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DIVERSITY AND PERFORMANCE IN ENTREPRENEURIAL TEAMS

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ABSTRACT

We study the role of diversity and performance in the entrepreneurial teams. We exploit a unique dataset of MBA students who participated in a required course to propose and start a real micro-business that allows us to examine horizontal diversity (i.e., within the team) as well as vertical diversity (i.e., team to faculty advisor) and their effect on performance. The design of the course allows for identification of the causal implications of horizontal and vertical diversity. The course was run in multiple cohorts in otherwise identical formats except for the team formation mechanism used. In several cohorts, students were allowed to choose their teams from among students in their section (roughly 90 students). In other cohorts, students were randomly assigned to teams based upon a computer algorithm. In the cohorts that were allowed to choose, we find strong selection based upon shared attributes. Among the randomly-assigned teams, greater diversity along the intersection of gender and race/ethnicity significantly reduced performance. However, the negative effect of this diversity is alleviated in cohorts in which teams are endogenously formed. Finally, we find that teams with more female members perform substantially better when their faculty section leader was also female. Because the gender of the faculty section leader is exogenous to the gender make-up of the entrepreneurial team, the positive performance effects can be interpreted as causal. These findings suggest that diversity policies should take adequate consideration of the multiple dimensions of diversity.

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1. Introduction

Economics research on diversity has explored both impediments to team diversity (Becker, 1957; Morgan and Vardy, 2009), the performance effects of diversity on team performance (Mello and Ruckes, 2006), as well as the effects of diversity in the mentor-employee relationship and its effects on performance and promotion (Athey, Avery, and Zemsky, 2000). Most of this work has focused on theoretical models that derive predictions about factors that may hinder or promote workplace diversity or shared attributes of supervisor and employees may aid groups with acquiring human capital and increasing the likelihood that they are promoted. Our paper fills the empirical gap in much of this research by exploring in a quasi-experimental setting the factors which shape team diversity and how both horizontal (team-level) diversity as well as vertical (supervisor-team) diversity affects performance.

In this paper, we contribute three major findings to the literature on diversity and its effects on performance. Our experimental design allows us to examine both exogenous horizontal diversity (i.e., team diversity) as well as vertical diversity (i.e., diversity at the advisor-team level). First, we explore what factors are important for limiting diversity in forming entrepreneurial teams. Becker (1957) was the first to model factors that might lead to homogeneity in organizations. More recently, both Cornell and Welch (1996) and Morgan and Vardy (2009) develop models in which the ability to better evaluate signals of quality in those who are similar to recruiters leads organizations to hire more people who look like their existing work force. Research has also documented the existence of homophily, the desire to associate with those similar to you, in various social networks, from the strongest social ties such as in marriage (Kalmijn 1998, Fiore and Donath 2005), close friendships (Marsden, 1987, 1988, Currarini, Jackson and Pin 2009), to professional networks (Gompers et al. 2016; Kleinbaum et al. 2013; Ruef et al. 2003; Reagans 2011;Sorenson and Stuart 2001) and acquaintances (Hampton and Wellman 2000).

Homophily can arise from the similarities in endowed demographic characteristics, such as race/ethnicity, country of origin, age, and gender. It can also be based on acquired characteristics, such as education, occupation and religion (Lazarsfeld and Merton 1954). Most past research has focused on homophily in race/ethnicity and gender. Relatively few studies[1] have examined homophily in educational and professional backgrounds due to limitation in data. However, given that diversity in professional background can impact team performance (Beckman et al. 2007), it is also important to understand the extent to which acquired characteristics affect team formation. Verbrugge (1977) and Louch (2000) explore homophily in both demographic and socioeconomic characteristics. While they confirm the existence of homophily along both dimensions, they do not distinguish the relative strength of homophily that each dimension engenders nor do they explore the interaction of those characteristics.

We estimate the relative economic magnitudes of homophily in race/ethnicity, gender, education, and work experience, i.e., which shared attributes are more likely to lead to team membership? Using a novel dataset of Harvard Business School MBA students' choices to co-found real micro-businesses, we find selection into team based upon endowed demographic characteristics is stronger than team selection based upon acquired characteristics. Individuals are 25% more likely to form groups with people of the same race/ethnicity or gender relative to randomly matching. Selection based upon education history and work experience is weaker than endowed demographic attributes, but it is still economically significant. School ties and shared work experience increases the probability of co-founding a micro-business with someone of the same school history or work experience by 17% and 11% respectively. Further, we find team selection effects of shared education and work experience are stronger among male students than female students.

When we examine how specific race/ethnic ties develop, we find homophily is weaker among Latinx American and Black students, two relatively underrepresented ethnic groups within the HBS student body compared to White Americans and Asian Americans in our sample. A likely explanation is that these underrepresented groups are making a strategic decision to partner with White and Asian Americans to broaden their networks among "in group" students. However, we find homophily is strongest among international students, students who graduated from non-Ivy league schools, and students who worked in

[1] Among studies that do include education homophily, most of them use education level instead of past educational institution as a dimension of homophily

industries that represent a small fraction of the MBA class's past experience[2]. Future theoretical work should explore the interaction between group size and different types of homophilic ties (other than race/ethnicity) with heterogeneous strengths.

Second, our paper contributes to the understanding of the causal relationship between horizontal team diversity and performance. Theoretical work on diversity focuses on the trade-off between the information gains and the communication costs. Heterogeneous teams benefit from more diverse pools of skill and knowledge, but at the same time, differences in race/ethnicity, culture, and mother language hinder efficient communication among team members, thus potentially lowering productivity (Alesina and La Ferrara 2003, Lazear 1999). Mello and Ruckes (2006) model the formation of teams and their effects on performance, showing under what circumstances more diverse teams perform better. In experimental settings in which group identification is assigned (i.e., red group, blue group, etc.), Chen and Li (2009) and Chen and Chen (2011) show that teams with greater group diversity perform worse. The argue that group identification leads team members to work harder and help others more when their team has other members of their group. Several experimental studies seek alleviate the endogeneity concern. Hoogendoorn and Praag (2012) and Hoogendoorn et al. (2013) find the benefit of information sharing is greater than communication cost in more diverse teams. Marx et al. (2021) find horizontal diversity (i.e., at the same level of authority) in race/ethnicity decreases team performance because people in heterogeneous teams are more likely to complain about their teammates. Knippenberg and Schipper (2007) review empirical literature on team diversity and performance from 1997 to 2005, and they conclude that the empirical results on diversity are "highly inconsistent" because of the endogenous process of group formation in the majority of the existing research. Our research design allows us to estimate the effects of random diversity and endogenous diversity on outcomes.

Most of the empirical literature on team diversity only focuses a single dimension, such as gender, racial/ethnic, or education. It rarely considers the interaction between different characteristics. However, a

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[2] Students who worked in non-finance, non-consulting and non-technology industries. Most of the students are from finance, consulting or technology industries

person's identity is often defined by an intersection of multiple attributes. Jackson et al. (2003) note the lack of work on multi-dimensional diversity and argue that the interaction of different attributes is likely to be important for understanding how these factors relate to team formation and success. Similarly, the idea of multi-dimensional diversity is well recognized in the field of psychology and counselling (Reynolds and Pope 1991, Robinson 1993 and Jones and McEwen 2000). For example, Jones and McEwen (2000) argue that the core of an individual's sense of self is defined by the intersection of multiple characteristics such as gender, race, and culture. Lau and Murnighan (1998) view group diversity as many subgroups based on one or more attributes. For instance, a team can be viewed as a subgroup of White males, White females, Asian females and Asian males. The authors argue that these subgroups can be the source of team conflict. One example of the examination of the intersection of attributes is Jackson and Joshi (2004), who examine the joint effect of gender, race/ethnicity, and tenure diversity on team performance using data from a Fortune 500 company. They find that the performance is best in teams with low tenure diversity, low gender diversity and low ethnic diversity. These results are, however, complicated by the endogenous nature of team formation in their data.

Our study provides a clean setting to test the causal relationship between horizontal diversity and team performance. By exploiting a quasi-experimental setting of exogenous team assignments in the 2013 MBA cohort in which students were assigned teams for starting their micro-businesses, we find homogeneity in race/ethnicity increases team performance. In other words, exogenously diverse teams performed worse than exogenously formed homogeneous teams. When we look at the intersection of race/ethnicity and gender, we find that the negative effect of diversity is driven by joint homogeneity of both gender and race/ethnicity. Teams that had homogeneity on both dimensions at the same time performed the best. This result is consistent with randomly-assigned diversity reducing communication efficiency and increasing the probability of conflict within the team. However, the negative effect between gender-race/ethnicity diversity and performance is eliminated when teams are endogenously formed in the 2014-2016 cohorts. Our results highlight the performance effects that arise from forced versus endogenous diversity.

Finally, our paper looks at the performance effects of diversity in the mentorship relationship between supervisors and team members. Athey, Avery, and Zemsky (2000) model the role that shared characteristics in the mentor-subordinate relationship play in performance and promotion. Bednar and Gicheva (2014) look at NCAA Division I athletic departments and find no effect of the gender of the athletic director on female representation within coaching and staff positions. Matsa and Miller (2011), however, find that boards that have more female directors tend to increase the number of women in senior management positions. Marx et al. (2021) find that vertical diversity (i.e., at different levels of authority) increases team performance, as workers tend to exert more effort when the manager is from a different ethnic background. Calder-Wang and Gompers (2020) find that having more daughters increases venture partners' propensity to hire female investment partners. Using the number of daughters (relative to the total number of children) that senior venture partners have as the instrument for venture capital firm gender diversity, the authors find gender diversity causally improves venture capital firm's investment performance.

Exploiting the random assignment of faculty advisors with micro-business teams, we find that vertical diversity has an effect on performance of the entrepreneurial teams. Each section of 90 students had a faculty member who served as section leader. The section leader both taught the material related to Field 3 and directly supervised the student teams. We examined how gender ties between the section leader and the student teams affected performance. These gender ties are exogenous to the gender make-up of the team because students had no control over who their faculty members were.[3] We find a significant effect of gender ties for teams with more female students. Teams for whom the section leader was a female had monotonically increasing performance as the number of female team members increased. The result is consistent with the importance of mentorship and the positive performance impact that woman have when they are mentored by woman.

Our results on the diversity and its performance implications are important beyond the context of our research setting. First, the main criteria for evaluating the micro-businesses were related to the actual business concept and the ability to attract real customers. Second, a significant minority of these micro-businesses continued to operate after the term and many raised external funding including venture capital.

[3] We only look at gender ties because there was not enough heterogeneity of section leader race/ethnicity in order to meaningfully look at race/ethnicity ties.

Finally, among the 3,864 MBA students in our sample, over 30% of them work in venture capital or technology related areas after graduation[4], representing a sizable labor inflow to the entrepreneurial eco-system. Thus, understanding the strength and performance implications of homophily in team formation, as well as the performance implications of team diversity, sheds light on the lack of diversity in entrepreneurship (Calder-Wang and Gompers 2018). Despite extensive research on diversity in various settings, only a few studies have explored the effect in entrepreneurship. Ruef, Aldrich, and Carter (2003) survey 830 entrepreneurs[5] on their founding team composition. They find that the probability of a team with the same gender or with the same race/ethnicity is higher than a random matching process would predict. However, they do not estimate the relative strength of homophily in each dimension, and their sample of entrepreneurs tend to be small business owners instead of VC-backed start-ups. Second, they cannot establish the potential partner set because they do not know the members of the entrepreneurs' social network, while we know each potential team member and each potential team member has been known to others for at least six months.

Further, our findings have important implications on broader policy considerations for workplace diversity initiatives. Workplace diversity (or more broadly inclusivity) has both short-term and long-term performance implications for firms and workers, as well as long-term effects as decisions tend to be forward-looking and long-term (e.g., education, occupational choices, etc.) In recent years, some policymakers have promoted diversity in workplace by implementing gender (or race/ethnicity) quotas. For instance, the Norwegian government enforced a gender quota on corporate boards (Ahern and Dittmar 2012). More recently, California has become the first state in the US to mandate board diversity. Our results suggest that mandated diversity may not always bring the performance benefits that diverse teams engender because biases against certain groups remain.

[4] https://www.hbs.edu/recruiting/data/Pages/detailed-charts.aspx?year=2016

[5] The authors start with a random sample of 64,622 individuals in the US, and conduct detailed phone interviews with 830 individuals who meet their screen criteria of nascent entrepreneurs.

2. Setting

First year MBA students at the HBS from 2012 through 2016 were required to take a field course in the spring semester of their first year. Throughout the course, students were required to design and launch a real micro-business. At the beginning of the semester, students formed teams of 5-7 people from within the same section[6]. Two months into the semester, students presented their projects to faculty members (section leaders). If the faculty members believed the proposed project was achievable, the team then proceeded to present their project to a panel of judges at the end of semester (IPO day). The panel of judges then ranked all the projects based on teams' performance and the quality of the idea during the IPO day.

When the field course was first introduced to the students in the spring semester of 2012 for the MBA Class of 2013[7], the school assigned each student to the teams based a computer algorithm. One goal of the assignments was to make teams somewhat diverse in terms of gender, race/ethnicity, education, and past working experience. After 2013, the school changed the team formation policy and started to have students choose teammates themselves. The school did not impose any restriction on how students formed their teams. Anecdotal evidence suggests that students frequently formed teams with friends who had similar demographic backgrounds. Figure 1 plots the probability of a student being matched to her classmate conditional on having the same race/ethnicity, gender, education, or industry backgrounds. The conditional probability of matching increases in all four dimensions when students were allowed to find teammates freely. This provides evidence on the existence of homophily during the process of team formation. In the next section, we explore the relative strength of homophily based upon race/ethnicity, gender, education and past industry experience. From there, we explore the performance implications of diversity on performance.

Because teams were assigned by the MBA Administration for the Class of 2013, the diversity of

[6] Harvard Business School students are assigned to one of ten sections in their first year and take all of their first year classes with the same roughly 90 students.
[7] 2013 refers to the class year of 2013, so do 2014, 2015 and 2016 later in the paper. Students take the field course during their first year, e.g., class year 2013 students took the field course in 2012.

teams is exogenous to each team member. As such, the causal implications of diversity for performance can be estimated for the Class of 2013. We also explore the performance impact of diversity for the Classes of 2014-2016, although endogeneity of team diversity makes interpretation of the performance results difficult.

3. Data

Our data were provided by the HBS MBA Program. In the data, we observe the gender, race/ethnicity, home country, undergraduate institution, past employer, and the industry of each MBA student from class year 2013 to 2016. We were not provided with students' actual names. Table I reports the summary statistics for the 3,684 MBA students in our sample. Females make up 40% of total student population. Approximately 40% of the students are white Americans, 12% are Asian Americans, 5% are Black, 4% are Lantinx Americans, and 35% are international students. India, Canada, and China represent the top three origin countries for international students[8]. In terms of past work experience, roughly half of the students worked in finance or consulting prior to business school, and not surprisingly, the big three consulting firms (McKinsey, Bain and BCG) and bulge bracket investment banks (Goldman and Morgan Stanley) are the top five past employers for Harvard MBA students (Table II). Approximately 11% of students had experience in the technology industry, and this number increased by more than 50% from 2013 to 2016. 27% of the MBA students graduated from Ivy League schools. Harvard, Stanford, and University of Pennsylvania are the top 3 undergraduate institutions (Table II).

We also observe the team selection of each student. From 2013 to 2015, there are 150 teams in each class year and the average team size is 6. In 2016, the average team size was changed to 5 and there were 180 teams. To examine the effects of homophily on team formation, we construct student-student pairs by matching each student to every other student within the same section and year. This process creates 335,686

[8] Online Appendix Table 1.

potential pairs. We then create a dependent variable real_match which equals to 1 if the two students are members of the same team and 0 otherwise. The independent variable ethnic (gender, education, industry) tie equals to 1 if two students belong to the same ethnic (gender, education, industry) group. Our data construction method is similar to Louch (2000). To illustrate, consider the following example: James Brown is a Section A student in 2013, and he has 5 teammates. We match Mr. Brown to all his section mates (89 of them) by creating 89 student-student pairs. Intuitively, each pair is a potential teammate with whom Mr. Brown could be paired. If the match happened randomly, Mr. Brown would pair with an arbitrary teammate with a probability of 5.6%[9]. Variable real_match equals 1 for the 5 pairs for which Mr. Brown is matched to his real teammates. To measure the effect of homophily on matching, we compare the probability of matching conditional for a pair having the same race/ethnicity (Gender, Education and Industry) to the probability of matching for a pair with different ethnicities (Gender, Education and Industry). Our baseline results are estimated using the following regression models:

$$Real\ Match_i = b_{11} * \ Ethnicity\ Tie_i + b_{12} * Team\ Size + Year\ FE + e_i$$

$$Real\ Match_i = b_{21} * \ Gender\ Tie_i + b_{22} * Team\ Size + Year\ FE + e_i$$

$$Real\ Match_i = b_{31} * \ Education\ Tie_i + b_{32} * Team\ Size + Year\ FE + e_i$$

$$Real\ Match_i = b_{41} * \ Industry\ Tie_i + b_{42} * Team\ Size + Year\ FE + e_i$$

4. Empirical Results on Matching

In this section, we examine the relative strength of homophily for race/ethnicity, gender, educational background and past work experience. While homophily is an economically significant force across all four dimensions, it is strongest in endowed demographic characteristics, namely race/ethnicity and gender. Table III Panel A presents the regression results for matching from 2014 to 2016, the years in which students were allowed to choose their own teams. Race/ethnicity ties increase the probability of matching by 1.38%. Given the base rate of matching is 5.6%, this represents a 25% increase from the baseline probability of randomly

[9] 5/89=5.6%

matching with a student from the same race/ethnicity. Similarly, we find common shared gender increases the probability of matching by 1.33%. The relative increase in propensity to match based upon shared education and past industry experience is smaller than the effect for gender and race/ethnicity. Attending the same undergraduate institution increases the probability of matching by 0.976%, a 17% increase from the baseline, and having the same industry experience increases the matching rate by 0.637%, an 11% increase from the baseline. Both these results are significant and economically meaningful. Panel B reports the regression result using 2013 subsample. Given that teams were exogenous assigned, we do not expect shared attributes to increase team matching. The coefficients on race/ethnicity tie, school tie and industry tie are negative and close to zero. The coefficient on gender tie is -1.67% and statistically significant at 1% level. The matching rate is much lower among student pairs of the same gender compared to student pairs of different genders. This reflects HBS's assignment scheme, which appears to have matched males to females to balance the gender ratio within each team. Interestingly, other dimensions do not seem to have been important in team assignment.

Table IV tests whether homophily based on endowed demographic characteristics is stronger than homophily based on acquired characteristics. In the regression, the dependent variable is a dummy variable if the pair is a real match as defined before. The independent variable Endowed Demographic Match is a dummy variable equals to 1 if race/ethnicity tie or gender tie equals to 1; Acquired Characteristics Match equals to 1 if school tie or industry tie equals to 1. In 2014-2016 subsample, the coefficient on Endowed Demographic Match (=0.015) is more than twice as large as the coefficient on Acquired Characteristics Match (=0.0066), and the difference is statistically significant at 1% level (F=32). The results indicate that when matching is voluntary, homophily based on endowed demographics is at least twice as strong as homophily based upon acquired characteristics.

Our results are largely consistent with prior research. McPherson et al (2001) give a comprehensive review on homophily in social networks. It is well documented that homophily exists in both endowed demographic characteristics and acquired characteristics. Verbrugge (1977) provides some early evidence that homophily bias is stronger in demographic characteristics (i.e., age) in friend formation, however, he does not examine race/ethnicity as a dimension of homophily. To the best of our knowledge, our study is the first attempt to estimate and compare the relative strength of various characteristics for ties in an entrepreneurial setting.

4.1 Race/Ethnicity Diversity

The strength of matching with someone of the same race/ethnicity varies across different ethnic groups. We attempt to look at how the relative size of the ethnic group influences how strong the attraction is. We find increase in the propensity to match is strongest among international students, followed by Asian Americans and White Americans. It is relatively weaker among Blacks and non-existent among Lantinx Americans.

In Table V, the first two columns show that the probability of matching based upon shared race/ethnicity increases by 1.08% and 1.16% among White American and Asian American MBA students respectively. Given the base rate of matching is 5.6%, this represents a 20% increase in the matching rate. The coefficient for Black students is 0.96%, but it is not statistically significant. Lantinx American MBA students are no more likely to match to another Latinx American MBA student. Breaking down the matching rate by year (Online Appendix Table 2), we observe large variance among Lantinx American students. The matching rate was 11.29% among Lantinx Americans in 2014, and it is twice as large as the sample average (5.6%). However, the matching rate drops to 3.7% and 0% in 2015 and 2016. The large variance in matching rates may be due to the small number of Lantinx American students in each class year. On average, there are only 3.8 Lantinx American students in each section. Similarly, the average number of Black students in each section is 5 and homophily among Black MBA students is relatively weak. One potential mechanism could be strategic decision making by underrepresented minorities. Black and Lantinx American students may intentionally form teams with White American and Asian American students to broaden their networks to groups that are potentially more heavily represented in the entrepreneurial and venture capital eco-system.

The propensity to match is highest among international students from the same region. An international MBA student is 3.77% more likely to find a teammate from the same region[10], three times greater than the effect among White and Asian Americans. A detailed breakdown of international students by region (Online Appendix Table 3) shows that the increase is highest among students from East Asia, the Middle East, and Latin America. The coefficients for these groups are around 6%, twice as large as the coefficients for Europeans and South Asian students. There are only 3-4 students from East Asia, Middle East and Latin America per section. One possible explanation is that our measure of the increase matching probability for international students also captures characteristics such as language, culture, and religion in these regions. The strength of ties is substantially stronger among these very small groups than it is for similarly sized minority groups, e.g., Black or Lantinx American students.

4.2 Gender Diversity

Gender is another important attribute that may affect team matching. In Table VI we look at how shared gender affects the probability of matching. We find that the increase in propensity to match based upon shared gender is for males and females is 0.72% and 1.22% respectively ($p<1\%$). Not surprisingly, the coefficient on shared gender is negative and significant for both males and females in 2013, reflecting the group assignment scheme used by the school that was intended to increase gender diversity in teams.

Table VII breaks down race/ethnicity homophily by gender. The interaction between gender and race/ethnicity yields several interesting results. On average, males are more likely to form teams with people from the same race/ethnic background. The first and third column shows that race/ethnicity tie increases the probability of match by 1.54% among males and 1.14% among females. More specifically, white male students are 50% more likely to choose to form a team with another white male student than white female students are to form a team with another white female student. Among Lantinx American and international students, race/ethnicity homophily is also stronger among males than females. Black female students, on the

[10] For other international students, we categorize their home countries by regions: Europe (7.7 students per section), South Asia (6.1 students per section), East Asia (4 students per section), Latin America (4 students per section), Middle East (3.3 students per section), Africa (1.6 students per section). Two exceptions are Canadians and Australians, we counted them also as white Americans (Online Appendix Table I).

contrary, have a higher probability of matching to another Black female student than are Black male students. The coefficient for Black female students is 2.45%, while the coefficient for Black male students is only 0.326%. The interaction between gender and ethnic is less well understood (Block and Grund 2014, Wimmer and Lewis 2010), as previous studies often treat gender and race/ethnicity as separate categorizes. The above results suggest the lack of diversity in entrepreneurship is not a simple problem of one gender or one race/ethnicity. It is a more complex story about the interactions of gender and race/ethnicity. Policies that fail to consider this interaction effects may be effective in one part of the population but futile for the rest. In Section 5 below, we explore the role that the intersection of race/ethnicity and gender diversity plays on performance.

4.4 Education Diversity

School ties have been shown to be an important source of social interaction. Individuals are more likely to interact with people with same level of education (Verbrugge 1977; Louch 2000; Marsden 1988). People form long-term friendships with their classmates (Neckerman 1996). Equity analysts are more likely to build relationship and acquire superior information through school ties with the management (Cohen, Frazzini and Malloy 2010).

In Table VIII, we examine the effect of education ties on matching in the student teams. The effect of shared education is relatively weaker than gender and race/ethnicity. Attending the same undergraduate institution increases the probability of matching by 0.976%, while the for shared gender and race/ethnicity it was 1.33% and 1.38% respectively. In column 2 and 3, we observe the effect is much stronger among students from non-Ivy league schools which typically have a lower number of students at HBS. While attending the same college increases the matching probability by 1.88%, among non-Ivy school graduate, it only increases the matching rate by 0.219% among Ivy-school graduates, despite the fact that there are far more Ivy graduates who attend HBS. It is important to note that the group size is much larger for Ivy-league graduates. 24% of students are from the eight Ivy-league schools. The remaining 76% of students are from 85 non-Ivy league schools and each school represents less than 1% of the student population.

Table IX explores the effect of school ties among male and female students. Brashears (2008) finds that homophily in education level is uniform among males and females using data from a 1985 general social survey. Our results point to a different story. The effect of a school ties is much stronger among males than it is among females. A school tie increases the matching rate by 1.71% among male students while it increases matching rate by only 0.096% among female students. Further, it is the strongest among male students from non-Ivy league schools. Our difference with Brashears (2008) could be caused by difference in the setting that we examine. Brashears (2008) examines common educational attainment in American's core discussion groups, people with whom Americans discuss important matters while we focus on actual school tie.

4.5 Past Industry Experience Diversity

Shared work experience is an important for socialization and friendships. This might encourage students with similar work experience to match. On the other hand, entrepreneurial teams may desire functional diversity as a way to improve performance, thus one might also expect that students who are seeking broad sets of skills may form teams with diverse work history (Ruef, Aldrich and Carter 2003). Table X reports the results on industry matching. Our results show that at least in the context of the micro-business formed as a part of Field 3, functional diversity was not an organizing principal. Shared industry experience increases the probability of matching by 0.637%. Breaking down the relative increase in matching by industry sectors, we find the effect strongest among people who worked in non-finance, non-consulting, and non-technology industries, increasing the matching rate by 2.12%. The magnitude of the effects is similar among finance, technology, and consulting industries, which is around 0.35%.

Table XI investigates the effect of shared work experience among male and female students. Much like race/ethnicity and school matching, male students are more likely to form groups with people who have the same industry experience. Industry ties increases the probability of matching by 0.887% among males. This is primarily driven by male students with experience in finance and technology. In contrast, industry ties only increase the matching rate by 0.292% among females. There is a large difference in the effect on matching between male and female students who worked in finance. Male students with finance backgrounds are 0.8% (1% statistical significance) more likely to form teams with people from finance, but having worked in finance does not increase the propensity of woman to match to other women with finance backgrounds.

5. Diversity and Performance

5.1. Team Diversity and Performance

The results in the previous section demonstrate that when students are allowed to choose their own teams to start a micro-business, the propensity to pair up is increased by common personal characteristics including race/ethnicity, gender, education, and work experience. Given that teams were exogenously assigned for the Class of 2013, we can examine the causal relationship between performance and diversity. In this section, we examine the effect of diversity on team performance. While we look at the results for all classes, the results for the Classes of 2014-2016 need to be viewed with caution because of the endogeneity of group diversity.

Our unit of performance analysis is at the team level. There are 150-180 teams in each class year, and each team has 5-7 students. We measure team diversity across four different dimensions: Race/Ethnicity, Gender, Education and Industry, and construct the homophily measure for each dimension as the following:

$$Homophily\ Score_{\,i} = \frac{\#\ of\ ties\ between\ team\ members\ with\ \ the\ same\ characterisitcs}{Total\ possible\ ties\ in\ the\ team}$$

To illustrate our diversity measure, consider a team with six people: Three of them are White, two of them are Asian Americans, and one is an international student from South America. Race/Ethnicity Score in this team will be (3+1)/(5+4+3+2+1)=4/15, as there are three ties between three white team members[11], one tie between two Asian American students and fifteen possible ties between six team members. Diversity is lower the higher the score. It equals to zero if everyone in the team has different characteristics and equals

[11] When counting the tie between White students, we count Canadians (3.41%) and Australians (1.26%) as White Americans. For other international students, we categorize their home countries by regions: Europe (8.8%), South Asia (6.9%), East Asia (4.6%), Latin America (4.6%), Middle East (3.8%), Africa (1.5%). A homophilous tie is recorded if two international students are from the same region (Online Appendix Table I).

one if everyone is the same type.

Table XII provides summary statistics on team diversity by year. The average Race/Ethnicity Score from 2014 to 2016 is 0.281, implying on average, there are 3 to 4 students with the same race/ethnic background in a team of 6 people. The standard deviation is also high (0.216), suggesting the existence of highly diverse teams and highly homogenous teams. The benchmark measure is the race/ethnicity score of the entire section. The average team race/ethnicity score is 19% higher than the race/ethnicity score of the entire section from 2014 to 2016, while it is roughly equal to the benchmark in 2013 which would be expected if teams were generally randomly assigned across this dimension. Further, we observe the increasing prevalence of teams with all White American students. The number of teams with all White American students was 1 in 2013, and average 4.7 after 2013 (Online Appendix Table 4).

The average Gender Score from 2014 to 2016 is 0.574, implying that, on average, 4 to 5 people have the same gender in a team of 6. The average team Gender Score is 12.38% higher in 2014-2016 than the section benchmark in 2014-2016, and it is lower than the benchmark in 2013, reflecting the team assignment scheme utilized by the MBA administration. In addition, in 2013, there are no teams with all male or all female members. From 2014 to 2016, there are, on average, 20 teams with all male members and 8.3 teams with all female members per year[12].

The average School Score is 0.018. Approximately 1 out of 4 teams will have a pair of students from the same school. The School Score is 20% higher than the section benchmark from 2014 to 2016, while it is 5% lower than the benchmark in 2013. It is interesting that the benchmark of School Score is much higher in 2013. This may due to higher proportion of top college graduates (41.2%) in 2013 compared to 2014 to 2016 (37%)[13]. The average Industry Score is 0.21, implying that, on average, approximately 3 people have the same industry background in a team of 6. The Industry Score is 8% higher than the section benchmark in 2014-2016. Comparing the 2013 cohort to the 2014-16 cohorts, homophily increases in all four

[12] See Online Appendix Table 4
[13] See Table I

dimensions in the 2014-2016 cohorts.

The HBS MBA Program office also provided the outcome of each team's micro-business. Outcomes were determined based upon the performance of the micro-business during IPO Day. Teams presented their micro-business first within their sections to a panel of judges that scored the teams based upon a variety of criteria. The top 3 teams within each section were then judged in a separate round to determine the overall class top 3. We coded outcomes into four binary indicators: (1) IPO Day: whether the team presented their micro-business on the IPO Day. Approximately 75% of the teams were determined to be sufficiently developed to present on IPO Day; (2) Viable: whether the team that presented on IPO Day was deemed by judges to be a viable business. Roughly 50% of all projects were deemed viable; (3) Section Top 3: whether the project was ranked in the top 3 of their section by a panel of judges. Approximately 20% of the projects were ranked in their section top 3; (4) Class Top 3: whether the project was top 3 in the entire class in a given year (2%).

We construct our performance measure based upon the median of the quantile of the team's outcome. For example, if a team did not present on IPO Day, their performance equals 0.125, i.e., 25% of teams do not present, hence the median of this quantile is 0.125. Similarly, if a team presented on IPO Day, but the project was deemed not viable, the performance equals 0.375. The quantile in which this project performs falls between 25% and 50% of the class. Projects that are deemed viable but are not top 3 in the section have performance equal to 0.65, as their quantile falls between 50% and 80%. Projects that are top 3 in the section but not in the class year top 3 have performance equal to 0.9, i.e., falling between 80% and 98%. Finally, if the project is top 3 in the entire class year, the performance is 0.99. Our performance measure is increasing in project outcome. The distribution of performance does not vary significantly by year.

Panel C of the Table XII provides correlation table between variables. We could interpret the results from the previous section through the lens of our score measures. From 2014 to 2016, years in which matching is voluntary, we observe highly positive correlation between team race/ethnicity score and school score, this is driven by White Americans and Asian Americans who attended top colleges. The correlation between gender score and industry score is also high driven by the high percentage of male students with finance and technology industry experience. In 2013, in which the matching was exogenously imposed by HBS, school score and industry score have slightly negative correlation with race/ethnicity score and gender score. There is also a high correlation between gender score and race/ethnicity score in 2013. Finally, race/ethnicity score is highly correlated with performance both in 2013 and in 2014-2016.

We split the sample into two groups: 2013 teams and 2014-2016 teams, and run OLS regression on each sample. Because team assignments in 2013 are exogenous, it provides a clean identification of the effect of diversity on performance when diversity is exogenously imposed. We estimate the following regression models:

$$Performance_i = b_{11} * \ Ethnicity \ \ Score_i + control + e_i$$

$$Performance_i = b_{21} * \ Gender \ Score_i + control + e_i$$

$$Performance_i = b_{31} * \ Education \ \ Score_i + control + e_i$$

$$Performance_i = b_{41} * \ Industry \ Score_i + control + e_i$$

Our performance measures are the median quantile of the team's project ranking. As our race/ethnicity (gender, education, or industry) score increases our team diversity decreases, i.e., teams with higher scores are more homogenous. Control variables include team size, percentage of students who graduated from a top college, and percentage of students who had start-up experience. Top college and start-up experience are potentially proxies for students' skill in starting a business and we expect these two variables to be positively correlated with performance.

Table XIII reports the regression result of diversity on performance. Panel A column 1 shows that one unit increase in our race/ethnicity score (less diversity) increases team performance by 0.482 (p<1%), or equivalently, one standard deviation increase in race/ethnicity score increases performance by 0.084[14]. Given the average performance of all teams is 0.5, this represents a 16.8% increase in performance. In other

[14] We simulated the distribution of race/ethnicity score under the assumption of random matching. The SD of race/ethnicity score is 0.174 (Online Appendix Table 6, Panel C). 0.174* 0.482= 0.084

words, in 2013 where teams were exogenously assigned, relatively less diverse teams (in terms of race/ethnicity) performed better than more diverse teams. Panel B of Table XIII reports the results of performance regression using 2014-2016 sample, where the team formation was endogenous. The coefficient on race/ethnicity score is still positive and significant, but the magnitude is less than half of the 2013 result. The difference between these two coefficients are statistically significant at 5% level[15]. These results suggest that voluntary team formation alleviates much of the underperformance of forced diversity. As a robustness test, we also use excess diversity score, defined as diversity score minus benchmark, as independent variables in Online Appendix Table 6. Our results are qualitatively identical with this adjustment.

In addition to race/ethnicity, lower diversity in educational background was also positively correlated with performance. A one unit increase in school score (less diversity background) increases performance by 92.5%. A one standard deviation increase in the school score increases team performance by 0.027[16], a 5.4% increase from the average performance. In column 6 of the panel A, the statistical significance on school score drops when we control for percentage of students who graduated from a top school and students who had start-up experience. Diversity in gender and past industry experience were not statistically significantly related to performance. Interestingly, the coefficients on school score and industry score reverse sign in 2014-2016 subsample (Panel B), but the coefficients remain statistically insignificant.

In Table XIV we look at the intersection of race/ethnicity and gender. Much like our diversity score variables for individual characteristics, we now calculate the race/ethnicity-gender diversity score by looking at the number of team members who share both the same race/ethnicity as well as gender. In column (1), we see that race/ethnicity score (lower diversity) in the 2013 cohort has a positive impact on performance. Once we include the race/ethnicity-gender diversity score in column (2), however, its magnitude is greatly reduced and becomes insignificant. The effect of the race/ethnicity-gender score is now large and statistically significant indicating that the negative relationship between race/ethnicity diversity and performance is driven by the intersection of race/ethnicity and gender. In columns (4) and (5) we find that the intersection

[15] Z = (0.482-0.176)/(sqrt(0.139^2+ 0.0536^2)=2.05 (Clogg et al. 1995)

[16] The SD of school score is 0.029 (Online Appendix Table 5, Panel C). 0.029*0.925= 0.027

effect is similar for both male and female students. Our result indicates that looking at multiple aspects of diversity at the same time may be important for understanding performance implications of diversity. In Panel B, we explore the relationship between race/ethnicity-gender and performance when team formation is endogenous. For teams from the 2014-2015 cohort, there is no relationship between the teams' race/ethnicity-gender score and performance. Allowing students to choose their team members eliminates the detrimental performance effects of diversity.

In Table XV, we investigate the relative impact of diversity on each measure of performance. We divide our performance measure into four dummy variables: ipo_day, viable, section top 3 and class year top 3. The results in panel A show that the higher race/ethnicity-gender diversity score increases the outcome in all four performance measures (i.e., less diversity is associated with higher outcomes for all four measures). The effect is relatively similarly across all four outcomes. The consistency of the race/ethnicity-gender diversity score to predict performance further supports a role for understanding more complex intersectional measures of diversity.

We explore the relationship between team diversity and performance when students were able to endogenously choose their team members in table XVI. To make the comparison of the performance implications comparable to the 2013 cohort when teams were exogenously defined, we include interactions for cohorts after 2013 and team characteristics. In columns (2) to (4), we find that the interaction of race/ethnicity-gender diveristy score and a dummy for post-2013 cohorts finds that the interaction is large, negative, and of similar magnitude to the coefficient on race/ethnicity-gender score. The result indicates that the negative effects of forced diversity on the race/ethnicity-gender intersection is eliminated when teams are endogenously formed.

The analysis of looking at diversity along two dimensions (race/ethnicity and gender) provides two important insights. First, the analysis demonstrates the importance of looking at the intersection of attributes. Our results indicate that there are profound differences between men and women in terms of homophily based upon race/ethnicity. There are also important performance implications that are discerned when looking at diversity along the intersection of race/ethnicity and gender. Second, we find that when team formation process is forced, more diverse teams underperform more homogenous team (in terms of race/ethnicity-gender). When team formation process is voluntary, such underperformance is alleviated. In other words, forced diversity does not guarantee harmony, as biases may still exist within the team. In fact, research has shown that mandatory diversity training can reduce diversity in organizations (Dobbin and Kalev 2016; Dobbin, Kalev and Kelly 2007).

One limitation of our results on race/ethnicity-gender is that it lacks generalizability beyond the range of diversity we see in our sample. Because the assignment of teams was done by the school with the intent of having relatively diverse teams, most teams in 2013 were at least modestly diverse in terms of race/ethnicity and gender. In Figure 2, the graph plots team performance against race/ethnicity score. The race/ethnicity score for most of teams falls below 50%, with the mean equal to 23.7%. This implies that, on average, a team of 6 is comprised of students from 3-4 different ethnic groups[17]. Since there are too few extremely homogenous teams, we are not able to draw a conclusion on the effect of race/ethnic diversity across the entire spectrum of diversity. Similarly, Figure 3 shows that gender score for the Class of 2013 cohort concentrates between 40%-45% and has very little variation.

5.2. Student-Professor/Judges Shared Gender and Performance

The role of diversity has been examined not only on a horizontal, i.e., team member setting, but vertically, i.e., supervisor to subordinate level. In our setting, we explore the vertical relationships in the Field 3 setting; the role of the professor/section leader and the role of judges. The results in this section can also be viewed as causal because from the teams' perspectives, the gender of the professor/section leader is exogenous. We examine the effect of student group-professor and student group-judge ties on performance. We examine whether greater overlap of team attributes with attributes of students' professor and/or judges influences outcomes. In particular, we look at gender ties between the professor or judges and students.

[17] For a team of 6, if 3 people are white, 1 person is Asian American, 1 person is Lantinx American and another person is from Europe, this team will have race/ethnicity score = 315=20%

As discussed earlier, the outcomes for each team was determined through the development of a micro-business and evaluation of those business by a panel of judges. Each team presented its project to a panel of judges at the end of the Field 3 class. These presentations were judged initially within sections, i.e., each section of 90 students had their businesses evaluated relative to their section peers. The key judge on each panel was the section leader. The section leaders was the member of the HBS faculty who supervised the section over the course of the entire year. The role of the section leader was critical to the performance of the team because of their role teaching and advising students over the course of the year.

Each panel then had an additional three or four judges from industry. Because of the important role played by the section leader, we separately analyzed the attributes of the section leader and the judges. Table XVII reports the summary statistics on section leader and judges' gender and race/ethnicity from 2014 to 2016. HBS did not have data on section leaders and judges for the class of 2013. Among the ten section leaders in each class year, there were two or three females each year, one or two Black section leaders, one Lantinx, one South Asian, and six to seven White section leaders. There were no East Asian section leaders in our sample. There were more than 40 judges in each class year in our sample. The percentage of female judge increased from 14% in 2014 to 34% in 2016, and the percentage of ethnic minority judge varied between 5% and 10%. Because there were so few minority judges, we focus on the gender ties between the section leader or judges and the students.

In Figure 4, we sort all teams into four quantiles based on the percentage of female team members. Conditional on the section leader being female, team performance increases monotonically as the percentage of women on the team increases. Specifically, the percentages of teams presenting on the IPO day, being rated as viable and being ranked section top 3 are 53%, 28% and 8% respectively for teams with a low fraction of members (Quantile 1) in sections with female section leaders. These numbers increase to 90%, 76% and 38% respectively for teams with a high female percentage (Quantile 4) in sections with female section leaders. The economic magnitude of performance increase is significant. For instance, teams with the highest number of female members were four times more likely to be in the section top 3 than teams with few or no female members if the section leader was a female. However, we do not find any relationship between male section leaders and the performance of male dominated teams. The second graph in Figure 4 shows that in section with male section leaders, team performance does not vary with the percentage of female (or male) in the team. The results suggest that performance of women may be improved with female mentors and supervisors.

Table XVIII presents the regression results for performance conditional on shared gender attributes of the Field 3 teams and the section leader or judges. The dependent variable is team performance, and the key independent variable is the interaction term between female section leader and percentage of women on a team. Consistent with Figure 4, the coefficient on the interaction term is positive and statistically significant at the 1% level indicating teams with a greater number of female members perform significantly better in sections with female section leaders.

We do not find any performance impact of female judges for team with a greater number of female team members. In the second column of Table XVIII, we regress performance on the interaction term between Have Female Judge and percentage of females on the team. Have Female Judge is a dummy variable equals to 1 if there is at least one female judge on the panel. The coefficient on the interaction term is positive, but not statistically significant. The magnitude of the coefficient is also much smaller. We believe that this highlights not the more favorable ranking of teams with female team members by female judges, but rather by female section leaders providing better mentorship throughout the year and during the Field 3 course for the woman.

6. Conclusion and Discussion

In this paper we examine the effect of homophily on entrepreneurial team formation and the effects of diversity on performance using a unique dataset of MBA students. We also investigate the causal relationship between randomly-assigned horizontal (team) diversity and performance as well as the effect of shared gender ties (vertical diversity) between team members and section leaders/judges on team performance. Our results are particularly important because the goal was to form real micro-businesses and many of those formed during Field 3 continued after the course with some attracting significant outside funding. Additionally, a significant fraction of HBS students for the classes of 2013-2016 pursued to careers in venture capital and startups.

In our sample, the strength of endowed shared attributes demographic (gender and race/ethnicity) for team formation is much stronger than team choice based upon acquired characteristics (education and industry). Specifically, shared gender and race/ethnicity increased the probability of becoming team members by 25%. Shared education and past industry experience increased the probability of becoming team members by 17% and 11% respectively. The strength of homophily in school ties and shared industry experience is significantly higher for males than it is for females. Male students exhibited significantly greater propensity to match with others from the same school or who worked in the same industry, particularly male students who had worked in technology and finance industry.

While prior research has shown that homophily is often stronger among smaller groups, our results indicate varying results based upon subgroup size. The effect on propensity to pair was strongest among international students from the same region, students who attended non-Ivy league schools, and students who worked in non-finance, non-consulting, or non-technology industries (small industries).

When we look at the effect of diversity on team performance, we find that teams in the 2013 cohort for which team membership was exogenously assigned, greater diversity across the intersection of race/ethnicity and gender was associated with poorer perform than more homogenous teams. This is consistent with forced diversity increasing conflicts and hindering communication efficiency within the group. When team formation was endogenous, however, such underperformance was not present. Second, we find that shared gender ties for female students with their professor/section leader improved performance of teams with more females. The results highlight the potentially important role that female mentors provide for the performance of females in a business setting.

Our results have important real-world implications given a significant portion of the MBA students will be working in the start-ups and venture capital industry. First, documenting the relative strength of the forces that cause people to associate in a business setting sheds light on which factors are critical for limiting diversity in organizations like venture capital and entrepreneurship. To the extent that we observe the significant effect of various measures of homophily among MBA students forming real micro-businesses, it is reasonable to infer that such homophily also exists in start-up team formation, venture capital investing, and hiring. If one goal of research is to identify the primary drivers that limit diversity, understanding the relative contribution of various factors is critical.

Second, in order to ensure benefits of diversity in entrepreneurship, one needs to think carefully about how subtle treatment effects may dislodge the biases that exist. We find that forced diversity does not improve team performance. To harness the full benefits of diversity, policymakers first need to eliminate bias against underrepresented groups. For instance, Calder-Wang and Gompers (2020) show that when venture capitalists have more daughters, they are more likely to hire a female investor, and subsequent firm performances improve after hiring. Our hope is the more research can explore the effectiveness of such subtle treatment effects for promoting greater organizational diversity.

Our results for the performance effects of vertical diversity have potentially important implications for female-led startups. The relationship between female teams and female section leaders in our setting resembles the relationship between female entrepreneurs and female VCs. Calder-Wang and Gompers (2020) and Gompers et al. (2020) document that females VC (and entrepreneurs) are underrepresented and under-supported. An effective policy to help women succeed in entrepreneurship and venture capital needs to take advantage of the superior mentorship that female venture capitalists may be able to provide to female entrepreneurs. This argues for increasing the number of woman in venture capital as a prerequisite for greater representation and performance of female entrepreneurs.

Finally, there are two limitations to our results. First, we define homophily as the probability of two students with the same characteristics being matched (i.e., gender, race/ethnicity), however, this measure may capture factors that are unobservable but correlated with the observed characteristics (i.e., career goals, etc.). Second, we do not attempt to trace the source of the desire to match. There are different views on why homophily exists in the economics literature. One view is that homophily is in an agent's preference function (Jackson, 2014). Another view is that homophily is the result of agents' strategic decisions to reduce uncertainty (Kets and Sandroni, 2016). Presumably, homophily that arises from these two different motivations may have different implications on the team formation process and performance. We do not, however, distinguish between these motivations. Additional research in this area is also warranted and important to answering these critical questions.

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Figure 1. Probability of Matching Conditional on Same Race/ethnicity, Gender, School, Industry

This figure plots the probability of a student being matched to another student with same race/ethnicity, gender, school or industry background. In 2013, the matching is randomized by the school. From 2014 to 2016, the matching process is initiated by students.

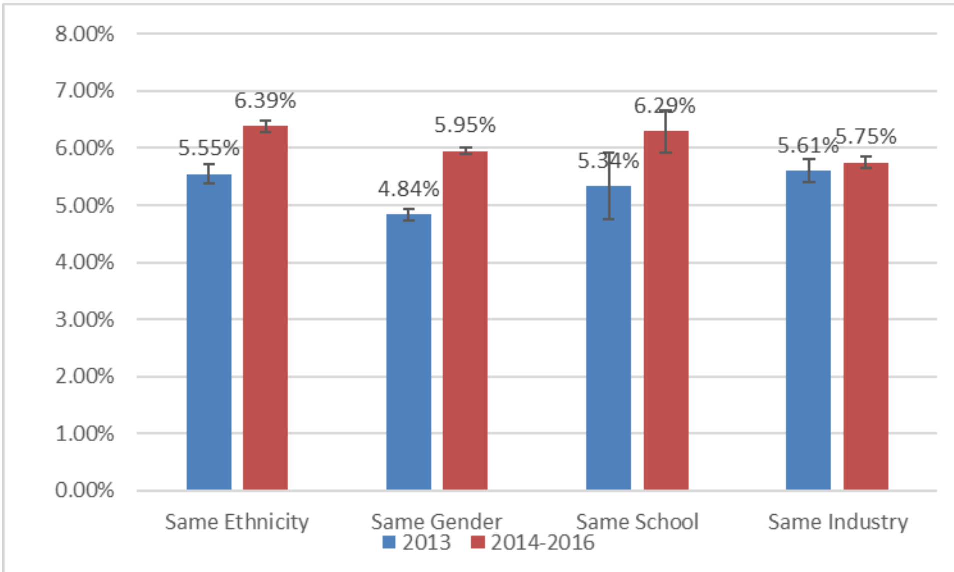


Table I. Summary Statistics of MBA Backgrounds

Table I presents the summary statistics of HBS MBA background from 2013 to 2016.

	2013	**2014**	**2015**	**2016**	**Total**
# of Students	907	915	931	931	3684
Team Size	6.06	6.13	6.25	5.2	5.91
Age	28.89	29.1	29.07	29.21	29.06
% of Female	39.25%	40.44%	41.14%	41.35%	40.55%
% of White American	37.16%	39.45%	37.70%	39.53%	38.46%
% of Asian American	14.33%	11.80%	11.92%	11.82%	12.46%
% of Black	4.52%	5.68%	5.59%	5.80%	5.40%
% of Lantinxs American	3.75%	4.26%	4.83%	3.65%	4.13%
% International	34.07%	34.32%	34.59%	37.06%	35.02%
Employment					
% Finance Background	29.66%	29.29%	33.83%	36.84%	32.44%
% Consulting Background	21.94%	20.55%	20.62%	25.13%	22.07%
% Technology Background	9.04%	9.84%	10.85%	13.96%	10.94%
% Healthcare Background	8.16%	7.87%	6.34%	8.92%	7.82%
Education Background					
% Ivy League	26.90%	25.03%	23.63%	22.99%	24.62%
% Top School	41.23%	37.92%	38.35%	34.26%	37.92%

Table II. Past Employment and Education Background

This table summarizes the employment and education background of HBS MBAs.

Rank	Company	Obs	Percent
1	McKinsey & Company	308	8.40%
2	Bain & Company	184	5.02%
3	Boston Consulting Group	173	4.72%
4	Goldman Sachs	166	4.53%
5	Morgan Stanley	138	3.77%
6	Google	78	2.13%
7	Credit Suisse	54	1.47%
8	J.P. Morgan	47	1.28%
9	Deloitte Consulting	45	1.23%
10	Booz & Company	44	1.20%
11	UBS Investment Bank	42	1.15%
12	Bank of America Merrill Lynch	38	1.04%
13	Bain Capital	32	0.87%
14	United States Marine Corps	29	0.79%
15	Accenture	26	0.71%
15	Citigroup	26	0.71%
15	Barclays Capital	25	0.68%
15	Oliver Wyman	25	0.68%
15	The Blackstone Group	25	0.68%
20	Deutsche Bank	24	0.65%
20	The Carlyle Group	24	0.65%
	Top 20 Total	1553	42.37%
	Sample Total	3,665	

Rank	School	Obs	Percent
1	Harvard University	286	8.17%
2	Stanford University	157	4.49%
3	University of Pennsylvania	151	4.31%
4	Yale University	124	3.54%
5	Princeton University	102	2.91%
6	Duke University	81	2.31%
7	MIT	72	2.06%
8	United States Military Academy	70	2.00%
9	Dartmouth College	67	1.91%
10	University of California	64	1.83%
11	Cornell University	63	1.80%
12	Georgetown University	60	1.71%
13	Brown University	57	1.63%
13	Columbia University	57	1.63%
15	Northwestern University	56	1.60%
16	University of Virginia	52	1.49%
17	Indian Institute of Technology	50	1.43%
18	University of Texas	45	1.29%
19	University of Michigan	38	1.09%
20	Brigham Young University	37	1.06%
	Top 20 Total	1689	48.26%
	Sample Total	3,500	

Table III. Matching Regression

This table reports the regression results of matching on race/ethnicity (gender, education, industry) ties. Each observation is a student-student pair. The dependent variable real_match equals to 1 if the pair is in the same team. The independent variables race/ethnicity (gender, education, industry) match equals to 1 if the pair has the same race/ethnicity (gender, education, industry). Robust standard errors are clustered at the student level (i.e. one student is matched to 89 potential matches, and they are treated as 1 observation).

Panel A. 2014-2016	(1)	(2)	(3)	(4)	(5)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match
Race/ethnicity Tie	0.0138***				0.0136***
	(0.00116)				(0.00116)
Gender Tie		0.0133***			0.0131***
		(0.00107)			(0.00106)
School Tie			0.00976**		0.00855**
			(0.00384)		(0.00383)
Industry Tie				0.00637***	0.00625***
				(0.00120)	(0.00120)
Team Mem Count	0.0106***	0.0109***	0.0108***	0.0107***	0.0105***
	(0.000114)	(5.65e-05)	(2.42e-05)	(5.04e-05)	(0.000132)
2015.ClassYear	-0.000746***	-0.000957***	-0.000983***	-0.00116***	-0.000895***
	(0.000123)	(6.21e-05)	(2.52e-05)	(5.48e-05)	(0.000145)
2016.ClassYear	-0.00121***	-0.000945***	-0.00105***	-0.00167***	-0.00174***
	(0.000162)	(7.82e-05)	(3.07e-05)	(0.000134)	(0.000223)
Constant	-0.0112***	-0.0167***	-0.00958***	-0.00981***	-0.0186***
	(0.000692)	(0.000680)	(0.000148)	(0.000273)	(0.000974)
Observations	254,318	254,318	254,318	254,318	254,318
R-squared	0.002	0.002	0.001	0.001	0.003
Panel B.2013	(6)	(7)	(8)	(9)	(10)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match
Race/ethnicity Tie	-0.00116				-0.000837
	(0.00170)				(0.00170)
Gender Tie		-0.0166***			-0.0166***
		(0.000716)			(0.000716)
School Tie			-0.00303		-0.00284
			(0.00604)		(0.00605)
Industry Tie				-0.000367	-0.000271
				(0.00215)	(0.00215)
Team Mem Count	0.0106***	0.0106***	0.0106***	0.0106***	0.0106***
	(5.93e-05)	(0.000220)	(5.49e-05)	(5.56e-05)	(0.000218)
Constant	-0.00772***	0.000630	-0.00788***	-0.00789***	0.000883
	(0.000490)	(0.00138)	(0.000359)	(0.000454)	(0.00143)
Observations	81,368	81,368	81,368	81,368	81,368
R-squared	0.000	0.001	0.000	0.000	0.001

Table IV. Matching Regression: Endowed Demographic vs. Acquired Characteristics

This table reports the regression results of matching on endowed demographic and acquired characteristics. Each observation is a student-student pair. In Panel A. the dependent variable real match equals to 1 if the pair is in the same team. The independent variables Endowed Demographic Match equals to 1 if the pair has the same race/ethnicity or gender. Acquired Characteristics Match equals to 1 if the pair has the same education or industry. Panel B. reports F statistics of null hypothesis that the coefficient on Endowed Demographic Match equals to the coefficient on Acquired Characteristics Match. Robust standard errors are clustered at the student level (i.e. one student is matched to 89 potential matches, and they are treated as 1 clustering group).

Panel A.

	2014-2016	2013
	(1)	(2)
VARIABLES	Real Match	Real Match
Endowed Demographic Match	0.0151***	-0.0149***
	(0.00102)	(0.00110)
Acquired Characteristics Match	0.00662***	-0.000386
	(0.00116)	(0.00210)
Team Mem Count	0.0106***	0.0107***
	(9.18e-05)	(0.000214)
2015.ClassYear	-0.000963***	
	(0.000100)	
2016.ClassYear	-0.00172***	
	(0.000173)	
2013.ClassYear		-
Constant	-0.0189***	0.000764
	(0.000811)	(0.00149)
Observations	254,318	81,368
R-squared	0.002	0.001

Panel B.

Endowed Demographic Match =Acquired Characteristics Match	F statistics
2014-2016	32.3
2013	37.04

Table V. Race/ethnicity Match Regression

This table reports the regression results of the probability of match on race/ethnicity ties. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables are race/ethnicity characteristics equals to 1 if both students share the same race/ethnicity. Robust standard errors are clustered at the student level (i.e. one student is matched to 89 potential matches, and they are treated as 1 clustering group).

2014-2016	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match
Both White	0.0108***					0.0118***
	(0.00114)					(0.00116)
Both Asian American		0.0116***				0.0145***
		(0.00421)				(0.00423)
Both Black			0.00956			0.0126
			(0.00869)			(0.00870)
Both Lantinx American				5.47e-05		0.00306
				(0.0125)		(0.0125)
Both International					0.0377***	0.0401***
					(0.00506)	(0.00508)
Team Mem Count	0.0106***	0.0108***	0.0108***	0.0108***	0.0109***	0.0107***
	(0.000104)	(2.93e-05)	(2.32e-05)	(2.37e-05)	(4.89e-05)	(9.12e-05)
2015.ClassYear	-0.000773***	-0.000982***	-0.000983***	-0.000983***	-0.00105***	-0.000827***
	(0.000111)	(3.18e-05)	(2.38e-05)	(2.42e-05)	(5.33e-05)	(9.79e-05)
2016.ClassYear	-0.00121***	-0.00105***	-0.00104***	-0.00104***	-0.000966***	-0.00114***
	(0.000146)	(3.75e-05)	(2.85e-05)	(3.03e-05)	(6.73e-05)	(0.000126)
Constant	-0.0103***	-0.00960***	-0.00957***	-0.00951***	-0.0106***	-0.0118***
	(0.000613)	(0.000179)	(0.000151)	(0.000153)	(0.000325)	(0.000564)
Observations	254,318	254,318	254,318	254,318	254,318	254,318
R-squared	0.001	0.001	0.001	0.001	0.001	0.002
2013	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match
Both White	1.17e-05					-0.000239
	(0.00174)					(0.00177)
Both Asian American		0.00222				0.00193
		(0.00508)				(0.00512)
Both Black			0.000214			-3.45e-05
			(0.0182)			(0.0182)
Both Lantinx American				0.00439		0.00414
				(0.0219)		(0.0219)
Both International					-0.0158***	-0.0158***
					(0.00530)	(0.00534)
Team Mem Count	0.0106***	0.0106***	0.0106***	0.0106***	0.0106***	0.0106***
	(6.02e-05)	(8.38e-05)	(7.71e-05)	(5.69e-05)	(7.45e-05)	(0.000117)
Constant	-0.00794***	-0.00816***	-0.00794***	-0.00793***	-0.00750***	-0.00766***
	(0.000372)	(0.000591)	(0.000451)	(0.000345)	(0.000478)	(0.000795)
Observations	81,368	81,368	81,368	81,368	81,368	81,368
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Table VI. Gender Match Regression

This table reports the regression results of the probability of match on Gender ties. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables are *Both Male (Female)* equals to 1 if both students are male (female). Robust standard errors are clustered at the student level.

	2014-2016	2014-2016	2013	2013
	(1)	(2)	(3)	(4)
VARIABLES	Real Match	Real Match	Real Match	Real Match
Both Male	0.00723***		-0.00897***	
	(0.000868)		(0.000596)	
Both Female		0.0122***		-0.0161***
		(0.00130)		(0.000897)
Team Mem Count	0.0109***	0.0107***	0.0106***	0.0106***
	(9.28e-05)	(0.000106)	(0.000320)	(0.000370)
2015.ClassYear	-0.000934***	-0.00104***		
	(0.000101)	(0.000115)		
2016.ClassYear	-0.000880***	-0.00123***		
	(0.000131)	(0.000151)		
Constant	-0.0126***	-0.0109***	-0.00468**	-0.00550**
	(0.000680)	(0.000654)	(0.00195)	(0.00225)
Observations	254,318	254,318	81,368	81,368
R-squared	0.001	0.001	0.001	0.001

Table VII. Gender Match Breakdown by Race/ethnicity

This table reports the regression results of the probability of match on Gender and race/ethnicity ties. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variable is race/ethnicity tie. First two columns look at the matching results of male subsample, last two columns look at the female subsample. Robust standard errors are clustered at the student level.

	2014-2016			
	Male	Male	Female	Female
	(1)	(2)	(3)	(4)
VARIABLES	Real Match	Real Match	Real Match	Real Match
Race/ethnicity Tie	0.0154***		0.0114***	
	(0.00151)		(0.00180)	
Both White		0.0135***		0.00914***
		(0.00150)		(0.00180)
Both Asian American		0.0147**		0.0141***
		(0.00672)		(0.00543)
Both Black		0.00326		0.0245*
		(0.0107)		(0.0142)
Both Lantinx American		0.0159		-0.0249
		(0.0158)		(0.0186)
Both International		0.0427***		0.0363***
		(0.00650)		(0.00815)
Team Mem Count	0.0105***	0.0106***	0.0107***	0.0107***
	(0.000170)	(0.000142)	(0.000143)	(0.000106)
2015.ClassYear	-0.000759***	-0.000802***	-0.000742***	-0.000878***
	(0.000181)	(0.000146)	(0.000159)	(0.000126)
2016.ClassYear	-0.00112***	-0.00103***	-0.00132***	-0.00122***
	(0.000235)	(0.000192)	(0.000214)	(0.000160)
Constant	-0.0111***	-0.0118***	-0.0112***	-0.0116***
	(0.00101)	(0.000856)	(0.000896)	(0.000698)
Observations	150,093	150,093	104,225	104,225
R-squared	0.002	0.002	0.001	0.002

Table VIII. Education Match Regression

This table reports the regression results of the probability of match on education ties. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables *Both Same (Non) Ivy School* equals to 1 if both students are graduated from the same (Non) Ivy schools. Robust standard errors are clustered at the student level.

	2014-2016	2014-2016	2014-2016	2014-2016	2013	2013	2013	2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match
School Tie	0.00976**				-0.00303			
	(0.00384)				(0.00604)			
Both Ivy School		0.00219		0.00232		0.00623		0.00611
		(0.00490)		(0.00490)		(0.00852)		(0.00852)
Both Non Ivy			0.0188***	0.0189***			-0.0145*	-0.0144*
			(0.00600)	(0.00600)			(0.00821)	(0.00821)
Team Mem Count	0.0108***	0.0108***	0.0108***	0.0108***	0.0106***	0.0106***	0.0106***	0.0106***
	(2.42e-05)	(2.30e-05)	(2.38e-05)	(2.45e-05)	(5.49e-05)	(5.64e-05)	(6.04e-05)	(6.35e-05)
2015.ClassYear	-0.000983***	-0.000981***	-0.000996***	-0.000994***				
	(2.52e-05)	(2.37e-05)	(2.64e-05)	(2.65e-05)				
2016.ClassYear	-0.00105***	-0.00104***	-0.00104***	-0.00105***				
	(3.07e-05)	(2.83e-05)	(3.04e-05)	(3.08e-05)				
Constant	-0.00958***	-0.00952***	-0.00960***	-0.00961***	-0.00788***	-0.00803***	-0.00786***	-0.00795***
	(0.000148)	(0.000137)	(0.000148)	(0.000148)	(0.000359)	(0.000366)	(0.000372)	(0.000408)
Observations	254,318	254,318	254,318	254,318	81,368	81,368	81,368	81,368
R-squared	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000

Table IX. Education Match Regression by Gender

This table reports the regression results of the probability of match on education ties by gender. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables *Both Same (Non) Ivy School* equals to 1 if both students are graduated from the same (Non) Ivy schools. Robust standard errors are clustered at the student level.

	2014-2016			
	Male	Male	Female	Female
	(1)	(2)	(3)	(4)
VARIABLES	Real Match	Real Match	Real Match	Real Match
School Tie	0.0171***		0.000960	
	(0.00540)		(0.00540)	
Both Ivy School		0.00893		-0.00391
		(0.00714)		(0.00671)
Both Non Ivy		0.0250***		0.00898
		(0.00804)		(0.00889)
Team Mem Count	0.0108***	0.0108***	0.0108***	0.0108***
	(3.59e-05)	(3.55e-05)	(3.42e-05)	(3.65e-05)
2015.ClassYear	-0.000971***	-0.000969***	-0.000993***	-0.00102***
	(3.66e-05)	(3.65e-05)	(3.67e-05)	(4.40e-05)
2016.ClassYear	-0.00106***	-0.00106***	-0.00106***	-0.00105***
	(4.53e-05)	(4.42e-05)	(4.35e-05)	(4.68e-05)
Constant	-0.00961***	-0.00961***	-0.00948***	-0.00953***
	(0.000212)	(0.000209)	(0.000220)	(0.000231)
Observations	150,093	150,093	104,225	104,225
R-squared	0.001	0.001	0.001	0.001

Table X. Past Employment Regression

This table reports the regression results of the probability of match on education ties. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables are industry backgrounds equals to 1 if both students worked in the same industry prior to MBA. Robust standard errors are clustered at the student level.

2014-2016	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match
Industry Tie	0.00637***					
	(0.00120)					
Both Finance Industry		0.00346**				0.00418***
		(0.00142)				(0.00144)
Both Tech Industry			0.00362			0.00455
			(0.00378)			(0.00378)
Both Consulting Industry				0.00354*		0.00432**
				(0.00190)		(0.00191)
Both Small Industry					0.0212***	0.0218***
					(0.00391)	(0.00392)
Team Mem Count	0.0107***	0.0107***	0.0108***	0.0108***	0.0109***	0.0108***
	(5.04e-05)	(5.04e-05)	(2.36e-05)	(2.81e-05)	(3.59e-05)	(5.25e-05)
2015.ClassYear	-0.00116***	-0.00107***	-0.000991***	-0.000985***	-0.000964***	-0.00108***
	(5.48e-05)	(4.73e-05)	(2.57e-05)	(2.66e-05)	(3.55e-05)	(5.02e-05)
2016.ClassYear	-0.00167***	-0.00129***	-0.00108***	-0.00110***	-0.00112***	-0.00154***
	(0.000134)	(0.000113)	(5.04e-05)	(4.57e-05)	(5.00e-05)	(0.000132)
Constant	-0.00981***	-0.00929***	-0.00952***	-0.00978***	-0.0102***	-0.0103***
	(0.000273)	(0.000229)	(0.000141)	(0.000216)	(0.000255)	(0.000309)
Observations	254,318	254,318	254,318	254,318	254,318	254,318
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
2013	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Real Match	Real Match	Real Match	Real Match	Real Match	Real Match
Industry Tie	-0.000367					
	(0.00215)					
Both Finance Industry		-0.000909				-0.000839
		(0.00254)				(0.00258)
Both Tech Industry			0.0215**			0.0213**
			(0.0102)			(0.0103)
Both Consulting Industry				-0.00538		-0.00517
				(0.00380)		(0.00384)
Both Small Industry					0.00692	0.00681
					(0.00542)	(0.00544)
Team Mem Count	0.0106***	0.0106***	0.0106***	0.0106***	0.0106***	0.0107***
	(5.56e-05)	(5.97e-05)	(9.53e-05)	(7.12e-05)	(6.61e-05)	(0.000111)
Constant	-0.00789***	-0.00788***	-0.00818***	-0.00776***	-0.00817***	-0.00817***
	(0.000454)	(0.000402)	(0.000593)	(0.000451)	(0.000443)	(0.000759)
Observations	81,368	81,368	81,368	81,368	81,368	81,368
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Table XI. Past Employment Regression by Gender

This table reports the regression results of the probability of match on education ties by gender. Each observation is a student-student pair. The dependent variable real match equals to 1 if the students are teammates. The independent variables are industry backgrounds equals to 1 if both students worked in the same industry prior to MBA. Robust standard errors are clustered at the student level.

	2014-2016			
	Male	Male	Female	Female
	(1)	(2)	(3)	(4)
VARIABLES	Real Match	Real Match	Real Match	Real Match
Industry Tie	0.00887***		0.00292	
	(0.00159)		(0.00181)	
Both Finance Industry		0.00801***		-0.00172
		(0.00188)		(0.00219)
Both Tech Industry		0.00869*		-0.00220
		(0.00484)		(0.00603)
Both Consulting Industry		0.00259		0.00564**
		(0.00278)		(0.00265)
Both Small Industry		0.0214***		0.0226***
		(0.00487)		(0.00659)
Team Mem Count	0.0106***	0.0107***	0.0108***	0.0109***
	(8.76e-05)	(9.53e-05)	(5.00e-05)	(7.81e-05)
2015.ClassYear	-0.00107***	-0.00108***	-0.00114***	-0.000823***
	(7.66e-05)	(6.68e-05)	(0.000104)	(0.000132)
2016.ClassYear	-0.00182***	-0.00178***	-0.00139***	-0.00113***
	(0.000179)	(0.000181)	(0.000212)	(0.000223)
Constant	-0.00976***	-0.00998***	-0.00966***	-0.0106***
	(0.000468)	(0.000533)	(0.000295)	(0.000523)
Observations	150,093	150,093	104,225	104,225
R-squared	0.001	0.001	0.001	0.001

Table XII. Summary Statistics on Team Homophily and Performance

This table reports the summary statistics on the team homophily scores and performance.

Panel A. Homophily Measures								
2013								
Variable	Obs	Mean	Benchmark	Mean/Benchmark	Std. Dev.	SE	Min	Max
Team Member Count	150	6.047			0.268	0.022	5.0	7.0
Race/ethnicity Score	150	0.237	0.242	98.01%	0.166	0.014	0.0	1.0
Gender Score	150	0.444	0.518	85.71%	0.038	0.003	0.4	0.7
School Score	150	0.017	0.018	95.75%	0.039	0.003	0.0	0.2
Industry Score	150	0.163	0.164	99.65%	0.136	0.011	0.0	0.9
2014								
Variable	Obs	Mean	Benchmark	Mean/Benchmark	Std. Dev.	SE	Min	Max
Team Member Count	150	6.100			0.414	0.034	5.0	7.0
Race/ethnicity Score	150	0.290	0.247	117.70%	0.214	0.017	0.0	1.0
Gender Score	150	0.582	0.513	113.46%	0.216	0.018	0.4	1.0
School Score	150	0.017	0.015	110.82%	0.035	0.003	0.0	0.2
Industry Score	150	0.181	0.153	118.26%	0.164	0.013	0.0	1.0
2015								
Variable	Obs	Mean	Benchmark	Mean/Benchmark	Std. Dev.	SE	Min	Max
Team Member Count	150	6.207			0.496	0.040	5.0	7.0
Race/ethnicity Score	150	0.271	0.232	116.89%	0.228	0.019	0.0	1.0
Gender Score	150	0.558	0.511	109.21%	0.202	0.017	0.4	1.0
School Score	150	0.019	0.016	115.87%	0.039	0.003	0.0	0.2
Industry Score	150	0.183	0.183	99.99%	0.145	0.012	0.0	0.7
2016								
Variable	Obs	Mean	Benchmark	Mean/Benchmark	Std. Dev.	SE	Min	Max
Team Member Count	180	5.172			0.393	0.029	4.0	6.0
Race/ethnicity Score	180	0.280	0.230	122.06%	0.241	0.018	0.0	1.0
Gender Score	180	0.582	0.510	114.11%	0.227	0.017	0.4	1.0
School Score	180	0.019	0.015	133.33%	0.047	0.004	0.0	0.3
Industry Score	180	0.255	0.235	108.59%	0.177	0.013	0.0	1.0
2014-2016 Average								
Variable	Obs	Mean	Benchmark	Mean/Benchmark	Std. Dev.	SE	Min	Max
Team Member Count	480	5.785			0.644	0.029	4.0	7.0
Race/ethnicity Score	480	0.281	0.236	119.04%	0.228	0.010	0.0	1.0
Gender Score	480	0.574	0.511	112.38%	0.216	0.010	0.4	1.0
School Score	480	0.018	0.015	120.60%	0.041	0.002	0.0	0.3
Industry Score	480	0.210	0.193	108.45%	0.167	0.008	0.0	1.0

Panel B. Performance Measures

Class Year	Freq.	ipo year	viable	section top 3	classytop3	Performance	SD
2013	150	78.67%	46.67%	20.00%	2.67%	0.502	0.275
2014	150	70.00%	39.33%	20.00%	2.00%	0.460	0.290
2015	150	73.33%	55.33%	20.00%	2.00%	0.512	0.287
2016	180	76.11%	52.78%	16.67%	2.22%	0.504	0.272
Total	630	74.60%	48.73%	19.05%	2.22%	0.495	0.281

Panel C. Correlation Between Variables

2014-2016	Race/ethnicity Score	Gender Score	School Score	Industry Score	Performance
Race/ethnicity Score	1				
Gender Score	-0.0262	1			
School Score	0.1415	-0.016	1		
Industry Score	0.0403	0.1253	0.0791	1	
Performance	0.1556	0.0203	-0.0042	-0.0355	1

2013	Race/ethnicity Score	Gender Score	School Score	Industry Score	Performance
Race/ethnicity Score	1				
Gender Score	0.1013	1			
School Score	-0.0166	-0.017	1		
Industry Score	-0.0371	-0.0819	0.0084	1	
Performance	0.2907	0.0324	0.1303	0.0309	1

Table XIII. Homophily and Performance Regression

This table regresses team performance on team diversity scores. The dependent variable Performance=0.125 if the team does not present on IPO day (0-25%), =0.375 if present but not viable (25-50%), =0.65 if viable but not top 3 (50-80%), =0.9 if top 3 in section (80-98%), =0.99 if top 3 in class year (98-100%). The independent variables are diversity scores described in the paper. Robust standard error is clustered at year-section level. Each coefficient's standard error appears directly below the coefficient estimate. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A. 2013	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			Performance			
Race/ethnicity Score	0.482***				0.488***	0.450***
	(0.110)				(0.105)	(0.0961)
Gender Score		0.211			0.0249	0.0802
		(0.678)			(0.658)	(0.627)
School Score			0.925		0.958*	0.809
			(0.519)		(0.476)	(0.469)
Industry Score				0.0635	0.0842	0.0719
				(0.134)	(0.165)	(0.179)
Top School Ratio						0.0845
						(0.0789)
Start-up Ratio						0.529
						(0.363)
Team Mem Count	0.0471	0.0402	0.0491	0.0433	0.0538	0.0515
	(0.0593)	(0.0713)	(0.0653)	(0.0689)	(0.0569)	(0.0656)
Constant	0.585	0.377	1.115	0.294	1.576*	1.383
	(0.358)	(0.662)	(0.723)	(0.429)	(0.844)	(0.894)
Observations	150	150	150	150	150	150
R-squared	0.087	0.003	0.019	0.003	0.107	0.122

Panel B. 2014-2016	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			Performance			
Race/ethnicity Score	0.176***				0.185***	0.168***
	(0.0542)				(0.0556)	(0.0600)
Gender Score		0.0273			0.0434	0.0641
		(0.0585)			(0.0593)	(0.0608)
School Score			-0.0915		-0.195	-0.298
			(0.300)		(0.295)	(0.315)
Industry Score				-0.110	-0.121	-0.113
				(0.0837)	(0.0825)	(0.0839)
Top School Ratio						0.0907
						(0.0604)
Start-up Ratio						0.341**
						(0.138)
Team Mem Count	0.0885***	0.0991***	0.0997***	0.105***	0.0942***	0.0847***
	(0.0262)	(0.0270)	(0.0266)	(0.0278)	(0.0273)	(0.0292)
Constant	0.0455	-0.133	-0.238	-0.268	-0.256	-0.341
	(0.165)	(0.178)	(0.314)	(0.200)	(0.313)	(0.309)
Fixed Effects	Year	Year	Year	Year	Year	Year
Observations	480	480	480	480	480	480
R-squared	0.049	0.030	0.030	0.033	0.056	0.074

Table XIV. Ethnic-Gender Homophily and Team Performance

This table regresses team performance on the interaction of Race/ethnicity Score and Gender Score. The dependent variable Performance=0.125 if the team does not present on IPO day (0-25%), =0.375 if present but not viable (25-50%), =0.65 if viable but not top 3 (50-80%), =0.9 if top 3 in section (80-98%), =0.99 if top 3 in class year (98-100%). The independent variables are diversity scores described in the paper. Robust standard error is clustered at year-section level. Each coefficient's standard error appears directly below the coefficient estimate. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A. 2013	(1)	(2)	(3)	(4)	(5)
VARIABLES			Performance		
Race/ethnicity Score	0.482***	0.144	0.0611	0.0635	0.00585
	(0.102)	(0.176)	(0.144)	(0.228)	(0.200)
Gender Score	-0.0103	-0.125	-0.0183	0.0715	0.121
	(0.638)	(0.644)	(0.610)	(0.692)	(0.678)
Ethnicity-Gender Score		0.728**	0.821***		
		(0.281)	(0.230)		
Ethnicity-Gender Score (Male)				0.762**	0.837**
				(0.298)	(0.246)
Ethnicity-Gender Score (Female)				1.292*	1.229*
				(0.761)	(0.748)
Top School Ratio			0.197**		0.185**
			(0.0745)		(0.0753)
Start-up Ratio			0.476		0.474
			(0.317)		(0.324)
Team Member Count	0.0473	0.0528	0.0584	0.0448	0.0518
	(0.0620)	(0.0613)	(0.0700)	(0.0589)	(0.0679)
Constant	0.579	0.143	-0.00518	0.219	0.0623
	(0.621)	(0.595)	(0.623)	(0.577)	(0.612)
Observations	150	150	150	150	150
R-squared	0.087	0.112	0.141	0.118	0.145
Panel B. 2014-2016	(6)	(7)	(8)	(9)	(10)
VARIABLES			Performance		
Race/ethnicity Score	0.177***	0.205*	0.169	0.182	0.152
	(0.0536)	(0.118)	(0.121)	(0.120)	(0.123)
Gender Score	0.0327	0.0454	0.0559	0.0470	0.0564
	(0.0588)	(0.0715)	(0.0724)	(0.0721)	(0.0725)
Ethnicity-Gender Score		-0.0471	-0.0142		
		(0.154)	(0.157)		
Ethnicity-Gender Score (Male)				-0.0507	-0.0181
				(0.153)	(0.155)
Ethnicity-Gender Score (Female)				0.157	0.150
				(0.215)	(0.213)
Top School Ratio			0.0748		0.0692
			(0.0586)		(0.0577)
Start-up Ratio			0.360***		0.353***
			(0.139)		(0.140)
Team Member Count	0.0882***	0.0882***	0.0792***	0.0866***	0.0783***
	(0.0264)	(0.0264)	(0.0284)	(0.0270)	(0.0288)
Constant	-0.148	-0.156	-0.142	-0.149	-0.136
	(0.171)	(0.174)	(0.172)	(0.174)	(0.172)
Year FE	YES	YES	YES	YES	YES
Observations	480	480	480	480	480
R-squared	0.050	0.050	0.067	0.054	0.070

Table XV. Performance Breakdown Regression

This table reports logit regression results on the effect of Race/ethnicity-Gender Score. Robust standard error is clustered at year-section level. The dependent variables IPO day/Viable/Section Top 3/Class year top 3 are indicator variables equals 1 if the team presented on IPO day/the project is deemed viable by judges/the team is section top 3/the team is class year top 3. The independent variables are diversity scores described in the paper. Robust standard error is clustered at year-section level. Each coefficient's standard error appears directly below the coefficient estimate. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Panel A. 2013	(1)	(2)	(3)	(4)
VARIABLES	IPO Day	Viable	Section Top 3	Class Year Top 3
Race/ethnicity-Gender Score	10.45***	6.955***	4.002**	6.209***
	(3.105)	(1.998)	(1.575)	(1.465)
Top School Ratio	1.772**	1.289**	1.267	0.559
	(0.830)	(0.533)	(0.982)	(1.568)
Start-up Ratio	2.819	3.613**	3.428	2.246
	(2.964)	(1.766)	(3.318)	(8.201)
Team Member Count	1.103	0.397	-0.153	-0.867
	(0.738)	(0.626)	(0.645)	(0.591)
Constant	3.374	2.984	2.367	6.600
	(5.372)	(4.485)	(3.266)	(4.045)
Observations	150	150	150	150
Panel B. 2014-2016	(5)	(6)	(7)	(8)
VARIABLES	IPO Day	Viable	Section Top3	Class Year Top 3
Race/ethnicity-Gender Score	1.927**	1.066**	1.291**	2.319
	(0.803)	(0.472)	(0.620)	(1.438)
Top School Ratio	0.784	0.677*	0.102	-0.288
	(0.510)	(0.352)	(0.546)	(1.052)
Start-up Ratio	2.257*	2.772***	2.966***	
	(1.286)	(1.023)	(1.123)	
Team Member Count	0.474*	0.739***	0.304	0.766
	(0.257)	(0.250)	(0.245)	(0.673)
Constant	-0.781	-4.424***	-2.323	-6.511
	(1.501)	(1.481)	(1.698)	(4.502)
Fixed Effects	Year	Year	Year	Year
Observations	480	480	480	375

Table XVI. Performance Under Endogenous Team Formation

This table studies the effect of endogenous team formation. The independent variable is interaction term between dummy variable "after 2013" and diversity measures. Robust standard error is clustered at year-section level. Each coefficient's standard error appears directly below the coefficient estimate. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
VARIABLES		Performance		
Race/ethnicity Score	0.484***			0.0600
	(0.100)			(0.139)
Gender Score	-0.0354			-0.0308
	(0.611)			(0.572)
Race/ethnicity Score * After 2013	-0.306**			0.109
	(0.114)			(0.185)
Gender Score * After 2013	0.0683			0.0869
	(0.613)			(0.575)
Race/ethnicity-Gender Score		0.916***	0.903***	0.825**
		(0.178)	(0.153)	(0.227)
Race/ethnicity-Gender Score * After 2013		-0.708***	-0.700***	-0.839**
		(0.188)	(0.166)	(0.275)
Top School Ratio			0.204***	0.198***
			(0.0743)	(0.0714)
Start-up Ratio			0.478	0.472
			(0.291)	(0.299)
Top School Ratio * After 2013			-0.121	-0.123
			(0.0935)	(0.0925)
Start-up Ratio * After 2013			-0.104	-0.111
			(0.321)	(0.328)
Team Member Count	0.0838***	0.0873***	0.0787***	0.0770***
	(0.0244)	(0.0246)	(0.0261)	(0.0263)
Constant	0.345	0.788***	0.726***	0.699
	(0.422)	(0.221)	(0.206)	(0.421)
Year FE	YES	YES	YES	YES
Observations	630	630	630	630
R-squared	0.058	0.058	0.081	0.084

Table XVII. Judge Characteristics

This table reports summary statistics on judges' gender and race/ethnicity. Each section has one section leader judge, who is a faculty member from HBS, and 3-4 other judges from industry.

Class Year	# Judges	% Female	% Black	% Lantinx	% East Asian	% South Asian	% White
Section Leader Judges							
2014	10	30%	20%	10%	0%	10%	60%
2015	10	30%	10%	0%	0%	20%	70%
2016	10	20%	20%	20%	0%	0%	60%
All Judges							
2014	49	14.29%	6.12%	4.08%	6.12%	6.12%	77.55%
2015	43	27.91%	6.98%	0.00%	9.30%	9.30%	74.42%
2016	44	34.09%	11.36%	4.55%	4.55%	6.82%	68.18%

Table XVIII. The Effect of Judge Gender on Team Performance

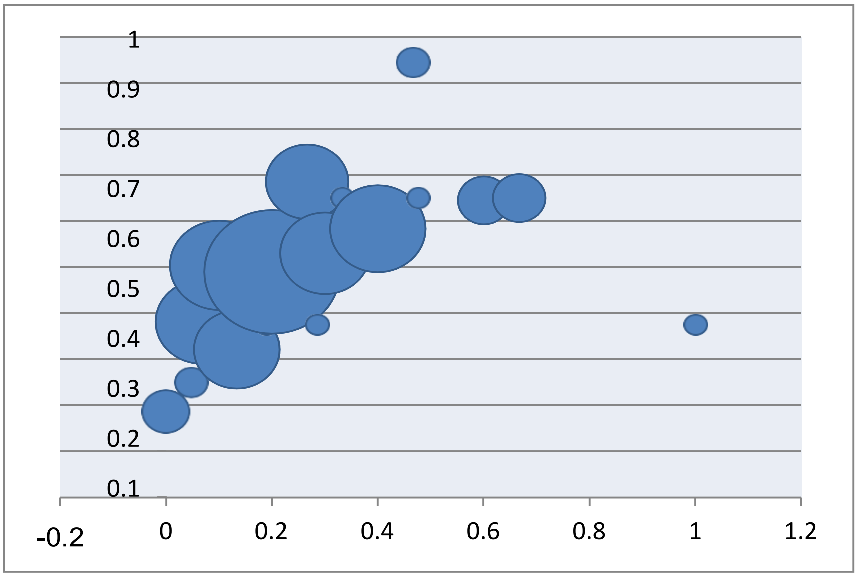
This table regresses team performance on judge's gender interacted with percent of female in the team. Each observation is a team matched to judge's gender in the section. The dependent variable performance =0.125 if the team does not present on IPO day (0-25%), =0.375 if present but not viable (25-50%), =0.65 if viable but not top 3 (50-80%), =0.9 if top 3 in section (80-98%), =0.99 if top 3 in class year (98-100%). The independent variable "Section Leader Female Judge" equals to 1 if the female judge is a section leader. "Have Female Judge" equals to 1 if there is at least one female judge in the section. "Female Team Member%" is the percent of females in the team. Robust standard error is clustered at year-section level. Statistical significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)
VARIABLES	Performance	Performance	Performance
Section Leader Female Judge * %Female Team Member%	0.309***		0.313***
	(0.0913)		(0.101)
Section Leader Female Judge	-0.153***		-0.157***
	(0.0433)		(0.0461)
Have Female Judge * Female Team Member%		0.0820	-0.0209
		(0.121)	(0.132)
Have Female Judge		-0.0362	0.0211
		(0.0549)	(0.0575)
Female Team Member %	0.0185	0.0343	0.0355
	(0.0656)	(0.103)	(0.104)
Top School Ratio	0.103*	0.0976	0.103*
	(0.0562)	(0.0576)	(0.0568)
Team Mem Count	0.0906***	0.0935***	0.0903***
	(0.0277)	(0.0276)	(0.0281)
Constant	-0.130	-0.159	-0.142
	(0.167)	(0.164)	(0.166)
Observations	480	480	480
R-squared	0.064	0.047	0.064
Class Year FE	YES	YES	YES

Figure 2. Performance and Race/ethnicity Score (2013, 2014-2016)

The Y axis is the performance of the team, X axis is the race/ethnicity score, ranges from 0 (most diverse) to 1 (homogenous). The size of the bubble is proportion to observation number.

2013 (Average Race/ethnicity Score=23.7%)



2014-2016 (Average Race/ethnicity Score=28.1%)

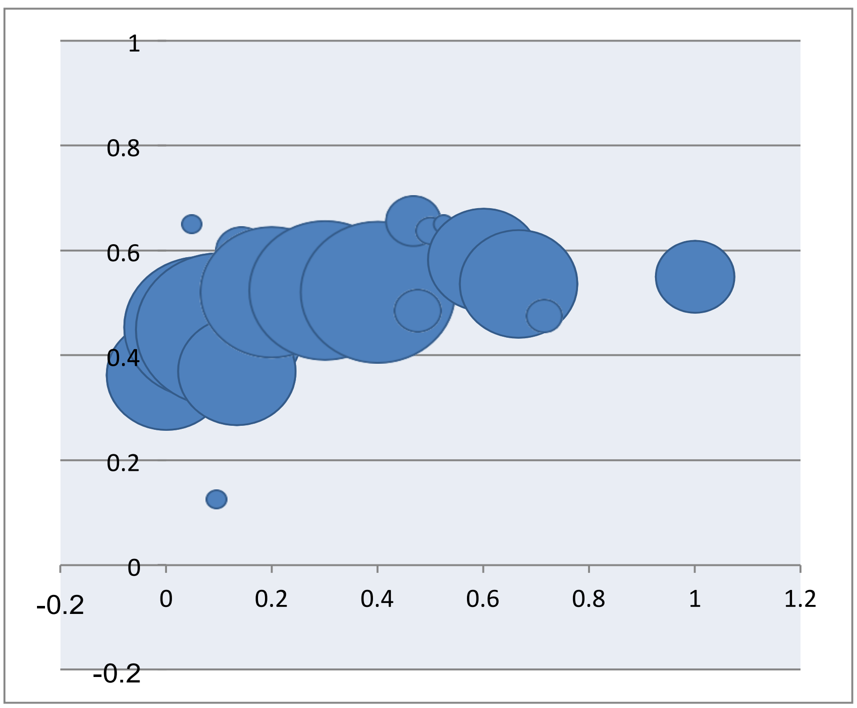
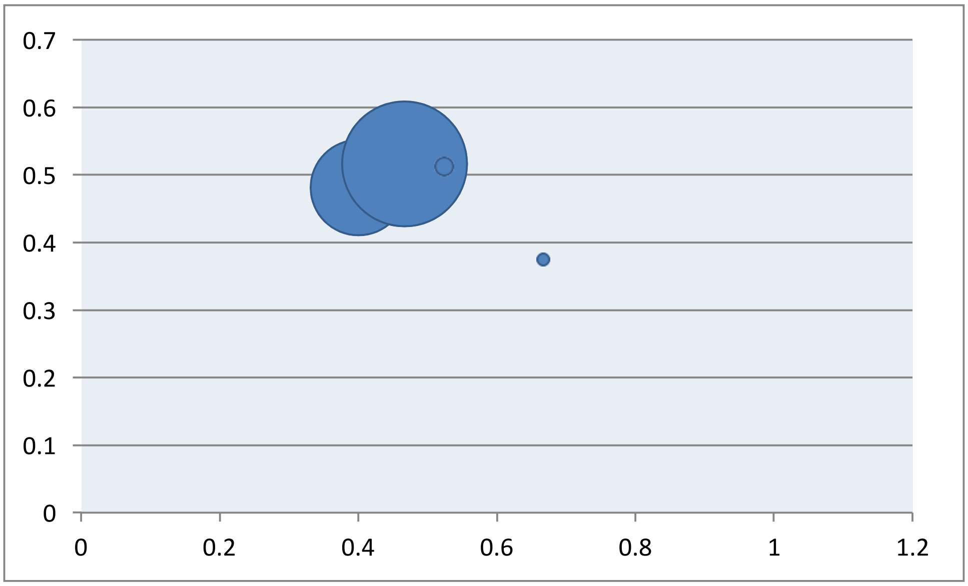


Figure 3. Performance and Gender Score (2013, 2014-2016)

The Y axis is the performance of the team, X axis is the gender score, ranges from 0 (most diverse) to 1 (homogenous). The size of the bubble is proportion to observation number.

2013 (Average Gender Score=44.4%)



2013 (Average Gender Score=57.4%)

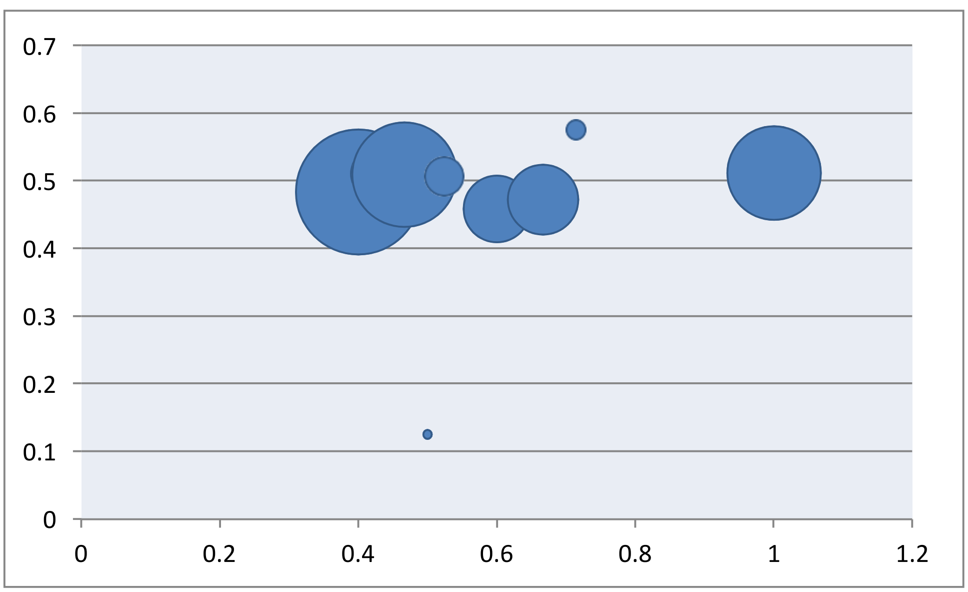


Figure 4. Team Performance Conditional on Judge's Gender (2014-2016)

These two figures plot the team performance conditional on judge's gender and female percent in the team. Team performance is measured by section top 3, viable and ipo day. Teams are sorted into four quantiles by percent female in the team.