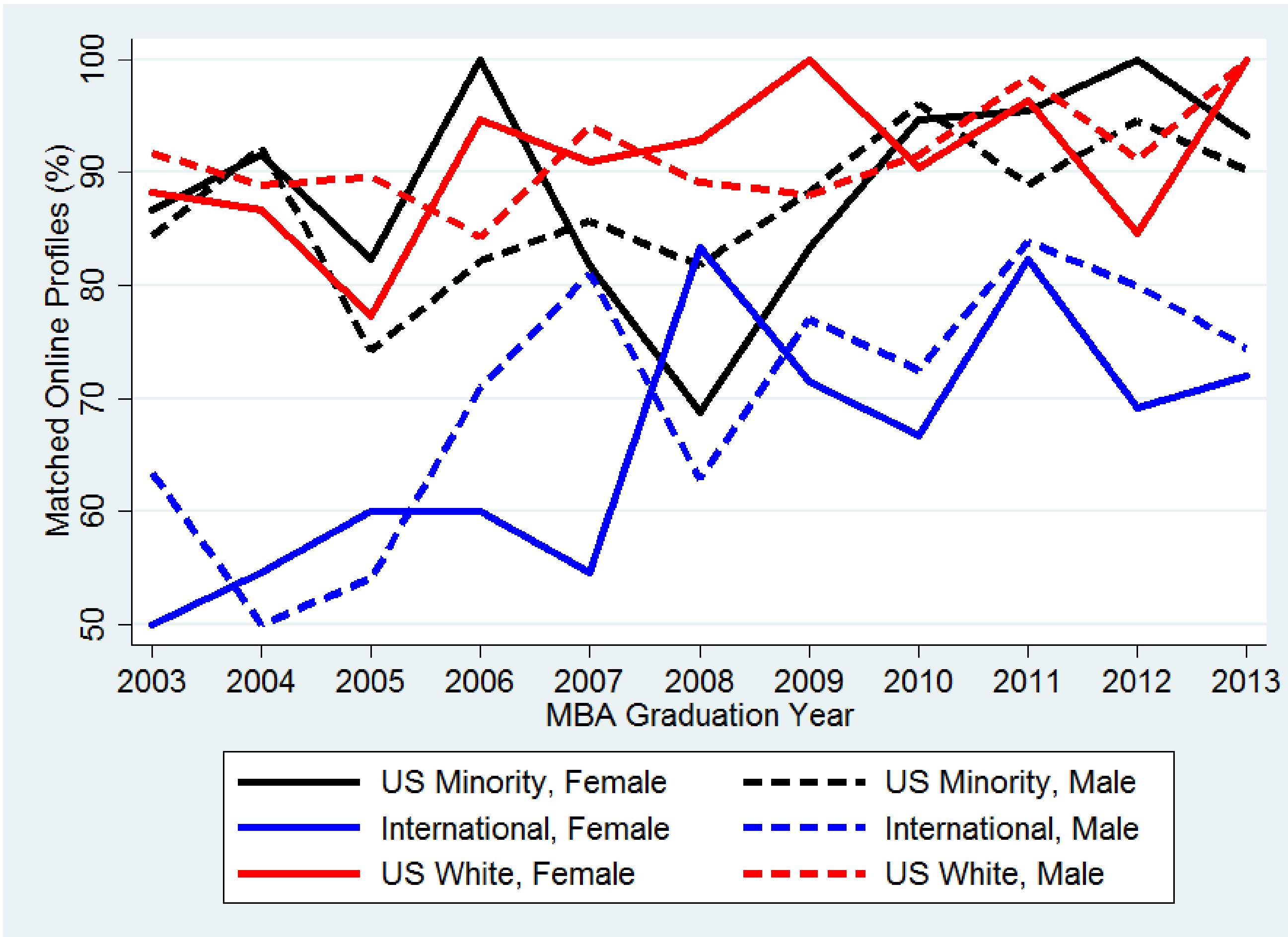

Figure 1: Profile Match Demographic by Gender, Citizenship, and Race

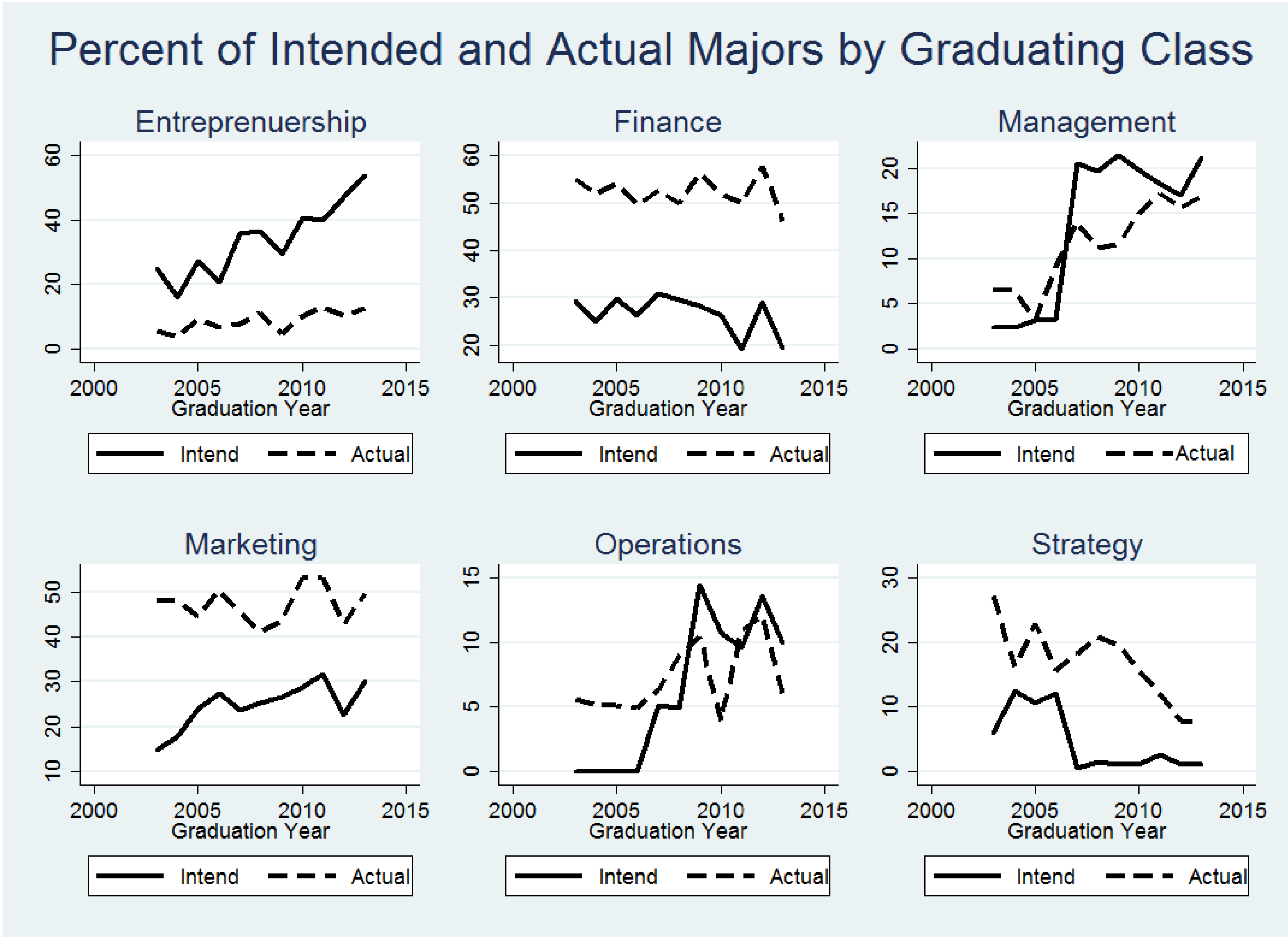

Figure 2: Intended and Actual Majors by Graduating Class.