Effects of Peer Groups on the Gender-Wage Gap and Life after the MBA: Evidence from Random Assignment of MBA Peers*

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Abstract

Using the historical quasi-random assignment of MBA students to peer groups at a top business school in the United States, I study the effect of the gender composition of a student's peers on the gender pay gap at graduation and long-term labor market outcomes. I find that a 10 percentage-point increase in the share of male peers leads to a 2.1 percent increase in the relative earnings of female students at graduation, closing the gender gap in earnings at graduation by two-thirds. The effects on women's long-term earnings grow even larger with time. Using novel data on job offers, I find that two different mechanisms drive the effects on short- and long-term earnings. Women with a greater share of male peers take more quantitative coursework in business school and receive job *offers* at graduation in occupations, industries, and firms associated with higher wages, longer hours, and greater earnings growth. However, the effect on women's earnings at graduation is primarily explained by female students' increased willingness to accept the maximum salary offered within their offer set. In contrast, peer-induced effects on human capital alone place female students on dramatically different long-term expected earnings paths due to changes in the initial occupation, initial industry, and initial firm accepted at graduation. This change in the characteristics of the first job at graduation largely explains the effect of peer gender composition on long-term outcomes.

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I. Introduction

Women have made enormous progress in educational attainment over the past several decades. In fact, there has been not only a narrowing, but a complete reversal of the gender gap in college attainment. The gender gap in graduate degree attainment has narrowed as well, including in business education.[1] In spite of this, women continue to be underrepresented at the higher ends of the wage distribution, and in particular, in the highest-paying managerial and technical occupations.[2]

However, not all educational tracks are equal. Differences between men's and women's highest degree type and field of concentration explains a substantial portion of the gender gap in earnings.[3] Figure 1 shows that women tend to specialize in fields with lower expected labor market earnings than men, even if men and women had the same expected earnings in each field.[4] The figure shows that there is gender segregation across fields of concentration, which produces a segregation in expected earnings.[5] It is therefore critical to understand the factors affecting gender segregation, not only in fields of concentration but also in the initial conditions of a career, and how these differences at the outset may translate into longer-term outcomes.

This paper studies the effect of the gender composition of a student's peers in business school on the gender wage gap at graduation, job offers at graduation, and on long-term labor market outcomes. The question of how peer gender composition affects students' educational choices and labor market outcomes - and female students', in particular - has been explored by previous literature, though identifying the causal impact is often empirically challenging. The voluntary formation of peer groups and social networks in the educational setting is likely to be endogenous to factors affecting both educational choices and labor market outcomes. While recent work has addressed some of these empirical challenges, the ability to identify effects of peer gender composition on realized labor market outcomes, specifically, on earnings - both short- and long-term - is rare. Moreover, the available data often do not lend themselves to identifying the channels through which the peer effects are linked to labor market outcomes and whether it is indeed the *same* mechanism that impacts women's earnings in the short-term - at graduation - as those that drive the effect of peers on the long-term earnings of women. Importantly, understanding the channels through which peer gender composition affects women's long-term earnings also reveals a deeper understanding of the gender gap itself - to what extent the effects of gender itself are malleable, subject to social and environmental forces, and to what extent, if any, there is a role for institutions in "undoing" the effects of gender.[6]

This paper leverages the historical quasi-random assignment of Master of Business Administration (MBA) students to peer groups at a top business school in the United States to identify the causal effect of the gender composition of a student's peers on labor market outcomes, on earnings at the time of graduation and on long-term earnings. In this paper, I exploit a unique feature of this particular institutional setting: within each entering cohort, students are randomly ordered within strata and assigned to peer groups of approximately 50 students, with whom they take their first semester courses. This institutional feature - together with rich

[1]See Goldin et al. (2006), Becker et al. (2010).

[2]See Bertrand, Goldin, and Katz (2010), Bertrand and Hallock (2001), Blau and Kahn (2017), Bertrand (2018).

[3]Bertrand (2018) reports the mean earnings and 80th and 90th percentile earnings among men working full time who have completed a given degree-field of study combination, and then reports, by birth cohort, the gender gap (men-women) in such education-based earnings potentials. Figure I(a) updates this analysis to include more recent birth cohorts.

[4]Expected labor market earnings are determined by taking the expectation over the combination of the highest degree type and field of study.

[5]For example, in the 1950 birth cohort, women chose degrees and fields of study with mean earnings 19 percent below the mean earnings in the degrees and fields of study chosen by men.

[6]This last phrase alludes to literature in gender studies that conceptualizes gender as a practice or a manifestation of individual traits and behaviors: something that one "does." See Butler (1999, 2004, 2011). The study of gender as an outcome of social forces or a practice, rather than a fixed characteristic, has entered the economics literature as well (Brenoe et al. (2022), Gneezy, Leonard, and List (2009), Bursztyn, Fujiwara and Pallais (2017), Shan and Zolitz (2022)).

data on background characteristics of each student, course transcript data, and employment and earnings data - allows for a direct test of how the gender composition of student peer groups causally affects both human capital choices and earnings outcomes without the concern of endogenous selection into peer groups, as detailed in Manski (1993).

In order to address the second and third challenges, I build a novel data set, drawing on unique, rich employment data that come from an annual survey conducted by the Career Services office of the business school. This data includes not only salaries at graduation for each student, but also the full set of job *offers* received, for each student from the 1999 through 2011 graduating classes, along with acceptance decisions of each student. Specifically, for each job offer received, students are asked about the characteristics of the offer, including a variety of components of pay (e.g., salaries, bonuses, tuition reimbursement, etc.), job characteristics (e.g., industry, occupation, job title, location, firm), and whether or not they accepted the offer. Therefore, an advantage of the data is that it allows one to distinguish between the effect of peers on the *set of offers* received, arguably a measure of welfare, from a potential effect on preferences: the choice of job students make from within their offer *set*.[7]

In addition to drawing on this unique job offer data, I use data from a retrospective alumni survey, which collects actual employment and earnings data for each position held since graduation for a subset of nearly 20 graduating cohorts of students, thus collecting labor earnings data for the earliest graduating cohorts of students for more than 15 years. The data allows not only for an analysis of the effect of peers on long-term earnings, but also for the construction of expected earnings paths, conditional on the characteristics of the first job accepted at graduation, for each student in the employment offer data. Such expected earnings paths can be constructed for each job *offer* received at graduation, rather than simply for the accepted job, as is more commonly observed in labor data. For example, expected future earnings paths given the first industry, occupation, and even the first firm job accepted at graduation can be constructed for each job offer by averaging actual earnings of graduates from the alumni survey a given number of years after graduation over all those whose first job was in the same initial industry, occupation, or firm at graduation.[8] An "offer" at graduation can be therefore be characterized by the expected future earnings path, given the initial conditions, regardless of the job in which they end up.

By characterizing the set of offers at graduation using a longer time horizon, this paper offers a unique approach relative to previous literature. The data affords the opportunity to examine how much of the change in actual long-term labor market outcomes was already present *at the time of graduation* in the change in the expected earnings paths of the offers received at graduation, whether or not an effect on earnings *at* graduation is realized.

I find that a 10 percentage-point increase in the share of male students in a peer group leads to a 2.1 percent increase in the salaries of female students at graduation relative to male, closing the gender gap in salaries at graduation by approximately two-thirds. In addition, women who are randomly assigned to a peer group with a greater share of male peers are more likely to enter male-dominated industries and job functions at graduation, such as investment banking, venture capital and investment management, and are less likely to enter relatively female-dominated industries, such as in marketing or product management. Specifically, I find that a 10 percentage-point increase in the share of male peers closes the existing gender

[7]Here, preferences are defined in a revealed preferences sense: by choosing one job offer in the choice set over all others, students who do not choose the maximum salary offer reveal their willingness to pay (WTP) for the non-wage amenities of the accepted job, relative to all other jobs in their offer set that offer a higher salary. See Mas and Pallais (2017), Sorkin (2018) for similar approaches.

[8]A benefit of the approach is that such expected earnings trajectories can be created even for students who do not appear in the alumni survey.

gap in entry into each of the most male-dominated job functions and industries by 50 percent or more and closes the gap in the "male-dominatedness" of industries and occupations accepted at graduation by more than two-thirds.

I examine the effect of peers on the characteristics of the industries and occupations into which graduates are more likely to sort. Women with a greater share of male peers accept job offers at graduation in occupations, industries, and firms associated with higher wages, longer hours, and greater earnings growth. Though the wage differences are not large in the first year after graduation, the results show that having a larger share of male peers places women into jobs at graduation with very different average wage paths over time. Specifically, a 10 percentage-point increase in the share of male peers causes female students to choose occupations with an average wage that is $0.69 per hour (1.7 percent) greater at graduation but that, 10 years after graduation, is $16.55 per hour (10 percent) greater - an effect nearly 25 times the magnitude of the one at graduation. Similarly, such an increase in the share of male peers causes female students to choose industries at graduation that have an average wage that is $1.21 per hour greater, but, 10 years after graduation, is $17.9 per hour greater - a sorting effect at graduation that produces 15 times the magnitude of the effect observed at the time of graduation. In addition, a greater share of male peers causes women to choose occupations and industries at graduation with a lower likelihood of part-time work, a greater likelihood of overtime work, and greater average weekly hours of work.

I then explore the underlying mechanisms through which these effects at graduation may take place. Analysis of coursework and course transcript data shows that greater exposure to male peers causes female students to choose courses and fields of concentration that are relatively more male-dominated. In particular, women with a greater share of male peers concentrate in fields with a greater proportion of male students, are more likely to concentrate in a majority-male field of concentration, take a greater share of quantitative courses in general, and take a greater share of finance courses in particular. Women with a greater share of male peers are more likely to concentrate in finance, one of the highest-paying areas of concentration as well as a documented source of the gender earnings gap among MBAs at graduation.[9] They are less likely to concentrate in fields that are relatively more female-dominated, such as marketing.

Using the data on job offers, I examine both human capital explanations for the effect of peers on the gender earnings gap at graduation as well as a potential role for preferences, or a change in female students' choice of offer from within their offer set. I find that the effect of a greater share of male peers on the starting salaries of women is almost entirely due to an increase in female students' likelihood of choosing the maximum starting salary offer within their offer set. While this is yet another dimension in which a greater share of male peers reduces the baseline gender gap, I show that this particular effect of male peers affects only women's earnings at graduation but has little persistence in terms of long-term earnings, given the offer *set* in-hand. However, women with more male peers also receive a better set of offers, when measured by the expected future earnings stream. I find that the effect of peers on the offers *set* is almost entirely explained by changes in human capital choices. Importantly, the results show that peer-induced changes in human capital choices place female students on dramatically different long-term expected earnings paths, due to changes in the initial occupation, initial industry, and even the initial firm in which female students begin their careers.

Analysis of long-term earnings data shows that having a greater share of male peers has large and positive effects on female graduates' earnings, long after graduation. I find that while the effect of peers on women's earnings is small or negligible at graduation and in the years immediately following graduation, women with

[9] See Bertrand, Goldin, and Katz (2010).

a greater share of male peers during business school face positive effects on their salaries of significantly larger magnitudes five, six, and seven years after graduation, with effects almost 25 times the magnitude of effects observed at graduation. In particular, a 10 percentage-point increase in the share of male peers increases female earnings six years after graduation by 27 percentage points relative to male, closing the gender earnings gap at this time by more than 50 percent. The same increase in the share of male peers increases female relative earnings by 50 percentage points seven years after graduation, reducing the gender earnings gap seven years after graduation by more than 70 percent.

Finally, I find that initial conditions matter. The occupation and industry accepted at graduation explain 43 percent and 50 percent, respectively, of the effect of peer gender composition on the long-term relative earnings of women. These results demonstrate that initial conditions at the start of the career - the initial occupation, industry, and firm - have lasting effects on the long-term earnings of women, and they reveal some underlying mechanisms through which the gender earnings gap, which is small at the time of graduation, can accumulate to the documented magnitudes over the course of the life cycle.[10] The results also reveal how environmental factors in the educational environment can influence the initial conditions of the career and mitigate some of the effects of gender in growing proportion as well.

This paper is related to three main strands of literature. First, it contributes to the literature on peer effects in higher education and to the small but growing literature on how peer gender composition in particular affects students' educational choices. The literature that studies educational effects of peer gender composition generally exploits year-to-year cohort variation in student gender composition. At the primary school level, Schneeweis and Zweimueller (2012) finds that girls with more *female* peers are *less* likely to choose typical female-dominated school types in Austria. At the middle school level, Gong, Lu, and Song (2025) shows using data from China that a greater share of female peers at the classroom level improves student test scores and noncognitive outcomes. At the high school level, Zolitz and Brenøe (2020) uses data from Denmark and shows that female students in high school cohorts with a greater share of female peers are less likely to complete a university STEM degree and, instead, are more likely to obtain a bachelor's degree in health or education. At the university level, Hill (2017) shows suggestive evidence that women exposed to a higher share of female peers in U.S. colleges are less likely to major in a STEM field.[11] However, using year-to-year cohort variation for identification carries its own challenges. For example, if the variation in the gender composition of the cohort is driven by a source that affects major choice, such as time-varying local labor demand for female-dominated occupations, then the source of variation would not be exogenous to factors affecting choice of major or field. Time-varying gender-specific selection into schools may, in fact, be in anticipation of such factors.[12] Leveraging random assignment of students to peer groups within-cohort resolves plausible concerns about endogeneity regarding the source of variation of the gender composition within school and across cohorts.

A smaller but important set of literature within this first strand uses random assignment to investigate how peer gender composition affects students' choices of fields of study. In particular, Zolitz and Feld (2021) uses the random assignment of university students in the Netherlands to study sections and, using a careful analysis, finds that women randomly assigned to sections with more female peers are less likely to choose

[10] See Kahn (2010) for literature on the persistence of the effect of labor market conditions at the time of graduation.

[11] Other studies show similar findings in the university setting, such as Anelli and Peri (2019), which shows that male students are more likely to choose a male-dominated college major when exposed to classes with over 80 percent male peers in Italian high schools.

[12] For instance, Zolitz and Brenoe (2020) must make the identifying assumption that the proportion of female students in particular schools or locations, in a given cohort, is exogenous to factors affecting STEM choice, such as time-varying local labor demand for female-dominated occupations.

male-dominated majors. In addition, Oosterbeek and van Ewijk (2014) conducts an experiment in which first-year students in economics and business are randomly assigned to work groups with varying gender composition. They find no substantial gender peer effects on academic achievement, though they do not examine labor market outcomes. However, the previous literature using random assignment to study gender peer effects generally focuses on short-term impacts: academic outcomes and labor market outcomes in the first year after graduation.[13] This paper studies the effects on long-term labor market outcomes, with a sufficiently long time horizon for the effects of two different mechanisms - preferences and human capital explanations - to be uncovered and disentangled.

In addition, it is worth noting that the previous literature has focused primarily on educational settings with much younger students. This paper investigates the effects of peer gender composition in an MBA setting, where students are, on average, significantly older at the time of entry, have greater prior work experience, and have significant industry-specific experience. It is possible that such students are more likely to have solidified their career aspirations and intended fields of study, and that human capital investments and career trajectories may be less malleable at this stage.[14][15] In a recent working paper, Hampole, Truffa, and Wong (2024) use quasi-random peer group assignment to examine the effect of peer gender composition in a top US business school setting, and find that women with more *female* peers have a greater likelihood of promotion, but their results focus on promotions, and they admittedly do not have wage or labor market earnings data. This paper provides new evidence about whether social and environmental forces may still influence career and *earnings* trajectories at this later stage in the lifecycle, when large prior investments have already been made.

Furthermore, none of the previous literature examines the effect of peers on the set of offers that students receive. By distinguishing between the effect of peers on the offer *set* and the effect on the choice of job female students make from *within* their offer set, this paper examines a new channel relative to the previous literature and can offer an explanation for why, in much of the prior work in this area, the effects of peer gender composition on earnings appear small or even negligible in the years immediately following graduation but have effects of much larger magnitudes over time. It sheds new light on the timing of these two channels - when the effects take place in the lifecycle, but separately, when the effects are realized in terms of earnings. It further contributes to an understanding of how much of the effect of peers on women's earnings is driven by the formation of preferences in the educational setting and how persistent such peer-induced effects on preferences are on the long-term earnings of women, relative to educational choices, such as field of study.

Finally, this paper contributes to the large literature on the gender wage gap and, in particular, among MBAs and other graduates of professional degree programs, including Bertrand and Hallock (2001), Bertrand, Goldin, and Katz (2010), Bursztyn, Fujiwara, and Pallais (2017), and Cortes, Pan, Pilosoph and Zafar (2023).[16] Notably, Bertrand, Goldin, and Katz (2010) finds that at the outset of their careers, male and female MBAs have nearly identical labor incomes, but their earnings soon diverge. But whereas Bertrand, Goldin, and Katz, among many others, document the sources of the gender wage gap, this paper examines whether differences often associated with gender, are, in fact, subject to social or environmental influences,

[13] A notable exception is Zolitz and Feld (2021).

[14] Wiswall and Zafar (2021) shows that career aspirations and expectations of college students at ages 18 to 21 are predictive of future outcomes. For women in particular, expectations about working full- or part-time, relationship status, and earnings of spouses are all predictive of actual outcomes six years later.

[15] Goldin's work has documented that young women's career and family aspirations are often formed by ages 14 to 21, and while they may not always match their labor market behavior at age 35, changes in expectations of labor market and family timing formed at younger ages were followed by changes in educational investments (Goldin (2002), Goldin (2006)).

[16] Other notable papers in the literature on the gender-wage gap among the highly skilled include Goldin (2014), Bertrand (2018), Blau and Kahn (2017), Cortes and Tessada (2011), and Cortes and Pan (2019).

even at as late a stage in the lifecycle as business or professional school. Furthermore, this paper, through its novel use of job offer data, combined with alumni survey data, contributes to an understanding of the *timing* of the divergence in earnings and hours by examining whether men and women receive - at the time of graduation - different initial job offers that already encapsulate different expected lifetime earnings and hours profiles.[17][18] A related paper is Beneito, Bosca, Ferri, and Garcia (2021), which examines the gender imbalance across subfields in economics and the timing of when these differences first emerge. A contribution of this paper relative to this literature is to examine whether a portion of these differences in both earnings and expected earnings growth at the start of the career are, in fact, causally affected by the peer environment.

II. Setting

This paper exploits the exogenous assignment of MBA students to peer groups (often called "sections," "clusters," or "cohorts" by comparable business schools) to address the classic set of challenges in the identification of peer effects. In this setting, first-year MBA students are quasi-randomly assigned to peer groups of approximately 50 to 60 students. MBA students assigned to the same peer group are required to take a set of classes together during their first semester of business school.[19] The stated goal of the requirement is that through this experience, students get to know one another well and begin forming networks early on in their academic experience. As with a number of other top MBA programs in the U.S., the compulsory aspect of the peer group experience does not last throughout the MBA program. The experience of convening as a group begins before the start of the term, and required courses only last for the first semester. However, these peer groups often continue to reconvene voluntarily for events and social activities.[20] Though requirements only last for one semester, prior literature that has studied similar peer groups in top business school settings has found that the social ties established in the first year remain extremely strong, even long after graduation.[21]

Each year, the university's Office of Student Records conducts peer group assignment using an algorithm that first randomizes the order in which admitted students are listed. Second, the university does make some attempt to balance peer groups with respect to some characteristics to ensure that peer groups are not too skewed in any one characteristic of students or another. Specifically, it orders students by gender, visa/permanent residency status, country of citizenship, ethnicity, and date of birth, preserving the randomized ordering within each stratum.[22] Finally, it then assigns each student, in the order listed, to a peer

[17] There may be multiple points in the lifecycle when earnings between men and women diverge, and there may be within-occupation, industry, and within-firm differences in earnings, as documented by a large literature on the "child-earnings penalty" (see Klevin et al. (2019)). However, prior research shows that differences across occupations still play a substantial role. See, for example, Denning, Jacob, Lefgren, and vom Lehn (2022).

[18] Goldin (2014) documents both within-occupation differences and between-occupation differences in earnings by gender and shows that differences in occupational sorting, even if men and women were paid the same within an occupation, accounts for almost 30 percent of the gender gap in earnings.

[19] Due to the data use agreement, details that would identify the particular business school must be omitted, but this type of peer group assignment is common among top business schools in the United States.

[20] For example, after the first-semester requirements are completed, it is common for the peer groups to voluntarily come together for intramural sports, competitions against peer schools, admitted students' weekends, and other social events. Groups often choose names and colors and may have a flag or mascot that reflects a group identity and kinship.

[21] For instance, Lerner and Malmendier (2013) finds that among Harvard Business School (HBS) students, at the 25th alumni reunions, fundraising and many activities are arranged on a section-by-section basis. Shue (2013) demonstrates the role of ongoing social interactions by showing that peer effects are more than twice as strong in the year following staggered alumni reunions, among HBS students, even though peer group requirements end after the first year of the MBA program. More recently, Hampole, Truffa, and Wong (2024) find that student peer groups in a top MBA setting affect social connections that last long after graduation, by providing job referral and work-related opportunities, support, and gender-specific information, affecting the likelihood that women reach a senior management position 15 years after graduation.

[22] This would be equivalent to ordering by gender, etc. first and then randomizing the order within each stratum.

group “bin,” rotating the bins in order until each student has been assigned to a peer group.[23] The office of student records uses this process in an attempt to keep peer groups relatively balanced across the subgroups on which sampling is stratified.

However, it should be noted that the variation in the gender composition of a peer group still comes from two exogenous sources. First - and most importantly - the assignment procedure is conducted prior to the offer of admission, but not all students accept their offer of admission. In particular, it is important to note that students do not have any knowledge of their peer group assignment at the time that they accept or reject their offer of admission. Therefore, students who reject their offer of admission do not do so on the basis of any peer group characteristics. The main identifying assumption is that, for a given cohort, the gender composition of a student’s peer group is unrelated to the pre-treatment characteristics of the student.[24] This assumption will be tested in Section IV. using the the vast number of observed pre-treatment characteristics unique to this data.

In addition, the admission acceptance or rejection decisions that vary exogenously across peer groups creates meaningful variation in the share of male peers across peer groups within the same cohort, that is arguably "as good as random," as will be explored further in Section IV.. This paper exploits this source of exogenous variation to study the effects of gender composition on human capital choices, job offers, the choice of offer from within an offer set, and labor market outcomes.

In this setting, members of the same peer group often continue to take classes together voluntarily, even after the requirement to take first-semester courses together has ended. Specifically, in our data, the average share of students in a course section who are members of a student’s assigned peer group is 14.4 percent, among courses taken over the remaining two years of the program. For comparison, the average share of students in a course section made up of an arbitrary subset of students of the same graduating cohort and of the same group size as the actual peer group is 7.4 percent.[25] In addition, a student has, on average, eight other members of his or her peer group taking the same course section. Appendix Table A.1 shows that this equates to twice the number of students from one’s own peer group in each course section than from an arbitrary subset of students from the same cohort, in any given course section. Therefore, the interactions between students of the same peer group throughout the course of their two years in business school lasts long after the first-semester compulsory coursework has been completed.

The compulsory aspect of the peer group system includes a discussion-oriented course that is designed to enhance students’ self-awareness by providing them with an opportunity to reflect on critical aspects of leadership – working in teams, influencing others, conflict management, interpersonal communication, presentation skills. The course is designed to challenge students to explore who they are as leaders and to create a personalized plan to guide their continued development in the MBA program and in life after the MBA. Students are encouraged to engage in self-reflection, discuss goals and aspirations, including

[23] For example, if there are 10 peer groups in a given cohort, the first student in the list is assigned to “Bin 1,” the second, to “Bin 2,” and so on, until the tenth student is assigned to “Bin 10.” After that, the progression repeats: the eleventh student is assigned to “Bin 1,” the twelfth student to “Bin 2,” and so on.

[24] A second source adds some additional variation: the number of women in the admitted class or the total number of admitted students may not be divisible by the number of peer groups, so some groups will be assigned a larger share of women than others.

[25] The difference is statistically significant, and the 95 percent confidence interval indicates that the share of a course section’s students made up of members of the peer group is, at a minimum, approximately twice the share made up of an arbitrary subset of students in the cohort of the same group size. See Appendix Figure A.1 and Table A.1 for more details.

those surrounding work-life balance, and work on desired leadership traits in alignment with personal and professional aspirations. Students and faculty members describe the required portions as not only teaching the fundamentals of the basic disciplines, such as economics, statistics, and behavioral science, but also including a focus on long-term growth, where students discuss career and personal aspirations as a group and make informed choices about academics, leadership, career management and work-life balance.

III. Datasets

A. Employment Offer Data

An unique data set used in this paper comes from survey data collected separately by the university that records data on the full set of job offers received for each student from the 1999 through 2011 graduating classes. Moreover, this employment offer data includes the job offer accepted by each student. The data comes from a salary survey conducted by the Career Services office at the time of graduation and consists of student self-reported salary and position information for each job offer received. By matching the administrative data to this employment offer data set, I can observe arguably the complete choice set of each student, along with salaries, bonuses, and a wide variety of pecuniary and non-pecuniary benefits. To date, this is the first paper in which a data set that contains the full choice sets of workers in a real, high-stakes setting has been used. Observing the full choice set as well as the accepted job offer allows us to distinguish between the effect of peer group gender composition on the distribution of starting salaries that students are offered and the salaries they accept, conditional on their choice set. Importantly, analysis of the full set of job offers and the choice of jobs, given each student's offer set, allows us to examine whether peer group gender composition also has an effect on preferences, as revealed through their choice of jobs and their revealed willingness to pay for non-pecuniary benefits.

Specifically, for each student, the survey records pecuniary characteristics of each job offer, including the base salary offered, signing bonuses offered, tuition bonuses offered, profit-sharing bonuses offered, relocation bonuses offered, stock options offered, guaranteed year-end bonuses, performance bonuses, and other bonuses.[26] In addition, for each job offer, the survey collects data on the industries, job functions, job titles, and job locations offered, as well as on the particular firm making the offer.[27] Furthermore, the survey collects information on student self-reported preferences - whether the job offer was the student's first-choice, second-choice, or third-choice job - and whether the student negotiated his or her offered salary.[28] Finally, by matching the employment offer data collected by career services at the time of graduation with the data from the alumni survey that follows students up to 16 years after graduation, based on the first job held at graduation, I can take advantage of the additional long-term job attribute data and observe the evolution of job function, industry, and even firm characteristics up to 16 years after graduation. Specifically, the average weekly hours of work, the frequency of part-time work, the frequency of overtime work, and the average hourly wage within a job function and within an industry are calculated from the alumni survey data. These job and industry attributes are then matched to the employment offer data in order to observe a wide array of the non-wage attributes of the job offers students receive and of the jobs that students accept at graduation.[29]

[26] For each of the pecuniary job characteristics, nominal values in each year were converted into real earnings in 2006 dollars using the Consumer Price Index for Urban Consumers (CPI-U).

[27] I aggregate job functions into 37 major categories, and industries into 54 main categories.

[28] Reported salaries are the final offered salaries, after negotiation.

[29] The survey did not include a question on "part-time" versus "full-time" work. I assign "full-time" status to those who report

The vast majority of MBA students who are offered a job through the university's on-campus recruiting system accepts one of the job offers. Across the 15 years of data for which employment offers are observed, only 201 students – approximately 3 percent of students – who are offered at least one job do not accept any of the jobs offered.[30] Of the remaining 97 percent of students, approximately 30 percent of students had more than one full-time job offer. The number of full-time job offers that students received ranged from zero to seven. Among students who received more than one job offer, more than one-third accepted a job offer whose salary offer was less than the maximum salary offer in their offer set.[31] The mean difference between the salary offer accepted and the maximum salary offered to a student, among students who received more than one job offer and accepted a job other than their maximum salary offer, was $32,500 in 2006 dollars.[32] The mean difference between the second-highest salary offer and the highest salary offer, among those who received more than one offer, was a 21.7 log point difference.

Weekly hours of work are high for almost all MBA positions. Across industries, weekly work hours are highest in investment banking and consulting, with averages of 69 and 61 hours per week, respectively. Just below consulting, those employed in the venture capital industry worked an average of 60 hours per week. Across occupations (job functions), hours are highest in investment banking as well, while product management and company finance job functions require fewer hours of work per week than the average MBA position, each averaging 53 hours per week. Interestingly, while the dispersion in average weekly hours falls over time since graduation, the dispersion in the average hourly wage across industries and job functions increases. Comparing across industries, weekly work hours at graduation average 74 hours per week in investment banking and 64 hours per week in consulting, but ten years after graduation, the average weekly work hours in the same two industries decline to 63 hours per week and 56, respectively. Among job functions, weekly hours at graduation are 53 hours per week in company finance and product management, but ten years after graduation, increases to 56 hours per week, while in product management, hours stay relatively stable at 53 hours per week.

In contrast, the dispersion in hourly wages across industries and job functions increases over time since graduation. Among industries, hourly wages are the greatest in investment banking, venture capital, and in the investment management industries. Hourly wages in the three industries at graduation are, on average, $43, $46, and $48, respectively, but ten years after graduation, average hourly wages in these three industries are $250, $235, $272 per hour, respectively. In contrast, hourly wages in the lower-paying industries and job functions do not increase at nearly the same rate. Among job functions, average hourly wages are among the lowest for product management and company finance and, at graduation, are $36 and $37 per hour, respectively. Ten years after graduation, average hourly wages in these two job functions are $62 per hour $75 per hour, respectively.

B. Data on Background Characteristics

Pre-MBA (pre-treatment) data comes primarily from administrative data collected by the university and includes all background characteristics known about students at the time of admission. The pre-treatment data includes the age of the student, work experience prior to business school, gender, race, marital sta-

working more than "30-40 hours per week" and "part-time" to those who report working at most "30-40 hours per week."

[30] Of these students, 17 percent reported not working at the time of graduation, while only 6 percent reported on the alumni survey being self-employed at the time of graduation.

[31] Salary offer, here, refers to "permanent salary," which is the sum of the base salary offer, guaranteed year-end bonuses, profit-sharing bonuses and stock options offered. Performance pay as well as one-time signing bonuses are not included.

[32] The median was $14,229 in 2006 dollars.

tus,[33] citizenship, visa, permanent residency, and work permit status, undergraduate major, the student's undergraduate institution, undergraduate GPA, any advanced degrees received prior to business school, the advanced degree-granting institution, and advanced degree GPA. In addition, the pre-treatment data includes student GMAT scores: scores and percentile attained separately on the quantitative, verbal, and analytical writing sections, as well as the total GMAT score. Finally, from the survey data, the pre-treatment data also includes the backgrounds of students prior to business school, including the previous industries, job functions, and job titles in their most recent job prior to business school. Summary statistics are provided in Table 1.

Of the group of nearly 8,000 (7,944) students for whom employment offer data is available, close to 93 percent or 7,353 student employment records were matched to university administrative records. Of these students, peer group data is available for all but 28 students, or 0.38 percent. Restricting the sample to only full-time and non-transfer students brings the sample to 7,048 students who are matched with university administrative records and admissions records data. These 5,074 men and 1,974 women form the basis of the sample.

C. Coursework and Transcript Data

In addition to the administrative data that provides information on student background characteristics at the time of admission, in this paper I also utilize coursework and course transcript data, including grades received by students during the course of their MBA program and their chosen fields of concentration, and I match this to the administrative data. In particular, I use data at the person-course level containing the course number, title, and the field of each course taken, as well as the grade achieved in each course and the semester and year in which the course was taken. From this data, I generate GPAs for each student for the first semester, the first year, and for the entire MBA program. In addition, I generate within-field GPAs for each student for the nine largest fields of study. Finally, students have an option to take a combination of courses that leads to a concentration in a particular area or field of interest, akin to a major in the undergraduate setting. While concentrations are not required, 97 percent of students fulfill requirements for one to four concentrations.[34] The coursework and course transcript data is merged with two additional university administrative data sets that provides data on chosen fields of concentration for each student within the MBA program.[35]

D. MBA Alumni Survey

The alumni survey data come from a retrospective web-based survey conducted of the MBA alumni from the graduating classes of 1990 to 2006.[36] The participants were asked detailed questions about each of the jobs or positions they had held since graduation, including earnings (both at the beginning and the end of a given position), usual hours of work per week, job function, industry, size of the firm, and type of firm.[37]

[33] I again classify those living with a partner as "married."

[34] The program curriculum description indicates that students typically fulfill concentration requirements in order to signal deeper knowledge within a particular field of study and to assemble a combination of skills relevant to particular areas and fields of interest. The set of courses required to meet the requirements of a "concentration" appears to vary from year to year. However, resume data indicates that students often declare their chosen fields of concentration on their resumes.

[35] There are two draws of administrative data that provide the data on fields of concentration - one draw took place in 2006 and the other in 2011. The most recent draw (from 2011) is used when the data conflicts, but an additional 1,450 observations of student fields of concentration can be included by using the 2006 data as a supplement. More information about potential sampling bias is provided in the appendix.

[36] The survey was taken between November 2006 and June 2007. Only full-time MBA graduates were included; part-time MBAs and executive MBAs were excluded. Employees were asked to include salary and bonuses.

[37] Job functions and industries are aggregated into the same set of 37 job function and 54 industry categories as was done

The earnings questions asked for total annual earnings, before taxes and other deductions, in the first and last year at each job. The responses to the earnings questions and usual weekly hours worked were collected in discrete bins that were transformed into real-valued variables, using the midpoint of each bin. Individual earnings in a given year were computed by linear interpolation between the first and last year at each job.[38] Information was also gathered on all post-MBA spells of non-employment (periods of six months or longer in which an individual was not working for pay). Among the MBAs in these classes who responded to the survey, 1,487 (or 97 percent) were matched to the university administrative records, of which 1,106 are men and 381 are women. Though the fraction of women in this sample is considerably lower than the national average of the fraction of MBAs earned by women, which was about 40 percent for the same period, the gender proportion is fairly representative of top business schools in the U.S. during this time period.[39]

The respondents do not differ much from the nonrespondents based on observables. Both survey respondents and the full sample with matched administrative data are approximately 28 percent female. Survey respondents have slightly lower undergraduate GPAs than nonrespondents,[40] but this is primarily because survey respondents' undergraduate GPAs and transcript records are *less* likely to be missing from the administrative data (i.e. the nonrespondents' are more positively selected into the non-missing undergraduate GPA category; respondents are arguably more representative of the full sample). Respondents do have slightly lower GMAT scores, though the differences are very small in percentage terms (a mean of 81.4 percent among respondents versus 82.6 among nonrespondents.) Respondents do not differ statistically from nonrespondents in their pre-MBA background (age at entry, prior work experience, whether they attended a top ten or top twenty undergraduate institution), but respondents were slightly more likely to be white relative to Black, Hispanic, Asian or "other." Respondents are disproportionately US citizens - 73 percent US citizens versus 55 percent US citizens of the nonrespondents - but slightly less likely to have permanent residency status, if not a US citizen, than nonrespondents. However, respondents have similar undergraduate academic backgrounds as nonrespondents. Relative to nonrespondents, respondents have slightly higher GPAs during their MBAs, but they don't differ significantly in terms of the coursework taken, the fraction of finance courses taken or the likelihood of concentration in finance.[41]

IV. Are Peer Group Assignments Truly Random?

Students are assigned to peer groups by a computer program developed by the Information Technology Services department of the business school, as described in Section II., that first randomizes the order of students within strata before assigning them to peer groups in rotating order. While the business school does make an attempt to keep peer groups balanced with respect to some characteristics including gender, as described in Section II., it should be noted that the variation in the gender composition of a peer group still comes from two exogenous sources. First - and most importantly - the assignment procedure is conducted prior to the offer of admission, but not all students accept their offer of admission. Of particular importance is the fact that students do not have any knowledge of their peer group assignment at the time that they accept or reject their offer of admission. Therefore, students who reject their offer of admission do not do so on the basis of any peer group characteristics. The main identifying assumption is that, for a given

with the employment offer data.

[38]Nominal values in each year were converted into real earnings in 2006 dollars using the Consumer Price Index for Urban Consumers (CPI-U).

[39]Among Harvard Business School MBAs from 1990 to 2006, 31 percent were female. Among University of Chicago MBAs for the same period, 25 percent of graduates were female (Bertrand, Goldin, and Katz, 2010).

[40]Undergraduate GPAs are normalized to a 4.0 scale.

[41]See Appendix Table A.2 for comparisons of survey respondents and nonrespondents.

cohort, the gender composition of a student's peer group is unrelated to the pre-treatment characteristics of the student. This assumption is justified as long as the information set of the student at the time of their decision to accept or reject their offer of admission is orthogonal to the characteristics of the other students in their peer group, within a given cohort, thus avoiding the self-selection problem described in Manski (1993). I test whether this assumption is justified in the data using a set of randomization tests and the vast number of observed pre-treatment characteristics unique to this data.

Second, while some students are admitted later from the waitlist as other students reject their offers of admission, admitted students who are added from the waitlist are added to peer groups in order by resuming the same order of peer group assignment.[42] The stated goal is to the keep the total number of students in a peer group balanced, but characteristics are not rebalanced across peer groups after the initial assignment. Here, the main identifying assumption is still justified, since students are not added to peer groups on the basis of the characteristics of other students in their peer group (and "open spots" in peer groups due to acceptance/rejection decisions are not available on the basis of characteristics of other students in the peer group).[43][44]

In addition, to properly identify peer effects, there must be sufficient variation in the pre-treatment characteristics across groups. Across the 15 entering cohorts of the sample, there are 156 separate peer groups with an average of 53.1 incoming first-year MBA students. Under pure random assignment, the standard deviation of each average peer group characteristic should be equal to the population standard deviation divided by the square root of 53.1. However, because peer group assignment is conducted within-cohort, and there is variation in the mean pre-treatment characteristics across cohorts, particularly in the fraction of women and the average GMAT score of an incoming cohort, the variance of the average peer group characteristic across peer groups should be equal to the sum of the expected within-cohort variance and the across-cohort variance of the cohort population mean. This is largely the case in my sample. For example, the standard deviation of the share of women in a peer group is 0.065, slightly larger than the standard deviation under pure random assignment, 0.062, while the expected standard deviation under pure within-cohort random assignment is 0.079. Among pre-treatment characteristics that are *not* aimed to be balanced in the initial assignment, for example, GMAT scores, the standard deviation of the average GMAT score of a peer group is 14.81, while the expected standard deviation of the average GMAT score under within-cohort random assignment is 14.57 (expectation of within-cohort variance = 44.01; across-cohort variance = 168.47). I explore in greater detail whether the distribution of the female share and the distribution of the wide array of other pre-treatment characteristics is as good as a random within-cohort draw.

I test whether the main identifying assumption - that, for a given cohort, the gender composition of a student's peer group is unrelated to the pre-treatment characteristics of the student - is justified in the data using a series of randomization tests. Within each entering cohort, I test for randomness in peer group assignments in Table 2, which shows the extent to which the main independent variable, the share

[42]For example, the first student on the waitlist is assigned to the first "bin" that has fewer assigned students than the average, the second, to the next bin in order that has fewer students than the average, and so on, until the list admitted from the waitlist is exhausted or all bins have the same number of students. After that, the progression repeats: the next student is assigned to "Bin 1," the next to "Bin 2," and so on.

[43]Students are placed on the waitlist and ordered prior to any peer group assignments or acceptance decisions are made by the first round of admitted students. Thus, their ordering is unrelated to the characteristics of students in their peer group or to those of students who decline their offers of admission.

[44]One can show, formally, that the gender composition of peer groups, based on these three assignment steps, creates an exogenous source of variation that is independent of the peer group assignment. Specifically, for a given cohort, $P(male|g) = P(male|g, initial) + P(decline|g)\,(P(male|nextonwaitlist) - P(male|g, initial))$, the probability of being male given a final peer group assignment to group g (after all three assignment steps have taken place), can be shown to be equal to $P(male)$, in a given cohort. In addition, nearly all of the variation in the gender composition of peer groups comes from the second term.

of women in a student's peer group, is correlated with individual pre-treatment characteristics - specifically, whether and to what extent the share of women in a student's peer group is correlated with the student's GMAT score, GMAT quantitative score, GMAT verbal score, undergraduate GPA, undergraduate major, work experience prior to business school, race, age, citizenship, and whether the student attended a "top 20" undergraduate institution. Table 2 shows that, conditional on cohort, there is no relationship between student i's background characteristics and the gender composition of i's peer group.

Table 2 shows the relationship between student characteristics prior to entering business school and the gender composition of the student's assigned peer group, for both the full sample, shown in columns (1) and (2), and separately for male and female students in columns (3) and (4). I separate the sample by gender because the expected share of a student's peer group that are women is mechanically lower for female students than for male students, due to the fact that individuals cannot be their own peers.[45] As a result, regressions shown without a correction for this bias can produce a slightly positive coefficient for the characteristics that are correlated with being male, such as the quantitative GMAT score, work experience, age at graduation, or having a hard-science undergraduate major type, even when peers are truly randomly assigned. Column (1) controls for whether the student is female. However, the bias due to the mechanical relationship between own gender and the share of women in randomly assigned peer groups is larger in small cohorts than in large cohorts, and larger in small peer groups than in large peer groups. Therefore, in column (2), instead of controlling for whether the student is female, I control for the average characteristics of possible peers in the peer group, to correct for the mechanical negative bias, as recommended by Guryan, Kroft, and Notowidigdo (2009). Columns (3) and (4), in which the sample is separated by gender, show that there is a minimal relationship between the student's pre-treatment characteristics and the share of women in the student's assigned peer group. In Appendix Table A.4, I also regress share of women on all of the student's pre-treatment characteristics, and I report the F-test for the joint significance of student background characteristics. The results show that student pre-treatment characteristics clearly remain unrelated to the share of women in the student's peer group.

The distribution of pre-treatment characteristics on which the program initially aims to balance are also examined and compared to that under pure random assignment. Under pure within-cohort random assignment, the variance of each average peer group characteristic should be equal to the sum of the expectation of the within-cohort variance[46] and the across-cohort variance of the cohort population mean. This is generally the case in my sample. For example, the standard deviation of the share of students who identify as "Black" across peer groups is 0.029, while the standard deviation of the share of Black students under pure random assignment would be 0.027 (with no across-cohort variation in population means), but under within-cohort random assignment, the standard deviation would be 0.033. The distribution of the characteristics on which peer groups are balanced are shown in Appendix Table A.3, along with the expected distribution under pure random assignment and within-cohort random assignment. Appendix Table A.3 shows that the distribution of characteristics across peer groups largely replicates the distribution from pure random assignment within-cohort. Appendix Figure A.2 shows the distribution of the (residualized) share of male peers, as a deviation from the within-cohort mean, providing further evidence of sufficient within-cohort variation that is as-good-as-random.

[45]Intuitively, as described by Guryan, Kroft, and Notowidigdo (2009), under true random assignment, the urn from which the peers of an individual are drawn does not include the individual.

[46] Population standard deviation within-cohort divided by the square root of the average peer group size within-cohort

V. Empirical Methodology

The goal of this paper is to exploit the exogenous variation in the share of male peers across peer groups to study the effects of peer gender composition on educational choices, job offers, the choice of offer from within an offer set, and labor market outcomes. The main labor market outcomes considered are annual earnings and the occupations and industries into which students enter at graduation. In addition, I distinguish between the effect of peers on the characteristics of the first job at graduation and that of the set of job *offers*. In order to understand some of the underlying mechanisms, I estimate the effect of peer group gender composition on choice of coursework and the field of concentration in business school. In this analysis, observations are at the individual (student) level.[47] Finally, I will estimate the effect of the gender composition of a student's peer group on long-term outcomes, such as annual earnings in each year a given number of years after graduation.

Specifically, I estimate peer effects with a linear-in-means model using the following specification:

$$Y_{ig(i)c} = \phi_0 + \phi_1 Female_i \times ShareMale_{ig(i)c} + \phi_2 ShareMale_{ig(i)c} + \beta X_i + \gamma_c + \varepsilon_{ig(i)c}, \tag{1}$$

where $Y_{ig(i)c}$ is the outcome of interest for student i in peer group g, in cohort c, where "cohort" is defined as the year of entry into business school,[48] and $ShareMale_{ig(i)c}$ is the treatment variable of interest: the fraction of all other peers in student i's peer group, other than student i, that are male.[49] To investigate heterogeneity by gender, I interact the share of male peers with the indicator variable, $Female_i$, which refers to the student's own gender. The parameters of interest are ϕ_2, which shows the causal effect of increasing the proportion of male peers on the outcome of interest for all students, and ϕ_1, which captures the relative effect of increasing the proportion of male peers for women relative to men. Thus, ϕ_1 captures the effect of peer gender composition on the gender gap in outcomes, conditional on other control variables.[50] The term X_i is a vector of student i's individual pre-MBA (pre-treatment) characteristics, including GMAT scores (quantitative, verbal, and total), undergraduate GPA (normalized for the maximum undergraduate GPA to a 4.0 scale), indicator variables for whether the student attended a "top 10" or "top 20" undergraduate institution, age at entry into business school, age-of-entry-squared, years of work experience prior to business school, experience-squared, indicator variables for race/ethnicity, gender, and visa or work permit status in the US. The term γ_c represents cohort fixed effects, which controls for any unobserved cohort-specific shocks common across peer groups, such as unobserved differences in employment outcomes or in academic outcomes across cohorts, and ε_{igc} is the error term. Given the potential for error correlation across individuals within a peer group, standard errors are clustered at the peer group level.[51]

Note that the main specification includes cohort fixed effects, because the desired form of variation to

[47] Effects on the set of job offers will use outcome variables such as the mean, median, and maximum of the set of job offers for each student.

[48] "Cohort" is defined as the year of entry into business school, rather than the graduation year, since graduation timing may be endogenous to such things as number of employment offers, salaries offered, and field of concentration and coursework taken in business school, all of which may be causally impacted by the gender composition of the peer group. Graduation timing may also be endogenous to the gender composition of the peer group itself. See Schwandt and von Wachter (2019) for a discussion.

[49] $ShareMale_{igc} = \left(\sum_{k \in G(g), k \neq i} Male_{kgc}\right) / (n_{gc} - 1)$, where all peers in student i's peer group are indexed by the set of indexes $G(g)$.

[50] In an additional specification, shown in the Appendix, I separately identify the coefficient on $Female_i x ShareMale_{igc}$ and on $Male_i x ShareMale_{igc}$ to capture the effect of peer gender composition separately on outcomes for men and women. However, the main specification uses only $Female_i$ interacted with $ShareMale_{igc}$ in order to test whether the effect on outcomes for women are significantly different from outcomes for men and to understand the effect of peer gender composition on the gender gap in outcomes. Further detail is provided in the next section.

[51] Note that each peer group is specific to a cohort, so this is equivalent to clustering at the peer group-by-cohort level.

exploit is the exogenous within-cohort variation in the share of male peers. One might be concerned with the possibility that there are cohort-by-gender-specific shocks common across peer groups, which may bias the causal parameter of interest if the share of male peers is also correlated with cohort. In a more conservative model, I use γ_{ic}, or cohort-by-gender fixed effects, to account for this possibility. While some of the results have some differences due to the relatively small proportion of women in the data, the inclusion of this interacted set of fixed effects does not significantly alter the main results.[52]

VI. Results

A. Labor Market Effects at Graduation

Table 3 presents the estimated coefficients from the ordinary least squares estimation of Equation (1) under different specifications, in which the dependent variable is the natural log of the annual base salary of the job offer accepted, in terms of gross earnings. The reported coefficients are from those in which $ShareMale$ and $Female \times ShareMale$ are each defined as deviations from the mean, so that the interpretation of the coefficient on $Female$ is the baseline gender-earnings gap for those with the average share of male peers, before accounting for any peer effects. Column (1) shows the estimated coefficients of a specification that includes no other pre-treatment characteristics than gender. Column (2) includes controls for student GMAT scores and undergraduate GPA[53]. Column (3) includes two additional dummy variables for whether the student attended a "Top 10" or a "Top 20" undergraduate institution.[54] Column (4) includes additional dummy variables for marital status at the start of business school, marital status interacted with female, age at the start of business school and age-of-entry squared. In addition, column (4) includes race indicator variables (indicators for Black, Hispanic, Asian, South Asian, and "other" are included). Column (5) controls for years of work experience prior to business school and years of experience squared, in addition to all controls included in column (4).

The estimates show that a 10 percentage-point increase in the share of male peers in a student's peer group leads to a 2.1 percent increase in the base salary of the job offer accepted by female students, relative to male, while there is no significant effect of the gender composition of a student's peer group observed for men.[55] It is interesting to note that the baseline gender gap in starting salary is between three and four percentage points, which is consistent with previous literature on the gender-wage gap among MBA students.[56] Importantly, the results also imply that a 10 percentage-point increase in the fraction of male peers - a little more than a one-standard-deviation increase - would close the gender gap in starting salaries at graduation by approximately two-thirds. The magnitude of these estimates is particularly important in light of literature showing that the gender wage gap for graduates of top MBA programs is primarily explained by

[52]Some of the short-term earnings results have some differences, but all effects on industry, occupation, firms, characteristics of the first job at graduation, willingness-to-accept the highest salary offered, human capital effects, and long-term earnings results are virtually unchanged. Results may be provided upon request.

[53]Since many students attended undergraduate institutions outside of the United States, where GPAs are not on a 4.0 scale, GPAs are normalized to a 4.0 scale based on the maximum GPA attainable at the undergraduate institution. Data on the maximum GPA attainable at the undergraduate institution is also included in the administrative data.

[54]Because a "top 10" institution is also a "top 20" institution, the coefficient on "top 10" should be interpreted as the coefficient on an interaction term.

[55]While it may be noted that there is a negative but insignificant coefficient on $ShareMale$, the effect on men is not robust to different measures of earnings, largely due to what appears to be a behavioral phenomenon, where men with more male peers are more likely to accept a relatively large cut in their base salary in exchange for an increase in the one-time bonuses offered. See Niederle and Vesterlund (2007), for example. I focus on the results that are robust to different measures of earnings.

[56]Cortes, Pan, Pilosoph, and Zafar (2023) find that that raw gender gap is about 10 percentage points at graduation. Bertrand, Goldin, and Katz (2010) finds that the raw gap in mean log earnings between men and women is small at graduation - 11 log points - but jumps to nearly 60 log points 10 or more years after graduation.

gender differences in coursework taken during business school, the types of jobs accepted at graduation, and weekly hours of work.[57] While the results shown here are not inconsistent with these findings, and effects on these proximate causes are addressed later in the paper, the evidence shown here suggests that a substantial portion of the documented effects of gender may, in fact, be malleable with respect to environmental factors during education.

I next examine the effect of peers on the characteristics of the industries and job functions into which students are more likely to sort at graduation.[58] Table 4 shows the estimated coefficients from the estimation of Equation 1, in which the dependent variable varies in each column but each specification uses the full set of controls in column (5) of Table 3. The dependent variable in each column is an indicator variable for the industry or job function accepted at graduation. I find that having a greater share of male peers causes women to be more likely to choose jobs in male-dominated industries and job functions at graduation and less likely to choose jobs in relatively more female-dominated industries and job functions. Table 4 reports the coefficients from a subset of the industry and job function categories. Specifically, the outcomes for a few of the topmost "gender-skewed" occupations and industries are reported.[59] The baseline gender differences in occupation and industry selection at graduation are large. In particular, the coefficients on $Female$ indicate that women, on average, are 11 percentage points (39 percent) less likely to accept a job in investment banking, five percentage points (63 percent) less likely to accept a job in investment management, and three percentage points (nearly 100 percent) less likely to accept a job in venture capital, as industries at graduation. However, a 10 percentage-point increase in the share of male peers increases the relative likelihood of women choosing investment banking by 5.5 percentage points, investment management by 2.2 percentage points, and venture capital by 2.4 percentage points. Such an increase in the share of male peers therefore closes the gender gap in selection into each of the most male-dominated job functions and industries by 50 percent or more.

In addition, the results in Table 4 indicate that an increase in the share of male peers also closes the gender gap in selection into relatively more female-dominated industries and occupations as well. In particular, product management is the most female-dominated job function, consistently across cohorts, with women being nine percentage points more likely to accept a job in product management at graduation than men (more than 100 percent relative to the mean). The reduction of the gender gap in selection into female-dominated occupations and industries is primarily a result of women with more male peers being less likely to accept jobs in female-skewed occupations and industries at graduation. The results show that a 10 percentage-point increase in the share of male peers reduces the likelihood that female students accept a job in product management at graduation by 3.9 percentage points (56 percent), again closing the gender gap in selection into female-dominated job functions by close to half (43 percent).

In order to examine the overall effect of peer gender composition on the characteristics of jobs selected at graduation for the entire set of job functions and industries, rather than on only a subset, the gender-skewedness of each industry and job function is categorized by "Industry Share Male" or "Job Function Share Male," which is defined as the fraction of graduating students in each student's cohort accepting a job in the same industry or job function as the student who are male (other than the student).[60] Table 5 shows that exposure to a greater share of male peers causes women to accept jobs at graduation in more male-dominated industries and occupations relative to men, and that this effect occurs generally, rather than

[57] See Bertrand, Goldin, and Katz (2010).

[58] Job functions are more narrowly defined occupations.

[59] The most "gender-skewed" occupations and industries reported are those in which more than three percent of graduating students accepted a job.

[60] "Industry Share Male" and "Job Function Share Male" are defined at the student-cohort level.

the effect being restricted to a few key occupations and industries. Although men with more male peers accept jobs at graduation in *less* male-dominated industries and job functions, Table A.9 in the Appendix shows that the decrease in the gender gap in selection into male-dominated occupations and industries is not driven by a change in the sorting of men, alone, across occupations and industries. Women with a 10 percentage-point increase in the share of male peers select industries and occupations at graduation that have 2.9 percentage-point (4 percent) and 3.9 percentage-point (5 percent) greater male shares, respectively, in absolute terms, not only relative to men.

In order to examine the effects of peer gender composition on the characteristics of the occupations and industries students choose, I examine the effects on the average weekly hours of work, the frequency of part-time work, the frequency of overtime work, and the average hourly wage in the occupation (job function) or industry at the time of graduation. The mean job characteristics of each occupation and industry job offer held at graduation are constructed using the alumni survey data collected on job attributes, among students who accepted such a job at graduation, and are defined for a given number of years after graduation.[61] The results in Table A.10 show that both men and women with a greater share of male peers accept jobs at graduation in occupations and industries with longer weekly hours of work, a greater frequency of overtime work, and a lower frequency of part-time work in the first year after graduation.[62] However, the effect on the weekly hours of work and frequency of overtime work in the occupations that women select is significantly greater than the effect on that of men, thus reducing the gender gap in selection into mean job characteristics by occupation. With respect to industry characteristics at graduation, only women with a greater share of male peers accept jobs at graduation in industries with greater weekly hours of work, greater frequency of overtime work, and a lower frequency of part-time work. In addition, women with a greater share of male peers enter into both occupations and industries at graduation with higher average hourly wages.[63]

Table A.10 shows that a 10 percentage-point increase in the share of male peers increases the mean weekly hours of work in job functions accepted by women at graduation by 1.4 hours (2.2 percent), and in the industries accepted by women at graduation, by 1.15 hours (1.8 percent). This reduces the gender gap in hours of work of job functions accepted at graduation by just under a half and in industries accepted by over a half. While the effect on hourly wages is a bit smaller as a percentage change relative to the mean, the effect is still a sizable portion of the baseline gender-wage gap at graduation. A 10 percentage-point increase in the share of male peers reduces the gender gap in mean hourly wages of job functions accepted at graduation by just over one-third. It reduces the gender gap in mean hourly wages of industries chosen at graduation by approximately two-thirds, a sizable reduction in the gender gap in hourly wages across industries.

Though the wage differences in the occupations and industries selected by women with more male peers are not large in the first year after graduation, having a larger share of male peers places women into occupations and industries at graduation with very different expected future wages. Columns (4) of Tables A.10 and 6 show that a 10 percentage-point increase in the share of male peers leads female students to choose occupations with wages that are on average \$0.69 per hour (1.7 percent) greater at graduation but are \$16.55 per hour (10 percent) greater 10 years after graduation - an effect nearly 25 times the magnitude as the one

[61] I use data on job characteristics specific to a given number of years after graduation, since the attributes of jobs in an occupation or industry may change over time. This is an advantage of the data relative to the previous literature, where survey results on job attributes are pooled across years.

[62] "Overtime work" is an indicator variable, equal to 1 if the usual hours of work per week reported is greater than 60 hours per week, and 0 otherwise.

[63] "Average hourly wage" is defined as the average of the self-reported annual earnings divided by the product of usual weekly hours of work and 52.

at graduation. Similarly, a 10 percentage-point increase in the share of male peers leads female students to choose industries at graduation with average wages that are \$1.21 per hour greater at graduation, but, 10 years after graduation, are \$17.90 per hour greater - a sorting effect at graduation that results in 15 times the effect on mean wages in the industry as that observed at the time of graduation.[64] Meanwhile, columns (3) of the tables show that the effect of peer gender composition on average weekly work hours is similar in magnitude over time since graduation, demonstrating that the rather large increase in the wage premium over time is not merely due to a premium in working longer hours. While the results shown in Tables A.10 and 6 use mean earnings and hours at the occupation and industry levels as dependent variables, rather than individual-level outcomes, the results show that peer gender composition causes a significant change in occupational and industry sorting at graduation along dimensions that not only change the average attributes of the job at graduation, but also the average attributes in the occupations and industries 10 years after graduation and to an even greater degree over time.

However, the average wages and other mean attributes of those who remain in the same job function or industry 10 years after graduation may be a biased measure of average wages in an occupation or industry, since those who remain in the same industry or job function for a given number years may be an increasingly selected sample. Therefore, I also use, as an outcome variable, the mean characteristics of the jobs that graduates hold 10 years after graduation, conditional on the *initial* job function or industry into which they entered at graduation, regardless of the occupation or industry into which the graduate moves in the years following graduation. The mean job characteristics a given number of years after graduation, conditional on initial occupation or industry, are then assigned to all students in the job offer data who accepted a job in the same initial occupation or industry at graduation. The effect of peers on the initial choices at graduation and the ensuing expected trajectory of students, conditional on initial job characteristics, is arguably a better measure of the expected lifetime consequences of peers on initial choices at graduation. Figure 2 and Appendix Table A.11 show these results.

Figure 2 plots the effect of peers on the gender gap in expected wages and hours, conditional on the initial occupation and industry chosen at graduation, for each year since graduation.[65] Specifically, I construct expected earnings and hours paths, conditional on the initial industry, occupation, and even initial firm of the offer accepted at graduation for each student in the job offer data by taking the mean of actual earnings of graduates from the alumni survey a given number of years after graduation over all those whose first job was in the same initial industry, occupation, or firm at graduation. In particular, each subfigure in Figure 2 plots the coefficients on $Female_i \times ShareMale_{igc}$ for a set of regressions, each with the same specification as Equation (1), but where the dependent variable for student i at time t is the expected job characteristic t years after graduation, averaged over all those students who began their careers in the same initial job function or industry as student i.[66][67] Appendix Figure A.4 uses the same construction of expected earnings and hours paths, but where the dependent variable is conditional on the initial firm.[68]

[64] I distinguish between average wages in the first year after graduation and 10 years after graduation, as opposed to simply using self-reported weekly hours across all years since graduation, a contribution relative to previous literature in this area.

[65] Note that these coefficients reflect the effects on expected wages of women relative to men. However, since the effects are not significant for men, I focus on the effects on women relative to men.

[66] $Expwage_{i,Ind_{i,0},t} = \sum_{j\epsilon I(Ind_{i,0})} wage_{j,t}$,where $Expwage_{i,Ind_{i,0},t}$ is the expected wage of student i t years after graduation, conditional on the industry in which student i accepts a job at graduation, $Ind_{i,0}$ is the industry in which student i accepts a job at graduation, $I(Ind_{i,0})$ is the set of all students other than student i who accept a job in the same industry as student i at graduation, and $wage_{j,t}$ is the wage of student j t years after graduation, regardless of the industry in which student j works at time t.

[67] $Expwage_{i,JobFunc_{i,0},t} = \sum_{j\epsilon I(JobFunc_{i,0})} wage_{j,t}$ is defined similarly.

[68] For each of these figures, averages are taken over hours and wages where "zeros" are used for for the value of hours and wages for those who are not working. Appendix Figure A.5 plots the coefficients of the same set of regression specifications,

The results show that a greater share of male peers causes women to select job functions and industries with longer expected weekly hours of work in each year after graduation. What is apparent from the figures is that a greater share of male peers causes a change in initial occupation, industry, and even firms chosen by women that result in expected wage trajectories that are greater than and increasingly divergent from the expected wage paths of women with less exposure to male peers.[69] The results suggest the possibility that peer-induced changes in the initial opportunities and choices of women at graduation have the potential to mitigate a substantial portion of the gender-wage gap at graduation as well as its growth over time. I will explore this possibility in greater detail using realized long-term outcomes in Part E..[70][71]

These results are largely consistent with findings from Zolitz and Feld (2021) and Zolitz and Brenoe (2020), which study the effect of peer gender composition on education and labor market outcomes in secondary and post-secondary education settings, though not in the MBA setting, and in settings with younger students on average. Zolitz and Brenoe (2020) utilizes Danish registry data and finds that a greater proportion of male high school peers increases women's likelihood of working in a STEM occupation and that such women have higher earnings at age 36. Zolitz and Feld (2021) finds results consistent with those shown here, using the random assignment of university students in the Netherlands to study sections. The paper finds that women who have had a greater proportion of male peers end up in jobs where they earn more and work a greater number of hours. They, too, find that only the labor market outcomes for women are affected with any consistent statistical significance.[72]

How do these results compare in magnitude? Zolitz and Brenoe (2020) find that a 10 percentage-point increase in the proportion of male peers in high school increases the probability that women work in a STEM occupation by 0.42 percentage points, a 3.9 percent increase from the baseline, but they find an effect on occupational sorting only 12 to 16 years after high school graduation. They find no significant effect on either men or women working in a STEM occupation 7 to 11 years after high school graduation. Notably, the effects that Zolitz and Brenoe find, while significant, are a much smaller fraction of the pre-existing gender gap in occupational sorting, a 3.6 percent reduction, than the effects measured here. Zolitz and Feld (2021) similarly find, though in the university setting, that exposure to more male peers has no significant impact on earnings in the first job at graduation, but results in greater earnings for women between one and five years after university graduation. Specifically, they find that a 10 percentage-point increase in the share of male peers increases women's earnings by 4.8 percent one to five years after graduation. The results shown here differ in that the analysis shows robust and significant effects on women's earnings even at the time of graduation. However, the magnitude of the effect on women's relative earnings at graduation estimated here is in the range of the estimated effects that Zolitz and Feld find one to five years after graduation. In the next sections, I explore two different mechanisms through which peer gender composition may operate, through which it may produce different effects on short- and long-term earnings. I offer an explanation for

but where expected values are taken only over the sample of those who are working.

[69]While the results shown in Figure 2 reflect the effect on women's expected wages relative to men's, I also show in Appendix Figure the absolute effect of peer gender composition on women's expected wage trajectories.

[70]To address the possibility that hours and earnings in an industry or occupation may be gender-specific, Appendix Figure A.6 panels (i) and (ii) examine the effect of peers on expected wage profiles for women, conditional on initial job function and industry, where wages computed from the alumni survey are averaged over a sample of only women. Panels (iii) and (iv) examine the same effects, but where expected wages are taken only over a sample of women with children.

[71]Panels (iii) and (iv) show that the estimated effect of peers on expected earnings for women and for women with children is non-negative for each year after graduation. The results suggest that while previously documented effects regarding the "child earnings penalty" may play a role concurrently, women with a greater share of male peers are sorting into occupations and industries at graduation with higher expected earnings, even when the earnings measure is the mean for women with children.

[72]While both Zolitz and Brenoe (2020) and Zolitz and Feld (2021) examine the effects of a greater share of *female* peers, the estimated coefficients can be used to understand the effects of a greater share of *male* peers on women's outcomes as well.

why the effects of peer gender composition may be smaller or negligible at the time of graduation but larger and of economically significant magnitude several years after graduation.

B. Underlying Mechanisms: Peers' Effect on Human Capital (Coursework and Concentrations)

In order to understand the underlying mechanisms of the effect of peer gender composition on women's labor market outcomes, I investigate whether peer gender composition affects the types of coursework, fields of concentration, and grades that women attain in business school. This is particularly salient since prior literature documents that a substantial portion of the gender gap in earnings among MBAs can be explained by grades attained and the type of coursework taken in business school.[73] Because it is women's labor market outcomes that are primarily affected by peer gender composition, and these are the outcomes I seek to explain, I focus on the effects of peers on the coursework and concentrations of women in this subsection.

Figure 3(i) shows the baseline gender difference in choices of concentration and coursework in business school. Women take roughly one-third of a finance class less than men, fewer accounting courses, and fewer statistics courses than men on average. On the other hand, on average they take more than half a marketing course more than men, more business policy courses, and more general management and behavioral science courses than men. In addition, women are less likely to concentrate in quantitative fields, such as finance and economics, than men but are significantly more likely to concentrate in general management and marketing. Neither the total number of courses women take nor the breadth of courses across fields of study differs statistically significantly from that of men.[74] Figure 3(ii) shows the estimated coefficients from Equation (1) which, along with their 95 percent confidence intervals, reflect how the gender composition of their peers affects students' choice of coursework and concentrations. The results show that greater exposure to male peers causes female students to choose courses and fields of concentration that are relatively more male-dominated at baseline. In particular, a 10 percentage-point increase in the share of male peers causes both male and female students to take an additional sixth of a finance course on average, increase their likelihood of concentrating in finance by 2.5 percentage points (3.0 percent), and to decrease their likelihood of concentrating in general management by 1.7 percentage point (50 percent).[75] Women with a greater share of male peers take more economics courses, are more likely to concentrate in economics and in international business, and have a larger share of their coursework is made up of quantitative courses, relative to men. In addition, greater exposure to male peers causes female students to take fewer courses in and be less likely to concentrate in subjects that are relatively more female-dominated. Specifically, such exposure causes women to take a lower fraction of general management and behavioral science courses, fewer product management courses, and to be less likely to concentrate in marketing. Additionally, while a greater share of male peers does not have a differential effect on women's likelihood of concentrating in finance that is statistically significant, it is interesting to note that if anything, a greater share of male peers has an even greater effect on women's likelihood of concentrating in finance than it does on men's.

[73] Bertrand, Goldin, and Katz (2010) notes that each additional finance course increases earnings by about 8 log points and that women take about half a class less in finance than men.

[74] The measure of course concentration across fields ("HHI Index") is calculated by summing the square of the share of courses taken in each of the nine largest fields of study, similar to the HHI index.

[75] The estimated coefficients show that there is no statistically significant difference between men and women in the effect of male peers on the number of finance courses taken, the likelihood of concentrating in finance, or the likelihood of concentrating in general management. Therefore, only the coefficient on $ShareMale$ is reported for those three dependent variables in Figure 3(ii).

While the share of male peers does not affect the total number of courses taken by female students, a greater share of male peers does increase the concentration of courses women take across fields of study, as measured by the HHI (Herfindahl-Hirschmann) concentration index applied to coursework shares in each field of study. The increase in the share of coursework in quantitative fields and areas of concentration is not largely driven by a reduction in the *number* of courses women take in female-dominated fields of study, with the exception of product management courses. Rather, the findings, taken together, indicate that women with a greater share of male peers increase the *concentration* of their coursework in particular fields of study and that they are more likely to increase the concentration of coursework in quantitative fields of study. In other words, women with greater exposure to male peers specialize more.

Table 7 shows that the effect of peer gender composition on women's fields of concentration in business school relative to men's is driven primarily by women with more male peers changing their *most* male-dominated field of concentration. Both men and women with more male peers are more likely to enter any male-dominated field of concentration. In Table 7, I distinguish between selecting a "male-dominated" field of concentration, defined as a field that is disproportionately male relative to the cohort, and a "majority-male" field, a field in which more than 50 percent of the students choosing the field in the cohort are male.[76][77] While some of the change in coursework and fields of concentration takes place at the higher end of the male-dominated coursework distribution, column (3) shows that a greater share of male peers also causes women to be more likely to concentrate in any majority-male field, crossing the 50 percent male share threshold. They are also more likely to have all majority-male concentrations. Men with more male peers, on the other hand, are less likely to concentrate in any majority-male field and are less likely to have all majority-male concentrations (more likely to enter at least one majority-female concentration). The effect sizes are large enough that a ten percentage-point increase in the share of male peers not only reduces, but reverses the gender gap in the likelihood of a student having any majority-male concentrations, relative to the mean. Table A.12 in the Appendix, shows the effects of a greater share of male peers on fields of concentration, separately for men and women.

The results are largely consistent with those of Zolitz and Feld (2021), which finds that an increase in the share of male peers leads to a decrease in gender segregation in major choices. However, in this context, where approximately two-thirds of each cohort is male, we can distinguish between the effect of peer gender composition on the selection of majority-male fields and coursework and *disproportionately* male fields and coursework. It is notable that peer gender composition seems to operate on the majority-male threshold, even in an environment that is already disproportionately male overall. In addition, in this context, where the average age of entry is greater, and where students have already attained undergraduate degrees, many have obtained graduate degrees as well, and they have significant work experience, it is notable that having a greater share of male peers causes women to significantly alter their coursework and fields of study in significant ways: women choose areas of concentration that are more male-dominated, such as finance and economics, and are less likely to concentrate in female-dominated fields, such as general management, product management, and marketing.[78] Having a greater share of male peers causes both men and women to take a greater number and fraction of quantitative courses in general and finance courses in particular, which

[76] Note that a field can be "majority-male" but still be disproportionately female, relative to the cohort, in this context.

[77] Proportion of male students in the field of concentration is determined separately, within each cohort, and excludes the student, to avoid the reflection problem.

[78] Another important difference in the context studied here relative to the previous literature is that students may choose more than one field of concentration. Yet, peer gender composition operates by both increasing the male proportion of the most male-dominated concentration and by increasing the male share in the *least* male-dominated course that women take. Further detail provided in Appendix Table A.12.

is notable as previous literature has documented this is often associated with higher salaries at graduation. I explore in Sections VI.C. and VI.D. whether the effect on coursework and concentrations is the primary mechanism driving the effect of peers on salaries at graduation and on long-term outcomes.

C. Underlying Mechanisms: Human Capital Versus Preferences

I next examine two possible mechanisms through which the effect of peer gender composition on earnings at graduation takes place. In particular, I exploit a unique aspect of the data, which is that for each of the 1999 through 2011 graduating classes, the employment offer survey records for each student the full set of job offers received through the centralized on-campus job market system, along with a variety of components of pay. Moreover, the data also includes the accepted job offer of each student. For the vast majority of students, the job offer accepted at graduation comes from the set of job offers received through the centralized on-campus recruiting system.[79] Therefore, an advantage of the data is that I can distinguish between the effect of peers on the set of *offers* from a possible effect on preferences: the choice of job students make from within their choice set.[80][81]

I examine, separately, the effect of peer gender composition on the distribution of salary *offers* that a student receives and its effect on the likelihood that a student accepts the greatest salary offer in his or her offer *set*. In this section, I explore the extent to which human capital explanations and its effect on the set of job offers received can explain the effects of peer gender composition on the gender earnings gap at graduation relative to an effect on the "willingness to accept" (WTA) the maximum salary offered.[82] In Appendix B, I explore more formally whether any observed effect on the WTA indeed reflects a change in preferences, or in the "willingness to pay" (WTP) for non-wage amenities.

Table 8 presents the estimated coefficients from Equation (1), where the dependent variable varies in each column, but each specification uses the full set of control variables as those used in Column (5) of Table 3. In columns (1), (2), and (3), the dependent variables are the natural log of the mean, median, and maximum, respectively, of the base salary offers to the student. In column (4), the dependent variable is the natural log of the maximum "permanent salary" offer, which, in addition to the base salary, includes all other forms of guaranteed annual compensation, such as guaranteed year-end bonuses, profit-sharing, and stock options, as well as other forms of annual compensation that are guaranteed and are not performance-dependent. Finally, in columns (5) and (6), the dependent variable is whether the student accepted the maximum salary offered within his or her offer set, given the set of base salaries offered and the set of permanent salaries offered, respectively.

The estimated coefficients in Table 8 show that there is no significant effect of peer gender composition on the mean, median, or maximum salary offer of female students relative to male.[83] Importantly, female

[79] Approximately 97 percent of students who are offered at least one job accepts one of the jobs offered.

[80] Students may hold the job offers simultaneously in-hand prior to making an acceptance decision. In this setting, employers may not give "exploding offers" or require students to make a decision prior to a fixed date, set by the university, which is the same for all employers interviewing within a given time frame, and the date is after all of the interviews have taken place. Therefore, the uncertainty with respect to future offers or the opportunity cost of accepting an offer as in Cortes et al. (2023) does not play a large role in this setting.

[81] The timing is such that all negotiation for salary, benefits, and other forms of compensation has been completed, and final offer terms are agreed upon prior to students making their decisions.

[82] Of course, human capital may also alter preferences, or the choices one makes from within one's choice set. Here, I distinguish between the effect of peers on the set of offers and the the effect on the offer chosen, conditional on the offer set.

[83] While there is an effect of peer gender composition on the maximum base salary offer of women relative to men (Column (3)), this is primarily due to the fact that an increase in the share of male peers decreases the maximum base salary offer men receive, but increases the bonuses offered and other forms of guaranteed pay. Column (4) shows that once the effect on "permanent salary" is considered - the sum of base salaries and a discounted measure of annual, guaranteed bonuses - there is

students with a greater share of male peers are more likely to accept the maximum salary offer within their offer set, while there is no significant effect on male students' likelihood of accepting their highest salary offer.[84] In particular, the estimates show that a 10 percentage-point increase in the share of male peers leads to a three to four percentage-point increase (4.4 percent) in the likelihood of female students accepting the highest salary offer in their offer set. The results show that the primary channel through which peer gender composition affects the gender gap in earnings at graduation is through its effect on female students' willingness to accept their highest salary offer rather than through an effect on their offer *set*.[85]

Appendix Table A.13 shows that, conditional on accepting a salary offer of less than the maximum salary offer, there is no significant effect of peers on the *difference* between the maximum salary offer and and the salary offer accepted, for either measure of salary. The mean difference between the maximum base salary offered and the second-highest base salary offer is approximately 18.6 percentage points among those who received more than one offer. The magnitudes suggest that the effect of peer gender composition on female students' salaries at graduation can be almost entirely explained by a change in the willingness to accept the maximum salary offer.[86]

Finally, the estimates in columns (5) and (6) of Table 8 also show that female students are, on average, 2 percentage points less likely to accept the maximum salary offer than male students. Interestingly, these estimates suggest that a 10 percentage-point increase in the share of male peers - a bit more than a one-standard deviation increase - not only closes but reverses the gender gap in willingness to accept the maximum salary offer in the offer set.

D. Human Capital and Long-Term Earnings Paths

In spite of a significant change in the coursework and fields of concentration of female students with a greater share of male peers, the results in the previous section show that there is no significant effect of peers on the distribution of salary offers at graduation. This finding is perhaps surprising given that a well-documented source of the gender-earnings gap at graduation and beyond for graduates of top business schools is the fraction of quantitative coursework taken and, in particular, the fraction of finance courses taken during business school. Indeed, the results shown in this paper show that a greater share of male peers causes female students to increase the fraction of quantitative courses that they take and their likelihood of concentrating in quantitative fields, including finance. Yet no effect on the distribution of salary offers at graduation is observed.

Does this mean that the changes in coursework and fields of concentration in this context have no effect on the earnings of women? In the Appendix, I examine whether a possible explanation is that the context studied here is different from those studied in the previous literature. First, I examine the effect of quantitative coursework on salary *offers*, rather than on accepted salaries.[87] Second, it is possible that

no effect of peer gender composition on the maximum "permanent salary" offer for men, either.

[84] There is no effect for male students for either base salary offers or for permanent salary offers.

[85] I distinguish between WTA and WTP because it is possible that, rather than reflecting a decrease in the WTP, the increase in the WTA is due to women with a greater share of male peers searching for jobs in different occupations and industries, specifically those in which the earnings foregone in exchange for an increase in the non-wage amenity value offered increases. The "price" of non-wage amenities may differ in male- and female-dominated occupations. I explore this in greater detail in Appendix B.

[86] A back-of-the-envelope calculation suggests that a three to four percentage-point increase in female students' likelihood of accepting their highest salary offer (relative to their second-best offer), combined with a 1.5 percentage point reduction in the maximum salary offer to male students (when men have a mean 91 percent likelihood of accepting their highest offer), fully explains the 2.1 percentage point reduction in the gender gap in base earnings due to a 10 percentage-point increase in the share of male peers.

[87] Prior literature has only explored the effect of quantitative coursework in business school on the salary accepted. It is

in this particular environment, there is not the same relationship between the fraction of finance courses taken and salaries as what has been documented in the previous literature. Appendix Table A.14 presents the estimated coefficients from Equation (1), where the dependent variables are the natural log of the mean, median, and maximum, respectively, of the base salary offers to the student, and each specification uses the full set of control variables as those used in Column (5) of Table 3. In addition, each regression here includes an indicator variable for whether the student concentrated in finance and an interaction term between concentration in finance and female. The results show that this context is no different from the others explored in previous literature and that a concentration in finance is indeed associated with a higher mean, median, and maximum salary offer, and in particular, for women. Appendix Table A.15 shows that a greater fraction of courses in finance is also associated with greater mean and median salary offers for women in particular.[88]

The results taken together suggest a simple hypothesis that the "movers" - those students who are randomly "nudged into" concentrating in finance due to the peer effect - do not receive the same return to concentrating in finance as those who concentrate in finance for reasons unrelated to the peer effect. Panel A of Table 9 uses an AKM-style wage decomposition to examine the effect of peer gender composition on the distribution of the "firm pay premia" among the firm offers received, where the "firm pay premium" is the firm component of pay from an AKM wage decomposition.[89] The results show that women with a greater share of male peers receive offers from higher-paying firms, yet their individual wage and salary offers are not higher. Mechanically, it can be concluded that the individuals "induced to move" by the peer effect are receiving offers from higher-paying firms but receive below-average offers from those firms. In other words, they are those with either lower-than-average individual wage effects (for that firm, i.e. more negative sorting) or lower-than-average match effects. The results are consistent with a standard Roy model, where the marginal student does not receive large returns to moving.[90] In Panels B and C, I examine the effects of peer gender composition on industry-level pay and job function-level pay, and I show that the same is true - women with a greater share of male peers receive offers from higher-paying industries and job functions, but receive below-average offers for those fields.[91] Thus, in spite of increasing quantitative coursework and the likelihood of concentration in quantitative fields, the net effect is that an increase in the share of male peers does not result in higher (or lower) salary offers for female students at graduation.

We further explore this hypothesis in Appendix C, using a standard instrumental variables (IV) approach to identify the causal effect of concentrating in finance among those who are randomly "induced to move" into concentrating in finance. The results of the OLS regression (shown in Appendix Table A.14) already show that the relationship between concentration in finance and offers is driven by the component that is orthogonal to the peer effect. The results suggest that for those female students who are randomly "induced to move" into concentrating in finance by the peer effect, concentrating in finance does not have a significant

possible that human capital has an effect on the offer accepted from the offer *set* rather than on the set of offers themselves, which would make the results shown here consistent with previous literature, even if human capital operated on salaries only through the student's choice of offer.

[88]For "maximum salary offer," the main outcome measure used is the maximum "permanent salary", since, as described earlier, men with more male peers make trade-offs between one-time, upfront bonuses and annual guaranteed pay. Using "permanent salary" allows us to examine a measure of long-term earnings, isolating away from short-term trade-offs and potential behavioral effects.

[89]Note that the firm effect can be identified because we observe multiple offers per student.

[90]It is also consistent with a story where differential treatment by the firm is known and anticipated by workers, and is accounted for in their selection into fields of study.

[91]In Appendix Table A.16, I show that the effect of peers on the distribution of (relative) firm pay for women is explained by a change in human capital, and in particular by a female-specific effect of human capital. Thus, human capital and field of concentration appear to explain peers' effect on the firm pay premia offers that women receive.

causal effect on the mean, median, and maximum salary offer.[92] The results do not contradict the findings in the previous literature that show that a concentration in finance is associated with a higher starting salary for women at graduation. However, the results still suggest that a program that encourages or induces women to concentrate in finance or take more quantitative courses does not necessarily yield the same increases in opportunities at graduation as what is observed among women who elect to concentrate in finance or to take a large number of quantitative courses.

Though the effect of more male peers does not have a significant effect on women's salary offers at graduation, it is possible that peer-induced changes in human capital choices affect the long-term expected earnings paths into which female students are placed, through their effect on the first job at graduation. In order to investigate this possibility, I examine the effect of peer gender composition on the distribution of "offers for future earnings," where an offer at graduation is defined not only by the starting salary, but by expected future earnings, conditional on the characteristics of the first job at graduation. Expected earnings a given number of years after graduation is measured over all those students who begin their careers in such a job at graduation, regardless of the whether the student remains in the same job or changes jobs over the course of their career. Thus, an "offer at graduation" is considered a stream of current and expected future earnings, conditional on starting in such a job at graduation.

Specifically, I examine the effect of peer gender composition on the distribution of "offers for wages 10 years after graduation," where each offer is defined as the expected wage 10 years after graduation, computed using actual earnings data from the MBA alumni survey averaged over the realized wages 10 years after graduation of all students who accepted their first job in the same job function or industry at graduation.[93] Each expected future wage profile computed using the MBA alumni survey data is then matched with each job offer from the employment offer data.

Panel A of Table 10 shows the estimated coefficients of Equation (1), where the dependent variables are the mean, median, and maximum, respectively, of "offers for expected wages 10 years after graduation," and where the expected value is conditional on the initial job function in columns (1) - (3) and conditional on the initial industry in columns (4) - (6). In contrast to the results shown in Table 8, the gender composition of a student's peers indeed has large and significant effects on the distribution of "offers for future wages" received by female students at graduation when offers are quantified in terms of their long-term expected value, conditional on the initial conditions. In particular, a 10 percentage-point increase in the share of male peers increases the median offer for expected wages 10 years after graduation, conditional on job function at graduation, by $9.89 per hour for female students (6 percent) - reducing the gender-wage gap in offers for expected wages 10 years after graduation (due to differences in initial job function offers) by nearly 30 percent. Moreover, a 10 percentage-point increase in the share of male peers increases the median offer for expected wages 10 years after graduation, conditional on industry at graduation, by approximately $16 per hour for female students (more than 10 percent)- closing the gender-wage gap in offers for expected wages 10 years after graduation (due to differences in initial industry offers) by nearly *one-half*.[94]

[92] Though IV estimators are often criticized for the local nature of the estimates, here, this is intentionally exploited, as in Arnold, Dobbie, and Yang (2018), to understand the causal effect of concentration in finance on salary offers at graduation for those near the margin.

[93] I use the MBA alumni survey to construct each of these expected earnings trajectories, using the salaries reported 10 years after graduation divided by the reported weekly hours of work 10 years after graduation times 52, averaged over all students who accept an offer in the same initial industry or job function at graduation.

[94] Appendix Table A.17 shows even greater effects of peer gender composition on the mean, median, and maximum of firm offers for long-term expected wages (expected wages, conditional on the starting firm at graduation.) The results show that a

The results show that not only is a large fraction of the gender wage gap 10 years after graduation already present, in expectation, in the differences in the offers received by men and women at the time of graduation, but also that the gender composition of one's peers causes female students to receive a set of offers with different starting conditions, placing them on dramatically different expected wage trajectories.[95] Female students with a greater share of male peers receive job offers at graduation from occupations, industries, and firms with significantly higher expected wages 10 years after graduation. These offers result in expected wage paths that are increasingly divergent over time from those they would have otherwise received.

To examine whether the effect of peer gender composition on offers for future expected wages is explained by peer-induced changes in human capital choices, I estimate Equation (1), including controls for the field of concentration as well as an interaction term between field of concentration and female, where the dependent variable is the mean, median, and maximum of the set of long-term expected wage offers received by the student at graduation. Panel B of Table 10 presents the estimated coefficients. The results show that the effect of peer gender composition on offers for long-term expected wages 10 years after graduation is entirely explained by peer-induced changes in human capital.

E. Long-Term Effects

Finally, I examine the effects of peer gender composition on the longer-term labor market outcomes of female students relative to male. The results shown earlier in this paper indicate that having a greater share of male peers causes female students to accept jobs at graduation in occupations, industries, and firms with significantly greater long-run earnings, in expectation. However, as we showed in Section D., women may not necessarily receive the expected returns. In addition, female "movers" may not necessarily receive the expected returns for women. In this section, I use the actual long-term earnings of students from the MBA alumni survey, which collects long-term employment and earnings data for a subset of the students, and link this data to the employment and job offer data, peer assignment administrative data, coursework and course transcript information, and data on background characteristics. The data from the MBA alumni survey allows us to observe labor market earnings information for each employment spell up to seven years after graduation, for each student whose peer group and administrative data is known.[96]

One thing to note is that because the alumni survey comes from a retrospective survey conducted of the 1990 to 2006 graduating classes, while employment offer data is available for the 1999 to 2012 graduating classes, the maximum number of years post-graduation for which we can estimate peer effects on labor market earnings is six, given that we include cohort fixed effects.[97] While the sample size is smaller than ideal, the contribution of this section is i) to examine how the effect of peer gender composition in the US

10 pp increase in the share of male peers closes the gender-wage gap in firm offers for long-term expected wages by more than 100 percent.

[95] It is particularly notable that peer gender composition affects the median wage offer more so than the mean or maximum wage offer.

[96] As noted earlier, the responses to the earnings questions from the MBA alumni survey were collected in discrete bins and transformed into real-valued variables using the midpoint of each bin. Therefore, the earnings measure for the long-term data has more measurement error than the data from the employment offer data, and estimated coefficients, though unbiased, will be less precise than with earnings data at graduation. Individual earnings in a given year were computed by linear extrapolation between the first and last year at each job.

[97] It is for this reason that we use expected earnings as the outcome variables of interest in the previous sections, as this exploits data from the entire 1990 to 2006 graduating classes, taking advantage of the fact that the same industries, occupations, and even firms recruit at the business school year after year.

educational setting compares to those found in the previous literature, which, among those that examine effects on earnings, shows that effects of peer gender composition are small or negligible at graduation, but seven to eleven years after graduation, effects on earnings are significant and meaningful (Zolitz and Brenoe (2018)), and ii) to then use these results to understand how the two different channels driving the effects of peer gender composition play out differently in terms of effects on long-term earnings and the timing of those effects. Finally, this section serves as an important counterpart to understanding results from other recent work studying the US MBA context, which examines effects of peer gender composition on promotions, but *not* on earnings (Hampole, Truffa, and Wong (2024)).

Table 11 shows the impact of peer gender composition on long-term labor market outcomes. It presents the estimated coefficients from a series of regressions similar to Equation (1), where the dependent variable is log earnings a given number of years after graduation. The results show that women with a greater share of male peers receive higher earnings relative to men at graduation and in the year following graduation. In fact, a 10 percentage-point increase in the share of male peers in the first year after graduation increases the female advantage in earnings by 8.7 percent (log points) - a 74 percent increase relative to the mean. In the second, third, and fourth years following graduation, the estimated effects of peer gender composition both diminish in magnitude and are not significantly different from zero. However, the results show that women with a greater share of male peers do, in fact, receive significantly higher earnings six and seven years after graduation, relative to men, and that the magnitude of the effect grows with time. Note that the estimated effect five years after graduation is close to statistically significant at the 10 percent level, but more importantly, the magnitude of the effect increases starting in year five.[98][99]

In particular, a 10 percentage-point increase in the share of male peers results in a 27.4 percent increase in the relative earnings of female graduates six years after graduation, reducing the gender earnings gap six years out by more than 50 percent. Seven years after graduation, it increases women's relative earnings by 50 percent, closing the gender earnings gap by more than two-thirds (71.4 percent).[100][101] While the results shown here as well as the previous literature show that the gender earnings gap accumulates over time, the findings here show that the *share* of the gender earnings gap mitigated by peer gender composition also grows with time.

Figure 4 shows the estimated coefficients and the associated 95 percent confidence intervals from a set of regressions, where each data point represents the estimated coefficient on $Female \times ShareMale$ from a separate regression similar to Equation (1), in subfigure (i), and in subfigure (ii), from a set of regressions where the effect of peer gender composition was estimated separately for men and women. The results show that the absolute effect on women's earnings is even greater than the relative effect, and while the effect on women's earnings is small at graduation, women with a greater share of male peers receive are significantly

[98] Note that while the effects are not statistically significant five years after graduation, the long-term salary outcome variable is based on the midpoint of bins. Therefore, the precision of the effect may be underestimated, and the measurement error creates a downward bias.

[99] The estimated effect on earnings at graduation (year 0) comes from the employment offer data, which provides an exact earnings level, rather than being defined as the midpoint of a bin. This explains why the the number of observations is greater at graduation than in the following 7 years and also why the estimates for Year 0 are more precise.

[100] The estimated coefficients shown in Figure 4 are based on earnings conditional on employment. To address selection bias, Appendix Figure A.8 shows the effect of peer gender composition on the likelihood of "ever not working" and on "total number of years not working," for female students relative to male, a given number of years after graduation. The results show that women with a greater share of men in their peer group have a small reduction in the likelihood of not working by the third year after graduation, but this effect dissipates by the fourth and fifth years.

[101] In Appendix Table A.20, we examine whether the effects are driven by attrition bias, repeating the analysis, but using only observations of those who have non-missing annual earnings six and seven years after graduation. The results are largely consistent - the magnitude of the estimated effect at graduation is remarkably similar, in spite of a low number of observations - and the effects on earnings five years after graduation become statistically significant at the 10 percent level.

better off in terms of earnings five, six and seven years after graduation and in growing magnitude as well.

The effects are somewhat consistent with those found in Zolitz and Brenoe (2020) and Zolitz and Feld (2021), which find that women with greater exposure to male peers have significantly greater earnings one to five years after graduation (Zolitz and Feld (2021)) and 11 to 16 years after graduation (Zolitz and Brenoe (2020)). However, the results are different in some important ways from the previous literature, which finds little significant effect on labor market earnings in the first job after graduation. The results shown here suggest that peer effects are operating on women's relative earnings through two different channels: one, through the increased likelihood of choosing the maximum salary within one's choice set, which primarily affects salaries at graduation, but whose effects are *not* persistent, and the second - through human capital and field of study - which affects the types of jobs and earnings paths that women select into at graduation, but whose effects do not materialize immediately in terms of earnings at graduation. The analysis of long-term earnings data shows, however, that it is through the latter mechanism that we see significant and persistent effects in terms of long-term earnings several years after graduation.

Finally, I investigate whether the human capital channel, through its effects on the characteristics of the first job at graduation, explains the long-term effects on women's earnings. I examine how much of the long-term earnings effects of peers can be explained by a change in the initial occupation, the initial industry, and the initial firms accepted at graduation, using occupation, industry, and firm fixed effects of the first job at graduation. Each column in Table 11 represents a separate regression where the dependent variable is one to seven years after graduation.[102] Looking first at Panels B and C, I find that changes in the initial industry at graduation explains much more of the effect of peer gender composition on women's long-term earnings, relative to men, than that of initial occupation. This is perhaps especially interesting given that the initial industry and occupation at graduation appear to explain similar fractions of the baseline gender-earnings gap. However, the effects of peer gender composition on the sorting of female students into different industries at graduation explains a larger fraction of the effects of peer gender composition five, six, and seven years after graduation than the change in occupational sorting.

In Panel D, I examine how much of the effect of peer gender composition on women's long-term earnings is due to changes in the firms into which female students enter at graduation. The starting firm explains almost all of the baseline gender earnings gap, even five and six years after graduation, where the documented magnitudes are greatest. In addition, the starting firm explains a significantly larger share of the variation in long-term earnings than either starting occupation or starting industry. The results appear to be consistent with a recent literature on the importance of the first job at graduation or the first firm at which one lands a job for long-term earnings, even through subsequent jobs.[103] The results suggest that it is a change in the characteristics of the first job at graduation (starting industry, occupation, and firm), in combination, that explains the effects of peers on the long-term earnings of women.

VII. Discussion and Conclusion

Using novel data from a top business school in the United States, this paper provides causal evidence that the gender composition of one's peers in business school affects the gender-earnings gap at graduation, choices of coursework and fields of concentration during business school, and the first job at graduation. This paper provides evidence that women with a greater share of male peers have significantly greater relative

[102] This allows occupation, industry, and firm fixed effects to take a non-linear time path, and the estimated effects of each initial job characteristic are specific to the years since graduation.

[103] See Kahn (2010) and Arellano-Bover (2024).

earnings at graduation and are more likely to enter more male-dominated occupations and industries in their first job after graduation. These jobs are those with a greater frequency of overtime work, a lower frequency of part-time work, greater weekly hours of work, and higher wages. The effects of a 10 percentage-point increase in the share of male peers not only reduces the gender earnings gap at graduation, but it reduces the gender segregation of entry into jobs at graduation by close to two-thirds.

Importantly, this paper shows that "initial conditions" matter. Peer gender composition has a dramatic effect on the long-term expected earnings paths of women through a change in the types of jobs in which they begin their careers - notably, the initial industries, occupations, and even initial firms into which women sort at graduation. Consistent with literature on graduating during a recession, the first job at graduation has large and persistent effects. The effects of peers on the characteristics of the first job at graduation together explain the relatively large effects of peer gender composition on the long-term earnings of women. The findings demonstrate that while there are large gender gaps in both field of study and in the starting conditions of the career, a particular environmental factor, the share of male peers, that decreases gender segregation in the "initial conditions" of the career, also has large long-term and positive consequences on the earnings of women.

The effects of peer gender composition on fields of study and on occupational sorting are consistent with previous literature based outside of the U.S., such as Zolitz and Brenoe (2020) and Zolitz and Feld (2021). At first glance, the findings shown here may not appear to be consistent with those from a recent working paper by Hampole, Truffa, and Wong (2024), which finds that at a similar top business school setting in the United States, women with more male peers are *less* likely to be promoted, though the authors admittedly do not have wage or earnings data. This paper offers additional insight using novel data on job offers that sheds light on why the two findings may not, in fact, be inconsistent. It shows evidence that women with a greater share of male peers receive offers from higher-paying industries, occupations, and even firms, but below-average offers from such jobs. The two papers can indeed shed light on two different aspects of the same story, both of which can be true if the variance in earnings across fields is sufficiently large relative to the variance within-field. In particular, a worker can simultaneously enter a field in which she is more likely to receive below-average wages, relative to the field (less likely to be promoted), but still have greater earnings relative to had she entered a lower-paying field but was more likely to advance within the field. This speaks to the importance of measuring both promotions *and* earnings in order to understand the effects of peer gender composition.

In addition, this paper leverages a unique aspect of both the data and the institutional setting in order to disentangle two possible channels for the observed peer effects: it allows one to distinguish between the effect of peers on the set of offers received, or the choice set of students, from a potential effect on preferences: the choice of job students make from within their offer *set*. While this paper uncovers two different mechanisms through which earnings is affected, it also shows that not all channels of reducing the gender gap in the short-term result in long-term earnings differences. While having a greater share of male peers causes an increase in women's likelihood of accepting their highest salary offer, and causes female graduates to face short-term earnings gains at graduation and in the first year following graduation, this particular effect does not result in persistent effects on earnings. It is the effect of peers on human capital choices that affects the overall offer *set* and moves female students into a set of dramatically different long-term expected earnings paths.

Finally, this paper provides evidence that the gender composition of peer groups in business school has large and persistent effects on the earnings of women long after graduation. In particular, a 10 percentage-point increase in the share of male peers closes the gender earnings gap 6 years after graduation by more than 50 percent and, seven years after graduation, by more than 70 percent. These results reveal some underlying mechanisms through which the gender-wage gap can accumulate to the documented magnitudes over the course of the lifecycle, but can also be mitigated in growing proportion.

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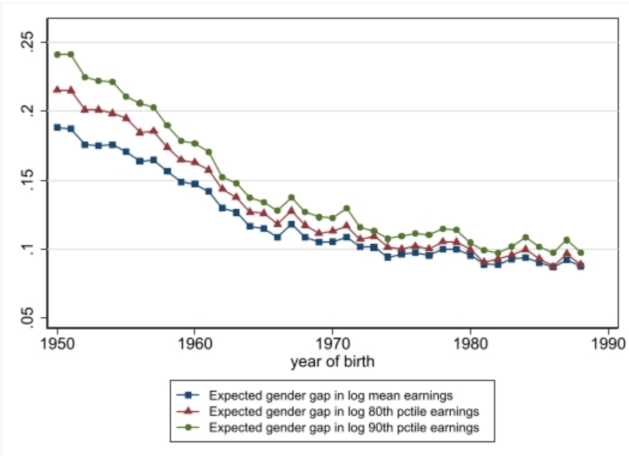
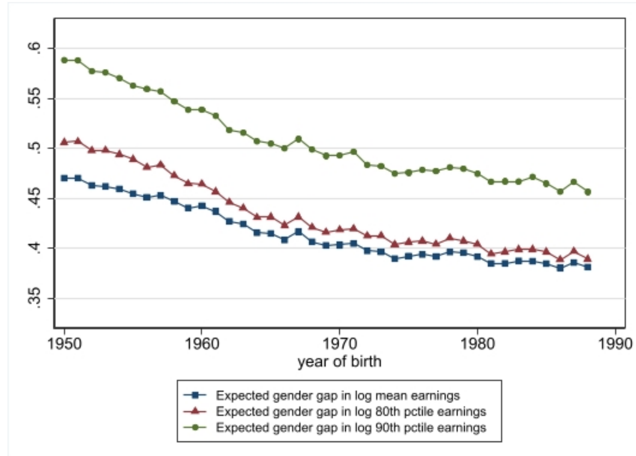
VIII. Tables and Figures

Figure 1
Effect of Gender Composition of Peer Group on Evolution of Job Characteristics After Graduation



(i)
Expected Earnings Based on Combination of Highest Degree Type and Field of Study



(ii)
Expected Earnings Based on Gender-Specific Earnings Associated with Highest Degree Type and Field of Study

Notes: For the earliest birth cohorts (1950-1953), I use data from the American Community Survey (ACS) from 2012-2015, as in Bertrand (2017), and for the remaining cohorts, I use data from the ACS from 2016-2019 and focus on individuals born between 1954 and 1989 (ages 30 to 65). The sample is restricted to those that have completed at least a four-year college degree by age 30. For each birth cohort, I proxy for the earnings potential of a given individual based on each combination of highest degree type (bachelor's degree, master's degree, professional degree, doctorate) and field of study (economics, English literature, etc.). In subfigure (i), I compute mean earnings and 80th and 90th percentile earnings among men working full time who have completed that degree-field combination. I then report, by birth cohort, the gender gap (ln[male potential earnings] - ln[female potential earnings]) in the education-based earnings potential. In subfigure (ii), I complete the same exercise, except mean earnings, the 80th, and the 90th percentile of earnings are computed separately among men and among women, so the gender gap is not only based on differences in the degree-field combination, but also on a gender difference in the returns to each degree and field combination.

Table 1
Summary Statistics for Classes of 1998-2012

	Obs.	Mean	SD	Min.	Max.
Female	8283	0.28	0.45	0	1
GMAT Total Score	7518	693.59	49.82	390	800
GMAT Quant Percentile	6544	75.61	26.11	0	99
GMAT Verbal Percentile	6544	79.23	26.67	0	99
Undergraduate GPA (4.0 scale)	5858	3.40	0.35	1.6	4
Work Experience	3911	4.81	1.94	0	14.08
Black	7694	0.04	0.20	0	1
Hispanic	7694	0.05	0.21	0	1
Asian	7694	0.16	0.37	0	1
South Asian	7694	0.06	0.23	0	1
Age at Entry	7685	28.06	2.61	21	47
Married	8091	0.36	0.48	0	1
US/Canadian Citizenship	7661	0.61	0.49	0	1
Visa: US Cit/Perm Res/Work Perm	8283	0.71	0.45	0	1
Undergraduate Major: Economics	6534	0.13	0.34	0	1
Undergraduate Major: Finance	6534	0.02	0.15	0	1
Undergraduate Major Type: Business	6534	0.32	0.47	0	1
Undergraduate Major Type: Hard Science	6534	0.21	0.41	0	1
Top Twenty Undergraduate Institution	7636	0.20	0.40	0	1
Top Ten Undergraduate Institution	7636	0.11	0.32	0	1
Prev Ind: Ibanking	1401	0.14	0.35	0	1
Prev Ind: Consulting	1401	0.18	0.39	0	1
Prev Ind: Imanagement	1401	0.06	0.25	0	1
Peer Group Share Female	156	0.28	0.07	0.12	0.39
Share Undergrad Econ Majors	130	0.13	0.11	0.00	0.34
Share Undergrad Finance Majors	130	0.02	0.04	0.00	0.18
Share Major Type: Business	130	0.30	0.23	0.00	0.61
Share Major Type: Hard Science	130	0.23	0.20	0.00	1.00
Peer GMAT Score	146	692.16	14.81	658.79	720.53
Peer GMAT Quant Pctle	146	65.26	29.70	0.00	87.25
Peer GMAT Verbal Pctle	146	68.13	31.56	0.00	91.67
Share from Top 20 Undergraduate Inst.	146	0.20	0.06	0.06	0.31
Share from Top 10 Undergraduate Inst.	146	0.11	0.05	0.02	0.25
Share Prev Ind: Ibanking	96	0.14	0.11	0.00	0.42
Share Prev Ind: Consulting	96	0.18	0.10	0.00	0.43
Share Prev Ind: Imanagement	96	0.06	0.06	0.00	0.23
Share Prev Job: Ibanking	96	0.09	0.08	0.00	0.30
Share Prev Job: Consulting	96	0.16	0.09	0.00	0.43
Share Prev Job: Imanagement	96	0.08	0.07	0.00	0.25
Share Prev Job: Company Finance	96	0.06	0.07	0.00	0.43

Notes: The sample consists of all full-time students who were members of the entering classes of 1996-2010, excluding transfer students (1,123 students) and students whose peer group assignment was unknown (15 students).

Table 2
Share of Males Peers Regressed on Own Pretreatment Characteristics

VARIABLES	(1) Share Male	(2) Share Male	(3) Share Male	(4) Share Male
GMAT Total Score	1.10e-06	9.76e-07	-3.94e-07	4.69e-06
	[8.73e-06]	[8.73e-06]	[1.07e-05]	[1.46e-05]
GMAT Quant Score	7.68e-05	7.51e-05	6.86e-05	7.02e-05
	[1.01e-04]	[1.01e-04]	[1.29e-04]	[1.54e-04]
GMAT Verbal Score	-2.57e-05	-2.55e-05	-3.56e-05	2.99e-05
	[8.89e-05]	[8.89e-05]	[1.07-04]	[1.59e-04]
Undergraduate GPA	6.30e-04	6.30e-04	4.85e-04	9.24e-04
	[1.34e-03]	[1.34e-03]	[1.59e-03]	[2.46e-03]
Undergraduate Major: Economics	-1.67e-03	-1.67e-03	-2.30e-03*	-9.48e-05
	[1.04e-03]	[1.04e-03]	[1.26e-03]	[1.80e-03]
Undergraduate Major: Finance	-2.55e-03	-2.55e-03	-3.15e-03	-9.53e-04
	[2.38e-03]	[2.38e-03]	[2.90e-03]	[4.07e-03]
Undergraduate Major Type: Business	-6.32e-06	-7.01e-06	-1.09e-03	2.36e-03
	[8.45e-04]	[8.45e-04]	[1.02e-03]	[1.47e-03]
Undergraduate Major Type: Hard Science	-2.17e-04	-2.12e-04	7.39e-04	-2.30e-03
	[9.05e-04]	[9.04e-04]	[1.06e-03]	[1.73e-03]
Work Experience (years)	-4.89e-05	-4.54e-05	1.08e-05	-1.38e-04
	[9.37e-05]	[9.37e-05]	[1.15e-04]	[1.64e-04]
Black	-9.82e-04	-9.73e-04	-8.74e-04	-2.47e-04
	[2.09e-03]	[2.09e-03]	[2.63e-03]	[3.28e-03]
Hispanic	-3.29e-03*	-3.34e-03*	-3.14e-03	-2.02 e-03
	[1.98e-03]	[1.98e-03]	[2.30e-03]	[3.92e-03]
Asian	-1.46e-03	-1.43e-03	-6.33e-04	-3.47e-03*
	[1.13e-03]	[1.13e-03]	[1.45e-03]	[1.74e-03]
Age at Graduation	-5.06e-05	-5.26e-05	-2.00e-04	3.72e-04
	[1.60e-04]	[1.60e-04]	[1.88e-04]	[2.97e-04]
US/Canadian Citizenship	-1.25e-03	-1.25e-03	-1.51e-03	-1.37e-04
	[9.13e-04]	[9.13e-04]	[1.08e-03]	[1.66e-03]
Top Twenty Undergraduate Institution	-1.12e-03	-1.10e-03	-8.17e-04	-1.44e-03
	[1.04e-03]	[1.04e-03]	[1.28e-03]	[1.74e-03]
Observations	7,694	7,694	5,456	2,121
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Sample	All	All	Males	Females

Standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Each coefficient represents a separate regression in which the share of male peers in the peer group is regressed on the individual pre-treatment characteristic. Column (1) regressions each control for an indicator variable for female. Column (2) controls for the share of women in the respondent's cohort other than the respondent. Column (3) shows regressions on a sample of male students only. Column (4) shows regressions on a sample of female students only. All regressions include cohort fixed effects.

Table 3

Effect of Peer Gender Composition on Salary Offer Accepted

VARIABLES	(1) Log Salary Accepted	(2) Log Salary Accepted	(3) Log Salary Accepted	(4) Log Salary Accepted	(5) Log Salary Accepted
Share Male Peers x Female	0.21**	0.19**	0.19**	0.21**	0.21**
	[0.091]	[0.093]	[0.095]	[0.096]	[0.096]
Share Male Peers	-0.09	-0.10	-0.10	-0.10	-0.10
	[0.058]	[0.060]	[0.060]	[0.062]	[0.062]
Female	-0.04***	-0.03***	-0.03***	-0.03***	-0.03***
	[0.005]	[0.006]	[0.006]	[0.007]	[0.007]
Race Indicator Variables	No	No	No	Yes	Yes
Observations	5,438	5,319	5,282	5,179	5,179
Cohort Fixed Effects	15	14	14	14	14
Mean	11.52	11.52	11.52	11.52	11.52

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the regression described in Equation (1). The dependent variable in all columns is equal to the natural log of the annual base salary of the job offer accepted, in terms of gross earnings, not including any bonuses, relocation expenses, tuition reimbursement, or stock options. "Share Male Peers" is the fraction of the student's peer group (excluding the student) who are male, reported as a deviation from the mean. Column (1) includes no other pre-treatment characteristics other than gender. Column (2) includes controls for student GMAT scores and undergraduate GPA, normalized to a 4.0 scale based on the maximum GPA attainable at the undergraduate institution, and includes a dummy for missing undergraduate GPA. Column (3) includes two additional dummy variables for whether the student attended a "Top 10" or a "Top 20" undergraduate institution. Column (4) includes additional dummy variables for marital status at the start of business school, marital status interacted with female, age at the start of business school, and age squared. In addition, column (4) includes race dummies (indicators for Black, Hispanic, Asian, and South Asian.) Column (5) controls for years of work experience prior to business school, and years of experience squared, in addition to all controls included in column (4). All columns include cohort fixed effects and are clustered at the peer group level.

Table 4
Effect of Gender Composition on Industry and Job Function of Job Accepted at Graduation

VARIABLES	(1) Industry: IBanking	(2) Industry: IManagement	(3) Industry: Venture Capital	(4) Job Function: IBanking	(5) Job Function: Product Mgmt
Share Male Peers*Female	0.55**	0.22*	0.24***	0.48**	-0.39**
	[0.217]	[0.120]	[0.083]	[0.207]	[0.166]
Share Male Peers	0.07	-0.08	-0.11**	0.24	0.07
	[0.198]	[0.104]	[0.042]	[0.143]	[0.093]
Female	-0.11***	-0.05***	-0.03***	-0.11***	0.09***
	[0.017]	[0.009]	[0.006]	[0.016]	[0.011]
Observations	5,590	5,590	5,590	5,610	5,610
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean	0.28	0.08	0.03	0.20	0.07

Table 5
Effect of Peer Gender Composition on Male Proportion
of Industry or Job Function Accepted

VARIABLES	(1) Industry Share Male	(2) Job Function Share Male
Share Male Peers*Female	0.42***	0.47***
	[0.086]	[0.075]
Share Male Peers	-0.13**	-0.08**
	[0.051]	[0.035]
Female	-0.06***	-0.06***
	[0.007]	[0.006]
Observations	7,167	7,231
Cohort Fixed Effects	13.00	13.00
Mean	0.72	0.72

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table reports estimated coefficients from the regression described in Equation (1). The dependent variable in each column of Table 4 is an indicator variable equal to 1 if the job offer accepted by the student is in the industry or job function indicated and 0 otherwise. In Table 5, "Industry Share Male" is the fraction of graduating students in student i's cohort accepting a job in the industry in which student i accepts a job who are male (other than student i). "Job Function Share Male" is the fraction of graduating students in student i's cohort accepting a job in the job function accepted by the student i who are male (other than student i). All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table 6
Effect of Gender Composition on Average Job Characteristics Ten Years after Graduation

Panel A: Average Hours and Wages in Job Function Accepted (Ten Years after Graduation)

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	8.48***	-0.07*	0.30***	165.50***
	[2.638]	[0.036]	[0.086]	[54.025]
Share Male Peers	1.69	0.02	0.08	-8.75
	[1.842]	[0.019]	[0.058]	[52.557]
Female	-1.88***	0.01***	-0.07***	-38.13***
	[0.187]	[0.002]	[0.006]	[4.179]
Observations	5,592	5,592	5,592	5,592
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	57.80	0.05	0.39	165.40

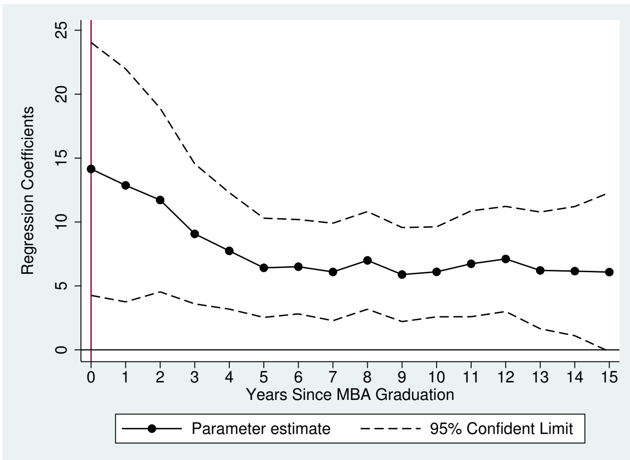
Panel B: Average Hours and Wages in Industry Accepted (Ten Years after Graduation)

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	6.62***	-0.08***	0.17**	178.53***
	[1.969]	[0.029]	[0.068]	[45.365]
Share Male Peers	-0.10	0.03**	0.04	-17.03
	[1.599]	[0.015]	[0.055]	[39.810]
Female	-1.25***	0.01***	-0.04***	-35.62***
	[0.159]	[0.002]	[0.006]	[3.580]
Observations	5,584	5,584	5,584	5,584
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	57.74	0.05	0.39	153.02

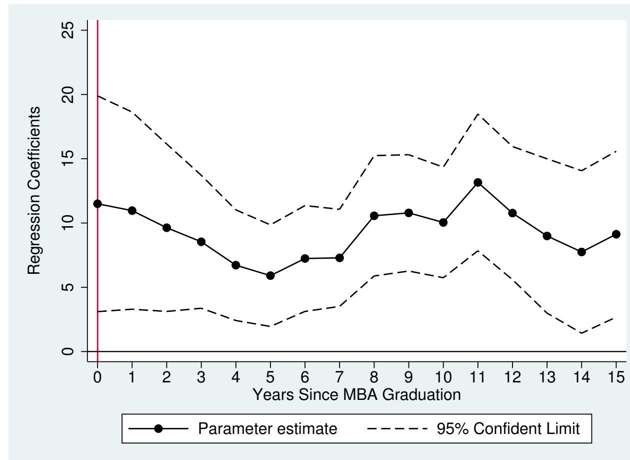
Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable in each column is the average characteristic in the job function or industry accepted by the student at graduation. The average characteristic of each job function is taken over all students working in the job function or industry of the accepted job 10 years after graduation. "Average weekly hours" is defined as the job function average of self-reported usual weekly hours worked in the position. Responses are collected in discrete bins and transformed into real-valued variables (at the midpoint of each bin). "Frequency of part-time work" is the job function or industry average of the indicator variable for part-time work, where "part-time work" is defined as usual weekly hours less than 40 hours per week. "Frequency of overtime work" is the job function or industry average of the indicator variable for overtime work, where "overtime work" is defined as usual weekly hours greater than 60 hours per week. "Average hourly wage" is defined as the job function or industry average of the self-reported annual earnings divided by the product of usual weekly hours of work and 52. Annual earnings are reported in discrete bins and transformed into real-valued variables at the midpoint of each earnings bin. Wages are in 2006 dollars. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

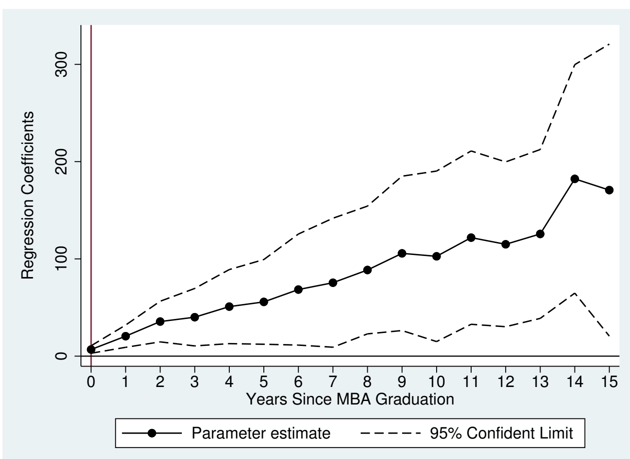
Figure 2
Effect of Peer Gender Composition on Gender Gap in Expected Hours and Wages after Graduation
Conditional on Initial Job Function and Industry at Graduation



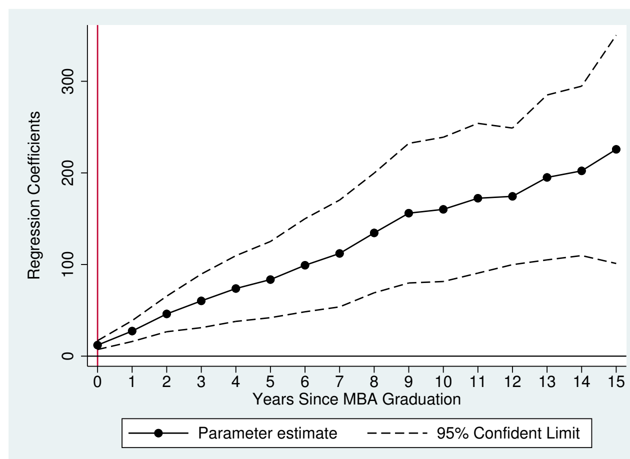
(i) Effect on Expected Weekly Hours Gap given Initial Job Function at Graduation



(ii) Effect on Expected Weekly Hours Gap given Initial Industry at Graduation



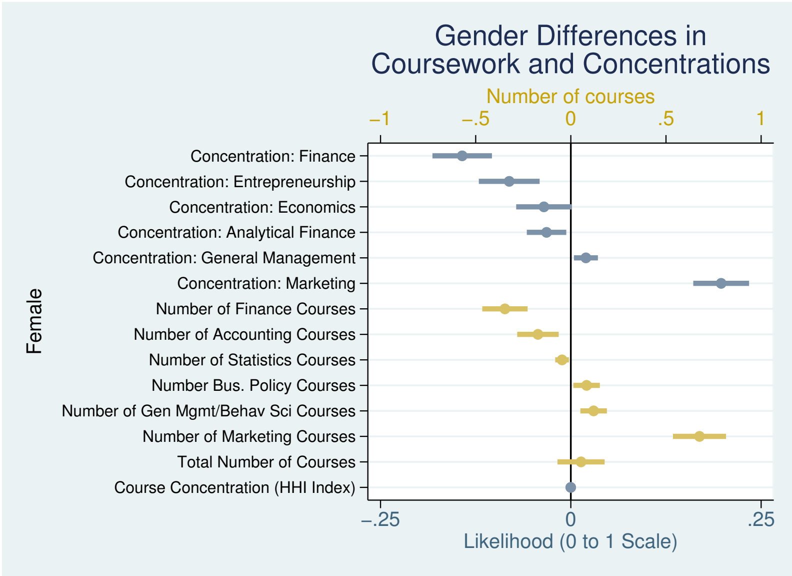
(iii) Effect on Gap in Expected Wages given Initial Job Function at Graduation



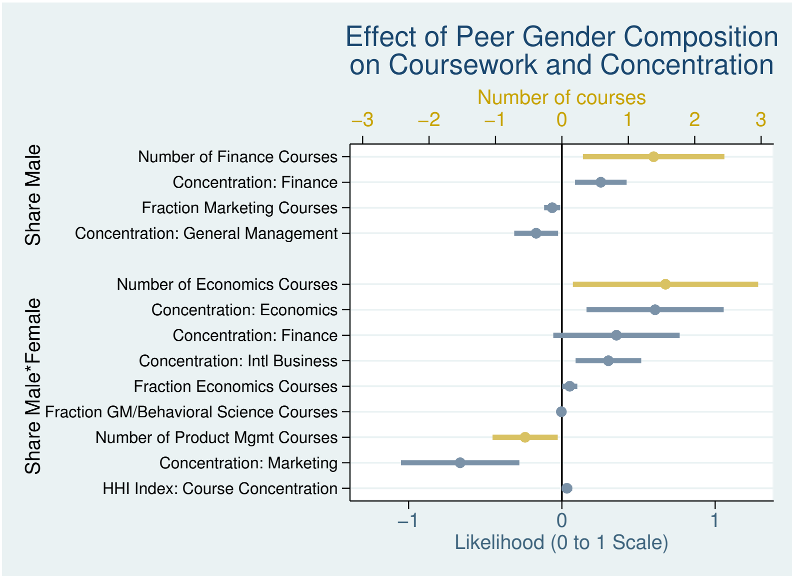
(iv) Effect on Gap in Expected Wages given Initial Industry at Graduation

Notes: Each regression coefficient shown in each of these figures represents a separate regression of the form described in Equation (1), where the dependent variable in (i) and (ii) is "Expected weekly hours of work X years after graduation, conditional on starting [job function/industry]," and the dependent variable in (iii) and (iv) is "Expected wages X years after graduation, conditional on starting [job function/industry]." The reported regression coefficients are the estimated coefficients on $Female_i \times ShareMale_{igc}$. The dependent variable is constructed by averaging actual hours or wages X years after graduation over all those who accepted the same initial job function or industry at graduation. Both expected wages and hours include "zeros:" wages and hours X years after graduation are averaged over both individuals who are working and those not working X years after graduation, where the value is zero for those who are not working.

Figure 3
Effect of Peer Gender Composition on Coursework and Concentrations



(i) Baseline Gender Differences in Coursework and Concentrations



(ii) Effect of Peer Gender Composition on Coursework and Concentrations

Notes: Each row in Figure 3(i) represents a separate regression in which the dependent variable (shown on the vertical axis) is regressed on the full set of controls (see notes for Table 3, column (5)), including an indicator variable for female. Each row shows the estimated coefficient on $Female$, along with the 95 percent confidence interval, from the regression with the specified dependent variable. Each row in Figure 3(ii) represents a separate regression of the following form:

$$Y_{igc} = \phi_0 + \phi_1 ShareMale_{igc} \times Female_i + \phi_2 ShareMale_{igc} + \beta X_i + \gamma_c + \varepsilon_{igc},$$

where Y_{igc} is the dependent variable specified on the vertical axis. Each row reports the estimated coefficient on either $ShareMale$ or $ShareMale \times Female$, and for the sake of brevity, only those coefficients that are statistically significantly different from zero at the 5 percent level are reported (in no case is the coefficient on both $ShareMale$ and $ShareMale \times Female$ significant.) All specifications include cohort fixed effects, and standard errors are clustered at the peer group level. Because the regressions that use concentrations data that comes from two different draws of administrative data - one draw from 2006 and one draw from 2011 - such regressions include controls for "missing 2011 concentration data" and the missing dummy interacted with female. More information on potential sampling bias is provided in the appendix.

Table 7
Effect of Gender Composition on Fields of Concentration

VARIABLES	(1) Max Proportion Male Among Concentrations	(2) Any Male-Dominated Concentration	(3) Any Majority-Male Concentration	(4) All Male-Dominated Concentrations	(5) All Majority-Male Concentrations
Share Male Peers	0.10**	-0.18	0.22***	0.34	1.27***
x Female	[0.044]	[0.201]	[0.065]	[0.334]	[0.300]
Share Male Peers	0.00	0.19**	-0.05***	0.21	-0.41***
	[0.021]	[0.085]	[0.019]	[0.177]	[0.077]
Female	-0.01***	-0.08***	-0.01**	-0.20***	-0.14***
	[0.003]	[0.012]	[0.005]	[0.022]	[0.020]
Observations	4,816	4,816	4,816	4,816	4,816
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean	0.78	0.94	0.87	0.44	0.87

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the regression described in Equation (1). The dependent variable in column (1) is the male proportion of the most male-dominated field of concentration, among all of the concentrations chosen by the student. The dependent variable in column (2) is a dummy variable equal to 1 if at least one of the fields of concentration chosen by the student is disproportionately male relative to their cohort. The dependent variable in column (3) is a dummy variable equal to 1 if at least one of the fields of concentration chosen by the student is more than 50% male. The dependent variables in columns (4) and (5) are each dummy variables equal to 1 if all of the fields of concentration chosen by the student are disproportionately male or greater than 50% male, respectively. Proportion of male students in the field of concentration is determined separately, within each cohort, and excludes the student. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table 8
Effect of Gender Composition on Distribution of Offers and Salary Offer Accepted

	Distribution of Offers				Willingness-to-Accept	
VARIABLES	(1) Log Mean Salary Offer	(2) Log Median Salary Offer	(3) Log Max Salary Offer	(4) Log Max Perm. Salary	(5) Accepted Max Offer	(6) Accepted Max Perm. Salary
Share Male Peers x Female	0.13	0.06	0.17*	0.12	0.36**	0.41**
	[0.093]	[0.105]	[0.096]	[0.144]	[0.144]	[0.165]
Share Male Peers	-0.08	-0.06	-0.15***	-0.05	0.03	-0.08
	[0.051]	[0.055]	[0.052]	[0.097]	[0.135]	[0.170]
Female	-0.03***	-0.02***	-0.03***	-0.06***	-0.02*	-0.02*
	[0.006]	[0.007]	[0.006]	[0.010]	[0.011]	[0.012]
Observations	5,433	5,433	5,433	5,433	5,433	5,433
Cohort Fixed Effects	13	13	13	13	13	13
Mean	11.51	11.51	11.54	11.64	0.90	0.90

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variables in columns (1)-(3) are the natural log of the mean, median, and maximum of the base salaries offered to the student, respectively. The dependent variable in column (4) is the log of the maximum "permanent salary" offered to the student. "Permanent salary" is equal to the base salary plus any other guaranteed compensation, including any guaranteed year-end bonuses, profit-sharing, and stock options, as well as other forms of compensation that are guaranteed annually and are not performance-dependent. The dependent variables in columns (5) and (6) are indicator variables for whether the student accepted the maximum salary offer within their offer set, for the set of base salaries and permanent salaries offered, respectively. The dependent variables in columns (5) and (6) are equal to 0 if the accepted salary is missing and if other salaries offered are non-missing when there is a range of salaries offered to a given student. If all other non-missing salaries offered are the same, then the accepted salary is imputed as the mean of the non-missing salaries. All regressions control for gender, marital status at the start of business school, marital status interacted with gender, age at the start of business school, age squared, student GMAT scores (quantitative, verbal, and total), undergraduate GPA (normalized to a 4.0 scale), a dummy for missing undergraduate GPA, indicator variables for whether the student attended a "Top 10" or "Top 20" undergraduate institution, for whether the student is Black, Hispanic, Asian, South Asian, or identifies as having another ethnic background (omitted category is white), and for years of work experience prior to business school and experience squared. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table 9
Effect of Peer Gender Composition on Industry, Occupation, and Firm Pay

Panel A: Effect of Gender Composition on Distribution of Firm Pay Offers

VARIABLES	(1) Mean Offer Firm Pay	(2) Median Offer Firm Pay	(3) Max Offer Firm Pay
Share Male Peers*Female	0.20*	0.19*	0.26**
	[0.112]	[0.111]	[0.128]
Share Male Peers	0.00	0.02	-0.11
	[0.084]	[0.078]	[0.091]
Female	-0.05***	-0.05***	-0.05***
	[0.009]	[0.008]	[0.009]
Observations	5,140	5,140	5,140
Cohort Fixed Effects	Yes	Yes	Yes
Mean	0.00	0.00	0.04

Panel B: Effect of Gender Composition on Distribution of Occupation and Industry Pay

	Job Function Pay Offers			Industry Pay Offers		
VARIABLES	(1) Mean Offer Job Func. Pay	(2) Median Offer Job Func. Pay	(3) Max Offer Job Func. Pay	(4) Mean Offer Industry Pay	(5) Median Offer Industry Pay	(6) Max Offer Industry Pay
Share Male Peers	0.19**	0.19**	0.16*	0.12**	0.12**	0.16**
*Female	[0.084]	[0.085]	[0.090]	[0.059]	[0.060]	[0.065]
Share Male Peers	-0.01	-0.01	-0.02	0.01	0.00	-0.02
	[0.068]	[0.068]	[0.072]	[0.032]	[0.033]	[0.033]
Female	-0.03***	-0.03***	-0.03***	-0.02***	-0.02***	-0.02***
	[0.007]	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]
Observations	5,580	5,580	5,580	5,869	5,869	5,869
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	-0.13	-0.13	-0.12	-0.03	-0.03	-0.01

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: In Panel A, the dependent variables are the mean, median, and maximum of the firm component of pay, taken over the student's offer set. The firm component of pay comes from an AKM wage decomposition, where the firm fixed effect can be identified because we observe multiple offers per student. The firm component of pay comes from estimating: $w_{ij} = F_j + \delta_i + \mu_{ij}$, where w_{ij} is the log of the permanent salary offered, δ_i is the individual fixed effect, F_j is the firm fixed effect, or the firm component of pay. The estimation includes a term for a match effect, μ_{ij}. Salaries are measured in 2006 dollars. In Panel B, the dependent variables are the mean, median, and maximum of occupation and industry pay, respectively, taken over the student's offer set. The occupation and industry pay are estimated using a similar AKM wage decomposition, where the industry pay premium and the job function pay premium are each estimated using data at the student-offer level using a two-way fixed effects model: $w_{ik} = Ind_k + \delta_i + \mu_{ik}$ and $w_{il} = JobFunc_l + \delta_i + \mu_{il}$, respectively.

Table 10
Effect of Peer Gender Composition on Offers for Expected Future Wages
Conditional on Initial Industry and Job Function at Graduation

	Job Function Averages 10 Years Out			Industry Averages 10 Years Out		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mean Wage Offer	Median Wage Offer	Max Wage Offer	Mean Wage Offer	Median Wage Offer	Max Wage Offer
Share Male Peers x Female	93.68**	98.92**	73.61*	151.92***	160.11***	137.20***
	[45.655]	[46.454]	[45.254]	[40.671]	[40.857]	[43.600]
Share Male Peers	-7.44	-7.53	-15.09	-2.94	-9.59	-21.06
	[45.711]	[45.765]	[46.911]	[31.490]	[32.018]	[37.829]
Female	-33.60***	-33.65***	-33.80***	-34.10***	-33.78***	-33.21***
	[3.277]	[3.307]	[3.289]	[3.253]	[3.248]	[3.320]
Observations	5,712	5,712	5,712	5,746	5,746	5,746
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	156.89	156.84	163.64	150.36	150.43	157.74

Panel B: Controlling for Concentration in Finance

	Job Function Averages 10 Years Out			Industry Averages 10 Years Out		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mean Wage Offer	Median Wage Offer	Max Wage Offer	Mean Wage Offer	Median Wage Offer	Max Wage Offer
Share Male Peers x Female	50.52	55.01	34.06	56.15	67.34	26.09
	[57.152]	[58.026]	[60.135]	[49.464]	[49.121]	[54.995]
Share Male Peers	-15.65	-15.18	-25.27	5.24	-2.94	-12.28
	[45.637]	[46.068]	[46.709]	[30.654]	[31.323]	[36.690]
Female	-31.79***	-32.18***	-30.19***	-33.62***	-33.82***	-31.09***
	[4.473]	[4.538]	[4.674]	[4.193]	[4.240]	[4.294]
Conc. Finance	54.74***	54.57***	57.50***	46.75***	47.02***	50.30***
	[4.144]	[4.176]	[4.186]	[3.583]	[3.590]	[3.709]
Conc. Finance x Female	4.85	5.43	3.11	6.03	6.63	6.23
	[5.252]	[5.254]	[5.299]	[4.650]	[4.642]	[4.845]
Observations	4,853	4,853	4,853	4,853	4,853	4,853
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	156.92	156.88	163.64	150.40	150.50	157.74

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variables in columns (1)-(3) are the mean, median, and maximum of offers for "expected wages 10 years after graduation" of the offer set of the student at graduation, where expected wages for each job offer is calculated by averaging hourly wages, 10 years after graduation, over all graduates who accepted a job in the same initial job function at graduation as that of the job offer. The dependent variables in columns (4)-(6) are the mean, median, and maximum "expected wages 10 years after graduation" offered to the student at graduation, where expected wages for each offer is calculated by averaging hourly wages 10 years after graduation over all graduates who accepted a job in the same initial industry at graduation as that of the job offer. The regressions in Panel B use concentration data from two different draws of administrative data - one in 2006 and one in 2011. The latest draw is used when the data conflicts, but an additional 1,450 observations of concentration data can be included by using the 2006 data. Regressions in Panel B include controls for "missing 2011 concentration data" and the missing dummy interacted with female. More information on potential sampling bias is provided in the appendix.

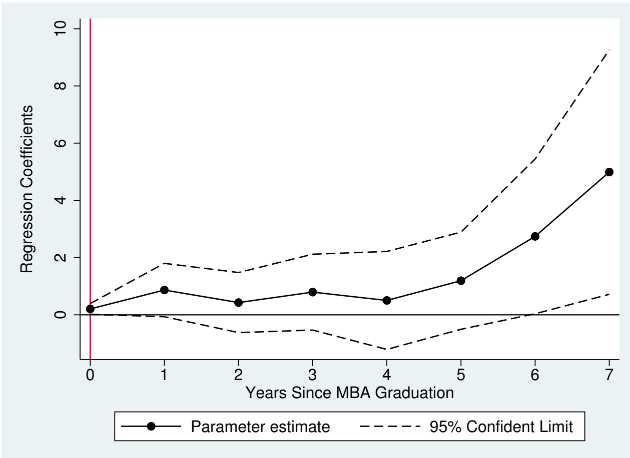
Table 11
Initial Conditions and Long-Term Salary Outcomes

	Years After Graduation							
Dependent Variable	0	1	2	3	4	5	6	7
Share Male Peers x Female	0.21**	0.87*	0.43	0.79	0.50	1.19	2.74**	4.99**
	[0.095]	[0.470]	[0.528]	[0.666]	[0.857]	[0.847]	[1.343]	[2.101]
Share Male Peers	-0.10	0.11	0.39	0.52	0.70	0.66	0.45	0.27
	[0.061]	[0.295]	[0.365]	[0.461]	[0.530]	[0.550]	[0.849]	[1.292]
Female	-0.03***	-0.20***	-0.24***	-0.34***	-0.31***	-0.35***	-0.50***	-0.70***
	[0.007]	[0.039]	[0.047]	[0.068]	[0.092]	[0.104]	[0.150]	[0.228]
R-squared	0.06	0.10	0.07	0.09	0.08	0.10	0.13	0.13
Observations	5,179	1,295	1,109	899	748	621	475	349
	B. Fixed Effects for Starting Job Function							
Share Male Peers x Female	0.18**	0.37	0.04	0.45	0.19	0.40	2.01**	2.84*
	[0.078]	[0.323]	[0.445]	[0.561]	[0.746]	[0.755]	[0.935]	[1.598]
Share Male Peers	-0.10	-0.17	0.08	0.18	0.34	0.26	-0.21	-0.06
	[0.064]	[0.245]	[0.299]	[0.348]	[0.391]	[0.413]	[0.557]	[0.904]
Female	-0.03***	-0.08**	-0.09**	-0.21***	-0.21**	-0.21**	-0.39***	-0.42**
	[0.006]	[0.035]	[0.044]	[0.064]	[0.082]	[0.095]	[0.117]	[0.197]
R-squared	0.27	0.42	0.37	0.42	0.40	0.41	0.45	0.41
Observations	5,179	1,295	1,109	899	748	621	475	349
	C. Fixed Effects for Starting Industry							
Share Male Peers x Female	0.18**	0.30	-0.32	0.17	-0.08	0.07	1.00	2.47
	[0.081]	[0.330]	[0.481]	[0.581]	[0.819]	[0.902]	[1.159]	[1.977]
Share Male Peers	-0.10*	0.02	0.20	0.36	0.49	0.44	0.27	-0.02
	[0.059]	[0.222]	[0.284]	[0.349]	[0.404]	[0.432]	[0.621]	[0.992]
Female	-0.02***	-0.10***	-0.09*	-0.22***	-0.21**	-0.23*	-0.27*	-0.44**
	[0.006]	[0.036]	[0.050]	[0.071]	[0.101]	[0.128]	[0.138]	[0.213]
R-squared	0.29	0.44	0.40	0.40	0.37	0.38	0.42	0.41
Observations	5,179	1,295	1,109	899	748	621	475	349
	D. Fixed Effects for Starting Firm							
Share Male Peers x Female	0.03	0.26	0.07	0.41	0.82	0.66	0.04	8.42*
	[0.072]	[0.584]	[0.765]	[1.069]	[1.528]	[1.603]	[2.136]	[4.281]
Share Male Peers	0.01	0.22	0.43	0.83	0.78	0.55	0.42	-2.61
	[0.045]	[0.318]	[0.456]	[0.737]	[0.745]	[0.857]	[1.132]	[2.672]
Female	-0.01	-0.12**	-0.10	-0.16	-0.18	-0.09	-0.11	-0.77
	[0.006]	[0.045]	[0.069]	[0.114]	[0.192]	[0.216]	[0.290]	[0.487]
R-squared	0.71	0.73	0.71	0.68	0.65	0.66	0.66	0.69
Observations	5,179	1,035	858	674	544	443	338	229

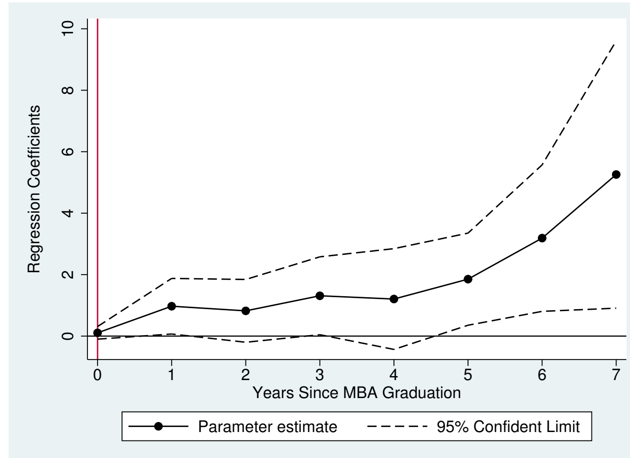
Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable in each column is log earnings a given number of years after graduation. Column "0" (years after graduation) uses the employment offer data and constructs the outcome variable from the job offer accepted. The outcome variable, "log base salary accepted," is the main outcome used in estimating Equation (1) and in Table 3. The outcome variables for Years 1-7 after graduation uses data from the MBA Alumni Survey, where annual earnings are a linear interpolation between earnings in the first and last year of the job, and where the earnings in the first and last year are defined as the midpoint of a range. All specifications include cohort fixed effects, and standard errors are clustered at the peer group level. Specifications in

Figure 4
Effect of Peer Gender Composition on Long-Term Earnings of Women



(i) Effect of Peers on Gender Earnings Gap



(ii) Effect of Peers on Women's (Log) Earnings

Notes: Each data point represents the estimates from a separate regression, where the dependent variable is the log of annual earnings a given number of years after graduation. In subfigure (i), the estimated coefficients are the coefficient on $ShareMale \times Female$ in a set of regressions of the following form:

$$Y(y)_{igc} = \phi_0 + \phi_1 Female_i \times ShareMale_{igc} + \phi_2 ShareMale_{igc} + \beta X_i + \gamma_c + \varepsilon_{igc},$$

where $Y(y)_{igc}$ is the log earnings of student i y years after graduation. In subfigure (ii), the estimates plotted are the coefficent on $ShareMale \times Female$ in set of regressions of the following form:

$$Y(y)_{igc} = \phi_0 + \phi_1 Female_i \times ShareMale_{igc} + \phi_2 Male_i \times ShareMale_{igc} + \beta X_i + \gamma_c + \varepsilon_{igc}.$$

Both specifications include cohort fixed effects. Standard errors are clustered at the peer group level, for each regression. Earnings measure at graduation comes from salary survey data on accepted jobs at graduation collected by the Career Services office. Earnings measures for years 1 through 7 come from self-reported salary data reported in the MBA Alumni Survey.

Appendix A: Tables and Figures

Figure A.1
Quantifying the Treatment:
Average Peer Group Interaction outside of Compulsory Period

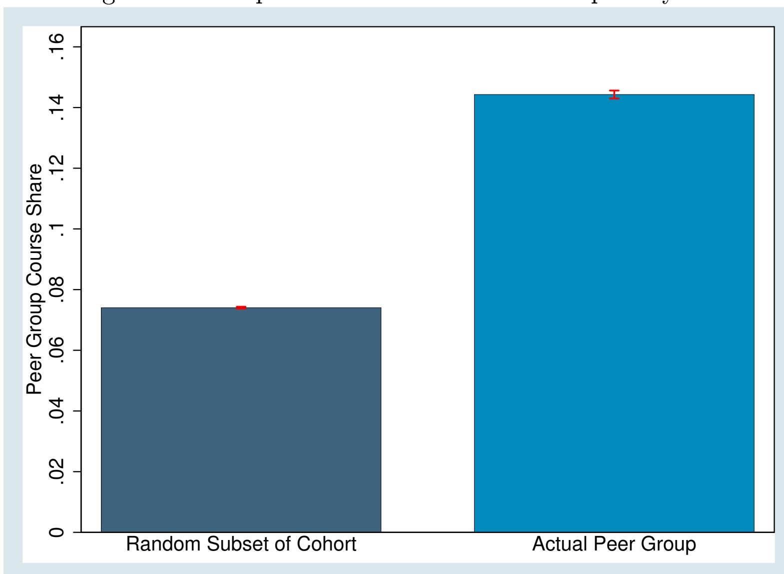


Table A.1
Average Peer Group Interaction in Courses
Relative to Randomly Selected Group of Same Size

	(1)	(2)	(3)
VARIABLES	Peer Group Course Share	Has Peer in Course	# of Peers in Course
Assigned Peer Group	0.070***	0.003**	4.165***
	[0.001]	[0.001]	[0.043]
Constant	0.074***	0.846***	3.821***
	[0.000]	[0.001]	[0.030]
Observations	256,540	256,540	256,540
Mean	0.11	0.85	5.90

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are at the individual-semester-course-group type level: each outcome variable is observed twice per individual-semester-course. For each individual-semester-course, the outcome variable is determined first, as a function of the student's exogenously assigned peer group (the "actual" peer group to which each student was quasi-randomly assigned prior to the start of business school), and then, as a comparison, using an arbitrary subset of students from the same cohort, of the same size as the actual peer group. "Assigned Peer Group" is a dummy variable equal to 1 if the outcome variable is determined using the peer group actually assigned, whereas the remainder of the observations are those where the outcome variable is determined using a randomly selected subset of students from the same cohort, of the same size as the actual peer group. "Peer Group Course Share" is equal to the number of students from the group, whether the actual peer group or the arbitrary group, who are enrolled in the same course in the same semester, divided by the total number of students enrolled in the same semester. "Has Peer in Course" is a dummy variable equal to 1 if the student has at least one member of the group enrolled in the same course.

Table A.2
Alumni Survey: Respondents versus Nonrespondents

	Respondents	Nonrespondents	p-value
Sample size	1,282	5,766	
Female	0.27	0.28	0.184
Undergraduate GPA	2.63	2.58	0.312
Undergraduate GPA (missing)	0.22	0.24	0.038
Age at Entry	28.06	28.10	0.645
Top 20 Undergrad Inst.	0.20	0.20	0.818
Top 10 Undergrad Inst.	0.10	0.11	0.491
Black	0.027	0.047	0.000
Hispanic	0.027	0.055	0.000
Asian	0.13	0.17	0.000
White	0.55	0.44	0.000
Prev. Work Experience (years)	4.86	4.85	0.952
Prev. Work Experience (missing)	0.85	0.45	0.000
US Citizen	0.73	0.55	0.000
Visa: Perm Res/Work Perm (non-US citizens)	0.25	0.30	0.053
GMAT Score - Total	691	696	0.002
GMAT Score (Quant)	45.26	45.79	0.000
GMAT Score (Verbal)	39.35	39.36	0.975
Undergraduate Major Type: Business	0.51	0.49	0.549
Undergraduate Major Type: Hard Science	0.34	0.33	0.515
Undergraduate Major Type: Soft Science	0.15	0.17	0.093
MBA GPA	3.32	3.27	0.000
Concentration in Finance	0.82	0.81	0.660
Fraction Finance Classes	0.17	0.17	0.958

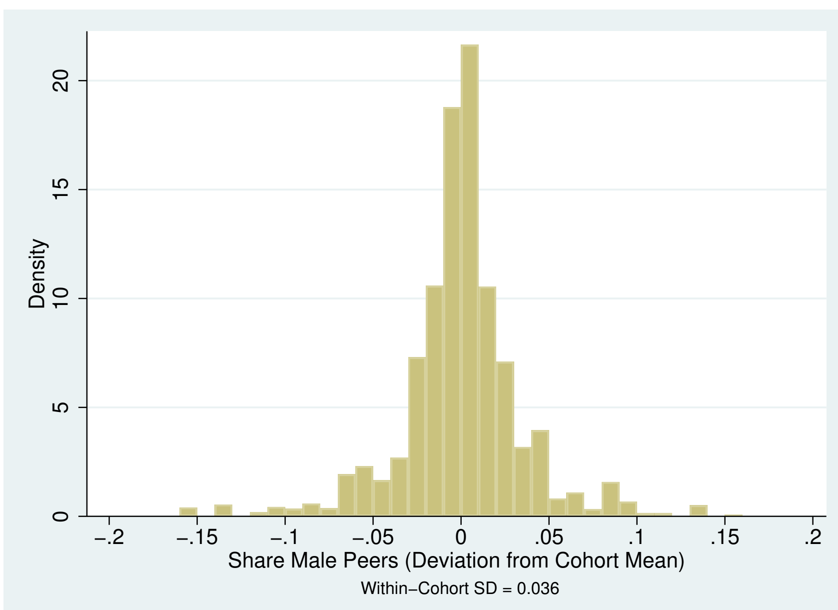
Notes: Observations are at the individual level. The table compares pre-MBA characteristics and MBA performance between survey respondents and non-respondents, among those who could be matched with administrative records, with peer group records, and who were full-time and non-transfer students. The last column reports a p-value on a test of comparison of means between the two groups. Undergraduate GPAs are normalized to being on a scale of 0 to 4.0, using administrative data on the maximum undergraduate GPA of each undergraduate institution. The quantitative and verbal GMAT scores are out of a total of 60. Total GMAT scores are out of a total of 800.

Table A.3
Distribution of Peer Group Mean Characteristics

Peer Group Characteristic	SD of Peer Group Characteristic (data)	SD under Random Assignment	SD under Within-Cohort Random Assignment
Share Male	0.065	0.062	0.079
Share Black (race/ethnicity)	0.029	0.027	0.033
Share Hispanic (race/ethnicity)	0.036	0.029	0.041
Share Asian (race/ethnicity)	0.062	0.051	0.058
Share Work Permit	0.071	0.062	0.082
Share US/ Can Citizenship*	0.072	0.065	0.085
Mean Age of Entry**	0.495	0.358	0.487

Notes: This table compares the distribution of peer group mean characteristics with what would be observed (in expectation) among pure random assignment and pure within-cohort random assignment. Standard deviations are based on observations of peer group characteristics at the individual level. Under pure random assignment, the expected standard deviation of each average peer group characteristic should be equal to the population standard deviation of the individual characteristic divided by the square root of mean group size. Under within-cohort random assignment, the expected variance of the average peer group characteristics is the sum of the expected within-cohort variance and the across-cohort variance of the cohort population mean. “Share Work Permit" is the share of students in a peer group who have either US citizenship, permanent residency, or a visa or work permit.
*Excludes two years of data where data on citizenship was sparsely collected - excludes 2009 and 2010 entering cohorts. Including 2009 and 2010 cohorts, the SD of Share US/ Canadian Citizenship is 0.237, 0.067 under pure random assignment, and 0.19 under pure within-cohort random assignment. Thus, peer groups still resemble pure within-cohort random assignment, even with large amounts of missing data where the likelihood of missing data varies substantially across cohort.
**Excludes 2010 entering cohort, since age of entry is computed from year of graduation and age at graduation. Data on graduation year and age is missing for majority of the 2010 entering cohort.

Figure A.2
Distribution of Share of Male Peers



*Notes:*The above graph shows the actual distribution of the share of male peers in a peer group, in terms of the deviation from the cohort mean. The sample includes the 1996-2010 entering cohorts.

Table A.4
Share of Male Peers Regressed on Own Pretreatment Characteristics

VARIABLES	(1) Share Male	(2) Share Male	(3) Share Male	(4) Share Male
GMAT Total Score	1.08e-05	1.12e-05	2.59e-05	-3.50e-05
	[4.46e-05]	[4.46e-05]	[5.40e-05]	[8.33e-05]
GMAT Quant Score	-1.17e-04	-1.19e-04	-1.99e-04	1.98e-04
	[3.56e-04]	[3.56e-04]	[4.36e-04]	[6.53e-04]
GMAT Verbal Score	2.94e-05	2.74e-05	-9.53e-05	4.20e-04
	[3.14e-04]	[3.14e-04]	[3.73e-04]	[6.02e-04]
Undergraduate GPA	2.04e-04	2.00e-04	6.71e-04	-2.11e-03
	[9.56e-04]	[9.56e-04]	[1.11e-03]	[1.92e-03]
Undergraduate Major: Economics	1.28e-03	1.28e-03	1.09e-03	1.66e-03
	[9.56e-04]	[9.59e-04]	[1.18e-03]	[1.66e-03]
Undergraduate Major: Finance	-7.93e-04	-7.98e-04	-1.04e-03	-3.18e-04
	[1.34e-03]	[1.34e-03]	[1.59e-03]	[2.55e-03]
Undergraduate Major Type: Business	-2.05e-03**	-2.05-03**	-1.45e-03	-2.46e-03
	[1.03e-03]	[1.03e-03]	[1.35e-03]	[1.63e-03]
Undergraduate Major Type: Hard Science	-1.06e-04	-1.07e-04	1.05e-03	-2.72e-03
	[9.94e-04]	[9.94e-04]	[1.27e-03]	[1.72e-03]
Work Experience (years)	1.71e-05	1.75e-05	2.25e-04	-3.81e-04
	[2.15e-04]	[2.15e-04]	[2.63e-04]	[3.83e-04]
Black	7.71e-04	7.70e-04	1.51e-03	-8.79e-04
	[1.51e-03]	[1.51e-03]	[1.81e-03]	[2.85e-03]
Hispanic	-8.29e-04	-8.34e-04	-6.85e-04	-7.83e-04
	[1.42e-03]	[1.42e-03]	[1.64e-03]	[2.91e-03]
Asian	3.81e-04	3.79e-04	2.30e-04	7.37e-04
	[8.37e-04]	[8.36e-04]	[1.09e-03]	[1.32e-03]
Age at Graduation	-3.66e-05	-3.76e-05	-2.37e-04	3.57e-04
	[1.97e-04]	[1.97e-04]	[2.41e-04]	[3.52e-04]
US/Canadian Citizenship	-1.04e-04	-1.09e-04	1.26e-05	-4.37e-04
	[8.52e-04]	[8.52e-04]	[1.03e-03]	[1.58e-03]
Top Twenty Undergraduate Institution	-7.48e-04	-7.50e-04	-6.28e-04	-1.04e-03
	[7.83e-04]	[7.83e-04]	[9.39e-04]	[1.45e-03]
F-test: All student pre-MBA characteristics coeff = 0			$F(15, 1103)$ = 0.78 $P > F$ = .70	$F(15, 468)$ = 0.65 $P > F$ = .83
Observations	1,614	1,614	1,125	489
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Sample	All	All	Males	Females

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column represents a single regression in which the share of male peers is regressed on a set of individual pre-treatment characteristics. Columns (1) and (2) use the full sample. Column (1) includes a control for "female," a dummy variable. Column (2) controls for the share of women in the respondent's cohort other than the respondent. Column (3) shows the results of a regression on only male students. Column (4) shows the results of a regression on only female students. All regressions include cohort fixed effects.

Table A.5
Gender-Skewedness across Occupations (Job Functions)

Job Function	% Male among Offer Holders	% Male among Job Holders	Number/ % of Job Holders at Graduation		Gender Classification
Education	100	100	1	0.02	-
Engineering	100	100	2	0.03	Male-Dominated
Insurance	90.9	85.7	7	0.12	Male-Dominated
Venture Capital	86.3	84.3	254	4.32	Male-Dominated
Analysis	85.5	85.7	63	1.07	Male-Dominated
Investment Management	82.9	82.8	530	9.00	Male-Dominated
Investment Banking	82.4	81.4	1,169	19.86	Male-Dominated
Sales and Trading	82.3	81.1	424	7.20	Male-Dominated
Client Services	80.2	78.8	66	1.12	Male-Dominated
Applications	80.0	100	2	0.03	Male-Dominated
Real Estate	79.5	76.4	55	0.93	Male-Dominated
Law	79.4	74.1	27	0.46	Male-Dominated
Risk Management	78.5	76.5	17	0.29	Male-Dominated
Business Development	77.8	79.0	138	2.34	Male-Dominated
Commercial Banking	76.3	67.2	64	1.09	Female-Skewed
Customer Relations	75.0	66.7	3	0.05	Female-Skewed
Consulting	73.9	71.1	1,492	25.35	Female-Skewed
General Management	70.4	67.1	249	4.23	Female-Skewed
Company Finance	70.2	63.9	479	8.14	Female-Skewed
Strategic Planning	70.0	66.1	168	2.85	Female-Skewed
Sales	69.2	69.0	29	0.49	Female-Skewed
Operations	67.4	65.5	29	0.49	Female-Skewed
Healthcare Professional	66.7	88.9	9	0.15	Male-Dominated
Public Finance	66.7	66.7	3	0.05	Female-Skewed
Accounting	65.7	50	10	0.17	Female-Dominated
Project Management	65.2	55.6	27	0.46	Female-Skewed
Research and Development	62.5	62.5	8	0.14	Female-Skewed
Multiple	60.8	41.4	29	0.49	Female-Dominated
Research/ Analysis	56.4	38.9	18	0.31	Female-Dominated
Product Management	51.8	43.7	405	6.88	Female-Dominated
Human Resources	45.5	28.6	7	0.12	Female-Dominated
Marketing	42.6	37.1	35	0.59	Female-Dominated
Non-Profit	16.7	0	5	0.08	Female-Dominated

Table A.6
Share Quantitative Coursework Among Offer Holders, Gender-Skewedness, and Earnings across Occupations (Job Functions)

Job Function	% Male among Offer Holders	Average % Finance Coursework among Offer Holders	Annual Earnings (in 2006 $)
Engineering	100	19.82	$105,438
Insurance	90.9	16.87	$92,059
Venture Capital	86.3	15.50	$111,105
Analysis	85.5	14.94	$102,107
Investment Management	82.9	22.18	$100,786
Investment Banking	82.4	19.10	$96,026
Sales and Trading	82.3	28.51	$98,394
Client Services	80.2	18.60	$94,632
Applications	80.0	15.85	$98,017
Real Estate	79.5	16.99	$93,824
Law	79.4	10.26	$140,630
Risk Management	78.5	22.20	$89,746
Business Development	77.8	13.85	$99,376
Commercial Banking	76.3	18.55	$91,502
Customer Relations	75.0	12.28	$87,141
Consulting	73.9	14.34	$114,874
General Management	70.4	13.65	$97,486
Company Finance	70.2	17.98	$95,436
Strategic Planning	70.0	13.37	$96,959
Sales	69.2	14.33	$89,276
Operations	67.4	13.64	$98,842
Healthcare Professional	66.7	11.78	$94,822
Public Finance	66.7	-	$73,872
Accounting	65.7	18.18	$103,714
Project Management	65.2	14.91	$93,895
Research and Development	62.5	22.22	$96,266
Multiple	60.8	14.53	$96,221
Research/ Analysis	56.4	10.56	$85,538
Product Management	51.8	10.16	$93,436
Human Resources	45.5	8.39	$95,933
Marketing	42.6	7.72	$92,918
Non-Profit	16.7	6.14	$75,773

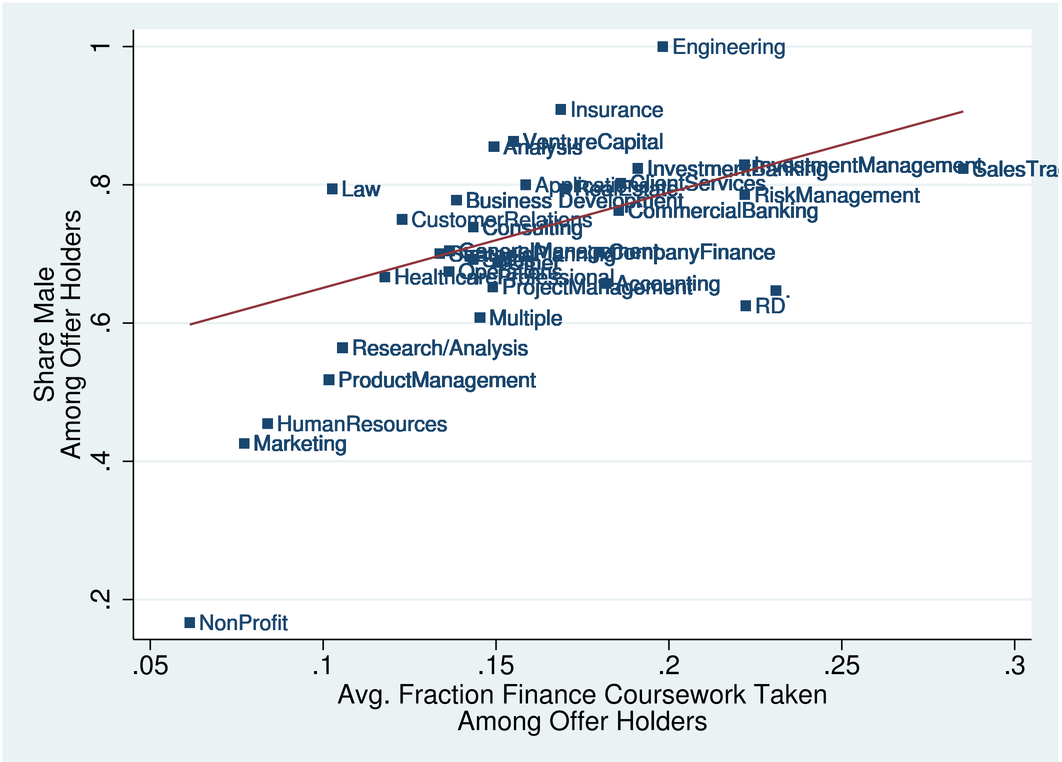
Table A.7
Gender-Skewedness across Industries

Industry	Percent Male among Offer Holders	Percent Male among Job Holders at Graduation	Number/ % of Job Holders at Graduation		Gender Classification
Wholesale	100	-	-	-	-
Extractive Minerals	100	100	1	0.02	-
Non-Manufacturing	100	100	1	0.02	-
Environment	100	100	4	0.07	Male-Dominated
Other Manufacturing	90.9	91.7	12	0.20	Male-Dominated
Accounting	89.6	72.2	18	0.31	Male-Dominated
Venture Capital	87.4	85.8	176	3.00	Male-Dominated
Machinery	85.3	86.7	15	0.26	Male-Dominated
Investment Management	84.4	84.9	451	7.68	Male-Dominated
Other Services	84.2	83.3	12	0.20	Male-Dominated
Transportation Services	83.8	78.0	41	0.70	Male-Dominated
Real Estate	81.9	79.2	53	0.90	Male-Dominated
Investment Banking	81.5	80.2	1,664	28.32	Male-Dominated
Construction	80.0	83.3	6	0.10	Male-Dominated
Agribusiness	80.0	77.8	18	0.31	Male-Dominated
Media	80.0	85.7	7	0.12	Male-Dominated
Banking	79.1	74.0	100	1.7	Male-Dominated
Computer Services	78.1	75.0	32	0.54	Male-Dominated
Telecommunications	77.8	73.3	45	0.77	Male-Dominated
Law	77.4	72.0	25	0.43	Male-Dominated
Software/ Printing	77.4	76.8	125	2.13	Male-Dominated
Energy	76.7	72.1	140	2.38	Male-Dominated
Automotive	76.3	77.1	35	0.60	Male-Dominated
Technology/Electronics	76.0	71.9	160	2.72	Male-Dominated
eCommerce	74.4	68.5	54	0.92	Female-Skewed
Consulting	74.0	71.2	1,470	25.02	Female-Skewed
Chemicals	73.7	67.7	31	0.53	Female-Skewed
Manufacturing	71.8	71.2	104	1.77	Female-Skewed
Diversified Services	70.8	71.4	14	0.24	Female-Skewed
Diversified Financial	68.9	66.2	299	5.09	Female-Skewed
Insurance	68.1	71.8	39	0.66	Female-Skewed
Government	68.0	65.0	20	0.34	Female-Skewed
Trading Companies	66.7	66.7	3	0.05	Female-Skewed
Packaging	66.7	75.0	4	0.07	Male-Dominated
Utilities	66.7	33.3	3	0.05	Female-Dominated
Healthcare Services	64.9	64.1	39	0.66	Female-Skewed
Education	63.6	66.7	21	0.36	Female-Skewed
Other	63.6	50.0	6	0.10	Female-Dominated
Advertising/Marketing	56.7	52.0	25	0.43	Female-Skewed
Rubber/ Plastics	55.6	57.1	7	0.12	Female-Skewed
Retail	55.4	51.3	78	1.33	Female-Skewed
Pharmaceutical	54.3	50.7	140	2.38	Female-Skewed
Entertainment	53.7	45.5	22	0.37	Female-Dominated
Food/ Beverage/ Tobacco	51.7	41.5	193	3.29	Female-Dominated
Aerospace	48.2	42.1	19	0.32	Female-Dominated
Lodging	47.6	40.0	15	0.26	Female-Dominated
Personal Products	41.2	34.0	97	1.65	Female-Dominated
Human Resources	33.3	50.0	2	0.03	Female-Dominated
Non-Profit	26.1	19.0	21	0.36	Female-Dominated
Textiles	25.0	28.6	7	0.12	Female-Dominated

Table A.8
Share Quantitative Coursework Among Offer Holders, Gender-Skewedness, and Earnings across Industries

Industry	% Male among Offer Holders	Average % Finance Coursework among Offer Holders	Annual Earnings (2006 $)
Wholesale	100	19.05	$96,807
Extractive Minerals	100	19.11	$77,283
Non-Manufacturing	100	17.65	$97231
Environment	100	9.30	$86,070
Other Manufacturing	90.9	14.99	$103,053
Accounting	89.6	15.82	$109,358
Venture Capital	87.4	15.05	$115,502
Machinery	85.3	16.27	$98,728
Investment Management	84.4	21.44	$103,270
Other Services	84.2	16.16	$85,314
Transportation Services	83.8	16.45	$89,502
Real Estate	81.9	16.61	$96,104
Investment Banking	81.5	21.31	$96,837
Construction	80.0	22.43	$95,911
Agribusiness	80.0	15.38	$92,608
Media	80.0	11.21	$84,623
Banking	79.1	21.31	$95,013
Computer Services	78.1	14.41	$103,002
Telecommunications	77.8	15.21	$98,403
Law	77.4	10.34	$139,410
Software/ Printing	77.4	13.56	$101,828
Energy	76.7	19.74	$97,474
Automotive	76.3	15.80	$96,112
Technology/ Electronics	76.0	15.16	$100,467
eCommerce	74.4	12.68	$100301
Consulting	74.0	14.38	$114,903
Chemicals	73.7	17.02	$99,976
Manufacturing	71.8	14.02	$93,269
Diversified Services	70.8	15.92	$98,623
Diversified Financial	68.9	18.44	$93,920
Insurance	68.1	19.17	$97,548
Government	68.0	14.99	$83,974
Trading Companies	66.7	14.51	$112,062
Packaging	66.7	9.43	$77,855
Utilities	66.7	16.58	$87,170
Healthcare Services	64.9	11.98	$98,580
Education	63.6	12.43	$81,403
Other	63.6	7.66	$89,165
Advertising/Marketing	56.7	11.01	$77,565
Rubber/ Plastics	55.6	12.71	$103,711
Retail	55.4	14.31	$101,058
Pharmaceutical	54.3	12.62	$94,435
Entertainment	53.7	12.84	$91,514
Food/ Beverage/ Tobacco	51.7	11.69	$92,132
Aerospace	48.2	10.72	$91,508
Lodging	47.6	11.38	$89,676
Personal Products	41.2	12.27	$87,405
Human Resources	33.3	9.08	$106,706
Non-Profit	26.1	12.42	$74,778
Textiles	25.0	14.37	$82,166

(A) Job Function



(B) Industry

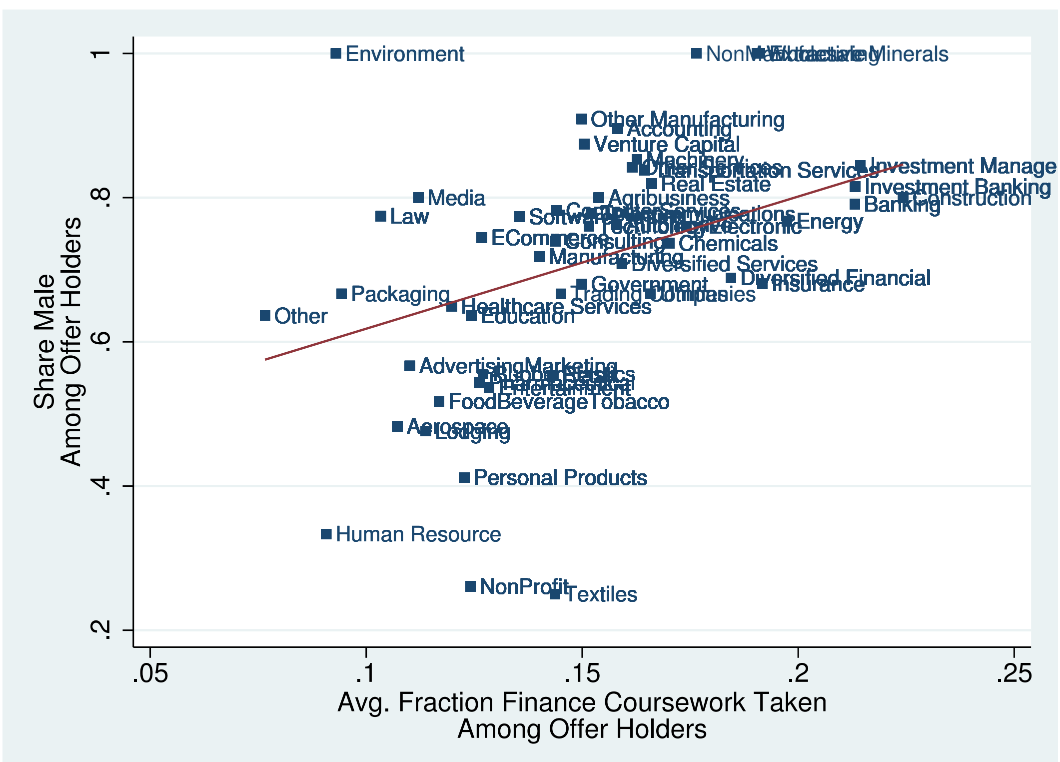


Figure A.3

Relationship between Share of Finance Coursework of Offer Holders and Gender-Skewedness of Job Function and Industry Offer Holders

Table A.9
Effect of Peer Gender Composition on Male-Skewedness of Industry or Job Function Accepted

	(1)	(2)
VARIABLES	Industry Share Male	Job Function Share Male
Share Male Peers*Female	0.29***	0.39***
	[0.081]	[0.068]
Share Male Peers*Male	-0.13**	-0.08**
	[0.051]	[0.035]
Female	-0.06***	-0.06***
	[0.007]	[0.006]
Observations	7,167	7,231
Cohort Fixed Effects	13.00	13.00
Mean	0.72	0.72

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the regression described in Equation (1). "Industry Share Male" is the fraction of graduating students in student i's cohort accepting a job in the same industry in which student i accepts a job who are male (other than student i). "Job Function Share Male" is the fraction of graduating students in student i's cohort accepting a job in the same job function in which student i accepts a job who are male (other than student i). All regressions control for gender, marital status, marital status interacted with gender, age at entry, age squared, experience at entry, experience squared, student GMAT scores, undergraduate GPA, a dummy for missing undergraduate GPA, whether the student attended a "Top 10" or "Top 20" undergraduate institution, and whether the student is Black, Hispanic, Asian, South Asian, or "other" (omitted category is white). All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.10

Effect of Gender Composition on Average Job Characteristics Accepted at Graduation

Panel A: Average Hours and Wages in Job Function Accepted (First Year after Graduation)

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	13.82***	-0.00	0.34**	6.90***
	[4.987]	[0.014]	[0.134]	[1.934]
Share Male Peers	6.84*	-0.02**	0.18*	-0.84
	[3.510]	[0.009]	[0.096]	[2.229]
Female	-3.36***	0.01***	-0.09***	-1.70***
	[0.369]	[0.001]	[0.010]	[0.167]
Observations	5,540	5,540	5,540	5,540
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	62.72	0.02	0.48	41.95

Panel B: Average Hours and Wages in Industry Accepted (First Year after Graduation)

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	11.50***	-0.05**	0.26**	12.06***
	[4.246]	[0.023]	[0.120]	[2.441]
Share Male Peers	3.19	0.01	0.10	-2.93
	[3.572]	[0.014]	[0.097]	[1.949]
Female	-2.39***	0.003**	-0.06***	-1.85***
	[0.321]	[0.001]	[0.009]	[0.206]
Observations	5,588	5,588	5,588	5,588
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	62.22	0.02	0.46	41.60

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable in each column is the average characteristic in the job function or industry accepted by the student. The average characteristic of each job function is taken over all students working in the job function or industry of the accepted job in the first year after graduation, using data on job characteristics in the first year after graduation. "Average weekly hours" is defined as the job function average of self-reported usual weekly hours worked in the position. Responses are collected in discrete bins and transformed into real-valued variables (at the midpoint of each bin). "Frequency of part-time work" is the job function or industry average of the indicator variable for part-time work, where "part-time work" is defined as usual weekly hours less than 40 hours per week. "Frequency of overtime work" is the job function or industry average of the indicator variable for overtime work, where "overtime work" is defined as usual weekly hours greater than 60 hours per week. "Average hourly wage" is defined as the job function or industry average of the self-reported annual earnings divided by the product of usual weekly hours of work and 52. Annual earnings are reported in discrete bins and transformed into real-valued variables at the midpoint of each earnings bin. Wages are in 2006 dollars. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.11

Effect of Gender Composition on Expected Hours and Wages Ten Years After Graduation

Panel A: Expected Hours and Wages Conditional on Intial Job Function Accepted

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	7.31***	-0.07**	0.21***	110.34**
	[1.719]	[0.032]	[0.053]	[46.294]
Share Male Peers	-0.59	0.01	-0.02	-8.14
	[1.529]	[0.020]	[0.041]	[43.841]
Female	-6.70***	0.06**	-0.19***	-113.80***
	[1.240]	[0.023]	[0.038]	[32.834]
Observations	5,532	5,532	5,532	5,532
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	56.65	0.05	0.32	158.19

Panel B: Expected Hours and Wages Conditional on Initial Industry Accepted

VARIABLES	(1) Average Weekly Hours	(2) Frequency of Part-Time Work	(3) Frequency of Overtime Work	(4) Average Hourly Wage
Share Male Peers*Female	9.45***	-0.10***	0.25***	172.68***
	[1.824]	[0.030]	[0.050]	[42.505]
Share Male Peers	-1.56	0.03*	-0.04	-18.00
	[1.499]	[0.015]	[0.044]	[35.637]
Female	-7.85***	0.08***	-0.21***	-158.98***
	[1.339]	[0.022]	[0.036]	[30.549]
Observations	5,576	5,576	5,576	5,576
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	56.33	0.05	0.31	152.12

Robust standard errors in brackets

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable in each column is the expected value of each characteristic of jobs held 10 years after graduation, averaged over all those in the same initial industry at the time of graduation as the student. "Average weekly hours" is defined as the average of self-reported usual weekly hours worked in the position. Responses are collected in discrete bins and transformed into real-valued variables (at the midpoint of each bin). "Frequency of part-time work" is the average of the indicator variable for part-time work, where "part-time work" is defined as usual weekly hours less than 40 hours per week. "Frequency of overtime work" is the average of the indicator variable for overtime work, where "overtime work" is defined as usual weekly hours greater than 60 hours per week. "Average hourly wage" is defined as the average of the self-reported annual earnings divided by the product of usual weekly hours of work and 52. Annual earnings are reported in discrete bins and transformed into real-valued variables at the midpoint of each earnings bin. Wages are in 2006 dollars. All columns include cohort fixed effects, and standard errors are clustered at the peer group by cohort level.

Table A.12
Effect of Gender Composition on Fields of Concentration

Panel A: Effect of Gender Composition on Entry into Male-Dominated Fields of Concentrations

VARIABLES	(1) Max Proportion Male Among Concentrations	(2) Any Male-Dominated Concentration	(3) Any Majority-Male Concentration	(4) All Male-Dominated Concentrations	(5) All Majority-Male Concentrations
Share Male Peers	0.10***	0.01	0.16***	0.55	0.85***
x Female	[0.039]	[0.203]	[0.052]	[0.336]	[0.263]
Share Male Peers	0.00	0.19**	-0.05***	0.21	-0.41***
x Male	[0.021]	[0.085]	[0.019]	[0.177]	[0.077]
Female	-0.01***	-0.08***	-0.01**	-0.20***	-0.14***
	[0.003]	[0.012]	[0.005]	[0.022]	[0.020]
Observations	4,816	4,816	4,816	4,816	4,816
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean	0.78	0.94	0.87	0.44	0.87

Panel B: Effect of Gender Composition on Male-Skewedness of Fields of Concentration

VARIABLES	(1) Proportion Male in Most Male-Dominated Concentration	(2) Proportion Male in Least Male-Dominated Concentration
Share Male Peers	0.10***	0.34***
x Female	[0.039]	[0.076]
Share Male Peers	0.00	-0.07**
x Male	[0.021]	[0.035]
Female	-0.01***	-0.06***
	[0.003]	[0.005]
Observations	4,816	4,816
Cohort Fixed Effects	Yes	Yes
Mean	0.78	0.67

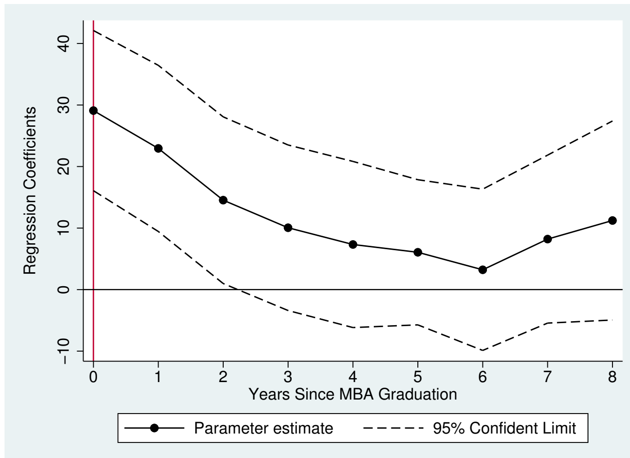
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the following regression:

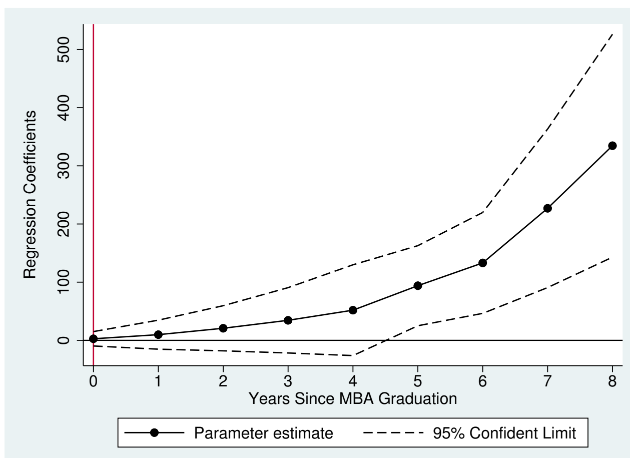
$$Y_{igc} = \phi_0 + \phi_1 Female_i \cdot ShareMale_{igc} + \phi_2 Male_i \cdot ShareMale_{igc} + \beta X_{igc} + \gamma_c + \epsilon_{igc},$$

where $Male_i \cdot ShareMale_{igc}$ is the proportion of male peers interacted with a male dummy, and where X_{ig} is a vector of the student's individual pre-MBA characteristics, as defined in Equation (1). The dependent variable in column (1) is the proportion male of the most male-dominated field of concentration, among all of the concentrations chosen by the student. The dependent variable in column (2), Y_{igc}, is a dummy variable equal to 1 if at least one of the fields of concentration chosen by student i is disproportionately male relative to student i's cohort. The dependent variable in column (3) is a dummy variable equal to 1 if at least one of the fields of concentration chosen by the student is more than 50% male. The dependent variables in columns (4) and (5) are each dummy variables equal to 1 if all of the fields of concentration chosen by the student are disproportionately male or greater than 50% male, respectively. In Panel B, the dependent variable in column (1) is the maximum proportion of male students in the field of concentration, among all of the concentrations chosen by the student, and in column (2), the minimum proportion of male students. Proportion of male students in the field of concentration is determined separately, within each cohort, and excludes the student. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Figure A.4
Effect of Peer Gender Composition on Gender Gap in Expected Hours and Wages after Graduation
Conditional on Initial Firm at Graduation



(i) Effect on Expected Weekly Hours
Given Initial Firm at Graduation



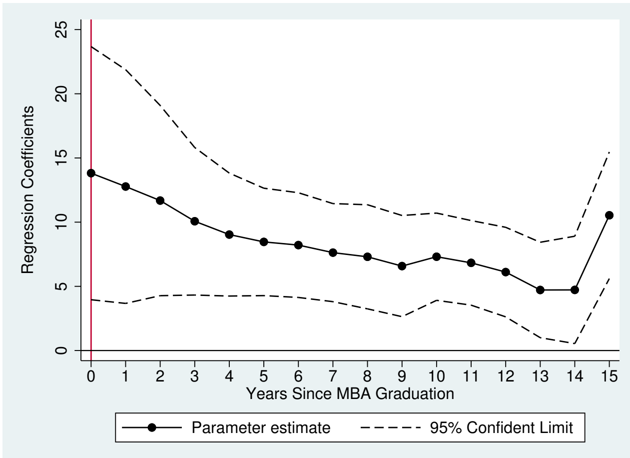
(ii) Effect on Expected Wages
Given Initial Firm at Graduation

Notes: Each regression coefficient shown in each of these figures represents a separate regression of the form described in Equation (1), where the dependent variable is "Expected weekly [hours/wages] X years after graduation, conditional on starting firm." The reported regression coefficients are the estimated coefficients on $Female_i \times ShareMale_{igc}$. The dependent variable is constructed by averaging (i) weekly hours of work or (ii) wages of respondents X years after graduation, averaged over all those who accepted a job at graduation in the same initial firm. Both expected weekly hours and wages include "zeros:" [weekly hours/wages] X years after graduation are averaged over both individuals who are working and those who are not working X years after graduation, where the value is zero for those who are not working.

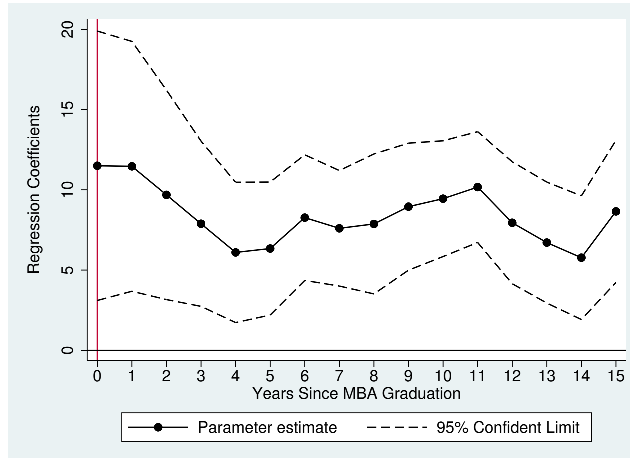
Figure A.5

Effect of Gender Composition of Peer Group on Gender Gap in Expected Hours and Wages (cond. on working)

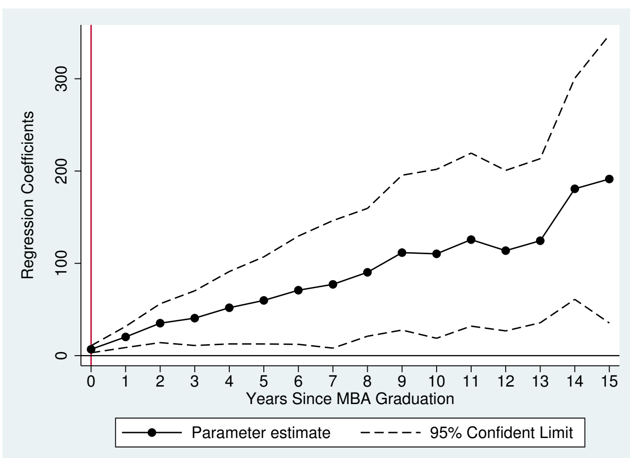
Given Initial Occupation and Industry Accepted at Graduation



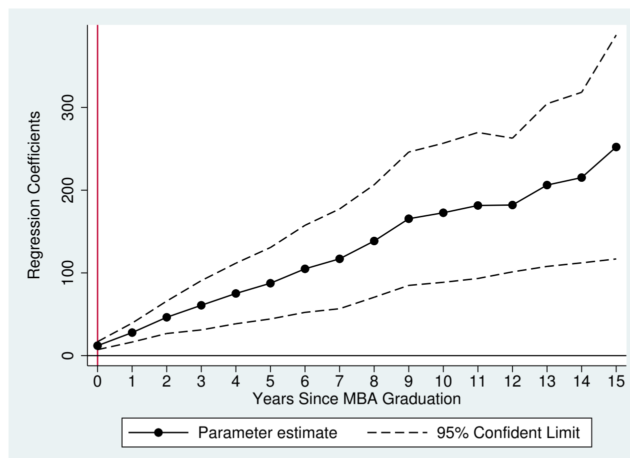
(i) Effect on Expected Weekly Hours Given Initial Job Function at Graduation



(ii) Effect on Expected Weekly Hours Given Initial Industry at Graduation



(iii) Effect on Expected Wages Given Initial Job Function at Graduation



(iv) Effect on Expected Wages Given Initial Industry at Graduation

Notes: Each regression coefficient shown in each of these figures represents a separate regression of the form described in Equation (1), where the dependent variable in subfigures (i) and (ii) is "Expected weekly hours X years after graduation, conditional on starting [job function/industry]." In subfigures (iii) and (iv), the dependent variable is "Expected wages X years after graduation, conditional on starting [job function/industry]." The reported regression coefficients are the estimated coefficients on $Female_i \times ShareMale_{igc}$. The dependent variable is constructed by averaging weekly hours of work or wages of respondents X years after graduation over all those who accepted a job at graduation in the same initial job function or industry. Weekly hours and wages are only averaged over individuals who are working X years after graduation.

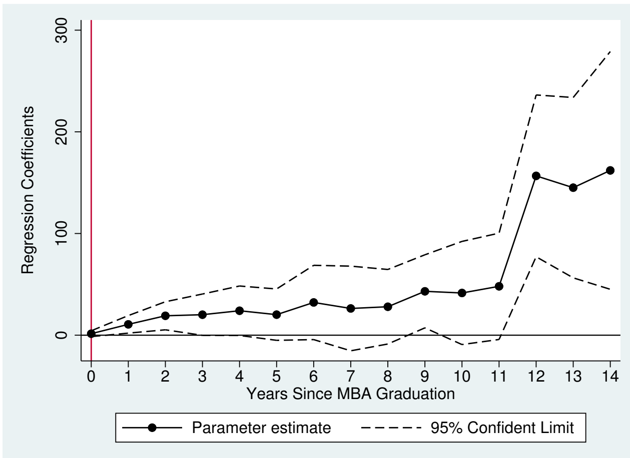
Table A.13
Effect of Gender Composition on Difference between Max Salary Offer and Salary Offer Accepted

VARIABLES	(1) Difference Log Base Salary	(2) Difference Log Base Salary	(3) Difference Log Perm. Salary	(4) Difference Log Perm. Salary
Share Male Peers*Female	-0.06	-0.22	-0.06	-0.02
	[0.042]	[0.297]	[0.042]	[0.287]
Share Male Peers	-0.01	-0.23	-0.01	-0.20
	[0.035]	[0.208]	[0.035]	[0.166]
Female	0.00	-0.01	0.00	-0.00
	[0.004]	[0.029]	[0.004]	[0.031]
Married at Entry	-0.00	-0.04	-0.00	-0.02
	[0.003]	[0.029]	[0.003]	[0.027]
Married Female at Entry	-0.00	0.03	-0.00	-0.02
	[0.005]	[0.048]	[0.005]	[0.047]
Undergraduate GPA	-0.01	-0.05	-0.01	-0.04
	[0.006]	[0.042]	[0.006]	[0.035]
Top 10 Undergraduate Inst.	0.00	0.04	0.00	0.03
	[0.004]	[0.033]	[0.004]	[0.029]
Top 20 Undergraduate Inst.	-0.00	-0.07**	-0.00	-0.06**
	[0.004]	[0.031]	[0.004]	[0.029]
Black	0.01	0.20	0.01	0.13
	[0.011]	[0.163]	[0.011]	[0.122]
Hispanic	-0.00	-0.02	-0.00	0.00
	[0.004]	[0.034]	[0.004]	[0.034]
Observations	5,286	521	5,286	560
Sample	All	Diff > 0	All	Diff > 0
Cohort Fixed Effects	13	13	13	13
Mean	0.02	0.17	0.02	0.20

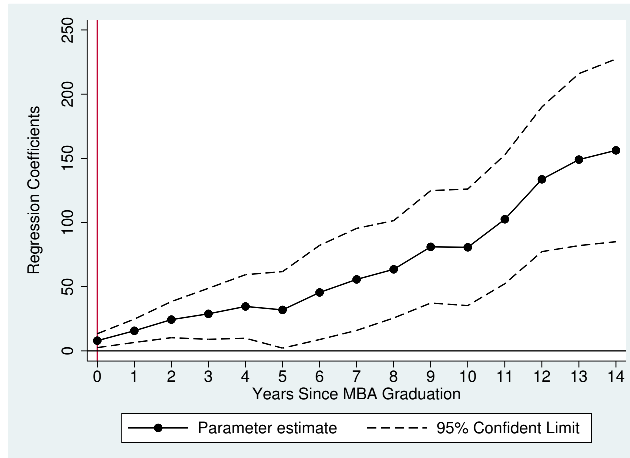
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the regression described in Equation (1). The dependent variable in columns (1) and (2) is the difference between the log maximum base salary offer received by the student and the log base salary associated with the job that the student accepted from their set of job offers. The dependent variable in columns (3) and (4) is the difference between the log maximum permanent salary offer and the log permanent salary associated with the job that the student accepted from their offer set. Columns (1) and (3) report estimates from specifications that use the full sample. Columns (2) and (4) show the results from a specification where the sample was restricted to only those who accepted a salary other than the maximum salary offered. All regressions control for gender, marital status, marital status interacted with gender, age at entry, age squared, experience at entry, experience squared, student GMAT scores (total, quantitative, and verbal scores), undergraduate GPA, whether the student attended a "Top 10" or "Top 20" undergraduate institution, and whether the student is Black, Hispanic, Asian, South Asian, or "other" (omitted category is white). All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

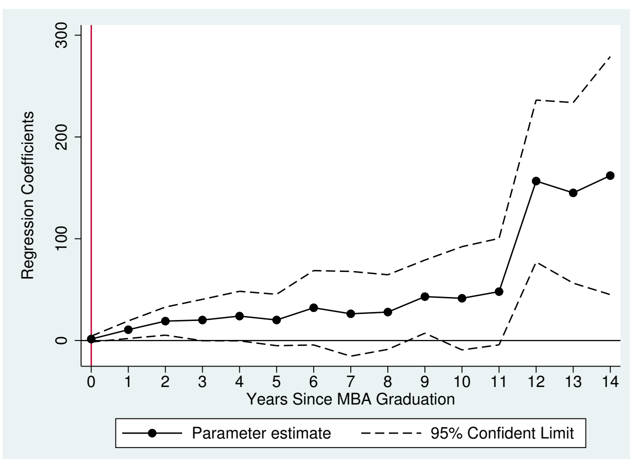
Figure A.6
Effect of Peer Gender Composition on Gender Gap in Expected Wages of Women and Women w/ Children
Conditional on Initial Occupation and Industry Accepted at Graduation



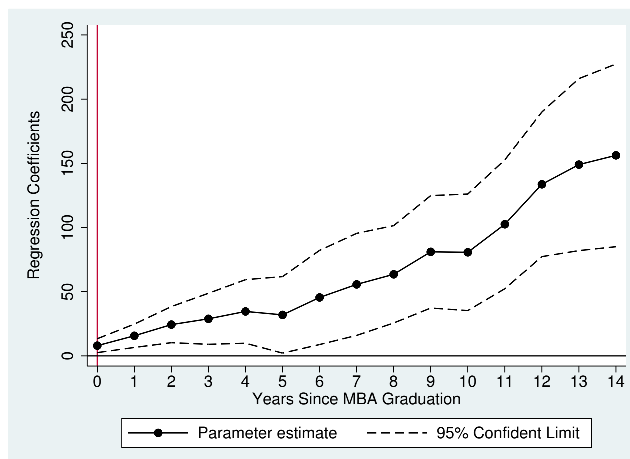
(i) Effect on Women's Expected Wages
Given Initial Job Function at Graduation



(ii) Effect on Women's Expected Wages
Given Initial Industry at Graduation



(iii) Effect on Expected Wages
of Women with Children
Given Initial Job Function at Graduation



(iv) Effect on Expected Wages
of Women with Children
Given Initial Industry at Graduation

Notes: Each regression coefficient shown in each figure above represents a separate regression of the form described in Equation (1), where the dependent variable in (i) and (ii) is "expected wages of women X years after graduation, conditional on starting [job function/industry]." The dependent variable in (iii) and (iv) is "expected wages of women with children X years after graduation, conditional on starting [job function/industry]." The reported regression coefficients are the estimated coefficients on $Female_i \times ShareMale_{igc}$. The dependent variable in (i) and (ii) is constructed by averaging actual wages of *women* a given number of years after graduation over all women who accepted the same initial job function or industry at graduation. The dependent variable in (iii) and (iv) is constructed by averaging actual wages of *women who have children* a given number of years after graduation over all such women who accepted the same initial job function or industry at graduation (whether or not they had children at the time of graduation). The regression is run on the full sample (male and female, with and without children). Average wages include "zeros:" the value for wages is zero for those who are not working.

Table A.14
Effect of Concentrations on Distribution of Salary Offers

VARIABLES	(1) Log Mean Salary Offer	(2) Log Median Salary Offer	(3) Log Max Salary Offer
Share Male Peers x Female	0.11	0.04	0.10
	[0.092]	[0.101]	[0.144]
Share Male Peers	-0.06	-0.03	-0.03
	[0.053]	[0.056]	[0.091]
Conc. Finance x Female	0.03**	0.03**	0.05**
	[0.015]	[0.015]	[0.021]
Conc. Finance	-0.01	-0.01	-0.01
	[0.011]	[0.011]	[0.016]
Female	-0.03***	-0.03***	-0.08***
	[0.009]	[0.009]	[0.013]
Observations	5,323	5,323	5,323
Cohort Fixed Effects	Yes	Yes	Yes
Mean	11.51	11.51	11.64

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variables in columns (1) and (2) are the natural log of the mean and median of the base salary offers to the student, respectively. The dependent variable in column (3) is the natural log of the maximum "permanent" salary offer. All regressions control for gender, marital status at the start of business school, marital status interacted with gender, age at the start of business school, age squared, student GMAT scores (quantitative, verbal, and total), undergraduate GPA (normalized to 4.0 scale), a dummy for missing undergraduate GPA, indicator variables for whether the student attended a "Top 10" or "Top 20" undergraduate institution, for whether the student is Black, Hispanic, Asian, South Asian, or identifies as having another ethnic background (omitted category is white), and for years of work experience prior to business school and experience squared. Data on concentrations comes from administrative data that includes coursework and transcript data. Dummy variables for missing concentration data and missing concentration data interacted with "female" are included. "Conc. Finance" is a dummy variable equal to 1 if the student's concentration is nonmissing and is declared as finance and 0 otherwise. "Conc. Finance" is reported as the deviation from the mean. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.15
Effect of Coursework on Distribution of Salary Offers

VARIABLES	(1) Log Mean Salary Offer	(2) Log Median Salary Offer	(3) Log Max Salary Offer
Share Male Peers xFemale	-0.06 [0.142]	-0.10 [0.148]	-0.05 [0.150]
Share Male Peers	0.06 [0.094]	0.08 [0.097]	0.01 [0.089]
Fraction Finance Courses x Female	0.20** [0.080]	0.16* [0.081]	0.20** [0.090]
Fraction Finance Courses	-0.09 [0.054]	-0.08 [0.055]	-0.15** [0.059]
Female	-0.06*** [0.010]	-0.06*** [0.010]	-0.06*** [0.010]
Observations	5,323	5,323	5,323
Cohort Fixed Effects	13.00	13.00	13.00
Mean	11.61	11.60	11.64

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variables in columns (1)-(3) are the natural log of the mean, median, and maximum of the "permanent" salaries offered to the student, respectively. All regressions control for gender, marital status at the start of business school, marital status interacted with gender, age at the start of business school, age squared, student GMAT scores (quantitative, verbal, and total), undergraduate GPA (normalized to a 4.0 scale), a dummy for missing undergraduate GPA, indicator variables for whether the student attended a "Top 10" or "Top 20" undergraduate institution, for whether the student is Black, Hispanic, Asian, South Asian, or identifies as having another ethnic background (omitted category is white), and for years of work experience prior to business school and experience squared. Data on coursework comes from administrative data that includes coursework, fields, and transcript data. Dummy variables for missing field data and missing field data interacted with "female" are included. "Fraction Finance Courses" is a variable equal to the fraction of total courses taken in the field of finance if the data on the field of the coursework is nonmissing, equal to 0 otherwise, and is reported as the deviation from the mean. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.16

Effect of Gender Composition on Distribution of Firm Pay

VARIABLES	(1) Mean Offer Firm Pay	(2) Median Offer Firm Pay	(3) Max Offer Firm Pay
Share Male Peers	0.17	0.16	0.22*
xFemale	[0.110]	[0.109]	[0.122]
Share Male Peers	0.01	0.03	-0.09
	[0.084]	[0.078]	[0.089]
Female	-0.07***	-0.06***	-0.07***
	[0.012]	[0.012]	[0.012]
Conc. Finance	0.01	0.01	0.00
	[0.013]	[0.013]	[0.011]
Conc. Finance	0.04**	0.04***	0.04***
x Female	[0.014]	[0.014]	[0.015]
Observations	5,140	5,140	5,140
Cohort Fixed Effects	Yes	Yes	Yes
Mean	0.00	0.00	0.04

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: Notes: The dependent variables are the mean, median, and maximum of the firm component of pay, taken over the student's offer set. The firm component of pay comes from an AKM wage decomposition, estimating: $w_{ij} = F_j + \delta_i + \mu_{ij}$, where w_{ij} is the log of the permanent salary offered, δ_i is the individual fixed effect, F_j is the firm fixed effect, or the firm component of pay. The estimation includes a term for a match effect, μ_{ij}. The firm fixed effect is identified using data at the individual-offer level. Salaries are measured in 2006 dollars.

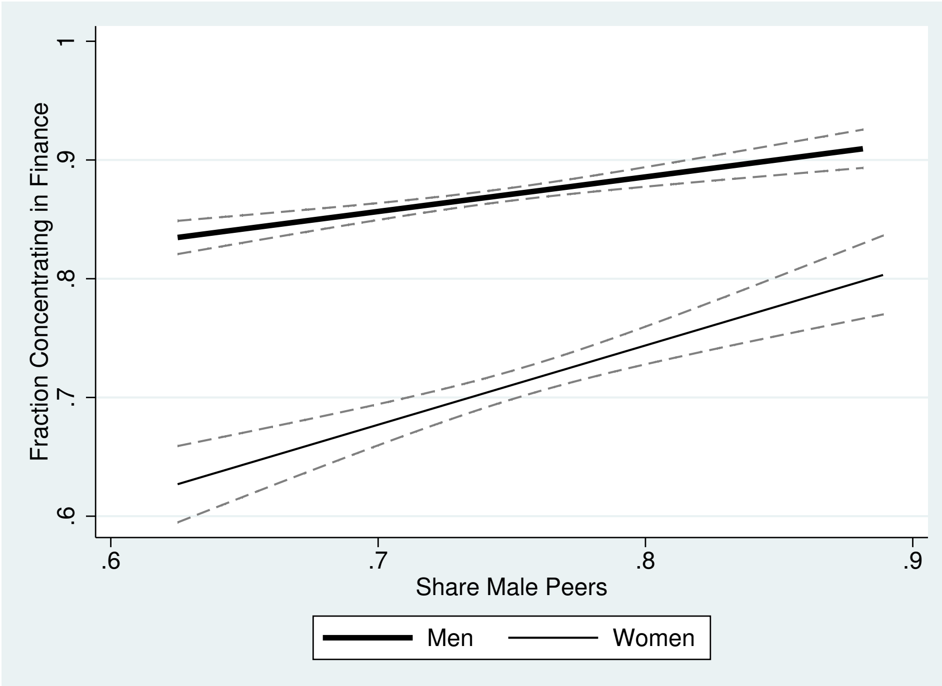
Table A.17
Effect of Peer Gender Composition on Distribution of Offers for Expected Future Wages Conditional on Initial Firm at Graduation

VARIABLES	(1) Mean Wage Offer	(2) Median Wage Offer	(3) Max Wage Offer
Share Male Peers x Female	322.21***	335.76***	269.31**
	[98.560]	[98.009]	[105.749]
Share Male Peers	-25.33	-30.42	-54.42
	[57.465]	[58.450]	[63.308]
Female	-26.56***	-26.49***	-26.55***
	[7.363]	[7.407]	[8.240]
Black	-46.32***	-46.46***	-48.53***
	[12.144]	[11.988]	[13.788]
Hispanic	-29.00***	-28.29***	-32.21***
	[10.276]	[10.294]	[10.779]
Observations	3,008	3,008	3,008
Cohort Fixed Effects	Yes	Yes	Yes
Mean	166.42	165.34	179.27

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variables are the mean, median, and maximum of the set of offers for "expected wages 8 years after graduation" in the offer set of the student at graduation, where expected wages for each job offer are calculated by taking the average of hourly wages, eight years after graduation, over all graduates who accepted a job with the same initial firm at graduation.

Figure A.7
First Stage for All Students, by Gender



Notes: This figure reports the first stage relationships between peer gender composition and the likelihood of concentrating in finance. The predicted likelihood of concentrating in finance shown here is estimated using the full sample, using the estimated coefficients from Equation (3), but residualized for cohort-specific and covariate-specific coefficients. Standard errors are clustered at the peer group level.

Table A.18

Effect of Concentration in Finance on Distribution of Salary Offers

VARIABLES	(1) Log Mean Salary Offer	(2) Log Median Salary Offer	(3) Log Max Salary Offer	(4) Log Max Perm. Salary
$\widehat{Conc.Finance}$ x Female	-0.01	-0.00	-0.01	0.04
	[0.044]	[0.045]	[0.046]	[0.064]
$\widehat{Conc.Finance}$	-0.07	-0.09	-0.21	0.07
	[0.178]	[0.166]	[0.198]	[0.322]
$\widetilde{Conc.Finance}$ x Female	0.04**	0.03**	0.04**	0.05**
	[0.016]	[0.016]	[0.017]	[0.022]
$\widetilde{Conc.Finance}$	-0.01	-0.01	-0.02*	-0.01
	[0.011]	[0.011]	[0.011]	[0.016]
Female	-0.03	-0.04	-0.05	-0.08
	[0.042]	[0.041]	[0.044]	[0.072]
Observations	3,855	3,855	3,855	3,855
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean	11.51	11.51	11.54	11.64

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column reports two-stage least squares results of the impact of concentration in finance on the distribution of salary offers. $\widehat{ConcFin}_i$ represents the predicted value of concentration in finance, as predicted by the first-stage equation, Equation (3). $\widetilde{ConcFin}_i$ represents the component of concentration in finance orthogonal to the peer effect, defined as $ConcFin_i - \widehat{ConcFin}_i$. The dependent variables are the mean, median, and maximum of the set of offers received by student i. All specifications include cohort fixed effects. Standard errors are clustered at the peer group level.

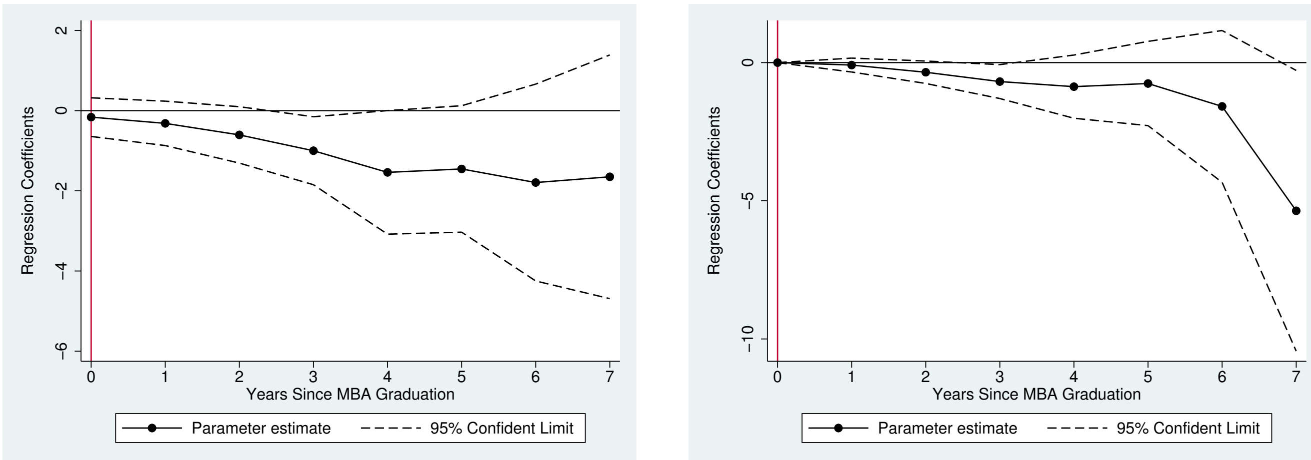
Table A.19
Effect of Concentration in Finance on Distribution of Offers for Expected Future Wages
Conditional on Initial Industry and Job Function at Graduation

	Job Function Averages 10 Years Out			Industry Averages 10 Years Out		
VARIABLES	(1) Mean Wage Offer	(2) Median Wage Offer	(3) Max Wage Offer	(4) Mean Wage Offer	(5) Median Wage Offer	(6) Max Wage Offer
$\widehat{Conc.Finance}$ x Female	60.12*** [21.954]	59.98*** [22.245]	62.03*** [22.543]	60.07*** [19.558]	62.44*** [19.117]	60.39*** [21.409]
$\widehat{Conc.Finance}$	94.86 [125.402]	109.68 [124.272]	34.81 [134.237]	130.02 [86.129]	137.07 [83.561]	57.63 [100.907]
$\widetilde{Conc.Finance}$ x Female	1.64 [6.056]	2.64 [6.104]	0.12 [5.999]	1.42 [5.232]	2.18 [5.218]	2.43 [5.308]
$\widetilde{Conc.Finance}$	53.82*** [4.655]	53.32*** [4.687]	56.55*** [4.593]	46.00*** [4.011]	45.95*** [4.026]	49.38*** [3.947]
Female	-61.89** [27.195]	-59.55** [27.148]	-72.65** [28.583]	-56.41*** [20.736]	-56.83*** [19.986]	-65.81*** [24.193]
Observations	4,153	4,153	4,153	4,152	4,152	4,152
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	158.98	158.94	165.73	152.56	152.61	159.99

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column reports two-stage least squares results of the impact of concentration in finance on the distribution of salary offers. $\widehat{ConcFin_i}$ represents the predicted value of concentration in finance, as predicted by the first-stage equation, Equation (3). $\widetilde{ConcFin_i}$ represents the component of concentration in finance orthogonal to the peer effect, defined as $ConcFin_i - \widehat{ConcFin_i}$. "Wage offers" 10 years after graduation are the expectation of wages, conditional on initial job function and industry at graduation. Expected wages are determined by averaging actual wages of graduates 10 years after graduation over students who began in the same initial job function in columns (1)-(3) and over those who began in the same initial industry in columns (4)-(6). All specifications include cohort fixed effects. Standard errors are clustered at the peer group level.

Figure A.8
Effect of Gender Composition of Peer Group on Long-Term
Labor Force Participation and Probability of Not Working



(i) Effect of Peers on Ever Not Working (ii) Effect of Peers on Total Years Not Working

Notes: Subfigure (i) shows the regression coefficients from a set of regressions where the dependent variable, "Ever Not Working X Years after Graduation" is the cumulative incidence of not working. It is defined as an indicator variable equal to 1 if there has been any spell of not working in the X years since graduation. Measures of employment or non-employment a given number of years after graduation come from the MBA Alumni Survey.

Table A.20
Initial Conditions and Long-Term Salary Outcomes
Controlling for Sample Attrition

	Years After Graduation							
Dependent Variable	0	1	2	3	4	5	6	7
Share Male Peers*Female	0.23	1.34*	0.94	1.70	1.33	2.39*	2.74**	4.99**
	[0.611]	[0.697]	[0.835]	[1.057]	[1.435]	[1.288]	[1.343]	[2.109]
Share Male Peers	-0.09	0.04	0.51	0.52	0.66	0.41	0.45	0.29
	[0.218]	[0.404]	[0.542]	[0.680]	[0.774]	[0.811]	[0.849]	[1.291]
Female	-0.02	-0.12	-0.15	-0.28**	-0.23	-0.36**	-0.50***	-0.70***
	[0.068]	[0.082]	[0.100]	[0.122]	[0.159]	[0.147]	[0.150]	[0.232]
R-squared	0.13	0.11	0.08	0.11	0.10	0.12	0.13	0.13
Observations	328	466	462	458	463	468	475	348

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This sample is restricted to those who have non-missing annual earnings six years after graduation. The dependent variable in each column is log earnings a given number of years after graduation. Column "0" (years after graduation) uses the employment offer data and contstructs the outcome variable from accepted jobs. The outcome variable, "log basesalary accepted," is used in Equation (1) and in Table 3. The outcome variables for Years 1-7 after graduation uses data from the MBA Alumni Survey, where annual earnings are a linear interpolation between earnings the first year of the job and the last year, and where the earnings in the first and last year are defined as the midpoint of a range. All specifications include cohort fixed effects, and standard errors are clustered at the peer group level. Specifications in Section B include fixed effects for the job function accepted at graduation. Specifications in Section C include fixed effects for the industry accepted at graduation.

Table A.21
Effect of Gender Composition on Preferences: Stated First Choice Job

VARIABLES	(1) Job Function: Investment Banking	(2) Job Function: Venture Capital	(3) Job Function: Product Management
Share Male Peers*Female	0.63***	0.14**	-0.37***
	[0.119]	[0.072]	[0.108]
Share Male Peers	-0.15***	-0.03	0.17***
	[0.051]	[0.031]	[0.034]
Female	-0.52***	-0.13**	0.33***
	[0.088]	[0.055]	[0.079]
Married at Entry	-0.02**	-0.00	0.02***
	[0.009]	[0.007]	[0.005]
Married Female at Entry	0.02	0.00	-0.02
	[0.015]	[0.009]	[0.013]
Undergraduate GPA	-0.01	0.01	0.01
	[0.013]	[0.008]	[0.007]
Top 10 Undergraduate Institution	0.02	0.01	-0.02**
	[0.017]	[0.014]	[0.011]
Top 20 Undergraduate Institution	-0.03***	0.00	0.01
	[0.013]	[0.010]	[0.010]
Black	0.00	-0.05***	-0.03*
	[0.022]	[0.009]	[0.014]
Hispanic	-0.03	-0.02	0.00
	[0.019]	[0.012]	[0.013]
Observations	6,494	6,494	6,494
Cohort Fixed Effects	Yes	Yes	Yes
Mean	0.10	0.03	0.04

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the regression described in Equation (1). The dependent variable in each column is an indicator variable representing the job function of the student's stated first-choice job. The data comes from employment offer data, where students indicate whether the offer was their "first choice," "second choice," or "third choice" job. All regressions control for gender, marital status, marital status interacted with gender, age at entry, age squared, experience at entry, experience squared, student GMAT scores, undergraduate GPA, whether the student attended a "Top 10" or "Top 20" undergraduate institution, and whether the student is Black, Hispanic, Asian, South Asian, or "other" (omitted category is white). All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.22
Effect of Gender Composition on Preferences: Stated First Choice Job

VARIABLES	(1) Job Function: Investment Banking	(2) Job Function: Venture Capital	(3) Job Function: Product Management
Share Male Peers*Female	0.48***	0.11*	-0.20**
	[0.107]	[0.058]	[0.090]
Share Male Peers*Male	-0.15***	-0.03	0.17***
	[0.051]	[0.031]	[0.034]
Female	-0.52***	-0.13**	0.33***
	[0.088]	[0.055]	[0.079]
Married at Entry	-0.02**	-0.00	0.02***
	[0.009]	[0.007]	[0.005]
Married Female at Entry	0.02	0.00	-0.02
	[0.015]	[0.009]	[0.013]
Undergraduate GPA	-0.01	0.01	0.01
	[0.013]	[0.008]	[0.007]
Top 10 Undergraduate Institution	0.02	0.01	-0.02**
	[0.017]	[0.014]	[0.011]
Top 20 Undergraduate Institution	-0.03***	0.00	0.01
	[0.013]	[0.010]	[0.010]
Black	0.00	-0.05***	-0.03*
	[0.022]	[0.009]	[0.014]
Hispanic	-0.03	-0.02	0.00
	[0.019]	[0.012]	[0.013]
Observations	6,494	6,494	6,494
Cohort Fixed Effects	Yes	Yes	Yes
Mean	0.10	0.03	0.04

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimated coefficients from the following regression:

$$Y_{igc} = \phi_0 + \phi_1 Female_i \cdot ShareMale_{igc} + \phi_2 Male_i \cdot ShareMale_{igc} + \beta X_{igc} + \gamma_c + \epsilon_{igc},$$

where $Male_i \cdot ShareMale_{igc}$ is the proportion of male peers interacted with a male dummy, and where X_{ig} is a vector of the student's individual pre-MBA characteristics, as defined in Equation (1). The dependent variable in each column is an indicator variable representing the job function of the student's stated first-choice job. The data comes from employment offer data, where students indicate whether the offer was their "first choice," "second choice," or "third choice" job. All columns include cohort fixed effects, and standard errors are clustered at the peer group level.

Table A.23
Effect of Gender Composition on Distribution of Value of Non-Wage Amenity Offers

	Non-Wage Amenity Values (All)			Non-Wage Amenity Values (Female)		
VARIABLES	(1) Mean Value Non-Wage	(2) Median Value Non-Wage	(3) Max Value Non-Wage	(4) Mean Value Non-Wage	(5) Median Value Non-Wage	(6) Max Value Non-Wage
Share Male Peers	0.90	1.04	0.81	-0.21	-0.32	0.10
x Female	[1.417]	[1.414]	[1.539]	[0.632]	[0.627]	[0.731]
Share Male Peers	-1.51	-1.09	-3.49**	-0.21	-0.13	-0.78*
	[1.331]	[1.333]	[1.597]	[0.413]	[0.399]	[0.439]
Female	-0.36***	-0.35***	-0.33***	-0.05	-0.06	0.08
	[0.109]	[0.108]	[0.124]	[0.053]	[0.053]	[0.054]
Observations	5,032	5,032	5,032	4,483	4,483	4,483
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	-1.57	-1.60	-0.91	0.63	0.63	0.83

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variables in columns (1)-(3) are the mean, median, and maximum of offers for "the non-wage amenity value," where the "non-wage amenity value" is defined at the firm level and in dollar terms, at the firm where student i received an offer. In columns (4)-(6), the "non-wage amenity values" are estimated using a sample of just women and therefore reflect women's valuations for the non-wage amenities offered at the firm where student i has received an offer. Each specification uses the same control variables as in column (5) of Table 3. All columns include cohort fixed effects and are clustered at the peer group level.

Table A.24
Effect of Gender Composition on Variance of Non-Wage Amenity Values Offered

VARIABLES	(1) Variance of Non-Wage Amenity Values	(2) Variance of Non-Wage Amenity Values (Female)
Share Male Peers	0.12	0.60
x Female	[9.511]	[2.076]
Share Male Peers	-8.86	-1.36
	[6.845]	[1.473]
Female	-0.88	0.38**
	[1.029]	[0.161]
Observations	1,561	1,168
Cohort Fixed Effects	Yes	Yes
Mean	9.11	1.35

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable in column (1) is the variance of the non-wage amenity values offered to the student, where the "non-wage amenity value" is defined at the firm level and in dollar terms, and the variance of the offer set is over all firms where student i received an offer. The dependent variable in column (2) is the variance of the female-specific non-wage amenity values, which are estimated using a sample of just women and therefore reflect women's valuations for the non-wage amenities offered at each firm where student i has received an offer. Each specification uses the same control variables as in column (5) of Table 3. All columns include cohort fixed effects and are clustered at the peer group level.

Table A.25
Effect of Peer Gender Composition on Choice of Future Salary Offers
Based on Initial Job, Industry, and Firm Averages

VARIABLES	(1) Accepted Max Offer Job Func 10 Years Out	(2) Accepted Max Offer Industry 10 Years Out	(3) Accepted Max Offer Firm 10 Years Out
Share Male Peers*Female	-0.05	0.01	0.44
	[0.209]	[0.205]	[0.305]
Share Male Peers	0.28	-0.07	-0.01
	[0.170]	[0.178]	[0.219]
Female	-0.05***	-0.06***	0.05**
	[0.018]	[0.018]	[0.024]
Observations	6,289	6,388	2,907
Cohort Fixed Effects	Yes	Yes	Yes
Mean	0.78	0.77	0.77

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable in columns (1) and (2) are dummy variables for whether the respondent accepted the maximum offer for expected salary 10 years after graduation, given the starting industry and occupation of the offer at graduation. The dependent variable in column (3) is a dummy variable for whether the respondent accepted the maximum offer for expected salary 10 years after graduation, conditional on the starting firm. Each specification uses the same control variables as in column (5) of Table 3. All columns include cohort fixed effects and are clustered at the peer group level.

Table A.26
Effect of Peer Gender Composition on Salary Offer Accepted
Among Those with and without Choice of Industry, Job Function or Firm

VARIABLES	(1) Accepted Max Salary Offer	(2) Accepted Max Salary Offer	(3) Accepted Max Salary Offer	(4) Accepted Max Salary Offer	(5) Accepted Max Salary Offer	(6) Accepted Max Salary Offer
Share Male Peers	0.16	1.13*	0.14	1.17**	0.02	1.40***
xFemale	[0.102]	[0.636]	[0.100]	[0.502]	[0.012]	[0.430]
Share Male Peers	0.05	-0.56	0.04	-0.65**	0.01	-0.46*
	[0.094]	[0.391]	[0.081]	[0.315]	[0.013]	[0.272]
Female	-0.01	-0.02	0.00	-0.03	-0.00	-0.03
	[0.008]	[0.050]	[0.007]	[0.044]	[0.001]	[0.036]
Observations	4,439	994	4,272	1,161	3,782	1,651
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.96	0.63	0.97	0.63	1.00	0.66
Sample	No Choice Industry	Choice of Industry	No Choice Job Func	Choice of Job Func	No Choice of Firm	Choice of Firm

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns (1), (3), and (5) are restricted to the sample of students who received offers from only one industry, job function, or firm, respectively. Columns (2), (4), and (6) are each restricted to the sample of students who received offers from more than one industry, job function, or firm, respectively. The dependent variable in each column is whether the student accepted the maximum salary offer in his or her offer set. Each specification uses the same control variables as in column (5) of Table 3. All columns include cohort fixed effects and are clustered at the peer group level.

Appendix B: On the Formation of Preferences

Recall that in Section C., the results showed that a 10 percentage-point increase in the share of male peers leads to a 4 percentage-point increase in the likelihood that female students accept the highest salary offer in their choice set. This increase in the "willingness to accept" (WTA) the highest salary offer could reflect a change in preferences, as measured by the “willingness to pay" (WTP) - the monetary trade-off one is willing to accept for other desirable non-monetary amenities of the job. Alternatively, peer gender composition may not influence preferences themselves, but rather, female students with a greater share of male peers may be searching in industries or among a set of jobs with a different distribution of non-wage amenity values. For example, suppose female students with a greater share of male peers take more finance courses and are therefore more likely to search for jobs in the finance industry relative to marketing. But suppose that the variance in the non-wage amenity values in marketing jobs is greater than the variance of non-wage amenities in finance. It is possible, for example, that the average gain to the worker in finance, in terms of the value of non-wage amenities gained from accepting a job offer other than the maximum salary job offer, relative to the earnings loss, is low in comparison to what one gains in non-wage amenity value for the same earnings loss in marketing. In other words, the price of non-wage amenities may be greater in finance than in marketing. Thus, it is important to test whether peers have an effect on the distribution of the non-wage amenity value offers in order to understand whether the increase in the WTA reflects a change in the WTP.

As in the discrete choice literature on the valuation of non-wage amenities, an inference about the value to the worker of the non-wage amenities at a given firm can be made if a student accepts a salary other than the maximum salary offered. The basic idea is as follows: if a student receives two job offers, from Firm A and Firm B, and Firm A is the higher-paying offer, but we observe that the student chooses Firm B, it must be the case that there is some other non-wage benefit or non-pay job characteristic associated with offer B that is at least as valuable to the student as the foregone monetary value of choosing offer B over offer A.[104] The value of non-wage amenities is defined in a revealed preferences sense: the discrete choices reveal how much income a student would be willing to give up in order to receive the increase in the non-wage amenities associated with a job other than the maximum salary offer, relative to the maximum salary offer. The goal is to determine whether the change in the WTA the maximum salary offer, documented in Section VI.C., is indicative of a change in the WTP, or whether it is simply due to a change in the distribution of the value of non-wage amenity offers they receive in the new industries and job types in which they are searching. These values of non-wage amenities will therefore be measured in dollar terms.

Appendix Table A.21 presents some suggestive evidence that the gender composition of one's peers has an effect on preferences. Using survey data from a survey conducted by Career Services prior to the start of the interview process, I first examine the effect of the gender composition of one's peers on the stated "first choice," "second choice," and "third choice" jobs. From students' stated preferences, I show that women with a greater share of male peers had a greater likelihood of stating that their first choice job was investment banking or venture capital and a lower likelihood of their first choice job being in product management.[105] However, this survey evidence still does not show, in a revealed preferences sense, whether students were indeed more likely to choose such jobs when faced with real offers in-hand.

Examining the choices of students at the final stage of the decision-making process, when final offers are made, and in an institutional setting where students can hold multiple offers simultaneously in hand, allows for a clear way to measure the WTP for the non-wage amenities of the job, using the data on the job offers they receive as well as their acceptance decisions. In order to do this, I use an approach from Mas and Thomas (2021), which builds upon the framework and methodology in Sorkin (2018), to estimate the dollar value of non-wage amenities at the firm level. The approach is summarized in Appendix D.

Using these estimated *dollar* values of non-wage amenities at the firm level, I then examine whether women with a greater share of male peers receive a different distribution of non-wage amenity offers at the firm level than those with a lower share of men in their peer group. Table A.23 shows the results from this analysis. The estimates shown are the estimated coefficients of a specification similar to Equation (1), where the dependent variables in columns (1) through (3) are the mean, median, and maximum, respectively, of the non-wage amenity offers associated with the set of job offers the student receives, in dollar terms. The dependent variables in Columns (4) through (6) are the mean, median, and maximum of the non-wage amenity values, estimated using only the acceptance decisions of female students rather than the entire sample, so that the values reflect a female-specific valuation of the non-wage amenities offered by each firm. Table A.24 in the appendix shows that while women do, on average, receive job offers with a greater variance

[104] Discrete choice experiments are an extension of the contingent valuation literature, whereby rather than directly asking people for valuations over an attribute (the stated preference method), people are given the choice of two or more scenarios and are asked to choose their preferred option. These scenarios usually vary the attributes and the prices, and WTP can be estimated using random utility models (McFadden 1973; Manski 1977). Choice experiments have been shown to have better properties relative to stated preference valuation methods (Hanley, Wright, and Adamowicz (1998)). A question is whether these experiments, which are usually survey-based, correspond to actual market behavior. In this case, the choices are based on acceptance decisions of real market behavior in a high-stakes setting with well-informed labor market participants. See Mas and Pallais (2017), Sorkin (2018) for similar approaches.

[105] Appendix Table A.22 shows results where $ShareMale$ is interacted separately with $Female$ and $Male$ in order to examine whether the likelihood of stated "first choice," "second choice," and "third choice" jobs increased for women, in the above-mentioned occupations, after taking into account that the likelihood for some of these were also influenced for men.

in the female-specific valuation of non-wage amenities, there is no effect of peer gender composition on the variance of non-wage amenity offers.

Overall, the results show that there is no significant effect of peer gender composition on the distribution of non-wage amenity values offered. The evidence suggests that rather than affecting the distribution of offers for non-wage amenity values that female students receive, a greater share of male peers affects women's likelihood of accepting their highest salary offer, holding fixed the distribution of non-wage amenity values of the offers. Women with a greater share of male peers exhibit, through their acceptance decisions, a lower willingness to pay for the non-wage amenities of the job.

The finding that peer gender composition causally affects women's preferences, as measured in a real-life, high-stakes environment, where actual job offers and acceptance decisions are concerned - notably, ones that influence the start of one's career - has not previously been documented in the existing literature. More broadly, this paper relates to a long-standing debate in the literature on the gender earnings gap, regarding how much of the earnings gap is due to differences in preferences for different job characteristics and the accumulated effects that anticipated future selection into such occupations and industries may generate (See, for example, Adda, Dustmann, and Stevens (2017)). However, the findings shown here document that the preferences themselves often considered so closely tied to gender may themselves be malleable and subject to social or environmental influences.

Although peer gender composition has a large and significant effect on women's likelihood of accepting the maximum salary offer, I show that this effect does *not* explain the effect of peers on women's long-term expected wage paths. Appendix Table A.25 shows that there is no significant effect of peer gender composition on the likelihood that female students accept the maximum "offer for expected earnings 10 years after graduation," given the initial industry, occupation, or firm accepted at graduation.[106] This occurs despite the fact that the effect of peers on women's likelihood of accepting their highest salary offer is driven primarily by those who have a choice between two or more occupations or industries, and in particular, those who have a choice across firms.[107] In other words, peer gender composition affects both human capital choices and preferences; while the effect of peers on women's salaries at graduation are explained primarily by their effect on preferences, these effects due to preferences do not result in persistent effects on earnings. It is the effect of peers on human capital that affects the *set of choices* that women have and results in persistent earnings differences.

Appendix C: An IV Approach: Measuring the Causal Effect of Human Capital on Salary Offers

The results shown in Section VI.C. show that in spite of an effect of peer gender composition on quantitative coursework taken by female students and their likelihood of concentrating in a quantitative field of study, peer gender composition does not have a significant effect on the distribution of salary offers that women receive, at least not in terms of salaries at graduation. In Section D., the results suggest a parsimonious

[106] In fact, salaries accepted at graduation and expected salaries 10 years after graduation, conditional on initial industry and occupation accepted, are negatively correlated. The same is true of the maximum salary offered and the maximum offer for expected earnings 10 years after graduation.

[107] See Appendix Table A.26. The effect of peer gender composition on women's likelihood of accepting their maximum salary offer is also strongly significant in an absolute sense, not only in a relative sense, in samples where students have offers from more than one industry, occupation, and firm. Peer gender composition also has no significant effect on whether students or female students in particular receive a choice of industry, occupation, or firms.

hypothesis that the “movers” - those students who are motivated to concentrate in finance due to the peer effect - do not receive the same return to concentrating in finance as those who concentrated in finance for reasons unrelated to the peer effect.

The model of this hypothesis, in which peer gender composition increases the likelihood of concentration in finance, $concFin_i$, which in turn has an effect on the distribution of offers, can be written as follows:

$$Y_i = \phi_1 ShareMale_i \times Female_i + \phi_2 ShareMale_i + \mu_1 concFin_i \times Female_i + \mu_2 concFin_i + \beta_1' X_{1i} + \varepsilon_{1i} \quad (2)$$

$$concFin_i = \pi_1 \left(ShareMale_i \times Female_i\right) + \pi_2 ShareMale_i + \beta_2' X_i + \eta_i \quad (3)$$

where Y_i represents the log mean, median, or maximum of the salary offers received by student i, and $concFin_i$ is the randomly-induced component of concentration in finance, and X_{1i} includes pre-MBA characteristics (including $Female_i$) of student i and indicators for cohorts (the term $\beta_1' X_{1i}$ includes cohort fixed effects).

If there were no effect of peer gender composition on student salary offers at graduation independent of an effect mediated by the likelihood of concentrating in finance, then Equation (3) would be the first stage for a 2SLS procedure that uses $ShareMale$ to instrument for $concFin$, under the assumption that the exclusion restriction holds (ϕ_1 and ϕ_2 are zero). Under this assumption, μ_1 and μ_2 would be the causal effects of interest. Such an assumption would admittedly be strong, given literature that finds direct effects of peers in the MBA setting on entrepreneurial and labor market outcomes several years after graduation, through social network effects and social interactions (Shue (2013), Hampole, Truffa, and Wong (2024)). However, I allow for the possibility that the exclusion restriction is violated using the zero-first-stage test (Bound and Jaeger (2000), Altonji et al. (2005), Angrist et al. (2010), van Kippersluis and Rietveld (2018)), and I implement the approach by finding a subsample of individuals for which the instrument is “locally irrelevant” - where the instrument, peer gender composition, does not have a significant effect on the treatment variable, concentration in finance (π_1 and π_2 are zero). This condition turns out to be satisfied by students whose age of entry into the MBA program is at least 30.[108][109]The reduced-form estimates of the effects of peer gender composition on the distribution [mean, median, and maximum] of salary offers for this subsample are not significantly different from zero, and I therefore fail to reject the exclusion restriction for these outcomes. This assumption is also made more palatable by noting that the outcomes in this case are the mean, median, and maximum of earnings offers *at graduation*, rather than in the years following graduation, when many of these network effects and social interactions effects have been observed.[110][111]

I estimate the causal impact of concentration in finance on the distribution of salary offers at graduation using peer gender composition as an instrument for concentration in finance. I construct the instrument

[108]The approach of van Kippersluis and Rietveld (2018) expands upon the plausibly exogenous approach by Conley, Hansen, and Rossi (2012) by allowing for heterogeneous first-stage effects but homogenous reduced-form effects.

[109]For older students, peer gender composition has little influence on their decision to concentrate in finance.

[110]D'Haultfoeille, Hoderlein, and Sasaki (2021) provides assumptions under which the exclusion restriction can be relaxed in the control function approach and shows that identification of causal effects can be achieved in a set of common special cases. In particular, if the peer effect is jointly independent from all unobservables (ε_1 and η), first-stage monotonicity holds (Equation (3)), and if there exists a subset of individuals for whom there is no first-stage effect (no effect of peers on concentration in finance), then the causal effect of the treatment can still be identified, using a two-step estimation strategy. Importantly, the model allows for a direct effect of peer gender composition on the main outcome of interest.

[111]Angrist and Krueger (1994), Altonji, Elder, and Taber (2005), Angrist, Lavy, and Schlosser (2010), and van Kippersluis and Rietveld (2018) use two-step approaches with a similar spirit.

according to Equation (3), which allows the first-stage effect of peer gender composition on concentration in finance to vary with gender. Figure A.7 presents provides a graphical representation of the first-stage relationship, separately for men and women, between peer gender composition and the likelihood of concentration in finance that accounts for cohort fixed effects (uses within-cohort variation in peer gender composition to predict the likelihood of concentration in finance, but plots the residualized likelihood of concentration in finance.) The results of estimating the first-stage equation shows that there is indeed a causal effect of peer gender composition on the likelihood of concentrating in finance and the effect of a marginal increase in the share of male peers on the propensity to concentrate in finance is, in fact, greater for women than for men.

Estimates from Equations (2) and (3) are presented in Table A.18. The results show that there is no significant causal effect of concentration in finance on the distribution of [mean, median, and maximum of] salary offers at graduation. For comparison, I also include as a covariate the component of concentration in finance that is orthogonal to peer gender composition, $\widetilde{concFin_i}$.[112] The results show that those female students who are randomly "induced to move" into concentrating in finance by the peer effect do not receive the same increase in their mean, median, and maximum salary offer as that associated with those who select into finance for reasons orthogonal to the peer effect. A standard Roy model would explain this result, though other models of student selection into fields, with full information of employer hiring behavior, are consistent with this as well. The results do not contradict the findings in the previous literature that show that a concentration in finance is associated with a higher starting salary for women at graduation. However, the results still suggest that a program that encourages or induces women to concentrate in finance or take more quantitative courses does not necessarily yield the same increases in opportunities at graduation as what is observed among women who elect to concentrate in finance or to take a large number of quantitative courses.

However, it is possible that peer-induced changes in human capital choices affect the long-term expected earnings paths into which female students are placed, due to changes in their first job at graduation, even if the earnings at graduation are not affected through this channel. In order to investigate this possibility, I examine the causal effect of concentration in finance on the distribution of long-term expected wage offers, specifically on the distribution of "offers for wages 10 years after graduation," where each offer is defined as the expected wage 10 years after graduation, conditional on the job function or industry at graduation (as defined in Section D.).[113] Note that we can again use the IV variables framework here, since we are not estimating the causal effect of concentration in finance on long-term earnings, but on the expected earnings 10 years after graduation, conditional on characteristics of the job offer *at* graduation. Thus, for the same reasons as provided earlier, using a subsample of individuals for which the instrument is "locally irrelevant" (students whose age of entry into the MBA program is at least 30), I fail to reject the exclusion restriction for outcomes at graduation.

Using the IV framework modeled above, I examine the effect of the peer-induced change in human capital among those "induced to move" to concentrating in finance on long-term expected wage trajectories, where the dependent variables are the mean, median, and maximum of the wage offers for long-term expected wages. I also include as a covariate, for comparison, the component of concentration in finance that is

[112] $\widetilde{concFin_i} = concFin_i - \widehat{concFin_i}$ is equivalent to the sum of the residual and the covariates' contribution, $\beta_2' X_i + \eta_i$, from Equation (3) and is orthogonal to peer gender composition by construction.

[113] Here, I again use the zero-first-stage test (Bound and Jaeger (2000), Altonji et al. (2005), etc.) and again use the subsample of individuals for which the instrument is "locally irrelevant:" students whose age of entry into the program is at least 30. I again fail to reject the exclusion restriction for the outcome variables of interest.

orthogonal to peer gender composition, $\widetilde{concFin_i}$. Appendix Table A.19 presents the estimated coefficients. The results show that female students who are "induced to move" into a finance concentration do, in fact, see a large and significant increase in the mean, median and maximum offer received at graduation, when an offer is measured in terms of the long-term expected wages associated with starting in such a job at graduation. Importantly, the effect of a finance concentration on the expected wages of female "movers" is comparable in magnitude to the increase in expected wages associated with those who select into a finance concentration for reasons orthogonal to the peer effect. No such effect is observed for male "movers."

Appendix D: Measuring the Willingness to Pay

In SectionVIII., we document that increase in the share of male peers leads to a 4 percentage-point increase in the likelihood that female students accept the highest salary offer in their choice set. Furthermore, we argue that the increase in the "willingness to accept" (WTA) the highest salary offer reflects a change in the "willingness to pay" (WTP) for the non-wage amenities associated with the job offer. In order to measure the WTP for the non-wage amenities of the job, we exploit a unique facet of the data, which is that we have data on each of the job offers students receive, as well as their acceptance decisions. In order to do this, I use an approach from Mas and Thomas (2021), which builds upon the framework and methodology in Sorkin (2018), to estimate the dollar value of non-wage amenities at the firm level. As in the discrete choice literature on the valuation of non-wage amenities, an inference can be made if a student accepts a salary other than the maximum salary offered: if a student receives two job offers, A and B, and A is the higher-paying offer, but we observe that the student chooses B, it must be the case that there is some other non-wage benefit or non-pay job characteristic associated with offer B that is at least as valuable to the student as the foregone monetary value of choosing offer B over offer A.[114]

Relative to the previous literature, this approach is closely related to Eriksson and Kristensen (2014), Wiswall and Zafar (2018), and Mas and Pallais (2017). Eriksson and Kristensen (2014) uses a vignette method to elicit WTP for various job amenities and fringe benefits in an Internet sample of Dutch respondents. Wiswall and Zafar (2018) uses a stated preference approach to understand how a sample of undergraduate students values job characteristics in hypothetical future jobs. The disadvantage of earlier approaches is that it is unclear to what extent responses to hypothetical questions are accurate and how well they approximate behavior in a market setting, one that involves real and significant stakes. Mas and Pallais (2017) elicits preferences on work arrangements by building a simple discrete choice experiment into the application process for a national call center. However, preferences are still elicited by asking applicants for their stated preference between two jobs with varying characteristics. Here, I observe the actual choice that a student makes with two or more real-world offers in hand, where the job they choose from their choice

[114]Discrete choice experiments are an extension of the contingent valuation literature whereby rather than directly asking people for valuations over an attribute (the stated preference method), people are given the choice of two or more scenarios and are asked to choose their preferred option. These scenarios usually vary the attributes and the prices and WTP can be estimated using random utility models (McFadden 1973; Manski 1977). Choice experiments have been shown to have better properties relative to stated preference valuation methods (Hanley, Wright, and Adamowicz 1998). A question is whether these experiments, which are usually survey-based, correspond to actual market behavior. In this case, the choices are based on acceptance decisions of real market behavior in a high-stakes setting with well-informed labor market participants. See Mas and Pallais (2017), Sorkin (2018) for similar approaches.

set is the actual job they accept and in which they are employed after graduation.[115][116]

Examining the choices of students in the final stage of the decision-making process, when all negotiation on offers has been completed, and when multiple final offers can be held simultaneously in-hand, allows for a clean way to measure the value of non-wage amenities and empirically test whether an increase in the likelihood of acceptance indicates a decrease in the willingness to pay, or whether the distribution of the non-wage amenity values offered to a student has changed. In order to do this, I use an approach from Mas and Thomas (2021) to estimate the value of non-wage amenities at the firm level, which can be summarized as follows:

1. Use an AKM-style model to estimate the firm component of the wage, F_j:

$$\ln w_{ijt} = F_j + \delta_{i(t)} + \mu_{i(t)j} \tag{4}$$

where $\ln w_{ijt}$ is the log of the permanent salary offer from firm j in year t to student i. Using this model, the wage can be decomposed into firm, individual, and match effects, F_j, δ_i, and μ_{ij}, respectively.[117] The effects are identified because (many) firms make offers to multiple individuals each year, and (many) individuals receive multiple offers. The estimates are adjusted using standard empirical Bayes shrinkage techniques to account for estimation error.[118] Further details are provided in Mas and Thomas (2021).

2. The WTP is estimated using offer and acceptance data, using a conditional logit model:

$$U_{ij} = \beta w_{ij} + a_j + \lambda_i + \xi_{ij} \tag{5}$$

where U_{ij} is an indicator variable for whether student i accepts an offer from firm j, a_j is the coefficient on the firm dummy variable for firm j, and λ_i is an individual fixed effect. Note that including individual fixed effects equates to examining how variation in wages, within a student's choice set, conditional on other firm-level characteristics, a_j, influences the likelihood of acceptance of an offer at firm j. The willingness to pay for, or the value in dollar terms of, the non-wage amenities associated with firm j, relative to the omitted firm, can be estimated by scaling the estimate of a_j by the inverse of the estimate of β.[119][120] In other words, the value of non-wage amenities associated with a firm is measured in terms of how many dollars, on average, students with offers from the same sets of firms are willing to give up in order to have

[115] One may note that it is possible for the gender composition of one's peers to influence preferences even if no effect is observed on the likelihood of accepting the maximum salary offer, since preferences could play a role in the set of offers that a student receives in the first place. Therefore, not observing any significant effect on the likelihood of a student accepting the maximum salary offer does not eliminate the possibility that peer gender composition influences preferences.

[116] The price of non-wage amenities (relative to the maximum salary job offer) can be considered the difference between the two salary offers, what one *must* pay, in terms of foregone income in order to receive the non-wage amenities of the lower-paying offer. See Rosen (1974, 1986) for the theoretical framework for hedonic pricing.

[117] The subscript i is written as a function of t because each student only receives offers in their final year, the year of graduation, so any year fixed effects are absorbed into the individual fixed effect.

[118] See Morris (1983). E[effect$|$Estimate] $= \alpha$Estimate$+(1-\alpha)$Mean, where α varies inversely with the noise of the estimate.

[119] The estimated dollar valuations are then adjusted using standard empirical Bayes shrinkage techniques to account for estimation error in the ratio.

[120] Standard errors of the estimated ratio is computed using the "delta method," an approximation appropriate in large samples.

the bundle of non-wage characteristics associated with the offer at the lower-paying firm. The estimate of β provides a scaling factor that converts the trade-off in utility into dollar terms.

3. Use the estimated worker-firm match component ($\hat{\mu}_{ij}$) of the wage as an instrument for wages.

An instrument for wages is needed due to the correlation of F_j and a_j, in the solution to the firm's cost-minimization problem. Specifically, firms may choose to compensate workers through an allocation of wages and non-wage amenities that minimizes the cost of "producing" a given level of utility compensation to the worker. Their desired level of utility compensation may be produced using a combination of dollars and non-wage benefits, and the relative use of these "factors of production" of utility depends on their comparative advantage in producing utility through other non-wage benefits relative to dollars.[121] As in Mas and Thomas (2021), I use the match component of the wage, $\widetilde{\mu}_{ij}$, which is orthogonal to F_j by construction, to exploit the uncorrelated component of wage variation as an instrument to estimate the effect of an additional dollar of income offered on the likelihood of offer acceptance.[122] The underlying assumption is that $\widetilde{\mu}_{ij}$ and ξ_{ij} are uncorrelated. In other words, it is assumed that there is no bargaining on the basis of idiosyncratic utility. More detail is provided in Mas and Thomas (2021).

[121] Firms may be heterogeneous in the cost of providing non-wage amenities to the worker, even for a given desired level of utility compensation. See Mas and Thomas (2021) for the full model.

[122] More precisely, we use the component of μ_{ij} that is uncorrelated with a time-varying firm effect (certain firms may be more productive in particular years, for example, with the business cycle, and thus, may also vary non-wage amenities due to a time-varying firm-specific productivity). Thus, we estimate: $\ln w_{ijt} = F_j + \delta_{it} + \widetilde{F}_{jt} + \widetilde{\mu}_{ij}$, where $\mu_{i(t)j} = \widetilde{F}_{jt} + \widetilde{\mu}_{ij}$. Because each individual is only observed during their final year in school, a time-varying firm effect would be absorbed by the match effect, $\mu_{i(t)j}$, if we did not specifically include it and use only the orthogonal component of the match effect.