Peer Effects and the Gender Gap in Corporate Leadership: Evidence from MBA Students*

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Abstract

Women continue to be underrepresented in corporate leadership positions. This paper studies the role of social connections in women's career advancement. We investigate whether access to a larger share of female peers in business school affects the gender gap in senior managerial positions. Merging administrative data from a top-10 U.S. business school with public LinkedIn profiles, we first document that female MBAs are 24% less likely than male MBAs to enter senior management within 15 years of graduation. Next, we use the exogenous assignment of students into sections to show that a larger proportion of female MBA section peers increases the likelihood of entering senior management for women but not for men. This effect is driven by female-friendly firms, such as those with more generous maternity leave policies and greater work schedule flexibility. A larger proportion of female MBA peers induces women to transition to these firms where they attain senior management roles. A survey of female MBA alumnae reveals three key mechanisms: (i) information sharing, especially related to gender-specific advice, (ii) higher ambitions and self-confidence, and (iii) increasing support from male MBA peers. These findings highlight the role of social connections in reducing the gender gap in senior management positions.

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1 Introduction

The glass ceiling—the barrier that females and minorities face in obtaining upper-level positions—has been enduring. Despite decades of progress in labor force participation and university enrollment, women remain underrepresented in top corporate leadership positions. For example, in the S&P 1500 companies, women make up 40% of the workforce but hold only 6% of CEO positions (Hindlian et al., 2018). This gender gap widens at each step of the corporate ladder (Lean In and McKinsey & Company, 2020). To the extent that managerial talent is equally distributed across genders, the underrepresentation of women in executive roles can be indicative of talent misallocation (Hsieh et al., 2016).[1] Due to the potential aggregate consequences of female underrepresentation in executive positions, understanding the barriers to advancement along the corporate pipeline is critical.

This paper studies whether access to a larger share of female peers in business school helps women reach leadership positions. Although a growing literature shows that social connections formed during business schools have long-lasting impacts on future career outcomes, little is known about how they affect the gender gap in leadership positions.[2] A priori, the effect of the gender composition of social connections is ambiguous. On one hand, women may benefit from information and support from same-gender peers. For example, female connections can provide women with gender-specific information on which firms are more supportive of women's careers and how to take advantage of female-friendly policies, such as maternity leaves and flexible work schedules. On the other hand, social connections created with men may be more beneficial, given that men are more likely to have larger networks and hold more powerful positions. As a result, the role of female peers in closing the gender gap in management is largely an empirical question.

Identifying the causal impact of female peers on management outcomes is empirically challenging. First, peers and networks are likely to be endogenous. Unobservable characteristics, such as extroversion, likely determine both the composition of an individual's

[1]Since executives have significant influence on firm performance, the loss of female talent along the corporate pipeline may translate into lower firm productivity (Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bloom et al., 2012; Rasul and Rogger, 2018). Beyond influencing their own firm's performance, female managers may act as role models and implement policies to reduce barriers for other women in the corporate sector (Chattopadhyay and Duflo, 2004; Beaman et al., 2009, 2012; Bhalotra et al., 2017). Thereby, female leaders can contribute to a more gender diverse and inclusive corporate culture.

[2]Examples of career outcomes affected by higher education peers are firm choice, likelihood of entrepreneurship, and executive decisions (Lerner and Malmendier, 2013; Shue, 2013; Yang et al., 2019; Gorshkov et al., 2021).

network and their likelihood of attaining leadership positions. Second, answering this question requires data on long-run career trajectories with detailed information on managerial positions.

To address the first challenge, we leverage a quasi-experimental setting provided by the Master of Business Administration (MBA) program at a top U.S. business school. At the beginning of the program, school administrators quasi-randomly assign students into sections based on alphabetical order. Students in the same section take core classes together and form strong social ties. We exploit the exogenous variation in the gender composition of the sections to study the effect of female peers on the probability of achieving a senior management position.[3]

We address the second issue by building a novel dataset with CV information from public LinkedIn profiles. In addition to complete education and employment history, this dataset contains two key pieces of information. First, it has job titles which allow us to identify an individual's progression along the managerial pipeline. Detailed information on hierarchical positions *within* management is usually unavailable in commonly used employment panel data in the literature. Second, it contains the names of employers, which enables us to merge in firm attributes that the literature has hypothesized to be important for women's career progression (Goldin and Katz, 2016; Hotz et al., 2018). Specifically, we use novel metrics of female-friendly characteristics from InHerSight.com, an online platform where female employees rate their companies. This data allows us to identify firms with work cultures and policies that aim to help women balance their work-family responsibilities and support their career advancement. Some examples of such policies include maternity leaves, flexible working schedules, and female mentoring programs.

In the first part of our analysis, we document new descriptive facts on the gender gap along the management pipeline. Although 96% of male and female MBA graduates enter management roles within the first 15 years post MBA, women are 24% less likely to hold *senior* management positions. This gender gap emerges as early as the first year after the MBA and persists for at least 15 years.

Then, in the main analysis, we use the exogenous assignment of students into sections to document three key findings. First, we show that having a higher proportion of female section peers during the MBA increases women's advancement into senior leadership positions. A 4 percentage point, or one standard deviation (SD), increase in the share of female MBA

[3]We define senior management positions as Vice President (VP), Director, Senior Vice President (SVP), or C-level Executive.

students leads to an 8.4% increase in the probability of holding a senior management position for women in the first 15 years after MBA graduation.[4] In contrast, there is no effect on male students. This overall effect is economically significant and translates into a 26% reduction in the management gender gap. We show that this increase does not come from women moving to smaller or lower paying firms, where it may be easier to reach higher positions of the corporate ladder. We also do not observe a shift in terms of job functions: the increase in female managers includes those with Profit and Loss (P&L) responsibilities, which have been shown to be important for executive promotions. Furthermore, we find the largest effects in *male-dominated* industries, where women are underrepresented. These results suggest that female MBA peer networks are important in industries where women are more likely to face barriers in accessing informal networks in the workplace.

In the next part of our paper, we investigate how firm characteristics play a role in explaining our main results. We show that our results are driven by *female-friendly* firms, firms that are characterized by policies such as maternity leave and flexible working schedules.[5] We show that women with more female peers are more likely to transition into these firms 6 to 10 years after MBA graduation, when women are most likely to have young children in the household.[6] These results suggest that the support of female peers may be more effective at a point in the career path when the gender gaps in the labor market start widening (Bertrand et al., 2010; Kleven et al., 2019).

Finally, we conduct a survey of the full sample of female MBA graduates in our study to provide evidence of the mechanisms underlying our main results. Our findings show that female peers help women advance into senior management positions through (i) information sharing, (ii) raising ambitions and self-confidence, and (iii) increasing support from male MBA peers. Women rely on their female MBA peers for gender-specific information and advice. In line with this hypothesis, we observe that women with more female peers experience fewer adverse career effects from having children. As a proxy of referrals and information sharing about employers, these women are also more likely to work in the same firms as their female section peers, especially when these firms are female-friendly. Additionally, female peers raise women's ambitions and self-confidence, providing emotional support and acting as role models. Interestingly, we also document that *male* MBA peers are perceived as more supportive as the female representation in the section increases, suggesting that

[4] A 4 percentage point increase along the female share distribution corresponds to 2.4 additional women, and is also equivalent to moving from the 25$^{\text{th}}$ (32%) to the 75$^{\text{th}}$ (36%) percentile.

[5] We identify female-friendly firms using InHerSight, a data source with firm ratings by female employees.

[6] See Bertrand et al. (2010).

a more gender-diverse MBA environment can foster a more supportive network for female MBA graduates.

A counterfactual exercise shows that even holding the total number of female students fixed, reallocating them such that they are in sections with at least 34% women would lead to between 2 and 5 additional female senior managers per graduating class (corresponding to a 2.4% to 8.4% increase).[7] Together, our findings show that the gender composition of MBA peers has important implications for the career outcomes of women.

Our study contributes to three strands of literature. First, our paper contributes to the large literature on gender differences in the labor market and their determinants (e.g., Olivetti and Petrongolo, 2016; Blau and Kahn, 2017).[8] For MBA graduates, seminal work by Bertrand et al. (2010) shows that despite similar initial earnings, a large gender gap of nearly 60 log points emerges in the decade after graduation, driven by career discontinuity and shorter working hours for women. Relative to this literature that has focused on earnings, industry choice, and labor supply, we provide novel evidence on *management* positions. In doing so, we speak to the growing literature on the gender promotion gap (Bertrand and Schoar, 2003; Matsa and Miller, 2011; Cullen and Perez-Truglia, 2019; Haegele, 2024; Azmat et al., 2024; Giorcelli, 2024). Due to data limitations, most evidence has been restricted to top managers of publicly-traded companies or based on proprietary data from individual firms. With our unique dataset, we are able to trace individuals' positions along the managerial pipeline across multiple firms and follow their career progression over time. We contribute to the gender gap literature by documenting that female MBA graduates are less likely to be promoted and are increasingly underrepresented in management positions despite having similar educational backgrounds as their male counterparts. Additionally, we use the exogenous assignment of students to peer groups to show that the gender composition of MBA peer networks can be an important determinant of the gender gap in leadership positions.

Second, our paper speaks to the large literature on social interactions and career outcomes.[9] Peer effects have been widely documented in many settings, including education,

[7]Note that this exercise assumes nonlinearities.

[8]These studies have highlighted many potential explanations that, among many others, include differences in labor supply (Bertrand et al., 2010), family responsibilities (Kleven et al., 2019), preferences for risk and competition (Niederle and Vesterlund, 2007; Buser et al., 2014; Wiswall and Zafar, 2014; Mas and Pallais, 2017), and marriage market concerns (Bursztyn et al., 2017).

[9]An important related literature investigates how social networks and homophily can lead to persistent inequality in the labor market (Granovetter, 1973, 1995; Montgomery, 1991; Calvo-Armengol and Jackson, 2004; Bayer et al., 2008; Hwang and Kim, 2009; Beaman and Magruder, 2012; Schmutte, 2015; Burks

managerial decision-making, and entrepreneurship.[10] The most related papers in this literature study the importance of gender composition on women's decisions to enter male-dominated fields, as well as their performance in these fields (Bostwick and Weinberg, 2018; Goulas et al., 2018; Olivetti et al., 2020; Schneeweis and Zweimüller, 2009; Anelli and Peri, 2017; Brenoe and Zölitz, 2020; Calkins et al., 2020). The results of these studies have largely been mixed. In some cases, more female peers can help women persist and excel in PhD STEM programs (Bostwick and Weinberg, 2018), whereas in other settings, more female peers lead female students to choose more female-dominated fields (Brenoe and Zölitz, 2020; Zölitz and Feld, 2021). For example, recent work by Thomas (2021) finds that an increase in the share of *male* students leads to an increase in the salaries of female MBA students at graduation and a greater likelihood of working in high-wage industries.[11] Our study has several unique features compared to the existing literature. First, in almost all cases, these gender peer effects papers focus on contemporaneous or short-term outcomes. Our paper shows that the networks formed during graduate school are not only sustained, but also have important and persistent impacts on the careers of women in the decades after graduation. Second, instead of compensation or major choices, we focus on promotions into senior management roles. We show that having access to a larger network of female peers helps women achieve leadership positions, especially in female-friendly firms. Moreover, disentangling the underlying channels leading to peer effects is intrinsically hard. Our paper sheds light on the mechanisms using survey evidence, showing that female peers support women's career advancement through information sharing, raising ambitions and self-confidence, and increasing support from male peers.

et al., 2015; Bolte et al., 2021; Friebel et al., 2021) In the MBA context, Yang et al. (2019) shows that the centrality of MBA students in their social networks, measured using email correspondences during the MBA, can predict first post-MBA placement into leadership positions. In line with our results, this paper suggests a more positive relationship for women with a mostly female network who are central in their network. We build on this study by leveraging the exogenous assignment of students to peer groups, combined with unique CV data to document the causal impact of a change in the gender composition on long-run career trajectories.

[10]For example, Epple and Romano (1998),Sacerdote (2001), Zimmerman (2003), Stinebrickner and Stinebrickner (2006), and Lavy and Schlosser (2011). In the MBA context, notable examples are Lerner and Malmendier (2013), Shue (2013), and Hacamo and Kleiner (2021).

[11]In contrast, we find a greater share of female peers positively influences women's career outcomes. The differences between Thomas (2021) and our findings may arise from several factors: Thomas (2021) focuses on earnings, while we investigate impacts on management positions using job titles; we primarily rely on LinkedIn CV data, which covers a larger sample; and Thomas (2021) studies MBA graduates from a different university and period (1999–2011). Additionally, our empirical strategy includes gender-by-cohort fixed effects to account for potential cohort-specific trends in female labor market outcomes and the proportion of female students in sections over time.

Finally, this paper contributes to a growing literature on female-friendly firm policies such as maternity leave, childcare, and flexible working schedules (Goldin and Katz, 2016; Mas and Pallais, 2017; Hotz et al., 2018; Cortés and Pan, 2019). This literature investigates the role that workplace attributes play in the career divergence of women and men, with the onset of parenthood. We contribute to this literature by showing that one potential mechanism for how female peer networks can assist in female advancement into senior management is by increasing the rate at which women enter these firms. Our results highlight that there may exist complementarities between the availability of these firm-level policies and the gender-specific information provided by female peers. In doing so, our paper provides novel evidence of how gendered social networks can facilitate information sharing about the amenities and attributes of prospective employers that may be difficult to observe (Sockin and Sojourner, 2023).

The paper is organized in the following way. Section 2 describes the setting. Section 3 presents the data used in the analysis. Section 4 illustrates new descriptive evidence on the gender gap in managerial positions along the pipeline. In Section 5, we turn to the role of female peers in the gender gap in management. Within this section, we present the empirical strategy (Section 5.1) and the main results (Section 5.2). We then explore the role of female-friendly firms (Section 6). In Section 7, we investigate potential underlying channels through which female peers help women advance into management positions. We then discuss the implications of these results in terms of compensation and career satisfaction in Section 8. Finally, Section 9 concludes.

2 Background

Our study focuses on the career outcomes of full-time two-year MBA graduates from a top business school in the United States. This setting is particularly well-suited for studying the relationship between peers and the gender gap in management positions for three reasons. First, MBA graduates are well-positioned to obtain managerial roles; a large part of the MBA curriculum trains students for these roles. Bertrand and Schoar (2003) and Bhagat et al. (2010) both find that around 40% of CEOs hold an MBA degree.[12] Second, there is evidence that social networks formed during MBA programs have important effects

[12] The samples in Bertrand and Schoar (2003) and Bhagat et al. (2010) slightly differ. Bertrand and Schoar (2003) use data from Forbes 800 files from 1969 to 1999, and Execucomp data from 1992 to 1999. Bhagat et al. (2010) uses the Execucomp database from 1992 to 2007.

on graduates' career outcomes after the MBA, including firm choice (Hacamo and Kleiner, 2020), entrepreneurship (Lerner and Malmendier, 2013), executive decisions (Shue, 2013), and compensation (Yang et al., 2019; Thomas, 2021). In fact, business schools often highlight peer networking opportunities as an important benefit of the educational experience (Zimmerman, 2019; Kalsi and Samuels, 2019). Finally, this setting allows us to exploit the exogenous variation in female peers due to the quasi-random assignment of students to sections, overcoming one of the key empirical challenges in the estimation of peer and network effects.

Each year, at the beginning of the program, incoming MBA students are quasi-randomly assigned to one of eight sections based on alphabetical order.[13] Each section has around 60 students. We define as peers the students that belong to the same section. Students who belong to the same section are required to take core classes together. Core classes represent around 20% of the MBA curriculum and are taken during the first year. In the second year, students can choose elective courses and thus may not necessarily be in the same classes as their section peers. Students are typically not allowed to change sections and faculty are not matched to sections based on section characteristics. The explicit aim of sections is to foster close ties and networking among peers. Prior studies and anecdotal evidence suggest that students form and maintain close bonds with peers in their section (Lerner and Malmendier, 2013; Hacamo and Kleiner, 2016; Hacamo and Kleiner, 2021). For this reason, it seems plausible that peers may affect managerial career outcomes.

The school aims to achieve balance over three characteristics: gender, undergraduate institution, and ethnicity. Therefore, the assignment is implemented by following the three steps: 1) students are assigned to eight sections in alphabetical order; 2) the balance across gender, ethnicity, and undergraduate institution is checked; 3) if some sections have a share of male students, white students, or students from a given university above a set threshold, students are randomly reassigned to hit the target. For this reason, the balance is not perfect and there is meaningful variation in the proportion of female peers across sections within the same graduating class, as shown in Appendix Figure A.1. We will exploit this variation to study the effects of gender composition on managerial career outcomes of MBA students. The average female share at the section level is 34%, with a standard deviation of 4 percentage points.[14] In Section 5.1, we show that the assignment of students to sections

[13]Specifically, the first student in alphabetical order is assigned to section 1, the second to section 2, and so on, until the eighth student is assigned to section 8. After that, the ninth student is assigned to section 1, the tenth to section 2, and so on.

[14]We computed these statistics by residualizing the share of female students by the graduating class and

is as good as random.

3 Data

We combine four novel sources of data: (i) school administrative data to construct the gender composition of section-mates, (ii) LinkedIn data for CV information on the entire education and employment history, (iii) data on employers' characteristics from a variety of sources, and (iv) alumni survey data for additional information such as timing of childbearing. In this section we provide an overview of the data sources and how we merge them together. We provide additional details, as well as the matching rate across all these datasets, in Appendix Section B.

3.1 Business School Administrative Data

Aggregate statistics on the number of students per MBA section by gender and race are provided by the university administrators. This data allows us to construct our treatment variable (i.e., share of female students per section) using the universe of MBA students from cohorts graduating between 2000 and 2018.

For MBA students graduating between 2011 and 2018, we also have individual school administrative data with information on demographics, pre-MBA educational background including GMAT scores, academic outcomes, and information on first job placement.

3.2 LinkedIn Profile Data

Data on employment and education background for two-year full-time MBA graduates who graduated between 2000 and 2018, excluding 2009, are obtained from public LinkedIn profiles, a professional networking social media platform. Class of 2009 is excluded due to lack of information on student section assignments, as described below. The profiles provide CV information on full education and employment history. The data include names of employers, start and end dates of employment, job titles, job location, schools attended, degrees received, and graduation dates. As is typical in resumes, individuals create new entries for

adding back the mean. In our setting, one standard deviation approximately corresponds to moving from the 25^{th} (32%) to the 75^{th} (36%) percentile. The proportion of female peers ranges from 19% at the 1^{st} percentile to 45% at the 99^{th} percentile.

each job position, even within the same firm. As a result, we are able to track promotion patterns both within and across firms. Using the start and end dates of each position, we parse the CV data to create a yearly panel. We define nonemployment periods as time periods during which we do not observe a job entry.

To match MBA graduates to their LinkedIn profiles, we employ two methods. First, the administrative records of the business school were matched to public LinkedIn profiles for graduates from 2011 to 2018. This is done securely by university personnel. Second, because administrative records are not available for earlier cohorts, we use alumni directory records to identify MBA graduates from 2000 to 2010. The matching is done manually using web searches based on information available in the alumni directory: first name, last name, and year of graduation.[15] Importantly, the directory also lists the MBA section of the graduate. We use this information to assign to each graduate the proportion of female students in their section (the key treatment variable for our analysis), calculated using administrative data. In Appendix Section B.8, we provide additional details on the alumni directory sample and how the match procedure was conducted. We exclude the class of 2009 from our analysis because a large majority of this class has private or missing alumni profiles, and as a result, we do not have section assignments for these students.[16]

In our final analysis sample, we further restrict to only MBA graduates who are currently based in the United States, using locality information on the LinkedIn profiles.[17] We will focus on career outcomes from year 1 to 15 post MBA graduation. Across all class years, we successfully match 77% of the full-time MBAs to their public LinkedIn profiles. In Appendix Section B.9, we present additional match statistics. Importantly for the validity of our analysis, the matching rate is uncorrelated with our treatment variable, share of women in the section. In Section 5.3, we present additional analyses to show our results are robust to concerns related to unmatched observations.

[15] We used undergraduate institution and current employer to confirm any potential matches.

[16] In 2009, only 94 out of 526 graduates had available directory records. Note that 2009 was the year where the employment rate fell for many business school programs. At the top ten business schools, MBA employment rates at graduation dropped an average of 21% from 2007 (Byrne, 2020).

[17] There are two motivations for this restriction. First, we obtain the sample of LinkedIn profiles via web searches on the U.S.-based LinkedIn webpage. Because LinkedIn may not be as widely used in other countries as in the United States, individuals based outside of the United States with U.S. LinkedIn profiles may be a selected sample. Second, we are interested in the role of MBA networks on long-term career outcomes. These peer ties are likely stronger in the United States, as a vast majority of graduates remain in the country. In addition, the role of networks may differ substantially across different countries with different labor market structures and cultural norms. Note that even though we focus on individuals based in the United States in our main analysis, the proportion of female peers assigned to their respective section is calculated using all classmates, including those who eventually will not work in the United States.

Gender

Information on gender is available for the graduating classes of 2011-2018 in the administrative dataset. However, we do not have administrative records for earlier cohorts, and neither the alumni directory nor the LinkedIn data contains gender information. Therefore, we utilize a series of customized name-matching algorithms to identify the gender of the graduate by comparing the first name of the graduate to established names databases.[18] Extending this method to the most recent cohorts, 2011-2018, for which we have administrative records, reveals that we are able to correctly identify the gender 96% of the time.

3.3 Firm Data

We collect firm-level information from a multitude of data sources. We linked this additional information to our individual-level dataset using the names of the organizations listed for each position on the LinkedIn CV data. In Appendix Table B.4, we summarize the match rate across the various datasets in our sample.[19]

First, we collected LinkedIn company profiles, which provide information on the number of employees and industries.

Second, we complement our dataset with compensation data provided by Glassdoor.com. This dataset contains 10.5 million self-reported compensation records for 639,422 firms from 2006-2017, and has information on base annual compensation and additional compensation in terms of cash or stock bonus, profits sharing, sales and commission, and tips. Notably, we also have information on the gender and job position for each record, enabling us to construct measures such as the gender gap in compensation at the firm level for all employees, and for managers specifically. We also utilize this dataset to estimate compensation for each individual by assigning each person to the average compensation level of the firm, gender, and job level (non-manager, first-level manager, or senior-level manager).[20]

[18]These include the U.S. Social Security Administration baby name data, the U.S. Census data in the Integrated Public Use Microdata Series, and census microdata from Canada, Great Britain, Denmark, Iceland, Norway, and Sweden from 1801 to 1910 created by the North Atlantic Population Project. We compare the first names of the alumni in our data to these databases using the R package, "Gender" (`https://cran.r-project.org/web/packages/gender/gender.pdf`). We consider a graduate to be female if at least two of these sources identify the name to be female. We verify the gender of unmatched alumni through web searches on various online sources such as news and social media platforms.

[19]Appendix Table H.1 shows that unmatched observations from each of the datasets are not systematically correlated with the share of female peers.

[20]Note that we do not disaggregate by year of the salary because the cell sizes over which the average compensation would be calculated become too small.

Third, we collect information on female-friendly firms from three sources. Our primary dataset on female-friendly workplaces comes from the online platform, InHerSight.com. We successfully matched 54% of our observations to this source.[21] This platform contains crowd-sourced data on firm policies that may be important for the careers of women. We obtain employee ratings on metrics that include work flexibility, parental leave policies, mentorship, and female representation in management. InHerSight also provides an overall rating for female-friendliness for each firm. This overall rating is constructed using all the metrics collected on the firm. We provide the full list of metrics and a description of the indices in Appendix Section B.5.1. We define a firm to be female-friendly if it has an above-median rating on InHerSight.[22] In addition to data from InHerSight, we also collect data on overall firm ratings and number of weeks of paid parental leave from another, but smaller, crowdsourced platform, FairyGodBoss.com.[23] Lastly, we also acquire data on female board members for the public companies listed on the Russell 3000 Index from 50/50 Women On Boards. We provide additional details on these measures of firm female-friendliness in Appendix Section B.5. Appendix Section B.5.3 shows that the primary IHS measure is positively correlated with all these different metrics. To provide further validation of the IHS measure, Appendix Section L.4 shows that IHS is strongly related to perceived level of overall female-friendliness using the survey responses of female MBA graduates in our sample.

3.4 Survey Data

We also conducted a survey in 2023 and 2024 on the full sample of female graduates from the classes 2000 to 2018, excluding 2009. The design of the survey was informed by qualitative interviews with 45 female MBA graduates (see Appendix Section M for details.) During the survey, we collect information in five areas that the interviews revealed as potential important factors in MBA graduates' careers. These include (i) networking and the role of MBA peer support, (ii) family background, such as marital status, children, and spousal income, (iii) current employment, job position, and past career breaks, (iv) negotiations, and (v) ambitions and self-confidence.[24] The response rate is 10% for a total number of

[21] In Section 5.3, we show our results are unchanged when we restrict to the sample with data on female-friendliness.

[22] We use the number of ratings to weight statistics related to InHerSight.

[23] Because InHerSight data is available for 1,416 firms in our sample compared to 439 firms in FairyGodBoss, our primary measure of female-friendliness is the InHerSight rating.

[24] Additional details are provided in Appendix Section L.

283 responses. We show in Appendix Table L.1 that the nonresponse is not correlated with pre-MBA characteristics, female share, or likelihood of being senior manager post MBA.

3.5 Definition of Managers

Our main outcome of interest is attainment of senior management roles. A unique feature of our CV dataset is the availability of exact job titles, which permits us to identify managerial positions based on keywords. This type of information is typically not available in large-scale surveys or datasets such as the Census or administrative tax data, where all managerial positions are often reported under a single occupational code. Following the guidelines offered by Lean In and McKinsey & Company (2020), we use common keywords in the job titles to identify managers ("manager," "supervisor"), Directors ("director"), Vice Presidents ("VP"), Senior Vice Presidents ("SVP"), and C-level executives ("Chief X Officer"). These positions form the corporate management ladder, allowing us to trace the gender gap and the effect of female peers across the pipeline. Appendix Section B.7 provides more details on how we constructed these managerial positions. In the rest of the paper, we will refer to: 1) managers as first-level managers and 2) any positions from director to C-level executives as senior-level managers.[25] In addition to managerial positions, we also identify founders and entrepreneurs using the keywords "Founder," "Owner," and "Self-employed."[26] Note that in our analysis, we exclude founders from the management outcomes and instead analyze founders separately.

In Appendix Table A.1, to provide evidence supporting our managers classification, we present summary statistics by each of these job titles using our survey data. As expected, firm hierarchy as measured on a 1-5 scale increases along the management pipeline. On average, first-level managers oversee 11 employees, including both indirect and direct reports, compared to over 20 employees for VPs and Directors, and 36 employees for SVP and C-level positions. Weekly hours worked and compensation also increase with each level of management. In particular, first-level managers earn \$248K in annual compensation compared to over \$333K for VPs and Directors and \$541K for SVPs and C-level executives.

[25] Note that in finance, unlike other industries, directors are at a higher position than vice presidents. As a result, we pool together all senior-level roles in our analysis. We also show our results are robust to when we include industry fixed effects and remove finance from the sample. See Appendix Figure H.1.

[26] We also use the job titles to classify job functions. See Appendix Section B.6 for details on how we define and identify job functions.

3.6 Summary Statistics

Appendix Table A.2 presents the summary statistics for demographics (Panel A) and pre-MBA background characteristics (Panel B) for the full sample and by gender. All statistics in this table are measured at the person-level. In our full sample, 36% of students are female. 39% of MBA students have held a management position prior to the MBA. A smaller percentage of students (13%) have held a senior management position. Interestingly, there is no gender difference in management experience prior to the MBA, but there is a 21% gender difference in total compensation.

Appendix Table A.3 presents the descriptive statistics for the set of academic outcomes measured at the person level (Panel A) and career outcomes at the person-year level (Panel B). During the MBA, male students have a higher overall GPA by 0.06 points and take 29% more finance classes as a proportion of all classes taken during the MBA.[27]

4 Gender Gap in Corporate Leadership Positions

In this section, we document three new descriptive patterns for the gender gap in senior management positions among MBA graduates. We show that (i) female graduates are 24% less likely to hold senior management positions, (ii) this gender gap emerges immediately after the MBA and persists for at least 15 years, and (iii) women are 26% less likely to be promoted into senior management positions from first-level management.

First, we show that despite no gender differences in the entry rate into the management pipeline, a gender gap emerges at the senior management position level. In Figure 1, we show the likelihood of ever holding a management position at each of the seniority levels in the 15 years after MBA graduation for male and female graduates. Nearly all graduates (96%) of both genders have held a management position in the first 15 years of their postgraduate career. However, a gender difference emerges when we consider each position of the senior management pipeline separately. Men are significantly more likely to attain one of the three senior leadership positions: VP or Director, SVP, and C-level executives. In Appendix Section C, we show that there is a substantial gender gap of 24% in senior management

[27] Previous work has found that the gender difference in finance courses can help explain the gender wage gap for MBA graduates (Bertrand et al., 2010).

when we control for class fixed effects, year fixed effects, and class interacted with year fixed effects. Controlling for gender differences in pre-MBA characteristics, firm characteristics, industry choice, and gaps in the employment history reduces this gender gap, but a 17.7% difference in likelihood of holding senior management positions remains unexplained. Given that there are no gender differences in overall management positions, these patterns suggest that, although female MBA graduates enter first-level management positions, many of them do not advance into senior management.

Second, the gender gap in senior leadership positions emerges immediately post MBA and persists over time. Figure 2 plots the dynamics in the likelihood of holding any senior-level management position over the years since MBA graduation.[28] The figure points to a persistent gender gap in senior leadership positions that emerges at the outset of the post-MBA career and widens slightly over time. Women begin their careers in management positions at lower levels or in non-management roles, and they do not catch up in the years post MBA. While 74% of men are holding a senior management position in year 15, only 59% of women are.

Third, we show that women are less likely to transition into senior-level management positions from first-level management positions. In Figure 3, we plot the five-year transition probabilities for first-level managers into either a senior management position, non-management position, nonemployment, or remaining in the same position.[29] We show that 57% of men in first-level management roles transition into a senior management role in the next five years compared to 43% of women. This difference is significant at the 5% level and suggests that women are not being promoted at the same rate as men. Women are also more likely to move to non-management positions or nonemployment, suggesting lower persistence in managerial positions. However, the gender gap in persistence is unlikely to explain the gender differences in representation in senior management positions given the smaller magnitudes of the transitions into lower positions.

The results indicate that female MBAs are less likely to reach senior leadership roles despite entering management at similar rates as male MBAs. They start at lower levels and are less likely to advance through the management pipeline, leading to a persistent gender gap in senior management that remains unchanged over 15 years.

[28] Note that these results are unconditional on employment.

[29] Nonemployment is identified based on gaps in the reported work history.

5 The Role of Female Peers in the Gender Gap in Management

We now investigate a potential determinant of the gender gap in senior management: the gender composition of MBA peers. We begin by describing the empirical strategy for identifying the causal impact of female peers on management. Then, we present the main results on senior managers.

5.1 Empirical Strategy

Empirical Challenges

The literature has highlighted three main issues in the identification of peer effects (e.g., Manski, 1993; Sacerdote, 2011, 2001; Brock and Durlauf, 2001; Moffitt, 2001; de Paula, 2017; Charles et al., 2018; Caeyers and Fafchamps, 2021). First, peers may be endogenous due to self-selection into peer groups and networks (Duflo and Saez, 2003; Kremer and Levy, 2008b). This is referred to as selection bias. In our context, unobserved characteristics, such as extroversion, may positively affect both the size of the network and the likelihood of attaining senior managerial positions. We address this issue by exploiting the exogenous variation in exposure to female peers that comes from the random assignment of MBA students to sections.[30]

Second, peer effect estimations may be affected by the presence of unobserved correlated effects within the pool from which peers are selected. For example, there may be common shocks, such as graduating during a recession year, that affect both peers and the individual (Sacerdote, 2001; Kremer and Levy, 2008a). We tackle this issue by including class fixed effects in our estimation. Common shocks may also emerge at the peer group level within classes (Lerner and Malmendier, 2013). By focusing on a predetermined characteristic gender we are able to isolate peer effects from the potential confounding effect of common shocks.[31] In fact, the random assignment makes it unlikely that common shocks are correlated with this predetermined characteristic (Lerner and Malmendier, 2013).

[30]For more details on the random assignment of students into sections, see Section 2.

[31]For example, by having the same professors in the core classes, students in the same section may have more similar labor market outcomes. However, the assignment of professors are not correlated with the share of female students in the section due to random assignment.

Third, peer effects estimation can also suffer from the reflection bias. In the commonly-estimated linear-in-means model, the outcome is modeled as a function of peers' average outcomes, individual's background characteristics, and peers' average background characteristics (Sacerdote, 2011).[32] Because individuals in the same peer group affect each other, estimates of this model are biased due to a multiplier effect, highlighted by Manski (1993) as the reflection problem. This introduces an endogeneity bias in these outcome-on-outcome linear-in-means models. However, because we are interested in the effect of a predetermined characteristic of the peers, we model the outcome only as a function of an individuals background characteristics and peers average background characteristics. Therefore, our estimates do not suffer from this problem.

Empirical Specification

We estimate peer effects using a linear-in-means model in which holding a senior management position depends on own gender and the proportion of female students among MBA section peers. Following Bertrand et al. (2010), we use a pooled sample in which we include all observations of an individual such that each observation refers to an MBA graduate in a given post-MBA year. Specifically, we use the specification:

$$\begin{aligned} y_{ikct} = &\alpha_1 \overline{FemaleShare}_{-i,kc} \times Male_i + \alpha_2 \overline{FemaleShare}_{-i,kc} \times Female_i + \\ &+ \alpha_3 Female_i + \sum_{j=0,1} (\delta_c + \phi_t + \omega_{ct}) \times I(Female_i = j) + X_{ikct}\gamma' + \epsilon_{ikct} \end{aligned} \tag{1}$$

where y_{ikct} is the outcome of interest, a dummy variable for holding a senior-level management position for individual i in section k from graduating class c in year since graduation t.[33] $\overline{FemaleShare}_{-i,kc}$ is the proportion of female peers of i in section k and graduating class c. $Female_i$ is a dummy that takes value 1 for female and 0 for male, while $Male_i$ is a dummy that takes value 1 for male and 0 for female. The specification also includes a series of class fixed effects (δ_c), year fixed effects (ϕ_t), class-by-year fixed effects (ω_{ct}), and their interactions with the gender dummy. Class-by-year fixed effects allow us to isolate only within-cohort variation in female share. By exploiting within-gender-within-class variation, our coefficients are not affected by changes in the gender composition of the program over time.

The term X_{ikct} represents a series of individual and section-level control variables. Be-

[32]For example, $Y_i = \alpha + \beta_1 \bar{Y}_{-i} + \gamma X_i + \gamma_2 \bar{X}_{-i} + \epsilon_i$, where $\bar{Y}_{-i}$ is the peers' average outcome, and X denotes background characteristics.

[33]This outcome is unconditional on employment. That is, in addition to those not in senior management, we also assign zero to anyone that does not report any work activity in year t on their CV. In Appendix Figure H.1, we show that results hold when we assign missing to individuals without any work activity.

cause the section assignment algorithm aims to achieve balance on gender, undergraduate institution, and ethnicity, we control for having attended a top-20 U.S. undergraduate university based on U.S. News Ranking. Hereafter, we will refer to this as a stratification variable. Unfortunately, we are unable to control for ethnicity due to lack of data availability. We also include pre-MBA characteristics that are predictive of becoming a senior manager: any senior management experience dummy, and having worked in finance for precision.[34] All individual level-characteristics are interacted with the gender dummy. Lastly, we include a series of section-level controls. As observed in Appendix Table A.2, gender differences exist across many pre-MBA characteristics. As a result, a larger share of female peers may capture alternative channels, such as having a larger share of peers from more female-dominated industries. Following the methodology employed by Lerner and Malmendier (2013), we control for section-level characteristics that are significantly correlated with the share of women in the section: share of section with management experience, senior-level management experience, finance experience, consulting experience, other industry experience, P&L experience, U.S. locality, and those with white and/or foreign backgrounds.[35,36,37] We cluster standard errors at the section level for all of our specifications.[38]

The exogenous variation in female peers allows us to interpret our two coefficients of interest, α_1 and α_2, as causal. α_1 and α_2 represent the total effect of having more section female peers on the outcome variable for men and women, respectively. α_3 captures the gender gap in outcomes conditional on controls.

[34]To identify the predictors, we regress a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and pre-MBA characteristics using the pooled sample. The results of this regression are presented in Appendix Table A.4.

[35]In Appendix Table A.5, we present section-level summary statistics for different pre-MBA characteristics. This table reports the coefficients from bivariate regressions of female share on each of the specified section characteristics controlling for class fixed effects. Nine characteristics are significant at the 5% level. These include share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, US locality, white, and foreign. Note that Lerner and Malmendier (2013) use a forward stepwise selection process to choose their final section-level controls, but because we have much fewer characteristics than in their case (16 vs. 68), we utilize linear regressions for this purpose.

[36]Share of white and foreign are computed using statistics aggregated at the section level from administrative data between 2000 and 2018. However, since we have individual administrative data only for years 2011 to 2018, in computing these shares we cannot leave out the individual, as we do for all other shares.

[37]In Section H, we show that our estimates are robust to alternative sets of controls.

[38]We cluster at the section level because there may be common shocks that affect the entire section, leading to correlation in the outcome variable within the section. However, as we discuss in the identification section, due to exogenous assignment and the focus on a predetermined characteristic, the common shocks would not bias our estimates. We show in Section H that our results are robust to clustering at the class level.

Identification Assumption and Randomization Test

In order to identify the causal effect of peers, our empirical strategy relies on the idea that the distribution of female share across sections is as good as random. We implement randomization tests to show that the assignment of students is as good as random. A natural first attempt is to test whether the gender of the student is correlated with the female share of the section. However, as first highlighted by Guryan et al. (2009) and recently expanded upon by Caeyers and Fafchamps (2021), there is a systematic negative correlation between the characteristic of the individual and her peers due to the fact that an individual cannot be her own peer when assignment is done without replacement.[39] Caeyers and Fafchamps (2021) refer to this bias as the "exclusion bias." As a result, we implement two alternative randomization tests proposed by Guryan et al. (2009) and Caeyers and Fafchamps (2021), respectively, that take this bias into account.[40]

The first randomization test is proposed by Guryan et al. (2009) and has been widely implemented in the peer effects literature (Carrell et al., 2009; Sojourner, 2013).[41] The rationale behind this test is that, after controlling for the leave-out mean of female share in the class, the section-level leave-out mean should be precisely estimated and not significantly different from zero. Appendix Table D.1 shows that the section-level leave-out mean is not significant either when using the full sample of cohorts between 2000 and 2018 (Columns 1-2) or when we restrict to the subsample of cohorts between 2011 to 2018, for which we have administrative data (Columns 3-4). It also does not depend on the inclusion of covariates.

The second randomization test, proposed by Caeyers and Fafchamps (2021), is an alternative to the test proposed by Guryan et al. (2009). Caeyers and Fafchamps (2021) provide an exact formula to quantify the magnitude of the exclusion bias in our setting with unequal section and class size, assuming homoskedastic errors. Instead of adding a bias correction term in the estimating equation as in Guryan et al. (2009), Caeyers and Fafchamps (2021) show that the randomization test can be implemented by netting out the asymptotic exclusion bias first.[42] We present the results of the randomization test in Appendix Table D.2 for the full sample (Columns 1-2) and for the cohorts between 2011 and 2018 (Columns 3-4).[43]

[39] When class fixed effects are included, the exclusion of an individual from the pool of potential peers creates a systematic negative correlation between the individual's characteristics and that of her peers.

[40] Caeyers and Fafchamps (2021) is a generalization of the methodology proposed by Jochmans (2020). For this reason, we decided to report the results from using the approach in Caeyers and Fafchamps (2021). Results from Jochmans (2020) are available upon request.

[41] See Appendix Section D.1 for details on this randomization test.

[42] See Appendix Section D.2 for details on this randomization test.

[43] Following Caeyers and Fafchamps (2021), the estimation is done by clustering at the class level. In

The coefficient for female share is insignificant across all specifications with or without the main set of controls used in our baseline specification.[44,45] The results of this test and the previous one suggest that the distribution of female share is in fact as good as random in both samples, and provide strong support for the validity of our empirical strategy.

Finally, in Appendix Section E, we provide an additional test to show that the within-class peer-gender variation is as good as random. Following the methodology in Bietenbeck (2020), we compare the actual distribution to a simulated within-class distribution of female share. Appendix Figure E.1 shows no statistically significant difference between the actual and the simulated distribution, providing supporting evidence of as-good-as-random assignment of the share of female peers.

5.2 Effect of Female Peers on Management Roles

In this section, we will first show that female peers increase women's likelihood of holding senior management positions. We will explore the dynamic effects and investigate the job characteristics of the senior management positions. We will then study whether this increase can be explained by changes in female MBAs' attachment to the management pipeline in terms of career breaks, entries into general management roles, or self-employment. We conclude the section by showing a series of robustness checks and empirical tests to support our results.

5.2.1 Effect on Senior Management

We begin by characterizing the impact of female peers on the likelihood of holding a senior management position. Figure 4a shows the binned scatterplot of the relationship between female peers and the probability of becoming a senior manager, controlling for only class fixed effects. Each dot represents the average likelihood of holding a senior management position within each decile of female share. Figure 4b shows the analogous binned scatterplot when both the outcome and female share have been residualized by the full list of controls in our

Section H, we show that our results are robust to clustering at the class level.

[44]Note that when implementing this test with covariates, we first partial out additional regressors using the methodology described by Caeyers and Fafchamps (2021).

[45]As additional evidence, in Appendix Table D.3 we conduct the same randomization test when the dependent variable is being a female student from a top-20 undergraduate institution in Column (1), being a female student with senior managerial experience in Column (2), and being a female student with experience in finance in Column (3). Consistent with the previous results, we do not find any significant effect.

main specification (1). Importantly, this figure shows the within-gender and within-class variation. Both figures show a strong positive relationship between the exposure to female peers and the likelihood of attaining a senior managerial position for female graduates, and limited effects for male graduates.

Table 1 reports the corresponding estimates. Column (1) controls for class fixed effects, year fixed effects class-by-year fixed effects, as well as their interactions with a female dummy. Then, in Column (2), we also include stratification variables as controls. Column (3) adds individual- level characteristics, as described in Section 5.1.[46] Finally, Column (4) presents our preferred estimates with the full set of controls, including section-level controls that are correlated with female share. Across all specifications, we show that female peers have a significant and positive effect on the career advancement of women.

Using our preferred specification, we find that a 4 percentage point (1 SD) increase in the share of female MBA students leads to a 8.4% (=$0.822 \times 0.04/0.391$) increase in the probability of holding a senior management position on average across the 15 years after MBA graduation.[47] In contrast, there is no effect on male students. This is consistent with the "old boys' club" hypothesis that male MBA graduates may have easier access to networking opportunities at their firms and may not need to rely on their MBA networks as much for their career advancement (Cullen and Perez-Truglia, 2019).

In Appendix Section F, we investigate whether there is nonlinearity in our effects. Table F.1 shows the estimated effect is large and significant for women in sections below the median female share (34%). However, we cannot reject equality between the two coefficients. These findings provide suggestive evidence that female peers may be more beneficial for women in sections with a lower female share, pointing to the presence of decreasing marginal returns of additional female students. The presence of decreasing marginal returns would also help explain the lack of effect for men.

In Appendix Section G, we explore additional management outcomes. We decompose the effects by individual positions within senior management (Appendix Table G.1). We find the largest increase for directors and VPs. We then show that female peers increase women's probability of ever holding senior management positions (Appendix Figure G.4), their years in senior management (Appendix Table G.3), and the number of senior management positions (Appendix Table G.4). Conditional on becoming a senior manager, female peers also reduce

[46]Note that for all of the controls we include, we also include missing indicators and all of their interactions with a female dummy.

[47]A 4 percentage point increase along the female share distribution corresponds to 2.4 additional women and is also equivalent to moving from the 25^{th} (32%) to the 75^{th} (36%) percentile.

the time to promotion for women. Finally, we show the increase in senior managers comes from both external and internal promotions (Appendix Table G.5).

Interpretation of Effect Size

To interpret the economic magnitude of our main results, we compare our estimates to the overall gender gap in leadership positions in our MBA sample. In Table C.1, we showed that female MBA graduates are 12.8 percentage points (24%) less likely to reach senior leadership positions compared to 54% of men. Our results in Table 1 suggest that a 4 percentage point (1SD) increase in the share of female MBA students leads to a 3.3 percentage point increase (8.4%) in the probability of holding a senior management position. This is equivalent to a 26% (=3.3/12.8) reduction in the gender gap on average across 15 years after MBA graduation.[48] These effects are economically large and consistent with prior studies that also documented substantial peer effects in the MBA context (Shue, 2013; Hacamo and Kleiner, 2021).[49] In sum, our results suggest that same-gender peers play a crucial role in the career advancement of women.

5.2.2 Dynamic Effects of Female Peers

In order to understand the dynamics of when female peers help female MBAs transition into senior management positions, we estimate equation (1) separately for each post-MBA year. Figure 5 plots the resulting coefficient estimates.[50] The dynamic patterns show that the increase in likelihood of holding a senior management position for women emerges as early as two years after graduation. The effect becomes larger over time, peaking around seven years after graduation.[51] The persistent effect of MBA peers is perhaps surprising, given that these peer ties are formed during the MBA program. However, as highlighted in Shue (2013), connections formed during the MBA can have long-lasting impacts. In support of this, using our survey data, we show in Appendix Section L.3 that MBA peers are important

[48]Note that this computation is conservative and does not account for the mechanical effect on the gender gap coming from the increase in the share of female students. Also, note that the gender gap from table C.1 accounts for class times year fixed effects. The raw gender gap, as shown in Table 1, is 14.3 percentage points (27%).

[49]For example, Shue (2013) finds that Harvard Business School alumni who become top executives at S&P 1500 have compensation and acquisitions propensities elasticities of 10-20% with respect to their section peers. Hacamo and Kleiner (2021) shows having a connection to an MBA classmate who was a former employee of a top-tier firm increases the odds of employment at the firm within the first year of graduation by 3.5 percentage points.

[50]Regression estimates are presented in Appendix Table A.6.

[51]The estimates are more imprecise towards the end of the sample period as the number of observations fall as more recent cohorts drop out of the sample.

professional contacts for women in our sample; on average, representing 27% of their closest contacts in the 20 years after graduation.

5.2.3 Job Characteristics of Senior Managers

Next, we explore whether female peers lead women to become senior managers in certain types of firms, functions, or industries. While we do not find much evidence that female peers affect these job characteristics, we will show that the increase in senior managers is driven by male-dominated industries.

Firm Size and Compensation

We first show that the increase in senior managers does not come from a shift in employment towards smaller or lower-paying firms. Appendix Table A.7 shows that female peers significantly increases women's likelihood of being a senior manager in both small (less than 500 employees) and large firms (greater than 5,000 employees), suggesting that women are not only being promoted in smaller firms where it may be easier to reach higher positions. Appendix Table A.8 also indicates that female peers do not affect the firm size of companies where female graduates are employed.

Next, in Appendix Table A.9, we explore whether the increase in female managers is driven by firms with a certain level of average compensation. We do not find a clear pattern that women are systematically being promoted in firms with higher or lower compensation on average. Similarly, Appendix Table A.10 also indicates limited effects on employment in firms of particular compensation levels.

Consistent with these findings, in Appendix Table A.11, we show that our main results on senior management are robust when we estimate equation (1), controlling for firm size and firm average compensation.

Job Function

We then explore effects on job functions, focusing on Profit and Loss (P&L) functions. Workers with P&L responsibilities monitor the net income after expenses for a department or an entire organization, with direct influence on how company resources are allocated. These responsibilities have been shown to be essential for promotions into top executive positions (Larcker and Tayan, 2020).[52] Appendix Table A.12 shows that the increase in female senior managers is also associated with an increase in female senior managers with

[52] We identify P&L positions as those in General Management, Operations/Logistics, Product Management, Sales or Strategic Planning.

P&L responsibilities. However, Column (2) shows the increase is not due to more women entering into positions with these responsibilities in general, suggesting that the rise in female managers with P&L responsibilities is not driven by a broader trend of women moving into these roles as a result of having more female peers.

Industry

Finally, we explore whether the increase in senior managers is driven by higher rates of promotion for women in male- or female-dominated industries. As shown in Appendix Figure A.2, there exists substantial gender variation in industry choice. We define male-dominated industries as those where women are underrepresented relative to their share in the MBA program, 36%. Specifically, we categorize consulting, tech, and finance as male-dominated industries, while consumer goods and healthcare are categorized as female-dominated.

Appendix Table A.13 shows that female share leads to a significant increase in the probability of becoming a senior manager in a male-dominated industry, with no effect for becoming a senior manager in a female-dominated industry. The difference between the two coefficients of interest is significantly different at the 3% level.

Moreover, Column (3) of Appendix Table A.13 shows that there is no significant effect on entries into male-dominated industries.[53] These results provide suggestive evidence that the increase of senior managers in male-dominated industries is driven by higher promotion rates of women in these industries, where women may face additional barriers in accessing informal networks and may therefore rely more on their MBA female peers.

5.2.4 Attachment to the Corporate Pipeline

Having explored the job characteristics of senior managers, we now investigate whether our results can be explained by changes in career dynamics. We will show in this section that our results on senior management are not driven by an increase in the attachment to the corporate pipeline as measured by (i) employment and career breaks, (ii) entry rate into the managerial pipeline, and (iii) likelihood of self-employment.

Appendix Table A.14 shows that there are limited effects on employment or career breaks. We define a career break as a gap between the end and start dates of two consecutive positions

[53]The evidence of how gender peer effects impact women's decisions to enter male-dominated fields and industries has been mixed. In some cases, female peers help women persist and excel in male-dominated fields (Bostwick and Weinberg, 2018), other cases show that female peers influence women to select more female-dominated areas (Calkins et al., 2020; Brenoe and Zölitz, 2020; Thomas, 2021).

of at least a three-month period.[54] In line with these results, using our survey data, we also find limited evidence that female peers affected the likelihood of nonemployment, total maternity leave duration, or having any career breaks (Appendix Table L.8). However, these results are suggestive due to the large standard errors from the small sample size.

Then, we test the hypothesis that female peers increase women's likelihood of entering management positions (including first-level positions), which would lead to a subsequent increase in senior management. Appendix Table A.15, however, shows limited evidence that female peers affected the likelihood of holding any managerial position.

Finally, we ask whether female peers may increase promotion rates into senior managerial positions by affecting the likelihood of self-employment.[55] There is suggestive evidence that women may use self-employment as a way to work part-time or lower hours and have a better work-life balance (Bertrand et al., 2010). If female peers help women, who otherwise would have moved into self-employment, remain attached to their firm, this may explain the increase in female senior management. However, in Appendix Table A.16, we find no significant effect on self-employment.

5.3 Robustness Checks

We conclude this section by presenting a series of robustness checks to provide supporting evidence that our results credibly identify the causal effect of female peers on senior positions for women. Additional details are provided in Appendix Section H.

Missing Data and Alternative Samples

First, we show that our results are not driven by unmatched observations or the restrictions to our sample. In Appendix Table H.1, we investigate whether unmatched observations from each of the datasets are systematically correlated with female peers. We report the regression results from estimating equation (1), where the dependent variable in each column is a dummy if the individual is matched to the specified dataset.[56] We do not find a correlation between female share and being in the sample in any case. This provides strong

[54] It is worth noting that career breaks may not be listed on the CV if they are temporary leaves of absence from the firm, such as the case of parental leaves. As a result, the CV data likely underestimate the number of career breaks. For example, the average cumulative number of months in nonemployment inferred from the CV data is 2.3 months at the end of 9 years, compared to 6.8 months Bertrand et al. (2010) documented in their sample of MBA graduates. See Table 1 of Bertrand et al. (2010).

[55] Our definition of senior manager does not include entrepreneurs.

[56] Note that we do not include controls beyond gender, class, and year fixed effects, because additional information is not available for unmatched individuals.

evidence that selection into the sample cannot explain our results.

We also conduct a series of robustness checks using alternative definitions and samples and re-estimating equation (1) for senior management. Results are summarized in Appendix Figure H.1. Specifically, we show that the main result is robust when we: (i) use an alternative nonemployment measure in which we assume all periods up to 2019 without a current position are nonemployment spells[57]; (ii) restrict to a balanced sample where we can follow individuals throughout the 15 years post-graduation; (iii) assign missing to the individual who does not report any work activity in that year; (iv) drop outlier sections (i.e., sections with a proportion of female students in the first and last percentile of the female share distribution); (v) include entrepreneurs in the definition of senior managers; restrict to observations for which we have information on (vi) industry and (vii) level of female-friendliness of the firm, as defined in Section 3.3; account for potential industry differences in hierarchies in job titles by (viii) including industry fixed effect; and (ix) remove individuals working in finance.[58]

Placebo Tests

Second, we run two placebo tests. First, following the methodology described in Athey and Imbens (2017), we conduct a randomization test in which we randomly reassign students to sections within the same class.[59] In Appendix Figure H.2, we plot the distributions of the placebo treatment effects for men and women, respectively. The vertical lines indicate the actual coefficients we estimated using the true section assignment. The true effect for men falls within the distribution of placebo effects, consistent with the null effect on men that we find in our main results (Section 5.2). On the contrary, the estimated true effect for women is much larger than any of the placebo effects, providing supporting evidence that the estimated impact of female peers on women's probability to become senior managers is unlikely to have occurred by chance.

Second, if female share in each section is exogenous, it should have no effect on our outcome variable in the years prior to the MBA, when peer groups have not been formed yet. Appendix Table H.2 shows the coefficients from regression (1) estimated separately for

[57]In our baseline analysis, we do not make this assumption, as it could simply reflect a lack of updates on their social media profiles.

[58]As noted previously, job titles differ slightly in finance. For example, compared to other industries, VPs are ranked lower than directors.

[59]The reassignment is performed without replacement and using uniform probability. We conduct this reassignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, the probability of holding a senior management position, for both men and women.

up to three years before the start of the MBA program. We find no consistent evidence of an effect of female share on female future graduates, supporting our identification strategy.

Alternative Empirical Strategies

We show that our results are also robust to alternative empirical strategies. First, we show that our estimates are robust to clustering at the class level to capture potential correlation in outcomes within the same graduating cohort. Appendix Table H.3 shows the coefficient of interest from estimating equation (1) when clustering at the section level (Column 1) and when clustering at the class level (Column 2). The two clustering levels lead to almost identical results.

Second, we show that our results are robust when we use a conditional logit model instead of OLS. Appendix Table H.4 reports the coefficients from our main specification in Column (1) and from the logistic specification in Column (2). We find that with this alternative model the effect of female peers is positive and significant at the 3.4% level. The marginal effect is 0.477, which translates into a 4.9% increase in the probability to be a senior manager for a 4 percentage point (1SD) increase in the female share distribution.

6 Female Peers and Female-Friendly Firms

How do female peers help women advance into senior corporate leadership positions? In this section we explore the role of firm characteristics and show that our results are driven by female-friendly firms. Section 5.2.3 showed that the increase in female senior managers cannot be explained by changes in firm size or firm-level compensation. However, firms may differ along other dimensions that can be beneficial for women's career advancement. In particular, a growing literature has documented the importance of female-friendly workplaces for the labor market outcomes of women (e.g., Hotz et al., 2018).

Characteristics of Female-Friendly Firms

To identify female-friendly firms, we leverage novel crowdsourced employee ratings data from InHerSight.com.[60] We classify a firm as female-friendly if it has an above-median rating. The ratings from InHerSight (IHS) capture female employees' perception on metrics such as generosity of the maternity leave policies, flexible work schedules, and professional support. Using our survey data, we also find that the IHS rating is strongly correlated to female MBA graduates' perceived level of overall female-friendliness of the firm (Appendix Section L.4).

[60] Additional details provided in Appendix Section B.5.1.

In Appendix Section B.5.4, we explore characteristics of female-friendly firms. We show that female-friendly firms are present in both male- and female-dominated industries, and are not significantly different in terms of firm size or firm average compensation.

In Appendix Figure A.3, we present descriptive evidence that female MBAs are more likely to hold senior management positions in female-friendly firms compared to those in non-female-friendly firms. This divergence occurs around eight years after graduation, coinciding with the life stage when they are likely to have young children at home. Although it is beyond the scope of this paper to identify the causal impact of working at a female-friendly firm on women's careers, these descriptive results suggest a positive relationship between working at a female-friendly firm and progressing into senior management.

Senior Managers in Female-Friendly Firms

Motivated by the descriptive patterns, we explore how much of the overall impact of female peers can be explained by women gaining senior leadership positions in these female-friendly firms. Table 2, Column (1), shows that female peers significantly increase women's likelihood of becoming a senior manager in a female-friendly firm, while they do not affect the probability of becoming a senior manager in a non-female-friendly firm (Column 2).[61] The difference between the two coefficients is significant with a p-value of 0.014. In Appendix Section I, we show that among the features of female-friendly firms, work schedule flexibility, family-friendliness, and professional enrichment are key drivers of the overall effect.

Together, these results suggest that our overall effects on senior management are driven by female-friendly firms, implying that there exist complementarities between female peers and promotion in these types of firms. For example, female peers may have a comparative advantage in identifying firms that are more friendly towards women, or that may provide women with the necessary advice to take advantage of the female-friendly policies (e.g., how many weeks of maternity leave to take). Female peers may also raise women's ambitions, leading them to seek out more female-friendly firms where they may be more likely to be promoted. In Section 7, we will explore how information-sharing and ambitions can be relevant mechanisms for these results.[62]

Entries vs. Promotion

What explains the increase in senior managers in female-friendly firms? This effect may

[61] In Appendix Figure A.4 and Appendix Table A.18, we show these results are robust to using alternative measures of female-friendliness from other data sources, such as weeks of paid maternity leave.

[62] Additionally, as discussed in Section 5.2.3, the overall impacts are concentrated in male-dominated industries. In Appendix Section J, we show that the increase in female senior managers is due to women transitioning into *female-friendly firms* within these male-dominated sectors.

be driven by a combination of new entries in female-friendly firms and higher promotion rates in these firms. We present evidence that entries play a nontrivial role in these results.

In Table 2, Column (3), we show that there is no effect on likelihood of working at a female-friendly firm, although the estimate is very imprecise. However, this null result masks considerable heterogeneity along the career path. In Figure 6, we plot the regression estimates for working in a female-friendly firm over time since graduation. There is an increasing effect on women joining female-friendly firms beginning six to seven years after MBA graduation. This period coincides both with an increase in female senior managers in female-friendly firms, as shown by our descriptive analysis in Appendix Figure A.3, and with the years when women are more likely to have childcare responsibilities. Specifically, in our survey data (Appendix Figure L.5), we find that 50% of graduates have children within five years after graduation.[63]

Moreover, while we have documented an increase in entries into these firms, these results do not rule out the possibility that female peers may also increase the rate of promotions of women at these firms. To provide suggestive evidence on this effect, in Appendix Table A.17 we study the likelihood of becoming a senior manager conditioned on working in a female-friendly firm or a non-female-friendly firm. We find a positive impact for women in female-friendly firms, suggesting that promotion can play a role. However, we acknowledge that these results are endogenous to women's decision to join different types of firms, and should be interpreted with caution.[64]

7 Mechanisms

Our results show that access to a larger proportion of female peers helps women advance into senior management positions. In Section 6, we show that, as a result of the effect of female peers, women are more likely to join female-friendly firms and be promoted in this type of firms. To understand the mechanisms underlying the treatment effects, we

[63] This pattern of childbirth is also similar to the results found by Bertrand et al. (2010) in their study of University of Chicago MBA graduates.

[64] Note that we cannot rule out that these results may also capture the impact of female managers on these female-friendly firm policies. The InHerSight data is collected in 2021, which in some cases is many years after the women in our sample have been promoted to senior management. Female peers potentially increase women's likelihood of becoming senior managers, and in turn, these female managers implement policies that make the firm more female-friendly today. However, as we show in Appendix Table A.19, the results are very similar when we restrict to only large firms with over 5,000 employees, where any single manager may be less influential. This suggests that this explanation is unlikely to explain these results.

conduct a survey of the full sample of female MBA graduates in our study.[65] The results of the survey, combined with evidence using the LinkedIn data and administrative school records, suggest that a larger share of women in the MBA peer group supports the careers of female MBAs through three key mechanisms: (i) information sharing, especially gender-specific information, (ii) raising ambitions and self-confidence, and (iii) increasing support from male MBA peers.

7.1 (Gender-Specific) Information

A longstanding literature in economics has identified information exchange and referrals as key drivers of the importance of social networks in labor markets (e.g Bayer et al., 2008; Beaman and Magruder, 2012; Schmutte, 2015; Beaman et al., 2018; Barwick et al., 2023). We begin by showing evidence that information-sharing also plays a crucial role in our results. Figure 7 shows the survey responses from female MBA graduates for the question "To what degree has your female (male) MBA network helped your professional career by providing the following types of support?"[66] For information-related support, we find that with the exception of job referrals, women rely relatively more on their female MBA peers across all categories. Importantly, female MBA peers are more likely to offer gender-specific advice and information to women, including guidance on work-life balance and assistance in identifying female-friendly firms.[67]

We provide two additional pieces of evidence in support of the hypothesis that women provide gender-specific information important for their careers. First, we document that women in sections with more female peers are less likely to experience adverse effects of children on their work and career. Similar to what has been documented in the literature (Bertrand et al., 2010; Kleven et al., 2019), female MBA graduates in our sample faced considerable challenges balancing work and family responsibilities after having children. Nearly 92% of all respondents made changes in their work as a result of having children, such as

[65]This survey is informed by a series of qualitative interviews. Results from the interviews are provided in Appendix Section M.

[66]This question was asked twice to each female graduate, once referring to the *female* MBA network and once referring to the *male* MBA network.

[67]In our qualitative interviews, around 64% of women mention gender-specific advice as a key support channel. For example, a female graduate from the class of 2015 said "If I receive an offer, I'm comfortable talking to a [female] friend [...] I'd ask how maternity leave works or generally what the female community looks like and what the support is. I probably wouldn't ask those questions [to a hiring manager] in the off chance the person uses this as a red flag."

reducing work hours. Moreover, 72% of respondents also experienced adverse effects at work, such as a delay in promotion.[68]

In Table 3, we investigate the effect of female peers on the work impact of children. We find that a 4 percentage point (1SD) increase in female share leads to a 5% decline in the likelihood that female MBAs experience any effects of children on work choices and a 9% decline in any adverse effects of children at work. Appendix Figure L.4 presents the analogous results by type of work impacts and shows that the declines are driven by lower likelihood of reducing work hours, change of sectors, and loss of clients as a result of children. These results suggest that female MBA peers may provide critical advice and information that help women combine their work and family responsibilities.

Second, we present evidence of job referrals or firm-related information sharing between female MBA classmates. While direct observation of referrals in the LinkedIn data is not possible, we provide supporting evidence using our CV data. We employ the dyadic analysis from Bayer et al. (2008) and Schmutte (2015) to test if MBA graduates are more likely to work in the same firm as a classmate when they are from the same section and share the same gender. The idea is that if female peers are important for referrals or sharing information about firms, then female students should be relatively more likely to work in the same firm of a female peer than that of a male peer. To investigate this effect, we form a new dyadic dataset in which all MBA graduates are matched to all possible classmates of the same graduating year. We then estimate the following:

$$\begin{aligned} y_{i,j} = {} & \alpha_1 SameSection_{i,j} \times BothMales_{i,j} + \alpha_2 SameSection_{i,j} \times BothFemales_{i,j} \\ & + \alpha_3 SameSection_{i,j} + \alpha_4 BothMales_{i,j} + \alpha_5 BothFemales_{i,j} + \delta_c + \phi_f + u_{i,j} \end{aligned} \tag{2}$$

where $y_{i,j}$ is a dummy that takes value 1 if the MBA graduate i and his or her classmate j work in the same firm. $SameSection$ is a dummy that takes value 1 if i and j were in the same section. $BothMales$ is a dummy that takes value 1 if i and j are both men, and analogously, $BothFemales$ is a dummy that takes value 1 if i and j are both women. We also include class fixed effects, δ_c, and firm fixed effects, ϕ_f. Because sections are exogenously assigned, α_3 measures the causal effect of having a connection from the same section on the likelihood of joining the same firm. The parameters of interest are α_1 and α_2, which provide the differential effect of coming from the same section and being both men or both women,

[68] See Appendix Figures L.2 and L.3 for the underlying categories. These survey questions were adapted from Azmat and Ferrer (2017).

respectively. We use two-way clustering, and cluster at both the individual and firm level.

Table 4 shows the results from estimating equation (2). While we do not find an effect for men, we show that female classmates are more likely to work in the same firm if they come from the same section. Notably, in Table 5, we find that these results are driven by female-friendly firms, providing additional suggestive evidence that female peers may help women enter female-friendly firms.

7.2 Ambitions and Self-Confidence

Next we explore the role of ambitions and self-confidence. The literature has identified self-confidence and ambitions as possible drivers of the gender gap in male-dominated fields and managerial positions (Kirkpatick and Locke, 1991; Rosenthal, 1995; Rosenthal et al., 1996; Carlana, 2019). Female peers may raise women's ambitions and self-confidence by providing a larger support system. For instance, recent studies indicate that an increase in female representation increases leadership opportunities for women (Karpowitz et al., 2023), as well as their willingness to take on leadership roles (Born et al., 2022). In line with this hypothesis, Figure 7 shows that female MBA respondents, to a great extent, agree that their female MBA peers increase their ambitions, act as role models, and provide emotional support. Indeed, in our qualitative interviews, the most frequent form of support (82%) interviewees mentioned is emotional support from other female peers, which in turn fosters their ambitions and self-confidence. For example, when referring to her female classmates, a female MBA alumna from the class of 2011 said, "Having seen my peers do really interesting things that have leadership positions and also start their own companies, I think it definitely encourages me as well."

To further shed light on this mechanism, we ask MBA alumni whether they would like to become top executives and in which position they expect to be in 5 and 10 years (non-managerial, low-level manager, director, VP, SVP, C-suite, or not working).[69] Appendix Table L.6 shows that female MBA peers have a positive, albeit imprecisely estimated, effect on these three measures. Column (3) shows that a 1SD increase in female share corresponds to a 9% increase, significant at the 10% level, in the likelihood of female MBA graduates seeing themselves as a SVP or C-level executive within 10 years, providing evidence of a positive effect of female MBA peers on ambition and self-confidence.

[69]This question is adapted from Lean In and McKinsey & Company (2015, 2019). Note that SVP or higher corresponds to above the median in the answer distribution.

7.3 Male MBA Peer Support

As shown in Figure 7, female MBA peers on average are more supportive for women in our sample than their male MBA peers. As a result, women in sections with more female peers would have more support due to the gender composition of their peer group. However, increasing female share in the MBA section may lead to changes in the support women and male MBA peers provide.

Figure 8 plots the coefficients from regressing survey responses for the type of MBA peer support on the female share in the section, while controlling for class fixed effects. Figure 8a shows that increasing female peers largely does not change the support women receive from their female peers. One exception is that having more female peers lead women to agree that their female MBA peers increased their ambitions and improved their MBA experience.

Interestingly, Figure 8b shows that women view their *male* peers as more supportive across multiple dimensions if they have more women (and, correspondingly, fewer men) in their section. One potential explanation for this surprising result is that increasing female representation in their MBA section may have raised women's confidence and assertiveness in asking for career support from their male classmates. An alternative explanation is that greater female representation may have also changed the attitudes of male MBAs towards their female classmates. This effect would be in line with recent evidence that shows increasing female representation in traditionally male-dominated settings can be effective in changing gender attitudes of men (Battaglini et al., 2020; Dahl et al., 2021). Unfortunately, we cannot test this hypothesis directly in our sample, as we did not survey male MBA graduates. Nonetheless, we observe in Figure 8b a strong increase in women's perception of their male MBA peers in contributing to a more positive MBA experience, suggesting that a more gender-diverse educational environment may have resulted in more positive gender attitudes and enhanced support from male peers.

7.4 Alternative Explanations

In this section, we discuss alternative explanations for-which there is more limited evidence of how female peers may have influenced women's likelihood of entering senior management roles.

Negotiations

Existing literature has highlighted that gender differences in willingness and ability to negotiate can explain the gender gap in career outcomes (Recalde and Vesterlund, 2023). In our setting, female MBA peers may increase women's confidence in asking for a raise and promotion. Female peers may also provide information or advice about negotiating, which can also increase the likelihood of a promotion. As part of the survey, we ask MBA alumnae whether they negotiated any component of their compensation, and whether they asked and/or obtained a raise or promotion. Results are reported in Appendix Table L.7. We find that a 1SD increase in female share leads to a 29% increase in the likelihood of negotiating for a promotion and a suggestive, but insignificant, increase in negotiating for a raise. However, conditional on negotiating, we do not find a significant effect on successful negotiation, although the sample size is very small. These results suggest that women are more likely to initiate negotiations when they have a larger proportion of female peers, which can lead to the positive impacts on advancement into senior management.

Network Composition

We explore whether the increase in female peers leads to changes in the composition of professional networks of female MBA graduates. Appendix Table L.2 suggests that the share of female peers is not correlated with an increase in women among their 10 closest MBA contacts, nor an increase in female *section* peers among their closest MBA contacts. Similarly, Appendix Table L.3 shows that, among their ten closest professional contacts (not necessarily from their MBA), there is not a significant change in the share of women nor the share of MBA peers. In addition, Appendix Table L.4 shows that female MBAs with more female peers are not more likely to attend alumni reunions, suggesting they are not more attached to the MBA program. These results suggest that changes in the gender or MBA composition of their networks are unlikely to be the key drivers of the overall effect.

Marriage and Fertility

We also leverage the survey data to explore whether female peers influenced marital and fertility decisions. In Appendix Table L.9, we do not find a significant effect of female peers on likelihood of marriage, meeting partner through the MBA, or on fertility. However, due to the small sample size of the survey, the coefficients in these regressions are imprecisely estimated and we cannot rule out the possibility that changes in marital status or fertility may partly drive our results.

MBA Education

Next, we explore whether changes to MBA educational experience can be an important mechanism. Bertrand et al. (2010) have shown that higher GPA and coursework, especially electives in finance, during the MBA are key predictors for postgraduate earnings. This may also reflect higher job seniority and greater management responsibilities. To test this hypothesis, in Appendix Table A.20 we use the school administrative dataset for the classes of 2011 to 2018 to study whether a higher proportion of peers that are female leads to a change in overall and core GPA. We find limited evidence that a greater share of female peers influenced overall grades. In Appendix Table A.21, we also investigate whether female peers influenced the share of elective courses in different fields. We find that having more female peers lead women to increase the share of their elective courses in management, while decreasing their elective courses in operations, with no impact on finance courses. This change in coursework may partly influence the later career outcomes of women. However, because we do not have course records information for a large part of the sample—those who graduated prior to 2010—we are hesitant to generalize these results to the earlier cohorts.

First Placement

Finally, we explore the role of first post-MBA placement which, in turn, can have persistent career effects. Previous studies have shown that initial job placement has important and long-run effects on career trajectories (Kahn, 2010; Altonji et al., 2016; Rothstein, 2021; Thomas, 2021). However, Appendix Table A.22 shows that there is no effect of female peers on probability of being a senior manager in the first year post MBA (Column 1). Moreover, we find no impact on the type of firms and industries graduates join as first post-MBA placement. Specifically, Appendix Table A.22 shows no effect on the probability of working in male-dominated industries (Column 2) or in female-friendly firms (Column 3). Finally, female peers do not affect the firm size and firm average compensation of the first post-MBA job (Columns (4) and (5)). In line with the results on MBA academic performance, these findings suggest the role of female peers on career outcomes is more relevant in the years post MBA graduation.

8 Discussion: Compensation and Career Satisfaction

The effect of female peers on women's advancement into senior management positions may have implications in terms of compensation and career satisfaction. In this section, we show that female peers lead to a positive but imprecisely estimated increase in overall compensation, driven by an increase in the non-base component, and a higher overall career satisfaction among the female MBA graduates.

Compensation

Because we cannot directly observe compensation in the LinkedIn data, we leverage our Glassdoor dataset to infer expected compensation based on firm, job title, and gender.[70] Using this measure, we show in Appendix Section K that there is a gender gap in imputed compensation of 33% among the MBA graduates of our sample. In Appendix Table A.23, we investigate the effect of female peers on imputed compensation. In Column (1), we find a positive effect, although not significant, on log total annual compensation. In Columns (2) and (3), we decompose total compensation into its base and non-base components. We find that the positive effect on compensation is driven by the non-base component, which displays a positive and significant increase: a one SD increase in female share represents a 12 log point increase in non-base compensation.

Career Satisfaction

In Appendix Section L.10, we use the survey results to explore whether women are more satisfied with their careers and to what extent this depends on the gender composition of their MBA section. We find that female MBA graduates with more female peers have higher career satisfaction. This positive association indicates that the gender composition of an MBA section can contribute not only to career progression of women, but also to the perceived quality of their professional experiences.

9 Conclusion

This paper provides new causal evidence on whether access to a larger network of female peers during the MBA provides a pathway to senior leadership positions. We combine school administrative records of MBA graduates from a top U.S. business school with novel CV data from a large professional social media platform. Importantly, these data contain detailed job positions that allow us to track individuals' progression along the management pipeline.

Descriptive results show that female MBA graduates are 24% less likely to hold a senior management position (VP, Director, SVP, or C-level) even though they are equally as likely as male MBAs to enter the management pipeline. They begin their careers in lower levels compared to men, and they are 26% less likely to be promoted into higher positions from first-level management.

Using the exogenous assignment of MBA students to sections, we show that increasing

[70] See Section 3.6.

the proportion of female section peers raises the probability of holding a senior management position for female MBA graduates. However, there is no effect for male MBA graduates. A 4 percentage point (1SD) increase in female share reduces the gender gap in senior management by 26%. These results are not driven by an increase in the attachment to the corporate pipeline and are concentrated in industries where women are underrepresented (i.e., male-dominated industries) and where women may rely more on their female MBA peers.

We find that a larger share of female peers increases the rate at which women become senior managers specifically in female-friendly firms. This effect is largely explained by a higher entry rate in the later part of women's careers, when they are likely to have children.

In the final part of the paper, we conduct a survey of the full sample of female MBA graduates in our study to provide evidence of the mechanisms underlying our main results. Our findings show that female peers help women advance into senior management positions through (i) information sharing, (ii) raising ambitions and self-confidence, and (iii) increasing support from male MBA peers. Women with more female peers receive gender-specific advice, experience fewer adverse career effects from having children, and are more likely to work in the same firms as their female section peers. Additionally, female peers raise women's ambitions and self-confidence, providing emotional support and acting as role models. Interestingly, we also document that *male* MBA peers are perceived as more supportive as the female representation in the section increases.

The results of this study have important implications for policies that aim to address the underrepresentation of women and minority groups in corporate leadership. Although the formalization of a policy recommendation is beyond the scope of this paper, we provide a back-of-the-envelope calculation in Appendix Section N to illustrate that the gender compositions of MBA peers can play a key role in the reduction of the gender gap in leadership positions. Specifically, extrapolating our results on nonlinearities from Appendix Section F and assuming no change in the total number of female students admitted in our MBA program between 2000 and 2018, we show that reallocating female students to reach a 34% female share across all sections would lead to 2 to 5 additional female senior managers per graduating class (corresponding to a 2.4% to 8.4% increase). While we recognize the limitations of this calculation, it illustrates that the gender composition of MBA peers can have important impacts on the gender composition of top executive positions.

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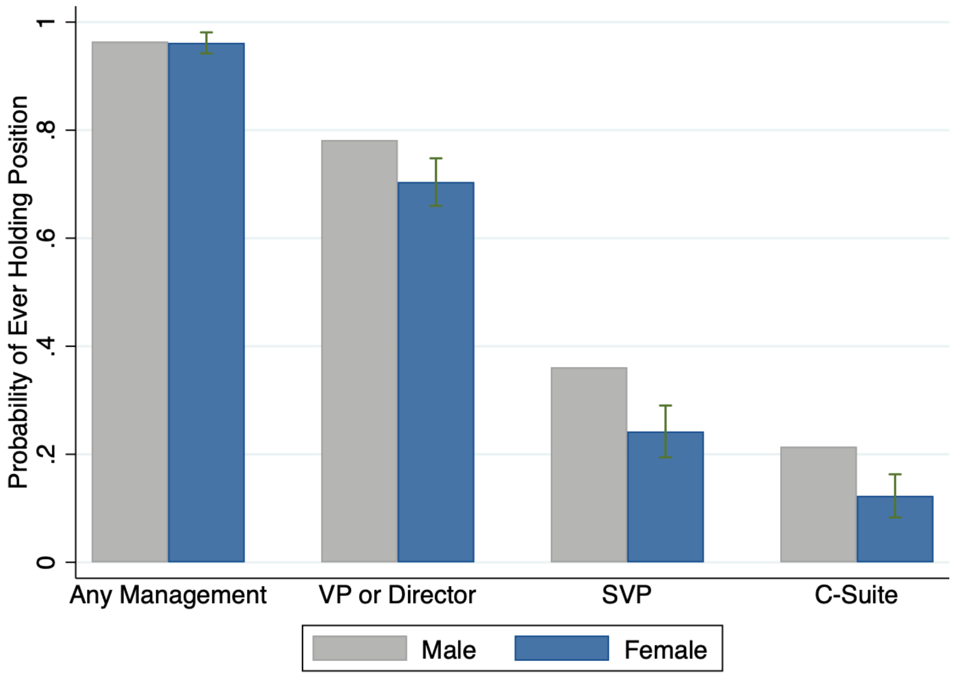
Figures and Tables

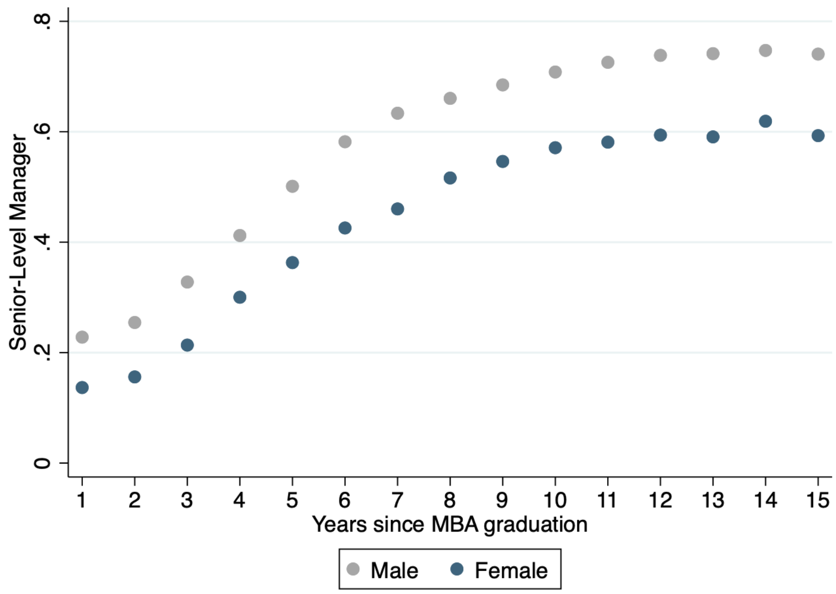
Figures

Figure 1: Representation in the Corporate Pipeline Among MBA Graduates in the First 15 Years Post-Graduation by Gender



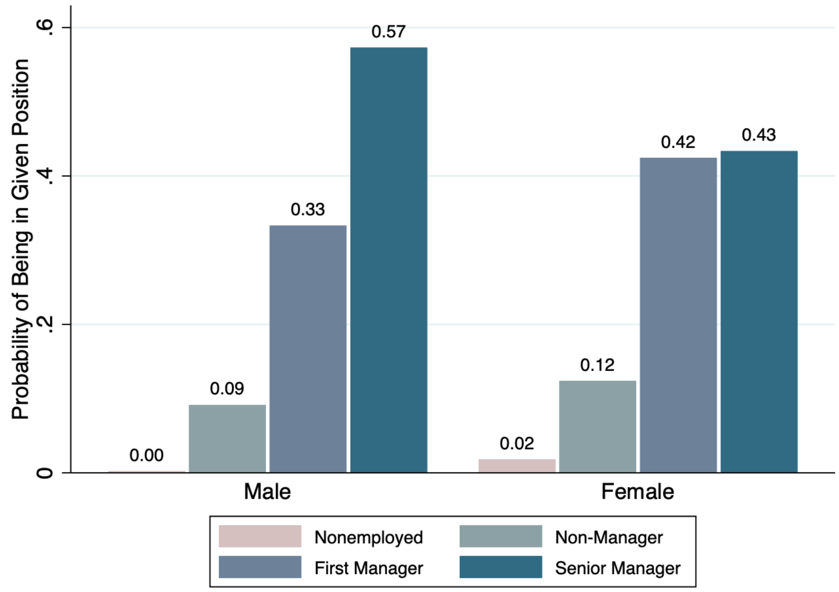
Notes: We plot the percentage of male and female graduates who ever held any managerial positions, a vice president or director position, senior vice president position, and C-level executive position within 15 years since graduation. We display the 95% confidence intervals from the t-test of gender equality. Sample includes students of the graduating classes 2000-2018, excluding 2009.

Figure 2: Probability of Holding a Senior-Level Management Position by Gender



Notes: We plot the percentage of male and female graduates who are holding a senior managerial position over time since graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation.

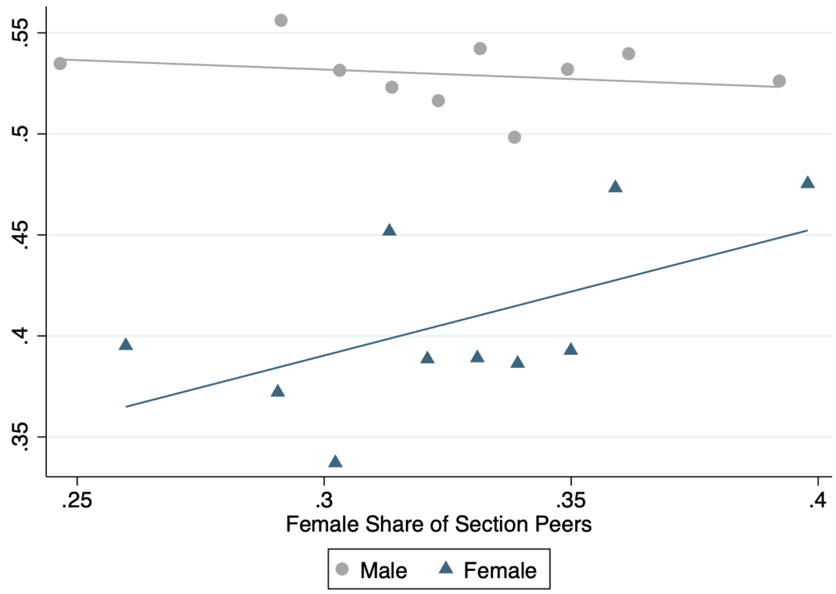
Figure 3: Five-Year Transition Probabilities for First-Level Managers by Gender



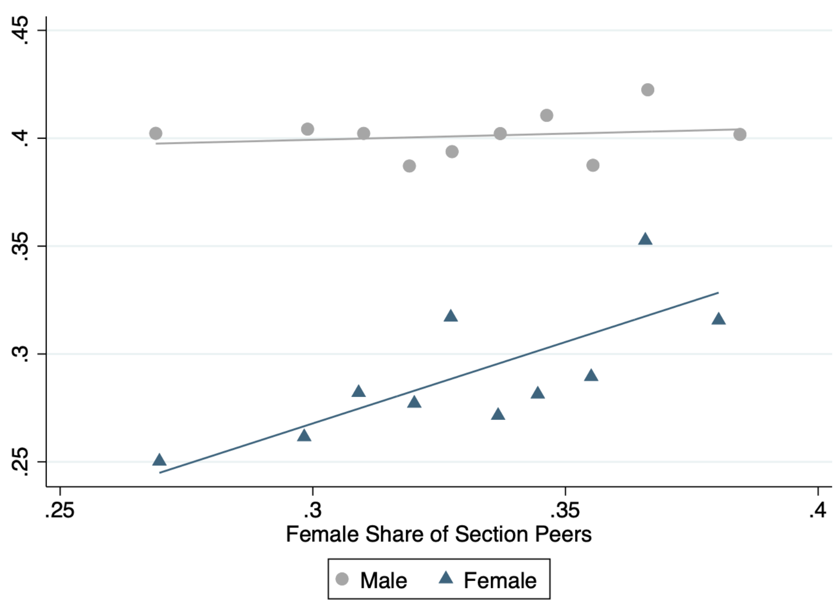
Notes: We plot the five-year transition probabilities from first-level managerial positions to non-employment, non-managerial positions, first-level managerial positions, and senior-level managerial positions by gender. Sample includes first-level managers from graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure 4: Probability of Senior-Level Manager

(a) Only Class Fixed Effects



(b) Controls as in equation (1)

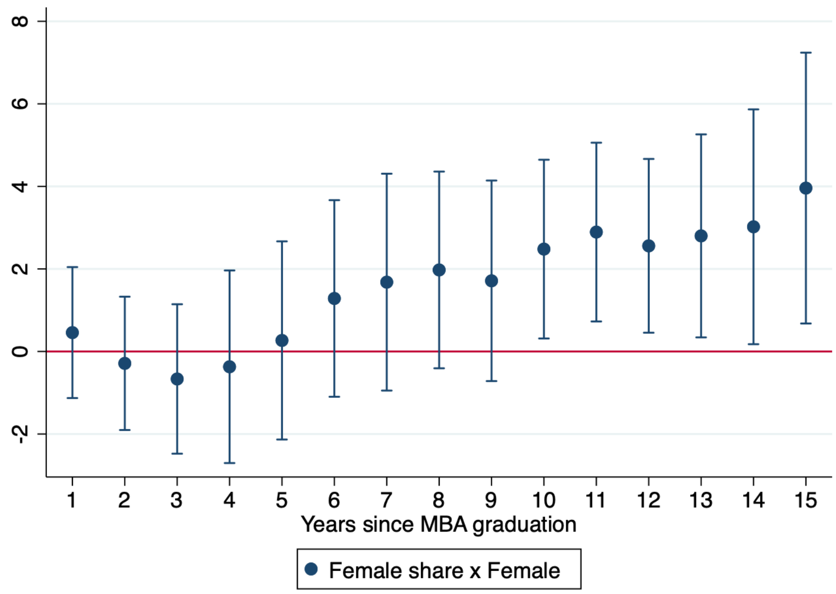


Notes: We plot the binned scatterplot of the relationship between female peers and the probability of becoming a senior manager. In Figure 4a, we control for only class fixed effects. In Figure 4b, both the outcome and female share have been residualized by the full list of controls in our main specification (1). Each dot represents the average likelihood of holding a senior management position within 10-percentile bins of female share. Estimates are separately run for men and women and include class fixed effects, year fixed effects, class-by-year fixed effects, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, indicators for having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign.Sample includes students of graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure 5: Effect of Female Peers on Senior-Level Management Positions By Year Since Graduation

Notes: We plot the coefficients for men and women and their 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is a dummy for holding a senior-level management position. Estimates include class fixed effect, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

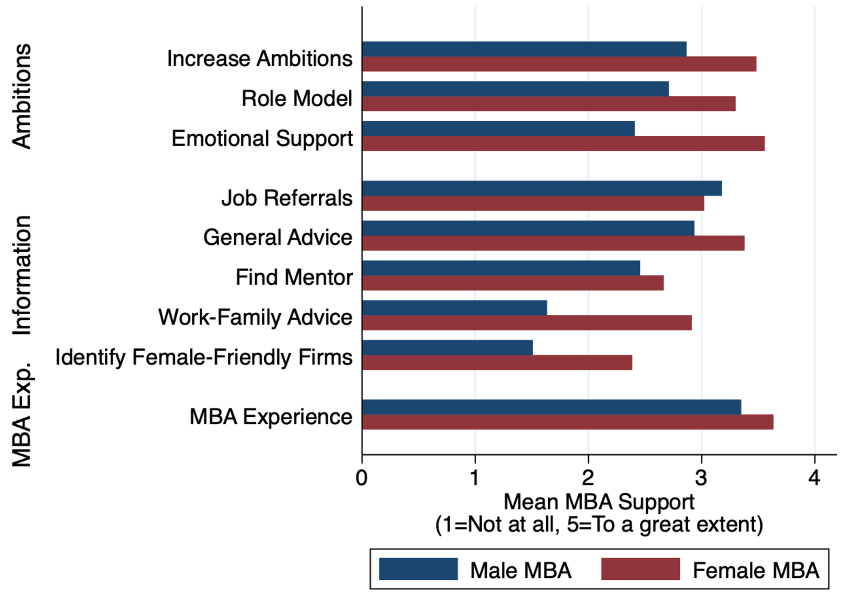
Figure 6: Effect of Female Peers on Working in a Female Friendly Firm by Year Since Graduation



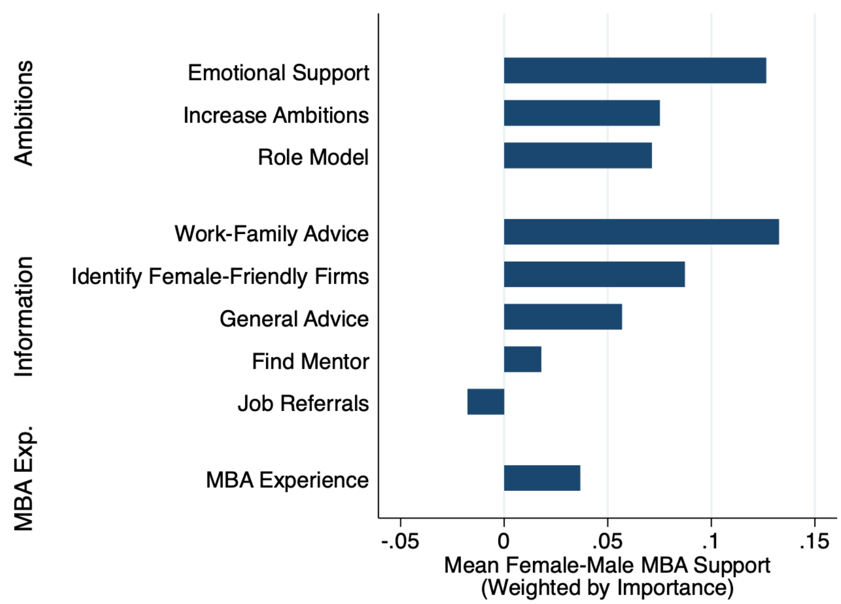
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is a dummy for working in a female-friendly firm. Refer to Table 1 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure 7: MBA Peer Support

(a) MBA Support by Gender

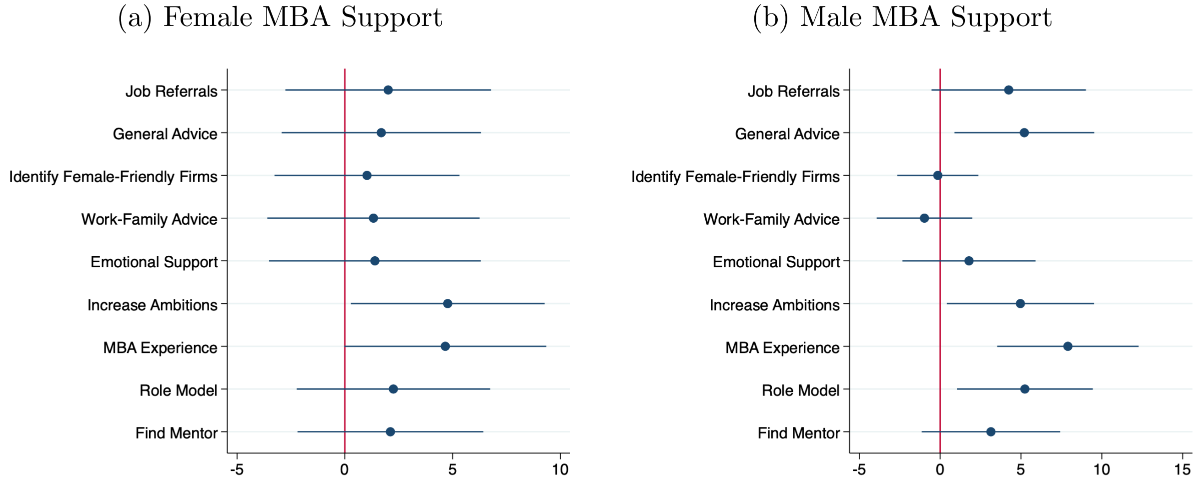


(b) Gender Difference in MBA Support



Notes: Figure 7a presents average survey responses to the question: "To what degree has your female/male MBA network helped your professional career by providing the following types of support (on a scale of 1 to 5, where 1 is not at all and 5 is to a great extent)?" Figure 7b presents the difference in means for female MBA support compared to male MBA support. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009.

Figure 8: Effect of Female Peers on MBA Peer Support



Notes: We present the coefficients and 95% CI from regressing survey responses to types of MBA support on share of female peers and class fixed effects. The dependent variable is based on survey responses to the question: "To what degree has your female/male MBA network helped your professional career by providing the following types of support (on a scale of 1 to 5, where 1 is not at all and 5 is to a great extent)?" Sample includes firms of female survey respondents who graduated in 2000-2018, excluding 2009.

Tables

Table 1: Effect of Female Peers on Senior Management

	(1) Senior-Level Manager	(2) Senior-Level Manager	(3) Senior-Level Manager	(4) Senior-Level Manager
Female share × Male	-0.0885	-0.0903	-0.102	0.0315
	(0.0916)	(0.0917)	(0.0937)	(0.115)
Female share × Female	0.674***	0.673***	0.681***	0.822***
	(0.182)	(0.182)	(0.183)	(0.204)
p-value Male vs. Female	0.000	0.000	0.000	0.000
Female Mean	0.391	0.391	0.391	0.391
Male Mean	0.534	0.534	0.534	0.534
R^2	0.166	0.166	0.172	0.173
N	51440	51440	51440	51440
Class x Year x Female FE	Yes	Yes	Yes	Yes
Stratification Controls	No	Yes	Yes	Yes
Pre-MBA Characteristics Controls	No	No	Yes	Yes
Section-level Controls	No	No	No	Yes

Notes: We present the coefficients for men and women from estimating equation (1) pooling together all years since graduation. The dependent variable is a dummy for holding a senior-level management position. Column (1) includes class fixed effects, year fixed effects, a female dummy, and their interactions. In Column (2) we also control for an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking and its interaction with a female dummy. Column (3) also includes indicators for having any senior management experience, having worked in finance, as well as their interactions with a female dummy. Column (4) is our preferred specification and it also includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Effect of Female Peers on Probability of Senior Management in Female-Friendly Firms

	Senior Manager		
	(1) Female-Friendly Firms	(2) Non-Female-Friendly Firms	(3) Female-Friendly Firms
Female share × Female	1.243***	-0.468	0.857
	(0.394)	(0.402)	(0.915)
Female Mean	0.161	0.118	0.532
Male Mean	0.238	0.186	0.542
R^2	0.167	0.242	0.123
N	28505	28505	28505
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. The dependent variables are holding a senior-level management position in a female-friendly firm (Column 1), holding a senior-level management position in a non female-friendly firm (Column 2), and working in a female-friendly firm (Column 3). Estimates include class fixed effects, year fixed effects class-by-year fixed effects, indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. We also control for the following section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effects of Female Peers on the Work Impacts of Children

	(1) Any Effects of Children on Work Choices	(2) Any Adverse Effects of Children at Work
Female share	-1.267**	-1.733*
	(0.600)	(1.032)
Class FE	Yes	Yes
Mean	0.918	0.753
SD	0.276	0.433
R^2	0.196	0.123
N	139	139

Notes: Table 3 presents the coefficients from regressing a dummy for experiencing any effect of children on work choices (see categories in Figure L.2) and a dummy for experiencing any adverse effect at work due to having children (see categories in Figure L.3) on the share of female peers and class fixed effects. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Probability of Entering the Same Firm

	(1)
Same Section	0.000071
	(0.000264)
Same Section × Both Males	-0.000092
	(0.000333)
Same Section × Both Females	0.001260**
	(0.000640)
p-value Both Male vs. Both Female	.034460
Female Mean	.006549
Male Mean	.006420
R^2	.040879
N	11,991,054
Class x Year FE	Yes
Firm FE	Yes

Notes: We present the coefficients for men and women from estimating equation (2). Estimates include class fixed effects, year fixed effects, class-by-year fixed effects, and firm fixed effects. Dataset is created by matching each MBA graduate (from graduating classes 2000-2018, excluding 2009) with all possible classmates of the same graduating year. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Probability of Entering the Same Firm by Firm Type

	(1)
Same Section × Both Males	0.000059
	(0.000473)
Same Section × Both Males × Female-Friendly Firm	-0.000215
	(0.000660)
Same Section × Mixed Gender	-0.000644
	(0.000487)
Same Section × Mixed Gender × Female-Friendly Firm	0.000428
	(0.000707)
Same Section × Both Females	-0.000118
	(0.000946)
Same Section × Both Females × Female-Friendly Firm	0.002810**
	(0.001430)
p-value Both Male vs. Both Female	.055300
Female Mean	.006549
Male Mean	.006420
R^2	.050743
N	7,623,733
Class x Year FE	Yes
Firm FE	Yes

Notes: We present the coefficients for men and women from estimating equation (2). In this specification, we additionally interact the coefficients in equation (2) with an indicator of whether a firm is female-friendly. Estimates include class fixed effects, year fixed effects, class-by-year fixed effects, and firm fixed effects. Dataset created by matching each MBA graduate (from graduating classes 2000-2018, excluding 2009) with all possible classmates of the same graduating year. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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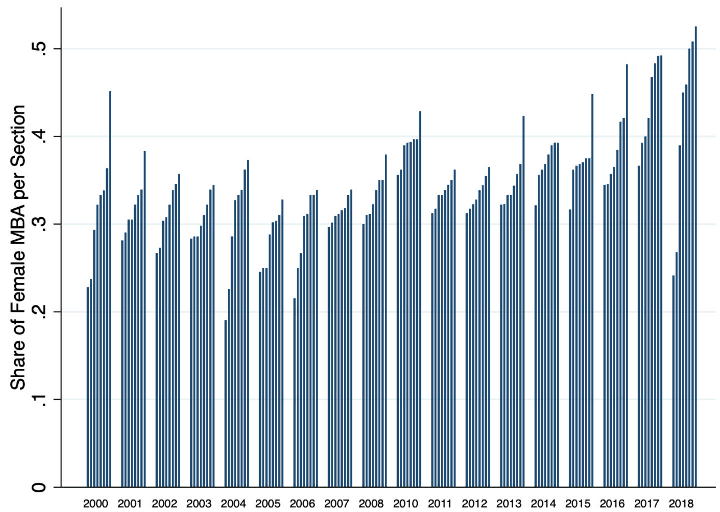
A Appendix Figures and Tables

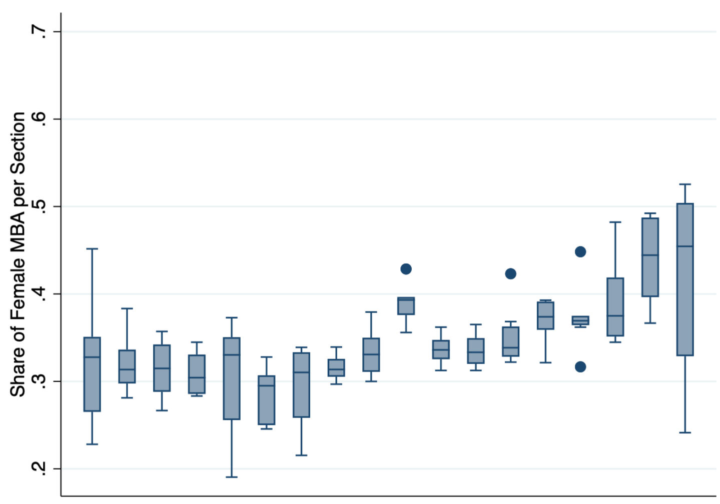
Appendix Figures

Figure A.1: Distribution of Female Share across Sections by Graduating Cohort

(a) Histogram

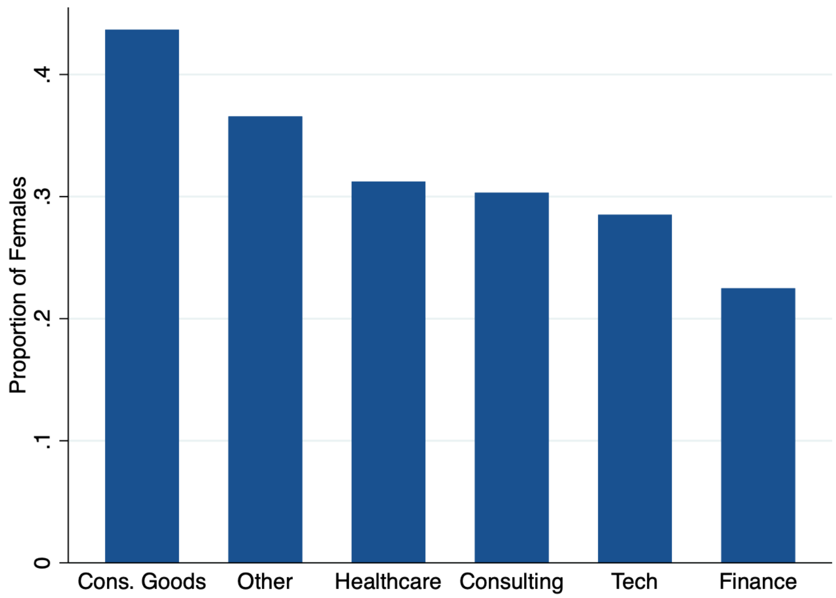


(b) Boxplot



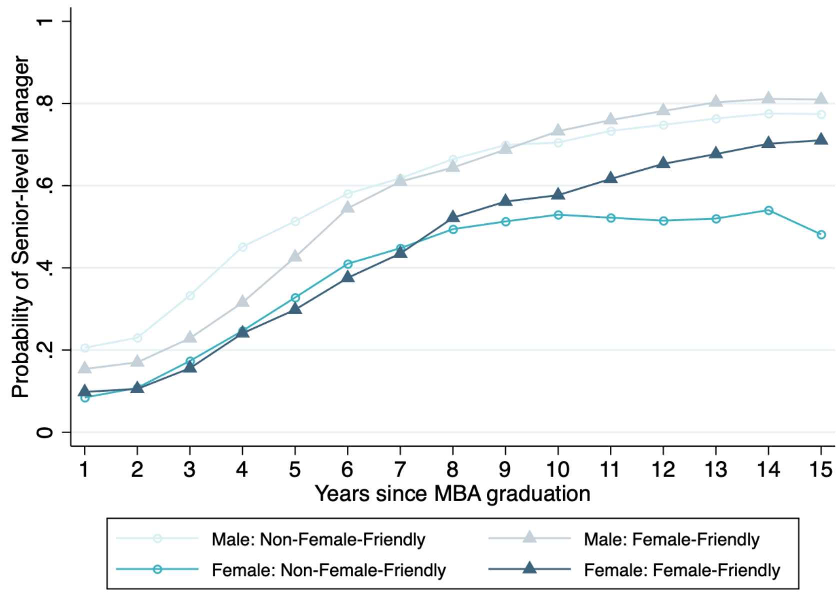
Notes: In Figure A.1, we plot the share of female MBA graduates per section by graduating year. In Figure A.1b, we plot the boxplot of share of female MBA graduates by graduating year. The sample includes graduating students from classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation.

Figure A.2: Female Representation by Industry



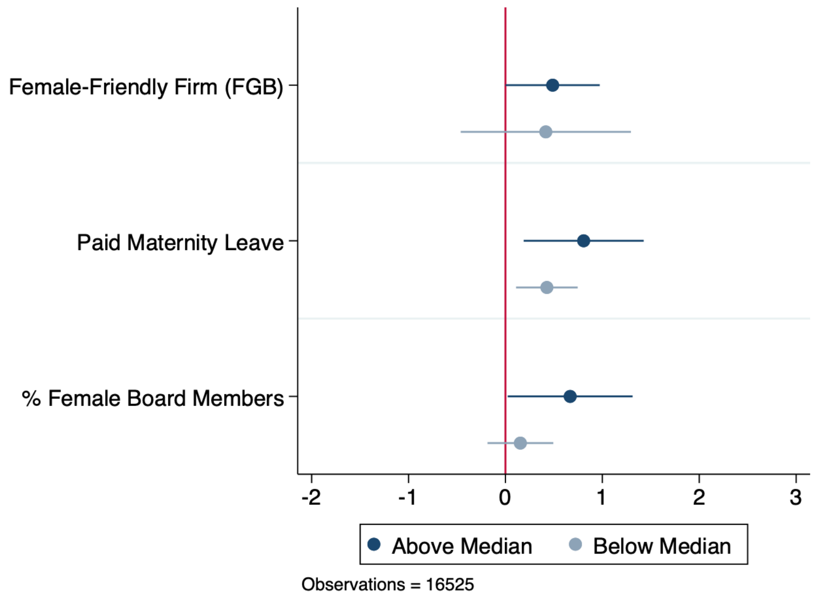
Notes: We plot the share of female graduates by industry. The sample includes graduates from classes 2000-2018, excluding 2009. The survey sample includes students from the graduating classes 2000-2015, excluding 2009. Observations are restricted to the first 15 years since graduation.

Figure A.3: Probability of Holding a Senior-Level Management Position by Gender and Female-Friendly Firms



Notes: We plot the percentage of male and female graduates who are holding a senior managerial position over time since graduation. We compare this percentage in female-friendly versus non-female-friendly firms. The sample includes students of the graduating classes 2000-2018, excluding 2009. The observations are restricted to the first 15 years since graduation.

Figure A.4: Senior Manager in Female-Friendly Firms: Alternative Measures



Notes: We plot the coefficients for $FemaleShare \times Female$ from estimating equation (1), pooling together all years since graduation. Each coefficient is the result of a separate estimation where the outcome variable is one of the alternative measures of female-friendly firms: firm rating from FairyGodBoss (FGB), weeks of paid maternity leave, or percentage of board members that are female. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Tables

Table A.1: Summary Statistics by Job Title (Survey Data)

	(1) Individual Cont	(2) Manager	(3) VP/Director	(4) SVP/C-Level
Total Reports	2.12	10.79	20.66	36.43
	(2.95)	(17.33)	(38.47)	(42.38)
Direct Reports	0.75	1.82	4.10	6.23
	(2.12)	(2.26)	(7.30)	(4.93)
Indirect Reports	1.38	9.03	16.55	30.20
	(2.56)	(17.22)	(37.41)	(40.22)
Firm Hierarchy (1=Lowest, 5=Highest)	2.50	2.82	3.35	4.30
	(0.76)	(0.45)	(0.59)	(0.65)
Weekly Hours	44.38	47.56	48.69	49.83
	(16.57)	(10.44)	(10.52)	(12.21)
Total Compensation	246428.57	247916.67	333139.53	541666.67
	(65237.66)	(108294.41)	(179519.04)	(289562.00)

Notes: Summary statistics by job title: individual contributor (Column 1), manager (Column 2), VP/Director (Column 3), and SVP/C-Level executive (Column 4). Means and standard errors in parentheses are reported. Data from survey. Sample includes female graduates of the graduating classes 2000-2018, excluding 2009.

Table A.2: Summary Statistics – Demographics and Pre-MBA Background

	All	Male	Female	Difference p-value in par.
A. Demographics				
Female	0.36			
	(0.48)			
Age	29.88	30.20	29.35	0.85**
	(1.98)	(2.06)	(1.73)	(0.00)
U.S. Citizen	0.65	0.62	0.70	-0.08**
	(0.48)	(0.49)	(0.46)	(0.00)
Race				
White	0.65	0.69	0.59	0.11**
	(0.48)	(0.46)	(0.49)	(0.00)
Asian	0.20	0.17	0.25	-0.07**
	(0.40)	(0.38)	(0.43)	(0.00)
Black / Hispanic	0.13	0.12	0.14	-0.03*
	(0.33)	(0.32)	(0.35)	(0.06)
Other	0.02	0.01	0.02	-0.01
	(0.13)	(0.12)	(0.15)	(0.12)
GMAT	716.45	720.76	709.04	11.72**
	(35.70)	(33.84)	(37.57)	(0.00)
B. Pre-MBA Background				
Pre-MBA Years of Experience	5.00	5.10	4.80	0.30**
	(1.95)	(1.98)	(1.87)	(0.00)
Any Management Experience	0.39	0.38	0.41	-0.02
	(0.49)	(0.49)	(0.49)	(0.13)
Any Senior-Level Management Experience	0.13	0.14	0.12	0.02*
	(0.34)	(0.35)	(0.32)	(0.05)
Average Total Compensation (Imp.) ('000s)	123.35	132.85	106.97	25.89**
	(120.74)	(134.42)	(90.29)	(0.00)
Worked in Male-Dominated Industry	0.63	0.64	0.61	0.03*
	(0.48)	(0.48)	(0.49)	(0.07)
Top-20 Undergrad	0.29	0.26	0.34	-0.07**
	(0.45)	(0.44)	(0.47)	(0.00)

Notes: Summary statistics reported for full sample, male students only, and female students only. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the male-female difference. The *p*-value of the two sample t-tests is reported in parentheses. Data in panel A: Demographics come from the school administrative dataset. Data in panel B: Pre-MBA Background comes from the public LinkedIn profile dataset with the exception of (i) average total compensation (imp.), which comes from the Glassdoor dataset, and (ii) top-20 undergrad, which comes from the school administrative dataset. Except for pre-MBA years of experience, the statistics are measured two to five years prior to MBA graduation, i.e., the three years prior to entry into the MBA program. For pre-MBA experience, we use the total number of years with work experience listed on the online profile for the 10 years prior to the MBA. Top-20 undergraduate programs are defined by the top-20 universities ranked by U.S. News in 2020. These universities are the Ivy League universities, as well as MIT, Stanford, University of Chicago, Caltech, Johns Hopkins, Northwestern, Duke, Vanderbilt, Rice, Washington University in St. Louis, University of Notre Dame, and UCLA. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Summary Statistics – Academic and Career Outcomes

	All	Male	Female	Difference p-value in par.
A. Academic Outcomes (Person Level)				
Overall GPA	3.52	3.54	3.48	0.06**
	(0.27)	(0.28)	(0.27)	(0.00)
Overall Core GPA	3.40	3.45	3.33	0.12**
	(0.36)	(0.36)	(0.35)	(0.00)
Fraction Finance Classes	0.15	0.17	0.12	0.05**
	(0.11)	(0.11)	(0.08)	(0.00)
B. Career Outcomes (Person-Year Level)				
Any Management Role	0.75	0.75	0.75	0.00
	(0.43)	(0.43)	(0.44)	(0.47)
Senior-Level Manager	0.43	0.47	0.34	0.14**
	(0.50)	(0.50)	(0.47)	(0.00)
Employed	0.99	0.99	0.99	0.01**
	(0.09)	(0.07)	(0.12)	(0.00)
Cumulative Months of Nonemployment	0.57	0.40	0.91	-0.51**
	(3.56)	(2.77)	(4.76)	(0.00)
Base Compensation (Imp.) (000's)	133.00	141.53	117.37	24.16**
	(52.00)	(53.18)	(45.82)	(0.00)
Total Compensation (Imp.) (000's)	223.31	253.25	168.42	84.83**
	(315.35)	(371.37)	(155.85)	(0.00)
Male-Dominated Industry	0.59	0.64	0.48	0.15**
	(0.49)	(0.48)	(0.50)	(0.00)
Firm Size	5888.06	5706.69	6261.87	-555.18**
	(4453.50)	(4475.86)	(4383.98)	(0.00)
Female-Friendly Firm	0.74	0.74	0.74	0.00
	(0.44)	(0.44)	(0.44)	(0.90)
P&L Role	0.60	0.60	0.60	0.00
	(0.49)	(0.49)	(0.49)	(0.60)

Notes: Summary statistics reported for full sample, male students only and female students only. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the male-female difference. The p-value of the two sample t-tests is reported in parentheses. Data in panel A: Academic Outcomes come from the school administrative dataset. Data is at the person level. Data in panel B: Career Outcomes come from the public LinkedIn profile dataset with the exception of (i) base compensation (imp.) and total compensation (imp.), that comes from the Glassdoor dataset, (ii) firm size that come from the LinkedIn company profile dataset, and (iii) female-friendly firm rating (1-5), that come from the InHerSight.com dataset. We define male-dominated industries as those with a share of female employees below 30% in our sample, that is finance, tech, and consulting. We define a firm to be female-friendly if it has an above-median overall rating on InHerSight.com. Data is at the person-year level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Gender Gap in Senior Management: Pooled Sample (Detailed Controls)

	(1)	(2)	(3)
Female	-0.128***	-0.126***	-0.122***
	(0.014)	(0.014)	(0.014)
Pre-MBA Experience		-0.000	0.001
		(0.004)	(0.004)
Pre-MBA Management Experience		0.005	0.013
		(0.018)	(0.018)
Pre-MBA Senior-Level Management Experience		0.097***	0.088***
		(0.021)	(0.021)
Top-20 Undergrad		-0.006	-0.009
		(0.015)	(0.015)
Worked in P&L Role		-0.022	-0.013
		(0.016)	(0.016)
Pre-MBA Firm Size		-0.000	-0.000
		(0.000)	(0.000)
Worked in Finance			0.074***
			(0.018)
Worked in Consulting			0.034
			(0.021)
Worked in Consumer Goods			-0.022
			(0.023)
Worked in Healthcare			-0.008
			(0.028)
Worked in Tech			-0.005
			(0.018)
Worked in Other Industries			0.006
			(0.018)
Class x Year FE	Yes	Yes	Yes
Mean	0.490	0.490	0.490
Mean (Male)	0.543	0.543	0.543
R^2	0.219	0.224	0.229
N	27309	27309	27309

Notes: We present the coefficients from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and pre-MBA characteristics using the pooled sample. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Section-Level Characteristics Correlated with Higher Proportion of Female Peers

Section Characteristics	(1) Full Sample	(2) Mean for Above-Median Female Share Sections	(3) Mean for Below-Median Female Share Sections	(4) Coefficient	(5) p-value
Share of Section with ...					
Pre-MBA Years of Experience	5.024	5.062	4.982	0.001	0.975
Any Management Experience	0.405	0.413	0.396	0.114	0.015**
Any Senior-Level Management Experience	0.131	0.135	0.126	0.196	0.021**
Entrepreneur	0.024	0.024	0.024	-0.199	0.275
Finance	0.338	0.318	0.361	-0.145	0.021**
Consulting	0.173	0.178	0.168	-0.128	0.043**
Consumer Goods	0.117	0.125	0.109	0.141	0.063*
Healthcare	0.056	0.051	0.061	-0.062	0.582
Tech	0.201	0.193	0.209	-0.031	0.551
Other Industries	0.374	0.388	0.360	0.120	0.027**
Less than 200 Employees	0.223	0.220	0.226	-0.038	0.508
200-4,999 Employees	0.220	0.217	0.223	0.064	0.292
5,000+ Employees	0.727	0.728	0.726	-0.108	0.062*
Worked in Female-Friendly Firm	0.746	0.736	0.757	-0.025	0.631
Worked in a P&L Role	0.429	0.446	0.410	0.148	0.003***
U.S. Locality	0.772	0.775	0.770	0.157	0.034**
Top-20 Undergrad	0.249	0.251	0.247	0.097	0.231
White	0.433	0.439	0.427	0.267	0.007***
Foreign	0.308	0.295	0.321	-0.486	0.000***
Observations	148	77	71	148	148

This table presents section-level summary statistics for the full sample (Column 1), for sections with above-median female share (Column 2), and for sections with below-median female share (Column 3). Column 4 reports the coefficient from a bivariate regression of female share in the section on the variable in the row header and a constant term. Column 5 reports the associated p-value (based on heteroskedasticity-robust standard errors). All results based on all sections in the baseline sample for the graduating classes 2000-2018, excluding 2009. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Effect of Female Peers on Likelihood of Holding a Senior Management Position by Year Since Graduation

	(1) Year 1	(2) Year 3	(3) Year 5	(4) Year 7	(5) Year 9	(6) Year 11	(7) Year 13	(8) Year 15
Female share × Male	0.0765	0.0331	-0.370*	-0.0164	0.166	0.235	0.340	-0.196
	(0.139)	(0.209)	(0.199)	(0.246)	(0.227)	(0.225)	(0.221)	(0.221)
Female share × Female	0.300	0.754***	0.686**	1.251***	1.127***	0.367	1.338***	1.140***
	(0.211)	(0.272)	(0.291)	(0.339)	(0.407)	(0.376)	(0.457)	(0.412)
p-value Male vs. Female	0.398	0.035	0.001	0.002	0.023	0.746	0.033	0.001
Female Mean	0.137	0.214	0.363	0.460	0.546	0.581	0.591	0.593
Male Mean	0.228	0.328	0.501	0.634	0.685	0.726	0.741	0.741
R^2	0.065	0.056	0.049	0.051	0.041	0.037	0.042	0.042
N	4972	4568	4236	3700	3212	2641	2302	1660
Class x Female FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for men and women from estimating equation (1) separately for each year since graduation. The dependent variable across all columns is holding a senior-level management position. Estimates include class fixed effect, an indicator for having attended a top-20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, finance experience, consulting experience, other industry experience, PL experience, U.S. locality, and those with white and/or foreign backgrounds. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effect of Female Peers on Senior Management and Firm Size

	Senior Manager		
	(1) Firm with Less than 200 Employees	(2) Firm with 200 to 4,999 Employees	(3) Firm with More than 5,000 Employees
Female share × Female	0.171*	0.0258	0.495**
	(0.0878)	(0.161)	(0.219)
Female Mean	0.064	0.089	0.240
Male Mean	0.106	0.115	0.313
R^2	0.035	0.037	0.089
N	45169	45169	45169
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are a dummy for holding a senior-level management position in a firm with less than 200 employees (Column 1), holding a senior-level management position in a firm with 200–4,999 employees (Column 2), and holding a senior-level management position in a firm with more than 5,000 employees (Column 3). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Effects of Female Peers on Firm Size

	(1) Number of Employees	(2) Less than 200 Employees	(3) 200 to 4,999 Employees	(4) More than 5,000 Employees
Female share × Female	-1673.1	-0.0449	-0.0246	0.0589
	(2178.0)	(0.164)	(0.176)	(0.246)
Female Mean	5975.751	0.158	0.147	0.678
Male Mean	5484.606	0.183	0.171	0.641
R^2	0.051	0.024	0.023	0.043
N	44759	45171	45171	45171
Class x Year x Female FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are number of employees (Column 1), a dummy for working at a firm with fewer than 200 employees (Column 2), a dummy for working at a firm with 200 to 4,999 employees (Column 3), and a dummy for working at a firm with more than 5,000 employees (Column 4). Data on firm size comes from LinkedIn company profiles. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Effect of Female Peers on Senior Management and Firm Compensation

	Senior Manager	
	(1) Firm with Total Compensation Above Median	(2) Firm with Total Compensation Below Median
Female share × Female	0.541	0.244
	(0.494)	(0.286)
Female Mean	0.178	0.061
Male Mean	0.309	0.081
R^2	0.239	0.127
N	34459	34459
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are a dummy for being a senior manager in a firm with above-median total compensation (Column 1) and a dummy for being a senior manager in a firm with below-median total compensation (Column 2). Data on compensation comes from Glassdoor. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Effect of Female Peers on Firm Compensation

	(1)	(2)
	Total Annual Compensation ('000s)	Senior Manager Total Annual Compensation ('000s)
Female share × Female	-639.4	-9252.0
	(425.9)	(5824.0)
Female Mean	152.985	361.564
Male Mean	206.503	980.066
R^2	0.013	0.015
N	34461	27582
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are firm-level average total annual compensation in thousands (Column 1) and firm-level average total annual compensation for senior managers in thousands (Column 2). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Effect of Female Peers on Senior Management Controlling for Firm Size and Firm Average Compensation

	Senior Manager	
	(1)	(2)
	Main Result	Additional Controls
Female share × Female	0.822***	0.622**
	(0.204)	(0.283)
Female Mean	0.391	0.391
Male Mean	0.534	0.534
R^2	0.173	0.260
N	51440	30257
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variable is holding a senior-level management position in both columns. Refer to Table 1 for the full set of control variables in Column (1). Additional controls in Column (2) include number of employees in the firm and total average annual compensation at the firm, plus all their interactions with the gender dummy. The difference in number of observations is due to missing data on firm size and compensation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Effect of Female Peers on P & L Functions

	Senior Manager	
	(1) P & L Functions	(2) P & L Functions
Female share × Female	0.461**	0.106
	(0.213)	(0.221)
Female Mean	0.264	0.598
Male Mean	0.363	0.612
R^2	0.108	0.026
N	43860	43860
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are having a senior management role with P&L responsibilities (Column 1) and having any P&L responsibilities (Column 2). Appendix Section B.6 provides details on how we identify job functions and classify P&L positions. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Effect of Female Peers on Probability of Senior Management in Male- and Female-Dominated Industries

	Senior Manager		
	(1) Male-Dominated Industries	(2) Female-Dominated Industries	(3) Male-Dominated Industries
Female share × Female	0.605**	-0.0269	0.243
	(0.243)	(0.107)	(0.260)
Female Mean	0.201	0.074	0.483
Male Mean	0.344	0.072	0.626
R^2	0.097	0.033	0.037
N	45389	45389	45391
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are holding a senior-level management position in a male-dominated industry (Column 1), holding a senior-level management position in a female-dominated industry (Column 2), and working in a male-dominated industry (Column 3). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. The p-value from a test of the pairwise difference of the coefficient $Femaleshare \times Female$ in Column (1) and (2) is 0.0297. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Effect of Female Peers on Employment and Career Breaks

	(1) Employed	(2) Cumulative Months In Nonemployment
Female share × Female	-0.0154	4.502
	(0.0487)	(4.795)
Female Mean	0.985	1.707
Male Mean	0.995	0.633
R^2	0.025	0.077
N	49991	51482
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are being employed, defined as having an ongoing position on the LinkedIn profile (Column 1), and total cumulative months in nonemployment since graduation (Column 2). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: Effect of Female Peers on Likelihood of Holding Any Management Position

	(1) Any-Level Manager
Female share × Female	0.229
	(0.182)
Female Mean	0.744
Male Mean	0.767
R^2	0.058
N	51440
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. The dependent variable is a dummy for holding any management position. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16: Effect of Female Peers on Entrepreneurship

	(1) Entrepreneurship
Female share × Female	-0.184
	(0.111)
Female Mean	0.035
Male Mean	0.040
R^2	0.019
N	51451
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variable is a dummy for being an entrepreneur. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Effect of Female Peers on Probability of Senior Management Conditioned on the Type of Firm

	Senior Manager	
	(1) Female-Friendly Firms	(2) Non-Female-Friendly Firms
Female share × Female	1.190***	-0.418
	(0.418)	(0.831)
Female Mean	0.303	0.252
Male Mean	0.439	0.407
R^2	0.314	0.504
N	20893	7612
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variable for both specifications is holding a senior-level management position. Column (1) restricts to only individuals working in female-friendly firms, while Column (2) restricts to only individuals in non-female-friendly firms. Refer to Table 1 for the full set of control variables. Data is at the individual level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. The p-value from a test of the pairwise difference of the coefficient $Femaleshare \times Female$ in Column (1) and (2) is 0.0141. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Effect of Female Peers on Senior Manager in Female-Friendly Firms: Alternative Measures

	Female-Friendly Firm (FGB)		Firm with Paid Maternity Leave		Firm with % Female Board Members	
	(1)	(2)	(3)	(4)	(5)	(6)
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Female share × Female	0.487*	0.417	0.807**	0.428***	0.668**	0.154
	(0.248)	(0.448)	(0.316)	(0.162)	(0.329)	(0.173)
Female Mean	0.084	0.152	0.245	0.062	0.263	0.070
Male Mean	0.128	0.223	0.341	0.095	0.346	0.145
R^2	0.092	0.189	0.177	0.068	0.143	0.085
N	18050	18050	19279	19279	16525	16525
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. The dependent variable is holding a senior-level management position in a female-friendly or non-female-friendly firm based on alternative measures of female-friendliness: female-friendly firm rating based on FairyGodBoss (Columns 1-2), weeks of paid maternity leave (Columns 3-4), and percentage of female board members (Columns 5-6). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19: Effect of Female Peers on Probability of Senior Management in Female-Friendly Firms (Restricted to Large Firms)

	Senior Manager		
	(1) Female-Friendly Firms	(2) Non-Female-Friendly Firms	(3) Female-Friendly Firms
Female share × Female	1.158***	-0.546	1.018
	(0.416)	(0.436)	(0.895)
Female Mean	0.164	0.123	0.503
Male Mean	0.246	0.186	0.532
R^2	0.176	0.260	0.151
N	23352	23352	23352
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are holding a senior-level management position in a female-friendly firm (Column 1), holding a senior-level management position in a non-female-friendly firm (Column 2), and working in a female-friendly firm (Column 3). All specifications are restricted to individuals working in a large firm (>5,000 employees). Refer to Table 1 for the full set of control variables. Data is at the individual level. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.20: Effect of Female Peers on GPA during MBA

	(1) Overall GPA	(2) Core Classes GPA
Female share × Female	-0.103	-0.0181
	(0.112)	(0.150)
Female Mean	3.482	3.332
Male Mean	3.541	3.450
R^2	0.067	0.076
N	3425	2522
Class x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1). The dependent variables are overall GPA (Column 1) and GPA in core classes (Column 2). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.21: Effect of Female Peers on Choice of Elective Classes

	(1) Finance	(2) International Business	(3) Management	(4) Marketing	(5) Management and Organizations	(6) Operations	(7) Social Enterprise	(8) Other
Female share × Female	-0.0519	0.0285	0.0410**	0.0539	-0.00160	-0.0682***	0.0115	-0.000883
	(0.0561)	(0.0236)	(0.0176)	(0.0521)	(0.0257)	(0.0234)	(0.0206)	(0.00428)
Female Mean	0.129	0.062	0.057	0.198	0.111	0.053	0.071	0.021
Male Mean	0.203	0.047	0.070	0.142	0.094	0.061	0.066	0.021
R^2	0.182	0.247	0.335	0.133	0.176	0.047	0.620	0.398
N	3425	3425	3425	3425	3425	3425	3425	3425
Class x Female FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1). The dependent variables are share of elective classes in each of the fields. "Other" includes elective classes taken by less than 5% of the students across graduating classes 2011-2018. These classes are: Accounting, Business Law, Decision Sciences, Entrepreneurship, Health Management, Architectures of Collaboration Initiative, Innovation and Entrepreneurship Initiative, Markets and Customers Initiative, Public-Private Initiative, Managerial Economics, Media Management, Real Estate, Strategy, and Data Science. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.22: Effect of Female Peers on First Post-MBA Placement

	(1) Senior-Level Manager	(2) Male-Dominated Industries	(3) Female-Friendly Firms	(4) Number of Employees	(5) Firm Annual Compensation ('000s)
Female share × Female	0.300	-0.132	0.458	38.34	-12.19
	(0.211)	(0.257)	(0.810)	(3580.8)	(136.2)
Female Mean	0.137	0.522	0.500	7018.639	154.070
Male Mean	0.228	0.671	0.587	6398.706	163.300
R^2	0.065	0.045	0.137	0.034	0.033
N	4972	4538	3239	4443	3580
Class x Female FE	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) the first year post MBA. The dependent variables are holding a senior-level management position (Column 1), working in a male-dominated industry (Column 2), working in a female-friendly firm (Column 3), number of employees at the firm of the first job placement (Column 4), and average total annual compensation in thousands at the firm of the first job placement (Column 5). Refer to Table 1 for the full set of control variables. Data is at the individual level, restricted to the first year post MBA. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.23: Effect of Female Peers on Compensation

	(1) Log Total Annual Compensation (Imp.)	(2) Log Base Annual Compensation (Imp.)	(3) Log Non-Base Annual Compensation (Imp.)
Female share × Female	0.417	-0.146	3.176***
	(0.449)	(0.339)	(1.093)
Female Mean	11.591	11.375	9.640
Male Mean	11.966	11.622	10.465
R^2	0.270	0.268	0.215
N	26567	26567	26567
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are log total imputed annual compensation (Column 1), log imputed base annual compensation (Column 2), and log imputed non-base annual compensation (Column 3). Imputation of compensation is based on firm, gender, and management position using the Glassdoor data. See Section B.4 for additional details on the imputation method. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Data Appendix

B.1 Description of Business School Administrative Data

The administrative data set is comprised of five sources of individual-level information between 2011 and 2018: (1) demographics which include gender, ethnicity, citizenship, and age; (2) pre-MBA educational background, which includes all prior degrees, GMAT scores, and previous GPA; (3) employment information, which includes pre- and post-career outcomes and associated industry, base salary, and bonus compensation; (4) coursework taken and grades; and (5) section assignment. This dataset was created via merging of several administrative datasets from different departments such as the registrar and career services.

B.2 Description of LinkedIn Data

LinkedIn is a social media platform used primarily for professional networking. It allows job seekers to post their CVs and employers to post jobs. The platform is widely used with over 740 million members worldwide in 2021. In the United States, there are over 170 million users (Osman, 2021). It is popular among professionals, with 50% of the users holding a college degree (Osman, 2021).

Users create online public profiles that contain CV information. This contains information on all previous work experience, including job title, employer, location, job descriptions, and start and end dates. Individuals can also post education and training, skills, and a personal photo. In addition, individuals can connect with other users on the platform in an online social network. In our analysis, we use the work and education background information.

Moreover, the platform also has public company pages. These pages contain information on the company website, industry, company size, headquarters location, type (public, private, nonprofit, government), founding year, and specialties. On individual profiles, the employer is often linked to one of these company pages. We use these pages to construct a unique employer identifier, as different firm aliases will often be linked to the same company profile.

We collected this data in May and June of 2019. As a result, the CV information is current up to 2019. In our main analysis, we restrict to individuals whose locality is the United States. The data is cleaned by parsing the information on the CV and reshaping the data such that a quarterly panel is created based on the start and end dates of employment.

We expand the data to include observations for when someone is in nonemployment, i.e., periods where there is a gap on the CV between the start and end dates of two consecutive positions. We then collapse the dataset to the yearly level. For each year, individuals are assigned to the position in which they have spent the most time during that year. If there are ties, the position with the longer tenure takes precedence.

One question is since individuals self-report their employment and educational histories, there is a risk that an individual will misreport. While we cannot directly test this in the data, we rationalize that the likelihood of falsifying information on one's public resume is low due to a very credible threat of LinkedIn canceling your account. The platform allows users to file complaints against those who have written inaccurate information on their resumes. This can lead to the threat of getting kicked off of the platform.

B.3 Description of Alumni Directory Data

The alumni directory provides alumni with the opportunity to contact and network with fellow alums. It contains full name, current location, all degrees conferred at the university, MBA section, undergraduate institution, student activities such as club affiliations, and current employer information, including employer name, industry, job title, and start dates. In some cases, alumni also include links to their social media platforms such as personal websites, LinkedIn, or WeChat ID. The directory also facilitates networking by providing a way for alumni to email each other through the platform. Information related to university degrees and sections is pre-filled by the school. Alumni can update their location and employment information at any time. This data was accessed and collected in May and June of 2019 for our analysis.

B.4 Description of Glassdoor Data

Glassdoor is an online platform where employees can anonymously submit salaries and rate their companies. We obtained 10.5 self-reported compensation records for 630,422 firms from 2006 to 2017. Each observation is a salary report with information on the employer, employment status (e.g., regular, part-time, contract), job title, gender of the reviewer, compensation and its components. For compensation, there is the base pay amount and whether the base pay period is denoted annually or monthly. Non-base compensation is also available for cash bonus, stock bonus, profit sharing, sales and commission, and tips.

In our analysis, we use only data from regular employees who reported their annual base pay. Using the same procedure described in Section 3.5, we assign management level using the job titles available in this dataset. We classify all positions into non-management, first-level management, and senior-level management. We then aggregated this data to the firm, gender, and management level by taking the mean base and total (i.e., sum of base plus non-base components) compensation of that corresponding cell. Note that we do not have gender information for 36% of the sample. Once aggregated, we construct the following measures: share of reviews by women (which proxies for female share of employees), share of reviews by senior managers that are women, average (base/total) compensation at the firm level by gender, and average (base/total) compensation for senior managers by gender. Using these measures, we also construct additional outcomes such as the gender gap in compensation. We then match these firm-level statistics to the firms in LinkedIn using the firm name.

We also use this dataset to impute compensation for individuals in the LinkedIn dataset. To do so, we match individuals to the average compensation of their firm based on their gender and management level.

B.5 Description of Female-Friendly Firm Data

B.5.1 InHerSight

Our primary measure of female-friendly firms comes from InHerSight. InHerSight is an online platform that allows women to rate their companies anonymously on a scale of 1 to 5 on 18 metrics in six categories that are designed to capture how well companies support women. These include:

1. Gender Equal Opportunities
    - Equal Opportunities for Women and Men (Promotions, leadership roles, salary increases, incentive programs)
    - Management Opportunities (Your chances of becoming a manager of teams and talent)
    - Women in Leadership (Women on the executive team, in senior leadership)
2. Work Schedule Flexibility
    - Paid Time Off (Sick days, vacation days, and personal days)

- Flexible Work Hours (Ability to set your schedule as long as you get your work done)
- Ability to Telecommute (Flexibility to work remotely)

3. Professional Enrichment

- Wellness Initiatives (On-site gym, gym discounts, walking desks, healthy food options)
- Learning Opportunities (On- and off-site skills training, speaker series, conferences)
- Sponsorship or Mentorship Program (Official mentorship program, women-focused initiatives or affiliate groups)
- Do you feel your growth and success are (or were) priorities for your manager(s) at this company?
- Do you feel you receive (or received) the necessary feedback to succeed at your job and achieve your goals at this organization?

4. Fair Compensation

- Salary Satisfaction (Salary, merit increases, cost of living adjustments, overall comp)
- When reflecting on your salary or pay when you were first hired at this company, do you feel you were paid fairly?

5. Family Friendliness

- Maternity and Adoptive Leave (Paid parental leave policies, job security, support for returning moms)
- Family Growth Support (Access to dedicated lactation rooms, child care, expense reimbursement)
- Does this company support employees caring for other members of their family or extended family other than children?

6. Workplace Culture

- The People You Work With (Respectful, professional, unbiased, all those good things)
- Social Activities and Environment (Happy hours, game room, company outings, and other perks)
- Support for Diversity (People and programs that prioritize diversity, inclusion, equity and belonging)
- Sense of Belonging (Comfortable bringing your whole self to work, you feel included and welcome)
- Employer Responsiveness (Effective channels for elevating issues and concerns)

In addition to the measures listed, InHerSight also creates an overall firm rating based on these metrics from 1 to 5, where 5 is the highest. The website also provides the number of reviews for each firm. In our analysis, we will use the overall rating and the individual components. For the main definition, we classify a firm as female-friendly if it has an above-median overall rating.

We also create standardized indices for each of the six categories by first standardizing each of the components and taking the average. We accessed the data on the website in May 2021 for all available companies. We then matched the companies based on the name to the firms in LinkedIn.

B.5.2 Alternative Data Sources on Female-Friendly Firms

FairyGodBoss

FairyGodBoss is an online crowdsourcing platform that aggregates online reviews and company data for women. The website collects information on the number of paid or unpaid weeks of maternity and paternity leave. It also collects employee reviews. For each firm, there is an overall company rating out of five. We collected the available data on parental leave from the web and then manually searched for the LinkedIn companies on this website to collect the company ratings.

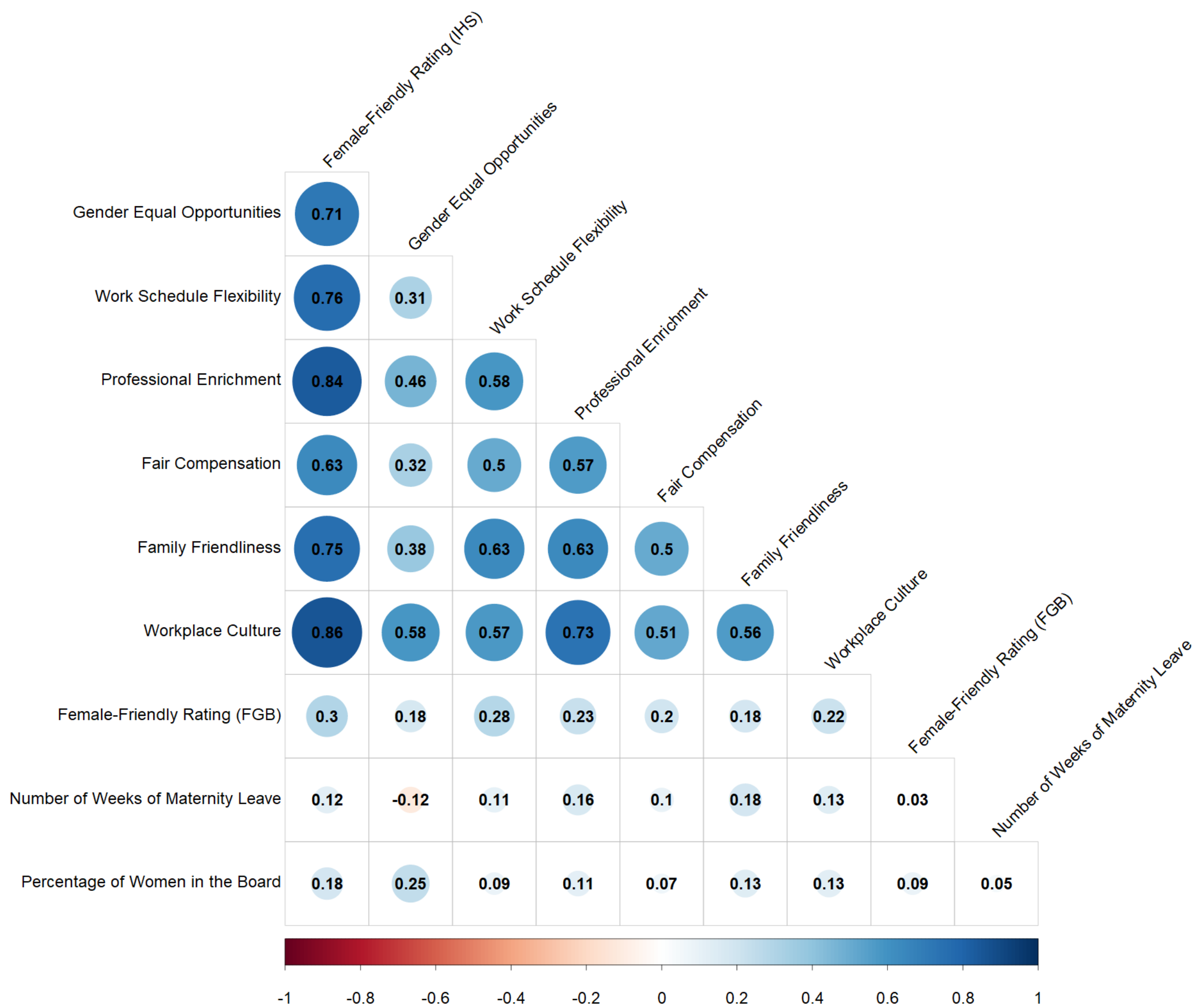
50/50 Women on Boards

50/50 Women on Boards is a nonprofit advocacy group that is committed to advancing women to corporate boards. The group has maintained a web directory, "50/50 Women on Boards Gender Diversity Directory and Index," that tracks the number of women among the corporate board members on the Russell 3000 Index. We downloaded and accessed this directory in May 2021.

B.5.3 Validation of the Female-Friendly Measure

To validate our primary measure of female-friendliness, we explore the correlation among these multiple metrics. Appendix Figure B.1 shows the correlation between the InHerSight overall rating, the InHerSight six standardized indices, the FairyGodBoss overall rating, the FairyGodBoss number of weeks of paid maternity leave, and the percentage of female board members from 50/50 Women On Boards. As expected, the InHerSight measures are highly correlated to each other. Interestingly, the FairyGodBoss overall rating has the highest correlation with the InHerSight overall rating. Similarly, the FairyGodBoss number of weeks of paid maternity leave has the highest correlation with the InHerSight index related to family-friendliness, which includes rating on maternity and paternity leave. Finally, the percentage of female board members from 50/50 Women On Boards has the highest correlation with the InHerSight index related to gender equal opportunities, which includes metrics such as female representation in leadership and management opportunities.

Figure B.1: Correlation Across Female-Friendliness Measures



Notes: We plot the correlation between female-friendly measures across multiple dataset: (i) the overall rating and the six standardized indices from InHerSight.com, (ii) the overall rating and number of paid weeks of maternity leave from FairyGodBoss.com, and (iii) the percentage of female board members from 50/50 Women on Boards. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation.

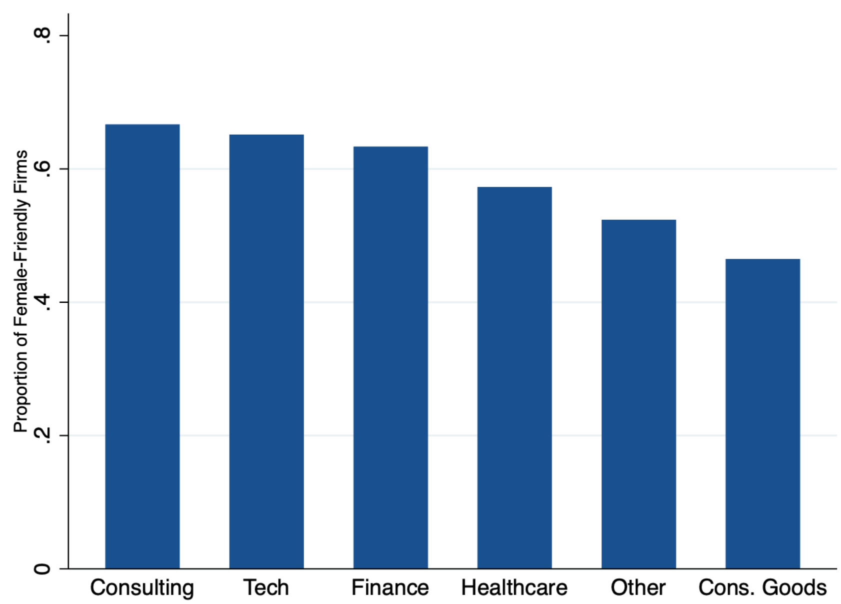
B.5.4 Characteristics of Female-Friendly Firms

In this section, we compare the characteristics of firms defined as female-friendly with those we defined as non-female-friendly.

Table B.1 presents the summary statistics of female-friendly and non-female-friendly firms. We find no significant difference between the two types of firms in terms of firm size, annual compensation of workers, or length of paid leave. However, they have a higher percentage of female senior managers and female board members.

Appendix Figure B.2 plots the share of female-friendly firms by industry. The figure shows that the proportion of female-friendly firms is higher in the three male-dominated industries (tech, finance, and consulting). We find the lowest share of female-friendly firms in consumer goods, which is the industry with the highest female representation in terms of employees.

Figure B.2: Female-Friendly Firms Representation by Industry



Notes: We plot the share of female-friendly firms by industry. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation.

Table B.1: Female-Friendly Firms versus Non-Female-Friendly Firms

	Female-Friendly	Non-Female-Friendly	Difference
Number of Employees	4660.93	4831.12	170.19
	(4185.63)	(4159.58)	(0.45)
Female Share of Employees (Glassdoor)	0.46	0.44	-0.02
	(0.20)	(0.20)	(0.14)
Female Share of Sr. Managers (Glassdoor)	0.36	0.33	-0.03*
	(0.22)	(0.25)	(0.03)
Total Annual Compensation ('000s)	147.31	261.59	114.28
	(559.26)	(3533.69)	(0.40)
Paid Maternity Leave	11.84	11.39	-0.45
	(6.31)	(7.57)	(0.59)
% Female Board Members	30.68	26.16	-4.53**
	(10.36)	(10.28)	(0.00)
Observations	786	601	1387

Notes: Summary statistics reported for female-friendly and non-female-friendly firms. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the difference. Data is at the firm level. Summary statistics on firm size, female share of employees, female share of senior managers, firm average compensation (reported in thousands), weeks of paid maternity leave, and percentage of female board members. Note data for female share of employees and senior managers are inferred from Glassdoor reviews. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.6 Classification of Job Functions

We utilize the job titles available on the LinkedIn profiles to classify job positions into functions. To do so, we match job titles to the open-source dataset, Thesaurus of Job Titles (Carty, 2017). This dataset links job titles and their synonyms to standardized SOC codes as well as detailed function categories. Using this dataset, we classify 93% (17,651 out of 18,982 job titles) of the job positions in our dataset into broad function categories. These are Accounting, Administrative, Consulting, Customer Service, Finance, General Management, Human Resources, IT, Legal, Marketing, Operations/Logistics, PR/Communications, Product Management, Research, Sales, Strategic Planning, and Other. Recent studies suggested that one barrier to female advancement into executive positions is the lack of profit and loss

(P&L) responsibilities, or having full control over the profitability of a department or an entire organization (Lean In and McKinsey & Company, 2015). We identify P&L positions based on whether the job function is in General Management, Operations/Logistics, Product Management, Sales, or Strategic Planning.

B.7 Definition of Managers

Our dataset allows us to identify management positions based on keywords in job titles listed on the MBA graduates' online profiles. We run a textual analysis on job titles to categorized managers in the following positions following the definitions suggested in the LeanIn.org and McKinsey & Company (2020) report:

- **C-Level Executives**: Executives such as CEO, CFO, COO, responsible for company operations and profitability. Keywords: "Chief X Officer," "President."

- **Senior Vice Presidents**: Senior leaders with significant business unit or functional oversight. Keywords: "SVP," "General Manager," "Managing Director."

- **Vice President and Director**: Leaders responsible for activities/initiatives within a sub-business unit, or who report directly to SVP. Keywords: "VP," "Director," "Regional Managers."

- **Managers**: Leaders responsible for teams and discrete functions or operating units. Keywords:"Manager," "Senior Product Manager."

B.8 Matching between Alumni Directory and LinkedIn Profile

Starting from our alumni directory for classes 2000 to 2010, we collected publicly available LinkedIn data for this sample. We exclude the class of 2009 because a large majority of this class had private or missing alumni profiles. We matched alumni to their online profiles based on the following variables:

- Full name

- Business school name listed on the social media profile
- Year of graduation
- Recent employment
- Undergraduate institution

We require names, business school, and class year to match perfectly to be considered a match. For women, we require only the first names to match and we conduct an online verification for those that may have changed their last names due to marriage (e.g., a wedding registry webpage). We utilize the name of recent employer and undergraduate institution when available to verify matches.

One potential concern of using the alumni directory records to define the sample universe for the older cohorts is the possible selection of graduates who choose to make their profiles public. For example, individuals who are more successful or have stronger connections to their MBA network may be more likely to have public directory records. However, Appendix Table B.2 shows that, compared to the total number of graduates from official administrative statistics, nearly all graduates, 96%, are represented in the alumni directory. Coverage rate by class year is provided in Appendix Table B.3. The high coverage rate of the alumni directory suggests that selection is likely limited in this setting. Moreover, because the alumni directory provides the section number of each graduate, individuals can be assigned to the true proportion of female peers in their section using the administrative records, despite not having a complete census of graduates in the alumni directory records.

Table B.2: Coverage Rate of Alumni Directory, 2000-2010 Records

	Overall		Male		Female	
	N	Non-Missing Share	N	Non-Missing Share	N	Non-Missing Share
Admin Data	4720	1.000	3210	1.000	1503	1.000
Alumni Directory	4532	0.960	3132	0.976	1380	0.918

Notes: We report the coverage rate of the alumni directory compared to the total number of graduates from official administrative statistics. Sample includes students of the graduating classes 2000-2018, excluding 2009.

Table B.3: Coverage Rate of Alumni Directory Records by Class, 2000-2010

	Overall		Male		Female	
	N	Non-Missing Share	N	Non-Missing Share	N	Non-Missing Share
Cohort 2000						
Admin Data	486	1.000	328	1.000	157	1.000
Alumni Directory	453	0.932	313	0.954	138	0.879
Cohort 2001						
Admin Data	479	1.000	323	1.000	153	1.000
Alumni Directory	443	0.925	306	0.947	136	0.889
Cohort 2002						
Admin Data	465	1.000	317	1.000	146	1.000
Alumni Directory	440	0.946	307	0.968	130	0.890
Cohort 2003						
Admin Data	460	1.000	318	1.000	142	1.000
Alumni Directory	438	0.952	309	0.972	127	0.894
Cohort 2004						
Admin Data	469	1.000	326	1.000	142	1.000
Alumni Directory	453	0.966	316	0.969	135	0.951
Cohort 2005						
Admin Data	456	1.000	326	1.000	130	1.000
Alumni Directory	449	0.985	320	0.982	126	0.969
Cohort 2006						
Admin Data	476	1.000	337	1.000	139	1.000
Alumni Directory	463	0.973	319	0.947	142	1.022
Cohort 2007						
Admin Data	479	1.000	328	1.000	151	1.000
Alumni Directory	470	0.981	327	0.997	139	0.921
Cohort 2008						
Admin Data	478	1.000	319	1.000	159	1.000
Alumni Directory	464	0.971	323	1.013	141	0.887
Cohort 2010						
Admin Data	472	1.000	288	1.000	184	1.000
Alumni Directory	459	0.972	292	1.014	166	0.902

Notes: We report the coverage rate of the alumni directory compared to the total number of graduates from official administrative statistics by class year. Sample includes students of the graduating classes 2000-2018, excluding 2009.

B.9 Match Statistics

In Appendix Table B.4, we summarize the match rate across the different datasets in our sample. Panel A describes the main analysis sample of individuals who graduated between 2000 and 2018, excluding 2009. Of the universe of two-year full-time MBAs, we matched 77% to their LinkedIn profiles. In Appendix Table B.5, we report the matching rate by class and gender. The match rate differs across classes, ranging from 65% to 90%. The match rate across genders also differs; 80% of males and 72% of females are matched.

We have in total 6,556 matched profiles and 71,546 observations for the first 15 years post-graduation. Restricting our sample to individuals that are based in the United States further reduces the number of individuals to 5,097 and 56,073 total observations. This restriction represents 60% of all graduates and 78% of the full LinkedIn dataset.

In Panel B, we present the match rate across the different firm datasets for our sample. There are 6,688 unique firms in the final U.S.-based LinkedIn sample for the first 15 years post MBA graduation. 67% of these firms have a LinkedIn company profile, which has information on industry and firm size. 44% of the firms are successfully matched to the Glassdoor compensation data. Information on female-friendly firms are available for a smaller number of firms, with 21% matched to InHerSight, 7% to FairyGodBoss, and 9% to 50/50 Women on Boards. It is important to note that larger firms are more likely to have information across all of these datasets. As a result, the match rate for unit-year observations is much higher. For example, even though only 21% of firms are matched to InHerSight, this information is available for 52% of the sample.

In Panel C, we report the number of observations for the administrative data and the number of matched observations to the LinkedIn data. 81% of the students represented in the administrative records have been matched to the LinkedIn dataset, and 61% are based in the United States.[71] Finally, in Panel D, we report the number of observations in the survey data.

[71] Note that the matching rate is not 100% because the school administration is currently still in the process of matching the LinkedIn profiles.

Table B.4: Match Statistics

Data Source	Units	Unit Match Rate	Unit-Year Observations	Unit-Year Match Rate
A. Individuals – Cohorts 2000-2008, 2010-2018				
All 2-Year Full-Time MBAs	8509	1.000		
...With LinkedIn Profiles	6556	0.770	66514	1.000
...With LinkedIn Profiles (U.S. Locality Only)	5098	0.599	52160	0.784
B. Firms – Cohorts 2000-2008, 2010-2018				
All Firms Listed on LinkedIn Profiles	6590	1.000	52160	1.000
...With LinkedIn Company Profiles	4397	0.667	44742	0.858
...With Glassdoor	2868	0.435	35493	0.680
...With InHerSight	1399	0.212	28168	0.540
...With FairyGodBoss	434	0.066	19305	0.370
...With Women On Boards	587	0.089	16531	0.317
C. Administrative Data – Cohorts 2011-2018				
All 2-Year Full-Time MBAs	3425	1.000		
...With LinkedIn Profiles	2783	0.813	14875	1.000
LinkedIn Profiles (U.S. Locality Only)	2097	0.612	10992	0.739
D. Survey Data – Cohorts 2000-2008, 2010-2018				
All 2-Year Full-Time MBA Respondents	283	1.000		
...With LinkedIn Profiles	197	0.696		

Notes: We report the match rate across the different datasets in our sample. Panel A describes the main analysis sample of individuals who graduated between 2000 and 2018, excluding 2009. In Panel B, we present the match rate across the different firm datasets for our sample. In Panel C, we report the number of observations for the administrative data and the number of matched observations to the LinkedIn data. In Panel D, we report the number of observations in the survey data.

Table B.5: Match Rate by Class

Class	All	Males	Females
2000	0.776	0.811	0.701
2001	0.756	0.774	0.732
2002	0.748	0.808	0.623
2003	0.685	0.714	0.620
2004	0.825	0.831	0.810
2005	0.862	0.868	0.846
2006	0.878	0.864	0.906
2007	0.820	0.835	0.775
2008	0.837	0.865	0.780
2010	0.805	0.844	0.739
2011	0.769	0.773	0.761
2012	0.681	0.695	0.653
2013	0.710	0.690	0.741
2014	0.904	0.920	0.876
2015	0.752	0.785	0.696
2016	0.682	0.696	0.659
2017	0.651	0.653	0.649
2018	0.734	0.735	0.734
All	0.770	0.788	0.735

Notes: We report the matching rate by class and gender of the LinkedIn profiles for the sample of individuals who graduated between 2000 and 2018, excluding 2009.

C Explaining the Gender Differences in Senior Management

In this section we turn to understanding what explains the gender gap in senior management positions. We show that education background, work experience, industry, and firm characteristics cannot fully explain this gender gap. In Table C.1, we present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls using the pooled sample of all individual-year observations. The female coefficient represents the gender gap in the likelihood of holding a senior management position. Column (1) shows that without any additional controls, there is a substantial gender gap of 24% (=0.128/0.543) in senior management despite similar educational backgrounds and levels of human capital among MBA graduates. Adding pre-MBA characteristics that include years of experience, top-20 undergraduate institution, management experience, and P&L experience explains only 0.2 percentage points of the gap in Column (2). Including the pre-MBA industry explains 4.6% of the gender difference (Column (3)). In Column (4), we include cumulative months of career break as a control. Career interruptions and breaks associated with parenthood have been linked to the gender gap in compensation and career outcomes of women (Bertrand et al., 2010; Kleven et al., 2019). While we do not have child-birth information, we are able to infer career breaks based on the employment dates listed on the online profiles.[72] Including this control explains a small percentage of the gap. Then in Columns (5) and (6), we include additional post-MBA controls such as experience, firm size, P&L role, as well as industry fixed effects. The gender gap, however, remains significant and sizeable at 17.7% (=0.0959/0.545), suggesting that the common determinants of the gender wage gap–such as industry and work experience–that we can observe in the LinkedIn dataset cannot explain most of the gap.

[72] Specifically, we identify career breaks if there is at least a three-month gap between the end and start dates of two consecutive positions.

Table C.1: Gender Gap in Senior Management: Pooled Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.128***	-0.126***	-0.122***	-0.120***	-0.111***	-0.0959***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0136)	(0.0137)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes
Cummulative Months of Career Break				Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes
Post-MBA Industry FE						Yes
Mean	0.490	0.490	0.490	0.490	0.490	0.490
Mean (Male)	0.543	0.543	0.543	0.543	0.543	0.543
R^2	0.219	0.224	0.229	0.230	0.251	0.272
N	27309	27309	27309	27309	27309	27309

Notes: We present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls. Pre-MBA characteristics include years of experience, top-20 undergraduate institution, management experience, and P&L experience. Cumulative months of career break is inferred based on the employment dates listed on the online profiles. Post-MBA controls include experience, firm size, and P&L role. Sample of all individual-year observations for students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Randomization Tests

D.1 Randomization Test (Guryan et al., 2009)

The randomization test proposed by Guryan et al. (2009) is implemented by estimating the equation:

$$x_{ikc} = \pi_1 + \pi_2 \bar{x}_{-i,k} + \pi_3 \bar{x}_{-i,c} + \delta_c + X_{ikc}\gamma' + u_{ikc} \tag{A1}$$

where x_{ikc} is the gender dummy for individual i in section k and class c. X_{ikc} is the class fixed effect. $\bar{x}_{-i,k}$ is the leave-out mean of female share in the section. $\bar{x}_{-i,c}$ is the leave-out mean of female share in the class. This last term is the bias correction term that addresses the exclusion bias. The rationale behind this test is that, after controlling for the class-level leave-out mean, the section-level leave-out mean should be precisely estimated and not significantly different from zero. That is, random peer assignment can be verified by testing if $\hat{\pi}_2 = 0$.

Table D.1 shows that the section-level leave-out mean is not significant either when using the full sample of cohorts between 2000 and 2018 (Columns 1-2) or when we restrict to the subsample of cohorts between 2011 to 2018, for which we have administrative data (Columns 3-4). It also does not depend on the inclusion of covariates.

Table D.1: Randomization Test (Guryan et al., 2009)

	2000-2018		2011-2018	
	(1)	(2)	(3)	(4)
	No Controls	With Controls	No Controls	With Controls
Average(X), Section Peers	0.00172	0.00159	0.0336	0.0339
	(0.0155)	(0.0154)	(0.0289)	(0.0290)
Average(X), Class Peers	-278.0***	-278.0***	-258.5***	-258.5***
	(2.750)	(2.751)	(3.301)	(3.303)
R^2	.9868657	.986869	.9892842	.9892892
N	5087	5087	2090	2090
Class FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (A1), pooling together all years since graduation (Guryan et al., 2009). The dependent variable is a female dummy. Estimations in columns (2) and (4) also include indicators for having attended a top-20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Randomization Test (Caeyers and Fafchamps, 2021)

The randomization test proposed by Caeyers and Fafchamps (2021) is implemented by estimating the equation:

$$\tilde{x}_{ikc} = \phi_1 + \phi_2 \bar{x}_{-ikc} + \delta_c + u_{ikc} \tag{A2}$$

where i is the individual, k is the section, c is the class cohort. $\tilde{x}_{ikl}$ is defined as $x_{ikc} - \rho\bar{x}_{-ikc}$ and $\rho = plim_{N\to\infty}[\hat{\beta}_1]$, which captures the asymptotic exclusion bias. As in Guryan et al. (2009), we would reject the null of random assignment if $\hat{\phi}_2$ is significantly different from zero. In Proposition 2 of Caeyers and Fafchamps (2021), the authors show that for cases with varying group (section) sizes and pool (class) sizes, ρ is given by

$$\begin{aligned}
plim_{N\to\infty}[\hat{\beta}_1] &= \sum_k \frac{K_k}{M} \frac{s^2_{z_k}}{s^2_z} plim_{N\to\infty}[\hat{\beta}_{1k}] \\
plim_{N\to\infty}[\hat{\beta}_{1k}] &= -1 \frac{(L_k - 1)(K_k - 1)}{(L_k - K_k)L_k + (K_k - 1)} \\
s^2_{z_k} &= \frac{(K_k - 1) + (L_k - K_k)L_k}{L_k(L_k - 1)(K_k - 1)} \\
s^2_z &= \sum_k \frac{K_k}{M} s^2_{z_k} \\
M &= \sum_k K_k
\end{aligned}$$

where K_k is the size of a given group (section) k and L_k is the pool (class) size. According to Caeyers and Fafchamps (2021), we can test random peer assignment by using OLS standard errors clustered at the pool (class) level. To include covariates, we first partialled out the regressors following the procedure described in Caeyers and Fafchamps (2021).

We present the results of the randomization test in Table D.2 for the full sample (Columns 1-2) and for the cohorts between 2011 and 2018 (Columns 3-4). In Appendix Table D.3, we conduct the same randomization test when the dependent variable is being a female student from a top-20 undergraduate institution in Column (1), being a female student with senior managerial experience in Column (2), and being a female student with experience in finance in Column (3).

Table D.2: Randomization Test (Caeyers and Fafchamps, 2021)

	2000-2018		2011-2018	
	(1) No Controls	(2) With Controls	(3) No Controls	(4) With Controls
Female share	-0.866	-0.932	-0.574	-0.587
	(0.635)	(0.656)	(0.917)	(0.876)
R^2	0.0188	0.00757	0.0145	0.00359
N	5087	4367	2090	1989
Class FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (A2), following the methodology by (Caeyers and Fafchamps, 2021) The dependent variable in all columns is a female dummy. Estimations in columns (2) and (4) also include indicators for having attended a top-20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the class level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.3: Randomization Test (Caeyers and Fafchamps, 2021)

	(1) Female Top-20 Undergrad	(2) Female Senior Manager	(3) Female Finance
Female share	0.129	0.142	-0.333
	(0.247)	(0.132)	(0.282)
R^2	0.0218	0.0124	0.0157
N	1759	1640	1546
Class FE	Yes	Yes	Yes

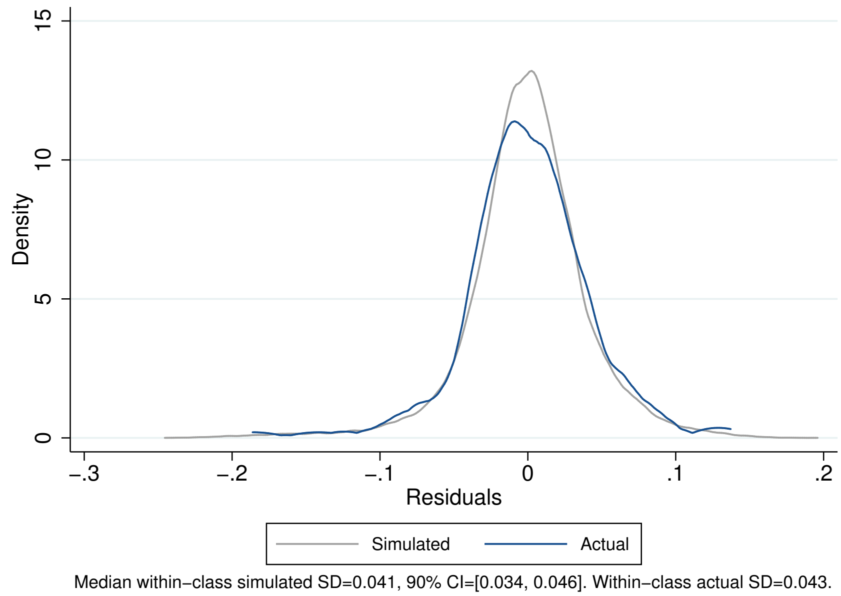
Notes: We present the coefficients for women from estimating equation (A2), following the methodology by (Caeyers and Fafchamps, 2021). The dependent variable is being a female student from a top-20 undergraduate institution in Column (1), being a female student with senior managerial experience in Column (2), and being a female student with experience in finance in Column (3). Estimations include class fixed effect. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the class level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Actual and Simulated Distribution of the Share of Female Peers

In this section, we provide additional evidence that the within-class distribution of the share of female peers is as good as random. Specifically, we follow the methodology in Bietenbeck (2020) and compare the actual within-class distribution to a simulated distribution of female share.[73] First, we produce Monte Carlo simulations in which we randomly reassign MBA students to sections within their graduating class, taking the number of sections and graduating years from the actual data. Second, we regress the share of female students on class fixed effects in both the actual and the simulated data, and collect the residuals. We replicate these two steps 1,000 times. We plot the simulated residuals from this random assignment alongside the residuals from the actual data in Appendix Figure E.1. From both a visual inspection and a two-sample Kolmogorov-Smirnov test, we show that there is no statistically significant difference between the actual and the simulated distribution, consistently with as-good-as-random assignment of the share of female peers. Also note that, across these 1,000 replications, the median standard deviation is 0.041 with a 90% empirical confidence interval of [0.034, 0.046]. This confidence interval amply contains the within-class standard deviation of 0.043 observed in the actual data.

[73]Note that these residuals represent the variation that we exploit in our analysis.

Figure E.1: Distribution of Residualized Actual and Simulated Female Share



Notes: We plot the actual and simulated share of female MBA graduates per section residualized by graduating year. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation.

F Nonlinear Peer Effects Estimation

Are there nonlinearities in the effects of female peers on women's likelihood of becoming a senior manager? Increasing female share may have a larger impact in sections with a lower share of female students.

In order to test this hypothesis, we use a one-knot spline regression, which allows us to identify significant changes in our coefficients of interest along the distribution of female share. Specifically, we modify equation (1) by interacting the main coefficients of interest with an indicator variable for being in a section with an above-median share of female peers (34%) across all classes:

$$\begin{aligned} y_{ikct} =& \beta_1 \overline{FemaleShare}_{-i,kct} + \beta_2 \overline{FemaleShare}_{-i,kct} \times I(\overline{FemaleShare}_{-i,kct} > 0.34) \\ &+ \sum_{j=0,1} (\delta_c + \phi_t + \omega_{ct}) \times I(Female_i = j) + X_{ikct}\gamma' + \epsilon_{ikct} \end{aligned} \tag{A3}$$

where y_{ikct} is the outcome of interest for individual i in section k from graduating class c in year since graduation t. $\overline{FemaleShare}_{-i,kc}$ is the proportion of female peers of i in section k and graduating class c. The specification also includes a series of class fixed effects (δ_c), year fixed effects (ϕ_t), class-by-year fixed effects ($\omega_{i,ct}$), and their interactions with the gender dummy. The term X_{ikct} includes all the controls listed for equation (1).[74] β_1 is the effect of a marginal increase in female share in sections with a share of female peers below the median (34%). β_2 represents the change in slope for sections with female share above the median.

Table F.1 reports the total effect of female peers for sections with female share below and above the median. While the estimated effect is larger for women in sections below the median, we cannot reject equality between the two coefficients. This null result is potentially due to a lack of statistical power. These findings, nonetheless, provide suggestive evidence that female peers are particularly beneficial for women in sections with a lower female share, pointing to the presence of decreasing marginal returns of additional female students. The presence of decreasing marginal returns would also help explain the lack of effect for men.

[74] Note that for simplicity, we did include the interactions with the female dummy when writing equation (A3). However, the estimation is performed by fully interacting the regressors with the female indicator.

Table F.1: Nonlinear Effect of Female Peers on Senior Management

	(1) Senior-Level Manager
Female Share Below Median	0.938***
	(0.285)
Female Share Above Median	0.608
	(0.374)
p-value Below Median vs. Above Median	0.520
Female Mean	0.391
Male Mean	0.534
R^2	0.173
N	51440
Class x Year x Female FE	Yes

Notes: We present the coefficients for sections with female share below and above the median (across all classes) from estimating equation (A3), pooling together all years since graduation. Estimates include class fixed effects, year fixed effects, class-by-year fixed effects, indicators for having attended a top-20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. We also control for the following section-level characteristics: share of section with management experience, senior-level management experience, finance experience, consulting experience, other industry experience, P&L experience, U.S. locality, and those with white and/or foreign backgrounds. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Additional Outcomes

In this section, we present results for additional management-related outcomes.

G.1 Effects on Individual Senior Management Positions

We decompose the effects on senior managerial positions into individual positions along the management pipeline: Directors and Vice Presidents (VP), Senior Vice Presidents (SVP), and C-level executives. We find that our main results on senior managers are driven by entries of women into VP and director positions. Appendix Table G.1 presents the overall effect on each management position using the pooled sample.[75]

We find that a 4 percentage point (1SD) increase in female share leads to a 9.6% (=0.029/0.304) increase in the likelihood of holding a director or VP position for women during the first 15 years from graduation (Column 1). On the contrary, we find no effect for SVPs and C-level executives in Columns (2) and (3), respectively. The null effect on SVPs and especially C-level positions should be interpreted cautiously, given that the vast majority of our sample has not reached the level of seniority to hold these positions yet.

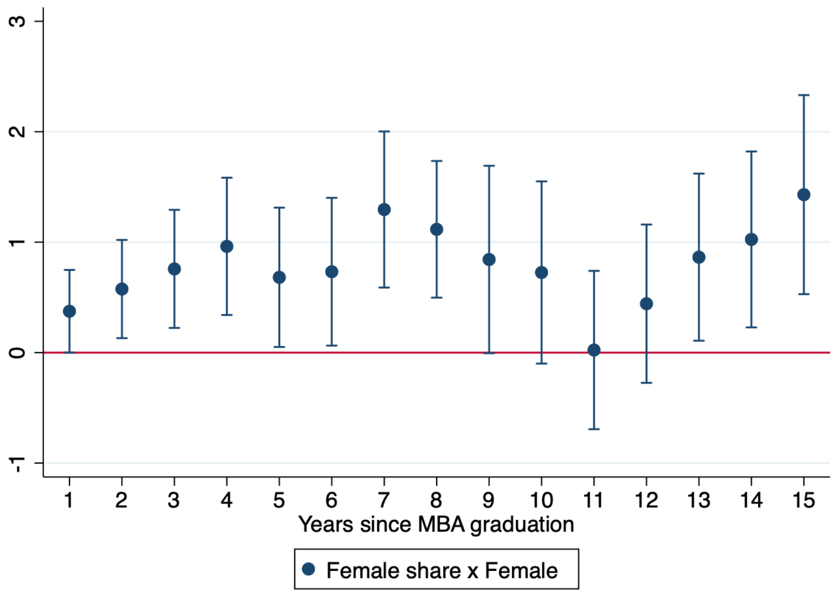
[75] The effects over time for probability of holding each management position are plotted in Appendix Figures G.1, G.2, and G.3 for Director and VP, SVP, and C-level executives, respectively.

Table G.1: Effect of Female Peers on Senior Management by Seniority Level

	(1) Director and VP	(2) SVP	(3) C-Suite
Female share × Male	0.107	-0.105	0.110
	(0.137)	(0.121)	(0.0782)
Female share × Female	0.733***	0.0941	-0.112
	(0.185)	(0.149)	(0.0872)
p-value Male vs. Female	0.002	0.302	0.078
Female Mean	0.304	0.069	0.037
Male Mean	0.372	0.120	0.062
R^2	.0709	.058	.0358
N	51440	51440	51440
Class x Year x Female FE	Yes	Yes	Yes

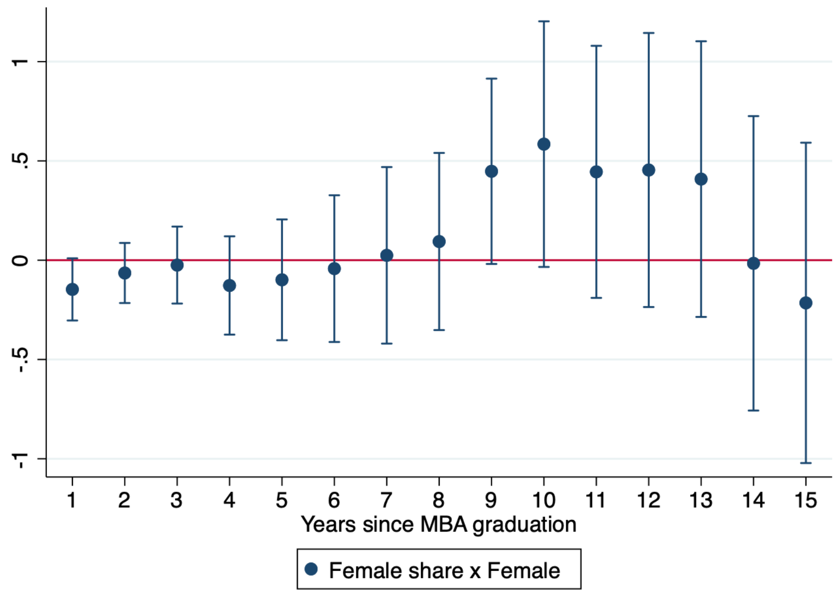
Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are holding a director or vice president position (Column 1), holding a senior vice president position (Column 2), and holding a C-level executive position (Column 3). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure G.1: Effect of Female Peers on Holding Director and VP Positions



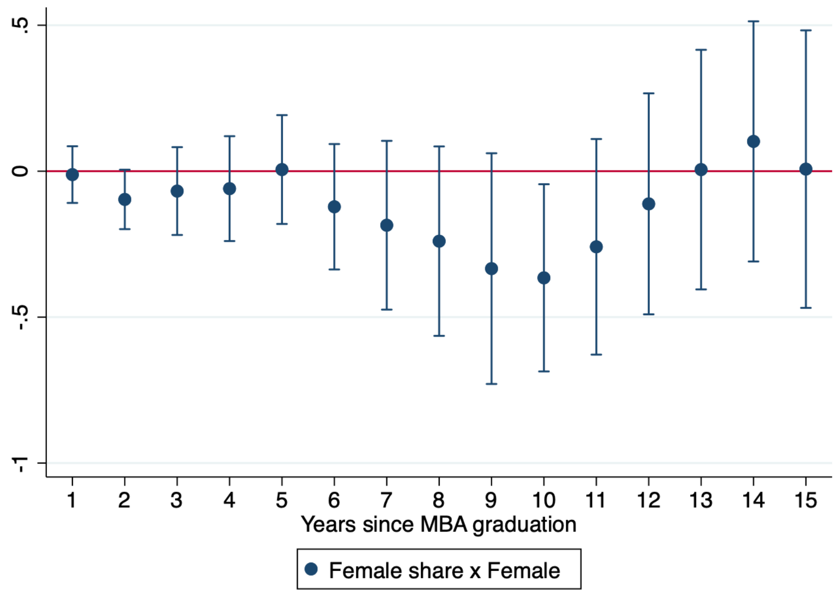
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is holding a director or vice president position. Refer to Table 1 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Standard errors clustered at the section level.

Figure G.2: Effect of Female Peers on Holding SVP Positions



Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is holding a senior vice president position. Refer to Table 1 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Standard errors clustered at the section level.

Figure G.3: Effect of Female Peers on Holding C-level Positions

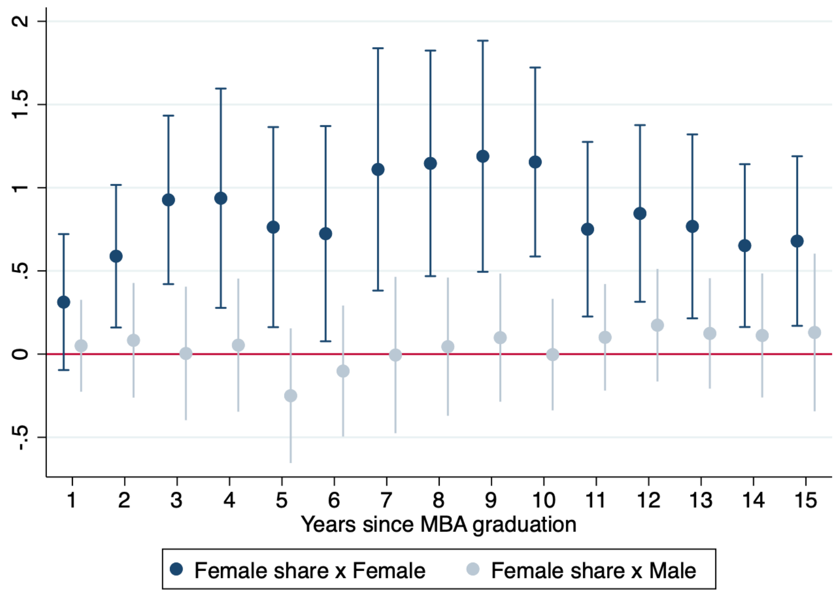


Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is holding a C-level executive position. Refer to Table 1 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

G.2 Effects on Ever Holding a Senior Manager Position

In Appendix Figure G.4, we show the results when we use as an outcome variable "ever holding a senior management position," which is an indicator variable that takes value 1 if the individual has held a senior management position in that year or any year before and 0 otherwise. We observe an increase in the entry rate into senior managerial positions beginning in the first year after graduation and persisting for at least 15 years, suggesting that a larger network of female peers leads to new entries into senior management. The corresponding regression estimates are presented in Appendix Table G.2.

Figure G.4: Effect of Female Peers on Ever Holding Senior-Level Management Positions



Notes: We plot the coefficients for men and women and their 95% confidence intervals from estimating equation (1) separately for each year since graduation. The dependent variable is a dummy for ever holding a senior-level management position in the years since graduation. Refer to Table 1 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Standard errors clustered at the section level.

Table G.2: Effect of Female Peers on Likelihood of Ever Holding a Senior Management Position by Year Since Graduation

	(1) Year 1	(2) Year 3	(3) Year 5	(4) Year 7	(5) Year 9	(6) Year 11	(7) Year 13	(8) Year 15
Female share × Male	0.0501	0.00394	-0.250	-0.00562	0.0989	0.101	0.124	0.130
	(0.141)	(0.205)	(0.207)	(0.240)	(0.196)	(0.163)	(0.169)	(0.242)
Female share × Female	0.313	0.927***	0.763**	1.110***	1.189***	0.750***	0.768***	0.679**
	(0.208)	(0.258)	(0.307)	(0.372)	(0.354)	(0.268)	(0.282)	(0.260)
p-value Male vs. Female	0.304	0.002	0.002	0.008	0.007	0.034	0.037	0.070
Female Mean	0.138	0.227	0.406	0.546	0.658	0.723	0.753	0.788
Male Mean	0.230	0.340	0.538	0.702	0.796	0.853	0.887	0.903
R^2	0.062	0.054	0.050	0.053	0.050	0.047	0.058	0.057
N	5001	4595	4270	3741	3263	2696	2359	1711

Notes: We present the coefficients for men and women from estimating equation (1) separately for each year since graduation. The dependent variables are dummy variables for ever holding a senior-level management position in the specified years since graduation. Refer to Table A.6 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.3 Effects on Years in Senior Management, Time to Senior Management, and Number of Senior Management Positions Held

In Appendix Table G.3, we show that the positive effect of female peers translates into 0.09 (=0.434/4.968) additional years (or approximately one month) spent in senior managerial positions for a 4 percentage point (1SD) increase in female share.

Table G.3: Effect of Female Peers on Number of Years in Senior Management Positions

	(1) Total Number of Years as Senior Manager Positions
Female share × Female	6.267***
	(2.053)
Female Mean	3.693
Male Mean	5.583
R^2	0.491
N	5087
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1). This is estimated at the individual level. The dependent variable is number of years in senior-level management position in the first fifteen years post-graduation. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) in Appendix Table G.4 shows that, among those who eventually end up becoming a senior manager, there is a decline in years to first position as senior manager of 6.8% (=0.335/4.940) for women.[76]

We also find that female peers increase the number of senior management positions held by women (Column (2) in Appendix Table G.4).[77] Specifically, a 4 percentage point (1SD) increase in female share increases the number of positions by 4.8% (=.054/1.126).

[76]Note that this regression is estimated at the individual level instead of using the pooled sample.
[77]Note that this is not restricted to individuals that eventually become managers.

Table G.4: Effect of Female Peers on Years to First Senior Management Position

	(1) Years to First Senior Manager Position	(2) Total Positions as Senior Manager
Female share × Female	-8.375***	1.362*
	(2.871)	(0.766)
Female Mean	4.940	1.126
Male Mean	4.359	1.562
R^2	0.088	0.314
N	3313	5087
Class x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1). This is estimated at the individual level. The dependent variables are years to first senior management position, restricted to those who ever become senior managers (Column 1) and total positions as senior managers (Column 2). Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.4 Effects on External and Internal Promotions

We show in Appendix Table G.5 that the increase in senior managers come from both external and internal promotions. Although the coefficient is larger for external promotions, we cannot reject the null hypothesis of equality.

Table G.5: Effect of Female Peers on External vs Internal Promotions

	Senior Manager	
	(1) External Promotion	(2) Internal Promotion
Female share × Female	0.591***	0.303**
	(0.153)	(0.152)
Female Mean	0.269	0.132
Male Mean	0.343	0.197
R^2	0.212	0.037
N	50506	50506
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are holding a senior-level management position obtained through external promotion, defined as starting the position with a new employer (Column 1), and holding a senior-level management position obtained through internal promotion, defined as starting the position with the previous employer (Column 2). Refer to Table 1 for the full set of control variables. Data is at the individual level. Outcomes defined as ever entering in each of the listed industries in the first 15 years post-graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. The p-value from a test of the pairwise difference of the coefficient $Femaleshare \times Female$ in Column (1) and (2) is 0.195. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Robustness Checks

We present a series of robustness checks to provide supporting evidence that our results credibly identify the causal effect of female peers on senior positions for women.

Missing Data

As shown in Appendix Table B.4, the match rate is not perfect across all the datasets and this may introduce bias to our estimates if missing data is systematically correlated with our treatment variable, share of women in the section. In Appendix Table H.1, we investigate whether unmatched observations from each of the datasets are systematically correlated with female peers. We report the regression results from estimating equation (1), where the dependent variable in each column is a dummy if the individual is matched to the specified dataset.[78]

Because this analysis requires microdata and we do not have individual data for the full census of MBA graduates prior to 2011, we use the alumni directory records as a proxy for the sample universe in Columns (1) and (2). That is, the missing dummy equals 1 if in the alumni directory records, and 0 otherwise. In Columns (3) and (4), we use the matched LinkedIn and administrative data to conduct the analysis for the 2011-2018 cohorts. We do not find a correlation between female share and being in the sample in any case. This provides strong evidence that selection into the sample cannot explain our results.

[78]Note that we do not include controls beyond gender, class, and year fixed effects, because additional information is not available for unmatched individuals.

Table H.1: Missing Data

	(1) Matched to LinkedIn Profile 2000-2010	(2) Matched to LinkedIn Profile (US Sample Only) 2000-2010	(3) Matched to LinkedIn Profile 2011-2018	(4) Matched to LinkedIn Profile (US Sample Only) 2011-2018	(5) Matched to LinkedIn Company Profile	(6) Matched to Glassdoor	(7) Matched to InHerSight
Female share × Female	-0.166	0.0976	0.00145	0.00646	-0.0971	-0.0313	-0.179
	(0.227)	(0.344)	(0.0184)	(0.0194)	(0.168)	(0.201)	(0.220)
Mean	0.845	0.383	0.469	0.353	0.858	0.680	0.540
R^2	0.0228	0.0104	0.617	0.374	0.0382	0.0314	0.0424
N	4512	4512	286	286	52094	52094	52094
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes	Yes
Class x Year x Female FE	No	No	No	No	Yes	Yes	Yes
Level of Observations	Person	Person	Person	Person	Person-Year	Person-Year	Person-Year

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variable in each column is a dummy if the individual is matched to the specified dataset. Estimates include gender dummy, class, and year fixed effects. Because this analysis requires microdata and we do not have individual data for the full census of MBA graduates prior to 2011, we use the alumni directory records as a proxy for the sample universe in Columns (1) and (2). That is, the missing dummy equals 1 if in the alumni directory records, and 0 otherwise. In Columns (3) and (4), we use the matched LinkedIn and administrative data to conduct the analysis for the 2011-2018 cohorts. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Alternative Definitions and Samples

We also conduct a series of robustness checks using alternative definitions and samples. Results are summarized in Appendix Figure H.1. First, we use an alternative definition for nonemployment. In our main analysis, we consider only nonemployment breaks between consecutive positions. However, there are some individuals whose last position ends before the date we obtained the profiles in 2019. Because it is unclear whether the individual is truly not employed or simply has not updated their profiles, we do not consider these spells as nonemployment in the main definition and do not include these observations in the analysis. As a robustness check, we assume that all these time periods up to 2019 are nonemployment spells and re-estimate equation (1) for senior management. We show in Appendix Figure H.1 that the main result is robust to the use of this alternative nonemployment measure.

Second, since our sample includes people graduating from 2000 to 2018, we do not observe everyone for up to 15 years. Therefore, our sample is not balanced over time. As a robustness check, we estimate the coefficients from regression (1) on our main outcome variable, restricting the sample to people we can follow throughout the 15 years post-graduation. Appendix Figure H.1 shows that the results obtained using this balanced sample are consistent with our main findings.

Third, in our main specification, our outcome variable is a dummy for being in senior management, unconditional on work status. As a result, in addition to those not in senior management, we also assign zero to anyone that does not report any work activity in that year. In Appendix Figure H.1, we show that results hold when we assign missing to the individuals who do not report any work activity in that year.

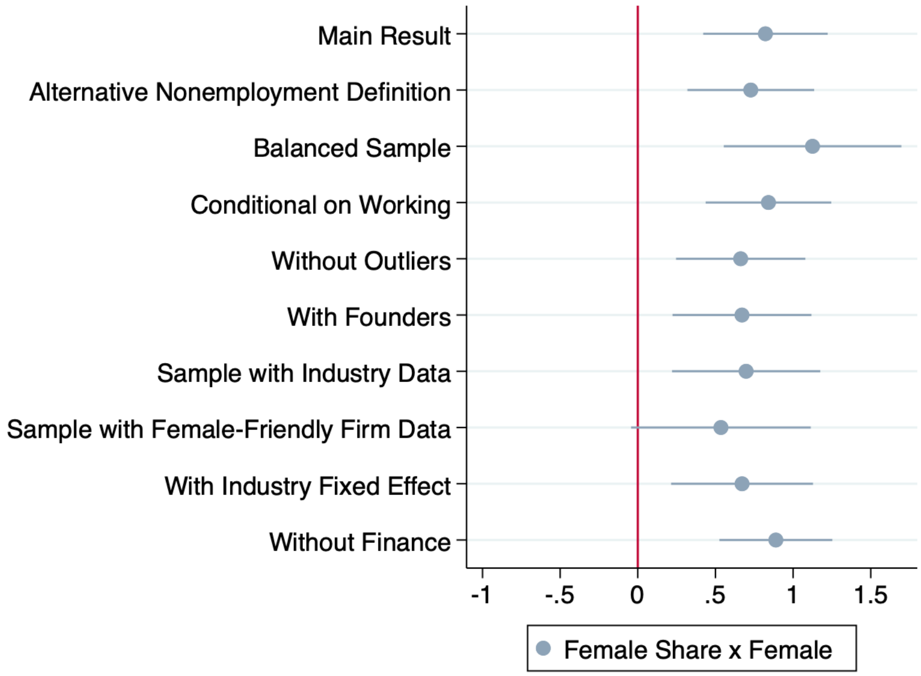
Fourth, to correctly interpret the results and infer meaningful policy implications, it is valuable to understand whether they are driven by outliers. To shed light on this, we drop from the sample the observations in sections with a proportion of female students in the first and last percentile of the female share distribution. We then re-estimate equation (1) on this new sample. Appendix Figure H.1 shows that the effect of female peers is still positive and significant when we apply this sample restriction.

Fifth, our main definition of managers does not include entrepreneurs or founders, as we are interested in analyzing the effects on self-employment separately from management. We show in Appendix Figure H.1 that the inclusion of entrepreneurs in the definition of senior managers does not change the results.

Sixth, we check whether our main results hold when we restrict the analysis to the observations for which we have information on industry and level of female-friendliness of the firm, as defined in Section 3.3. In Appendix Figure H.1, we show that the results are consistent albeit noisier for these subsamples of observations.

Finally, we include industry fixed effects and remove finance to show that our results are robust to potential concerns about industry-norms on hierarchies of job titles. For example, in finance, directors are ranked higher than VPs, unlike most other industries.

Figure H.1: Effect of Female Peers on Senior Management: Robustness Checks



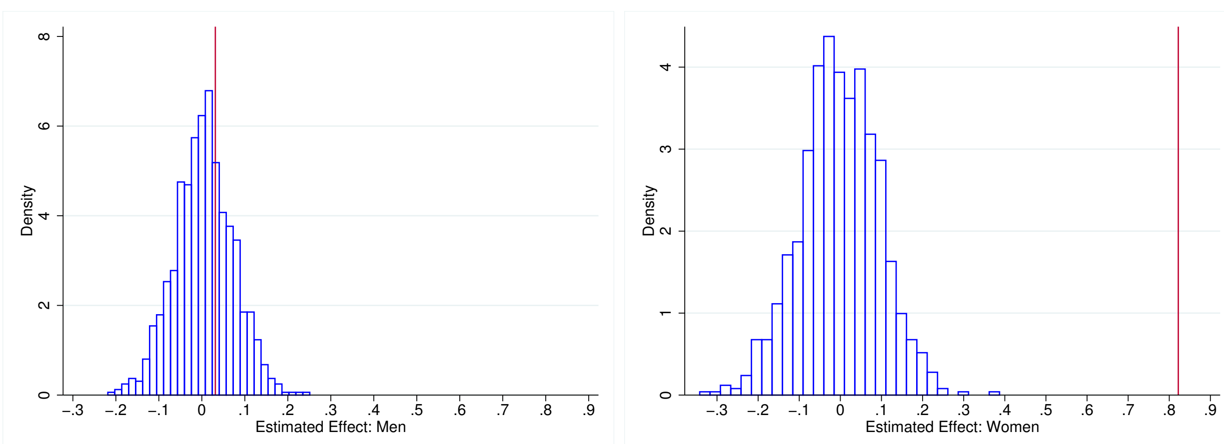
Notes: We plot the coefficients for women from estimating equation (1), pooling together all years since graduation. In all specifications, the dependent variable is holding a senior management position. Each coefficient is the result of a separate estimation from a series of alternative sample restrictions and specifications. "Main Result" refers to the the main analysis results. "Alternative Nonemployment Definition" uses the assumption that all time periods up to 2019 since the last position on the CV are nonemployment spells. "Conditional on Working" restricts the sample to those that report work activity in that year. "Balanced Sample" restricts to people who we can follow throughout the full 15 years post-graduation. "Without Outliers" drops observations in sections with a proportion of female students in the first and last percentile of the female share distribution. "With Founders" includes founders and entrepreneurs in our definition of senior-level manager. "Sample with Industry Data" restricts to the sample of individuals for which we have the industry information of their firms. "Sample with Female-Friendly Firm Data" restricts to the sample of individuals for which we have the female-friendliness information of their firms. "With Industry Fixed Effect" includes industry fixed effects in the specification. "Without Finance" drops observations in the finance industry from the regression. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Placebo Test: Random Reassignment of Sections

Following the methodology described in Athey and Imbens (2017), we conduct a randomization test in which we randomly reassign students to sections within the same class. The reassignment is performed without replacement and uses uniform probability. We conduct this reassignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, the probability of holding a senior management position, for both men and women. In Appendix Figure H.2, we plot the distributions of the placebo treatment effects for men and women, respectively. The vertical lines indicate the actual coefficients we estimated using the true section assignment. As shown in the figure, the true effect for men falls within the distribution of placebo effects, consistent with the null effect on men that we find in our main results (Section 5.2). On the contrary, the estimated true effect for women is much larger than any of the placebo effects, providing supporting evidence that the estimated impact of female peers on women's probability to become senior managers is unlikely to have occurred by chance.

Figure H.2: Effect of Female Peers on Holding Senior Management Positions Using Placebo Sections

(a) Men (b) Women



Notes: We plot the distributions of the placebo treatment effects computed using a randomization test in which we randomly reassign students to sections within the same class. The reassignment is performed without replacement and using uniform probability. We conduct this reassignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, the probability of holding a senior management position for men and women. The vertical lines indicate the actual coefficients we estimated from the baseline specification.

Placebo Test: Pre-MBA Years

If female share in each section is exogenous, it should have no effect on our outcome variable in the years prior to the MBA, when peer groups have not been formed yet. Appendix Table H.2 shows the coefficients from regression (1) estimated separately for up to three years before the start of the MBA program. We find no consistent evidence of an effect of female share on female future graduates, supporting our identification strategy.

Table H.2: Effect of Female Peers on Senior Management: Pre-MBA

	(1) Year -4	(2) Year -3	(3) Year -2
Female share × Female	0.0616	-0.0902	0.0218
	(0.102)	(0.0831)	(0.0855)
Female Mean	0.075	0.095	0.106
Male Mean	0.083	0.110	0.123
R^2	0.572	0.764	0.868
N	4669	4710	4716

Notes: We present the coefficients for women from estimating equation (1). The dependent variables are holding a senior-level management position in each specified year since graduation. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Clustering at the Class Level

Table H.3: Effect of Female Peers on Senior Management: Clustering at Alternative Levels

	Senior Manager	
	(1) Clustered at Section Level (Main Result)	(2) Clustered at Class Level
Female share × Female	0.822***	0.822***
	(0.204)	(0.195)
Female Mean	0.391	0.391
Male Mean	0.534	0.534
R^2	0.173	0.173
N	51440	51440
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1), pooling together all years since graduation. The dependent variables are holding a senior-level management position for both specifications. Column (1) clusters standard errors at the section level. Column (1) clusters standard errors at the class level. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level in Column (1) and at the class level in Column(2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Logistic Model

Table H.4: Effect of Female Peers on Senior Management: Pooled Sample (Logit)

	(1) Senior-Level Manager (Linear)	(2) Senior-Level Manager (Logit)
Female share × Male	0.0315	0.831
	(0.115)	(1.408)
Female share × Female	0.822***	5.328**
	(0.204)	(2.504)
p-value Male vs. Female	0.000	0.088
Female Mean	0.391	0.391
Male Female	0.534	0.534
R^2	0.173	
N	51440	51429
Class x Year x Female FE	Yes	Yes

Notes: In Column (1), we present the coefficients for women from estimating equation (1), pooling together all years since graduation. In Column (2), we show the coefficients for women from the corresponding logistic specification. The dependent variables are holding a senior-level management position for both specifications. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2015. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

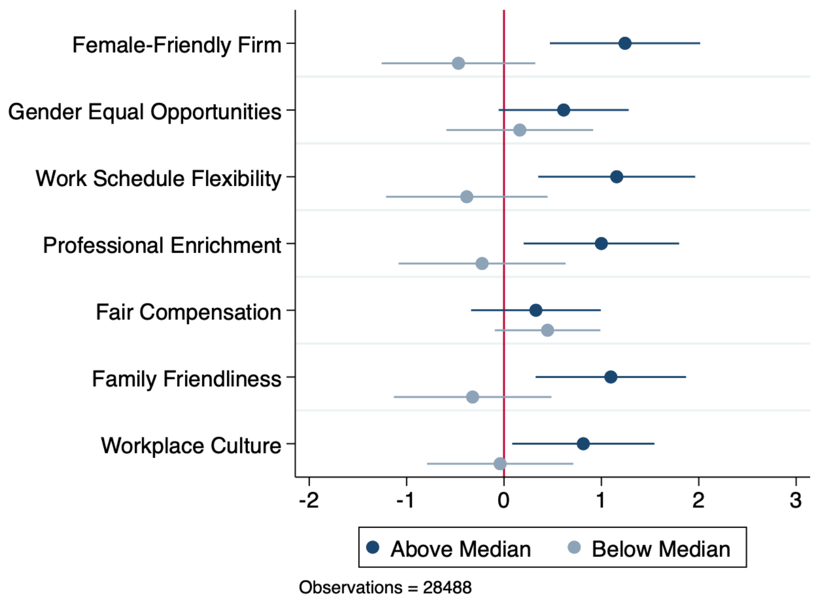
I Components of Female-Friendly Firms

In this section, we explore which features of female-friendly firms are driving our results. The overall IHS female-friendly measure comprises of 18 metrics. We create six standardized indices by grouping these 18 underlying metrics into six broad topics: 1) gender equal opportunities, 2) work schedule flexibility, 3) professional enrichment, 4) fair compensation, 5) family friendliness, and 6) workplace culture.[79] In Appendix Figure I.1, we report the analogous results for firms that are above or below the median in each of the component indices. The results suggest that women are most likely to be senior managers in firms with higher work schedule flexibility and family-friendliness, such as those providing more

[79]More details on the index creation can be found in Appendix Section B.5.1.

generous maternity leave policies. We also find positive effects for firms with greater professional enrichment, better workplace culture, and gender-equal opportunities. In contrast, we do not find a differential effect for the index capturing whether a firm is perceived to have fair compensation. This aligns with earlier results that find no impacts on firm-level compensation.

Figure I.1: Effect of Female Peers on Senior Management in Female-Friendly Firms by Component



Notes: We plot the coefficients for women from estimating equation (1), pooling together all years since graduation. Each coefficient is the result of a separate estimation where the outcome variable is an indicator of being a senior manager, whether the firm is above or below the median in each of the six female-friendly component indices (gender equal opportunities, work schedule flexibility, professional enrichment, family-friendliness, workplace culture, and fair compensation), as well as the overall female-friendly rating. Refer to Table 1 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

J Female-Friendly Firms and Male-Dominated Industries

In this section, we investigate whether the findings on female-friendly firms can explain the increase in senior managers in male-dominated industries. For example, the advancement of women in finance, tech, and consulting may be driven by better knowledge or increased access to firms that are more supportive of women as a result of their female MBA peers.

In Appendix Table J.1, we test this hypothesis by investigating the probability of becoming a manager in a female-friendly firm versus a non-female-friendly firm when restricting to male-dominated industries. Consistent with the results in Section 6, the magnitude of the coefficient for achieving a senior management position in a female-friendly firm is much larger than the corresponding coefficient for non-female-friendly firms. Indeed, the two coefficients are statistically different from each other at the 9% level. This provides suggestive evidence that, indeed, the overall effect on male-dominated industries can be explained by female-friendly firms.

Table J.1: Effect of Female Peers on Probability of Senior Management in Female-Friendly Firms (Restricted to Male-Dominated Industries)

	Senior Manager (Restricted to Male-Dominated Industries)	
	(1) Female-Friendly Firms	(2) Non-Female-Friendly Firms
Female share × Female	1.407**	0.0990
	(0.562)	(0.405)
Female Mean	0.239	0.089
Male Mean	0.294	0.136
R^2	0.205	0.248
N	16887	16887
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. The dependent variables are holding a senior-level management position in a female-friendly firm (Column 1) and holding a senior-level management position in a non-female-friendly firm (Column 2). Both specifications are restricted to only those working in male-dominated industries. Refer to Table 1 for the full set of control variables. Sample includes graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

K Explaining the Gender Differences in Compensation

In this section we explore what explains the gender gap in imputed compensation.

Appendix Table K.1 presents coefficient estimates from regressing total log annual compensation on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls using the pooled sample of all individual-year observations. The female coefficient represents the gender gap in total log compensation. We find that a substantial portion of the gender gap can be explained by industry choice, suggesting that male MBAs are more likely to enter more lucrative industries. The gender gap further shrinks when we include the broad managerial category (non-manager, first-level, or senior manager). This captures the fact that men are more likely to be in senior management positions. Notably, even after controlling for management level, the gender gap in compensation does not close completely; we move from a 33% gender gap in Column (1) to a 21% gender gap in Column (7). Since the imputation is based on current firm, broad managerial category, and gender, this may indicate that women may be sorting into firms that are lower paying in general.

Table K.1: Gender Differences in Total Compensation (Imputed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.307***	-0.305***	-0.300***	-0.297***	-0.304***	-0.240***	-0.195***
	(0.0223)	(0.0226)	(0.0228)	(0.0227)	(0.0223)	(0.0203)	(0.0170)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes	Yes
Cummulative Months of Career Break				Yes	Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes	Yes
Post-MBA Industry FE						Yes	Yes
Current Broad Managerial Category							Yes
Mean	12.12	12.12	12.12	12.12	12.12	12.12	12.12
Mean (Male)	12.23	12.23	12.23	12.23	12.23	12.23	12.23
R^2	0.104	0.111	0.115	0.117	0.151	0.265	0.468
N	16769	16769	16769	16769	16769	16769	16769

Notes: We present coefficient estimates from regressing log total annual compensation on a female dummy and the same variables as in Table C.1. Sample of all individual-year observations for students of the graduating classes 2011-2018, excluding 2009. Observations are restricted to the first 15 years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L Alumnae Survey

L.1 Description of Survey Data

The survey was distributed online by the university alumni relations office via email in August 2023 and in February 2024 to a 100% sample of the female two-year full-time MBA graduates residing in the United States at the time of the survey.[80] The response rate is 10%. Total number of responses was 283. Using the names collected during the survey, we are able to match 197 or 70% of survey responses to the LinkedIn data. This is not 100% because it is possible that some women did not have a LinkedIn profile or used nicknames/alternative names on the survey form. In analyses with the survey data, we utilize all responses.

The survey collected information on the following:

1. Demographic background and MBA education

    - Name, MBA degree, MBA section number, ethnicity

2. MBA network and support system

    - "Thinking about your professional network, how important are the following types of support for your career on a scale from 1 to 5, where 1 is not at all important and 5 is extremely important:"
        - Providing you with job referrals or other work-related opportunities (e.g., highlighting job openings, connecting with professionals who may be potential employers)
        - Providing you with general work advice, such as strategies for career advancement (e.g., negotiating an offer, finding a mentor)
        - Helping you identify female-friendly firms: i.e., firms that provide policies/benefits (e.g., maternity leave, flexible working schedule, mentoring programs for women) and/or have a work culture that support women's career advancement
        - Providing you with advice on how to balance work and family responsibilities (e.g., how to take advantage of maternity/parental leave)

[80] The survey was rolled out in two waves because the alumni office imposed restrictions on how many alumni can be surveyed at a time.

- Providing you with emotional support
  - Increasing your ambition and self-confidence
  - Improving your MBA academic experience (e.g., contributing to a supportive/intellectually stimulating learning environment)
  - Acting as your role models
  - Connecting you with mentors/sponsors
- "To what degree has your female (male) MBA network helped your professional career by providing the following types of support on a scale from 1 to 5, where 1 is not at all and 5 is extremely important" (Same categories as above)
- Number of referrals received from male (female) MBA network
- MBA contacts by gender
- Professional contacts (from MBA, from MBA section, by gender)
- Reunion attendance

3. Employment background
   - Employment status
   - Management position
   - Ambitions to be top executive
   - Career satisfaction
   - Educational debt
   - Current employer (name, female-friendliness, % women in c-level)
   - P&L responsibilities
   - Negotiations
   - Work hours
   - Compensation
4. Entrepreneurs
   - Number of employees
   - Sales and revenues

- External capital

5. Durations of nonemployment

6. Family background

    - Partner's education, compensation
    - Children
    - Maternity leave
    - Effects of children on work

L.2 Balance Table

In this section, we explore whether there is a systematic relationship between those that responded to the survey and those that did not. Table L.1 uses the LinkedIn data from the full sample. Note that because we were only able to match 77% of alumni to their LinkedIn profiles, some of the survey respondents also were not matched to their LinkedIn profiles.

Table L.1: Survey Response Balance

	All	Non-Respondents	Respondents	Difference
Share of Female Section Peers	0.35	0.35	0.36	-0.00
	(0.06)	(0.06)	(0.06)	(0.70)
Pre-MBA Years of Experience	4.80	4.79	4.92	-0.13
	(1.87)	(1.88)	(1.87)	(0.38)
Any Pre-MBA Management Experience	0.41	0.41	0.37	0.04
	(0.49)	(0.49)	(0.48)	(0.27)
Any Pre-MBA Senior-Level Management Experience	0.12	0.12	0.10	0.02
	(0.32)	(0.33)	(0.30)	(0.41)
Ever Post-MBA Senior-Level Management Experience	0.57	0.57	0.57	-0.00
	(0.50)	(0.50)	(0.50)	(0.97)
Top-20 Undergrad	0.33	0.34	0.30	0.04
	(0.47)	(0.47)	(0.46)	(0.28)
Class	2009.41	2009.34	2009.98	-0.64
	(5.64)	(5.63)	(5.76)	(0.14)
Observations	1763	1574	189	1763

Notes: Table L.1 shows the summary statistics by survey response status of the individual. The sample size is restricted to only female graduates. The difference column refers to the difference in means between non-respondents and respondents. The p-value of the difference is reported in parentheses. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.3 Composition and Persistence of Peer Ties

To understand the composition of the peer ties formed during the MBA, we asked female respondents in our survey, among their 10 closest professional contacts, how many are women, MBA peers, or MBA section peers.

We plot the results in Figure L.1. The graph shows that a majority of women's closest network ties are women (over 60%). Between 10% and 40% of their closest ties are individuals met through the MBA. Importantly, we see that the ties formed between MBA peers remain persistent over time.

Figure L.1: Composition of 10 Closest Professional Contacts

Notes: Figure L.1 shows the average number of contacts that are women, from MBA class, and from MBA section among the 10 closest professional contacts of survey respondents. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009.

We also explored whether the share of female peers influence the composition of networks.

Table L.2: Effect of Female Peers on the Composition of MBA Contacts

	(1) Female Share Among 10 Closest MBA Contacts	(2) Female Section Peer Share Among 10 Closest MBA Contacts	(3) Female Section Peer Share Among Closest Female MBA Contacts
Female share	-0.144	0.267	0.827
	(0.450)	(0.336)	(0.762)
Class FE	Yes	Yes	Yes
Mean	0.612	0.156	0.276
SD	0.253	0.182	0.431
R^2	0.132	0.0856	0.149
N	201	200	199

Notes: We present the coefficients from regressing the female share among 10 closest MBA contacts, the female section peer share among 10 closest MBA contacts, and the female section peer share among closest female MBA contacts on female peers share and class fixed effects. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table L.3: Effect of Female Peers on the Composition of Professional Contacts

	(1) Female Share	(2) MBA Peer Share	(3) MBA Section Peer Share
Female share	0.0765	-0.0925	0.0316
	(0.417)	(0.549)	(2.359)
Class FE	Yes	Yes	Yes
Mean	0.632	0.274	0.722
SD	0.220	0.291	1.203
R^2	0.0752	0.104	0.0446
N	195	195	195

Notes: We present the coefficients from regressing the female share of 10 closest professional contacts (not necessarily from the MBA), the MBA peer share among 10 closest professional contacts, and the MBA section peer share among 10 closest professional contacts on female peers share and class fixed effects. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table L.4: Effect of Female Peers on Reunion Attendance

	(1) Any Reunion Attended	(2) Number of Reunions Attended
Female share	1.164	0.510
	(0.874)	(2.340)
Class FE	Yes	Yes
Mean	0.668	1.488
SD	0.472	1.385
R^2	0.128	0.295
N	195	195

Notes: We present the coefficients from regressing a dummy for having attended any reunion, and the number of reunions attended on female peers share and class fixed effects. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.4 Perceived Female-Friendliness of Employer and InHerSight Rating

Additionally, we perform a validation exercise using our survey data (described in more details in Appendix Section L). As part of the survey, we asked three questions to understand the female-friendliness of the firms in which women are currently employed:

1. "Approximately what percentage of c-level executive positions and board members in your firm are women?"

2. "How often do the demands of your job interfere with your family life? (Often, sometimes, rarely, never)"

3. "Thinking about your current job (or if not employed, your last job), how female-friendly would you rate your employer on a scale from 1 to 5, where 1 is not at all and 5 is extremely (we define as female-friendly firms that provide policies/benefits (e.g.,

maternity leave, flexible working schedule, mentoring programs for women) and/or have a work culture that support womens career advancement)"

Using the employer names provided by the survey respondents, we matched them to the InHerSight (IHS) ratings. Table L.5 presents the results from regressing these measures on the InHerSight ratings, controlling for class fixed effects. The table shows that IHS ratings are highly correlated with respondents' perception of the overall level of female-friendliness of their employer. Note we do not include year fixed effects because we only have this information for the current employer.

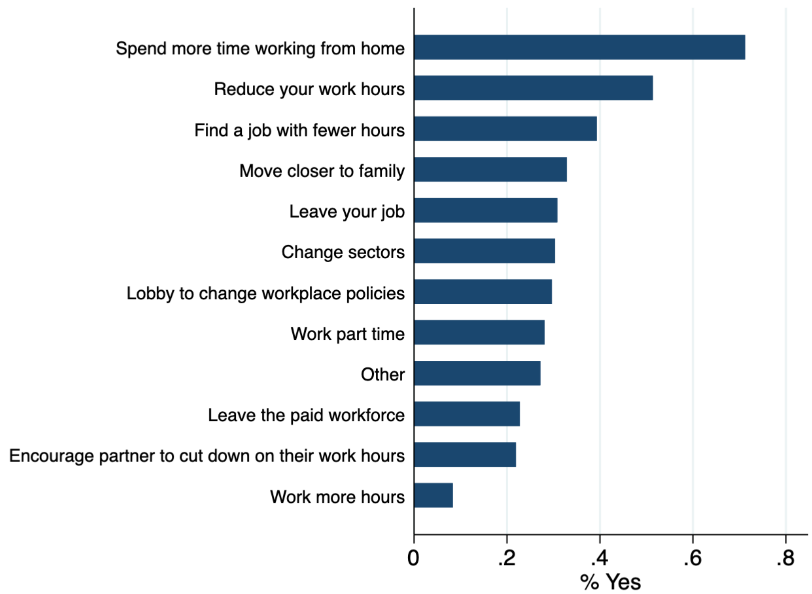
Table L.5: Comparison of IHS Ratings and Female-Friendliness Measures from Survey Responses

	(1) Female % of C-level positions	(2) Demands of job interfere with your family life	(3) Level of female-friendliness
IHS Rating	-3.917	0.144	0.731***
	(4.100)	(0.210)	(0.205)
Class FE	Yes	Yes	Yes
Mean	29.31	3.437	3.900
R^2	0.245	0.141	0.297
N	74	80	80

Notes: We present the coefficients from regressing survey measures of female-friendliness on the InHerSight overall rating and class fixed effects. The dependent variables are (1) female percentage of C-level positions, (2) demands of job interfering with your family life on a 1-4 scale where 1 is "often" and 4 is "never," and overall level of female-friendliness on a 1-5 scale where 1 is "not at all female-friendly" and 5 is "extremely female-friendly." Sample includes firms of female survey respondents who graduated in 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

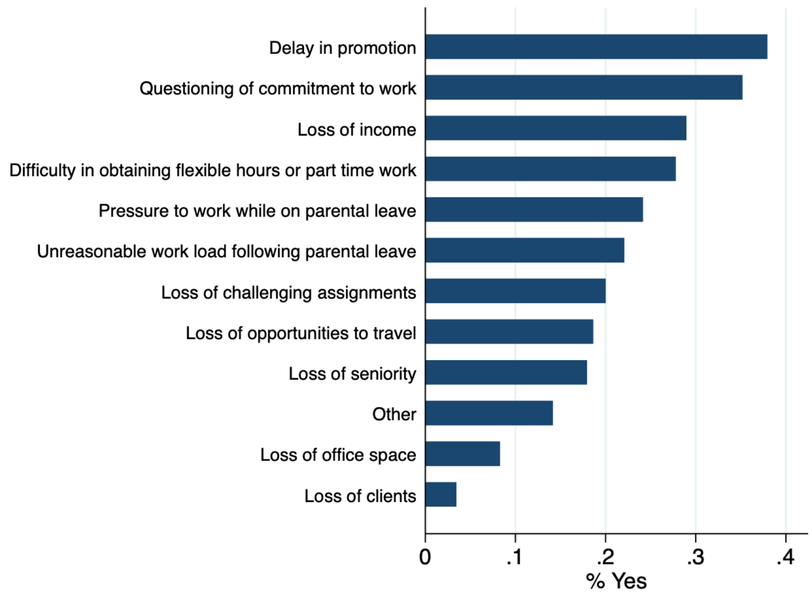
L.5 Work and Career Effects of Children

Figure L.2: Work and Career Choices Due to Children



Notes: Figure L.2 presents share of survey respondents who agreed to making the specified change in their work and career due to having children. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009.

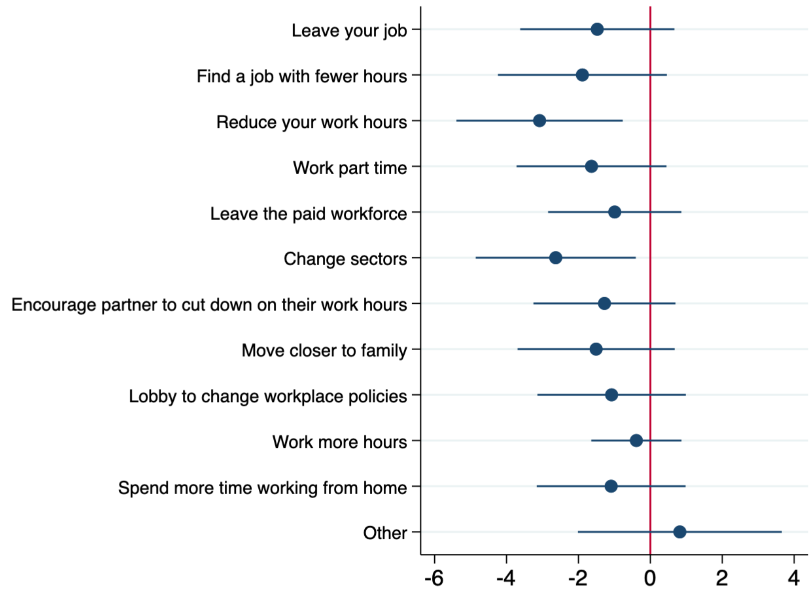
Figure L.3: Adverse Effects at Work Due to Children



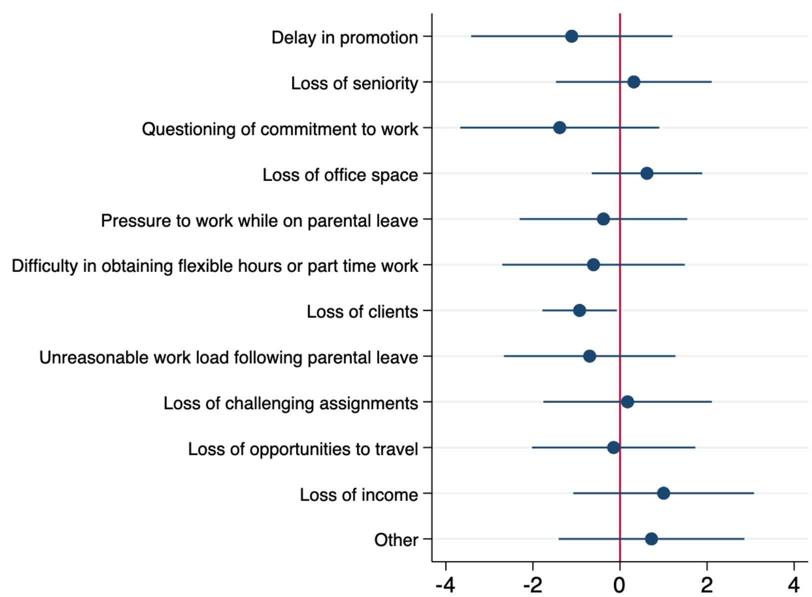
Notes: Figure L.3 presents share of survey respondents who agreed to experiencing the adverse effect at work due to having children. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009.

Figure L.4: Effects of Female Peers on the Work Impacts of Children

(a) Effects on Work/Career Choices



(b) Adverse Effects at Work



Notes: Figure L.4a presents the coefficients and 95% confidence intervals from regressing dummies for experiencing each type of potential effect of children on work choices on female share and class fixed effects. Figure L.4b presents the analogous results for dummies for experiencing each potential type of adverse effect at work due to having children. Sample includes female survey respondents who graduated in 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.6 Ambition and Self-Confidence

Table L.6: Effect of Female Peers on Ambition and Self-Confidence

	(1) Would Like to Be or Already Top Executive	(2) See Myself as SVP/C-Level in 5 years	(3) See Myself as SVP/C-Level in 10 years
Female share	1.025	0.748	1.656*
	(0.859)	(0.962)	(0.912)
Class FE	Yes	Yes	Yes
Mean	0.736	0.508	0.739
SD	0.442	0.501	0.440
R^2	0.0929	0.147	0.0949
N	187	178	154

Notes: Table L.6 presents the coefficients from regressing negotiation outcomes on female peer share and class fixed effects. The dependent variables are dummy variables constructed based on yes/no responses to the questions: "In general - not just thinking where you work now - would you like someday to be a top executive, or is this not something you would like to do?" "What job level do you expect to be at in five years?" "What job level do you expect to be at in 10 years?" Sample includes female survey respondents from graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.7 Negotiation

Table L.7: Effect of Female Peers on Negotiation

	(1) Negotiated Raise	(2) Successful Negotiated Raise	(3) Negotiated Promotion	(4) Successful Negotiated Promotion
Female share	1.345	-1.782	2.378**	0.426
	(0.951)	(1.696)	(0.943)	(1.566)
Class FE	Yes	Yes	Yes	Yes
Mean	0.353	0.847	0.327	0.904
SD	0.479	0.363	0.471	0.298
R^2	0.156	0.246	0.165	0.320
N	162	57	160	51

Notes: Table L.7 presents the coefficients from regressing negotiation outcomes on female peer share and class fixed effects. The dependent variables are dummy variables constructed based on yes/no responses to the questions: "Have you negotiated for a raise at this [current/last] firm?" "Were you successful in obtaining a raise through negotiation?" "Have you negotiated for a promotion at this [current/last] firm?" "Were you successful in obtaining a promotion through negotiation?" Sample includes female survey respondents from graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.8 Nonemployment, Career Breaks, Maternity Leave

As highlighted by Bertrand et al. (2010), one important explanation for the widening gender gap in earnings for high-skilled workers is career breaks incurred by women after having children. In this section, we explore how the likelihood of career breaks among the MBA graduates in our survey data relates to the gender composition of their MBA peer group.

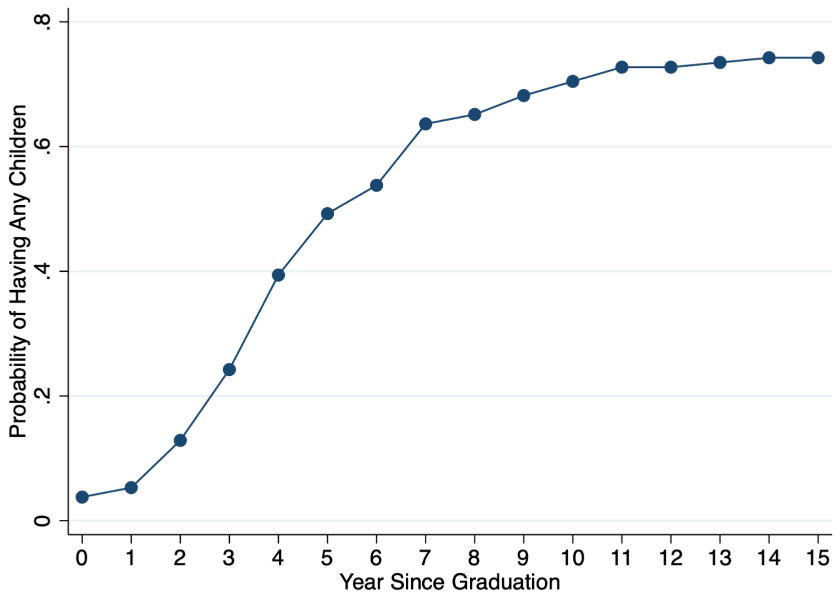
Table L.8: Effect of Female Peers on Nonemployment and Career Breaks

	(1) Nonemployed	(2) Cumulative Materity Leave (Weeks)	(3) Any Leave (Not Including Family Leave)
Female share	-0.459	51.36	1.073
	(0.823)	(40.77)	(1.174)
Class FE	Yes	Yes	Yes
Mean	0.112	13.17	0.381
SD	0.316	14.76	0.487
R^2	0.125	0.124	0.249
N	138	166	129

Notes: Table L.8 presents the coefficients from regressing nonemployment career break outcomes on female peer share and class fixed effects. The dependent variables are (1) dummy for being nonemployed, (2) cumulative maternity leave in weeks, (3) dummy for having any leave or absence from work, excluding family leave. Sample includes female survey respondents from graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.9 Marriage and Fertility

Figure L.5: Probability of Having Children



Notes: Figure L.5 shows the average likelihood of having a child since each year post MBA graduation among survey respondents.

Table L.9: Effect of Female Peers on Marriage and Fertility

	(1) Married	(2) Met Partner from MBA	(3) Any Children	(4) Number of Children
Female share	-0.259	-0.670	-1.658	-2.613
	(0.959)	(1.027)	(1.072)	(2.302)
Class FE				
Mean	0.833	0.171	0.744	1.459
SD	0.374	0.379	0.438	1.041
R^2	0.197	0.256	0.240	0.347
N	127	101	128	128

Notes: Table L.9 presents the coefficients from regressing family background outcomes on female peer share and class fixed effects. The dependent variables are (1) dummy for being married, (2) dummy for having met partner from MBA if married, (3) dummy for having any children, and (4) number of children. Sample includes female survey respondents from graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

L.10 Career Satisfaction

As part of the survey, we explored whether women are satisfied with their careers and to what extent this depends on the gender composition of their MBA section. Appendix Table L.10 presents the results for career satisfaction, which is measured via the survey question: "How satisfied are you with your career (on a scale of 1 to 5, where 1 is not at all and 5 is extremely satisfied)?"

Table L.10: Effect of Female Peers on Career Satisfaction

	(1) Career Satisfaction
Female share	3.875**
	(1.622)
Class FE	Yes
Mean	3.887
SD	0.872
R^2	0.0959
N	194

Notes: Table L.10 presents the coefficients from regressing career satisfaction (on a scale 1-5, 5 being highly satisfied) on female peer share and class fixed effects. Sample includes female survey respondents from graduating classes 2000-2018, excluding 2009. Mean female share of a section is 34%; one standard deviation is 4 percentage points. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

M Qualitative Evidence

Qualitative evidence comes from 45 interviews we conducted on female MBA alumnae in our sample. The women were randomly sampled, stratified by year of graduation and if they were ever a senior manager. We oversampled those that attained senior management positions to understand how female peers may have affected their career trajectories.

The interviews were conducted by a sociology PhD student using an in-depth narrative approach following the methodology employed by Bergman et al. (2019). During the interview, we asked the respondent to describe her career path after the MBA, the challenges she may have faced in the workforce, and how she dealt with these challenges. We also inquired about the role of their MBA female peer network. In total we collected 1,644 minutes of transcripts.

To analyze this data, we follow the approach in Bergman et al. (2019). First, we fully read interview transcripts and manually coded the transcripts by categorizing the information.

Specifically, we categorized the type of challenges mentioned by interviewees into four groups: 1) gender bias and discrimination, 2) lack of flexibility and time demand, 3) difficulties in networking, and 4) lack of family-friendly firm culture and policies. Similarly, we coded the type of support they received from their female MBA peers as part of one of six groups: 1) emotional support, 2) information (including both general advice and gender-specific information), 3) job referrals and work-related opportunities, 4) ambition and self-confidence, 5) role models, and 6) improved academic environment.

M.1 Challenges Faced by Female MBAs

Our qualitative interviews with female MBA alumnae highlighted four challenges that women face during their career progressions. First, nearly all in our sample (91% of respondents) mentioned that they have experienced some form of gender bias or discrimination. A large share report having difficulties forming relationships with male leaders or felt they did not have a "fair shot" to be promoted. For example, a female MBA alumna from the class of 2015 said, "When working at this startup, there seems to be an aversion to females, because [...] it was a very clique-y company and the top clique was all white males who had worked at the same company before... It seemed to appear that a lot of the males who were less qualified and had worked in the business less time were getting promotions faster and were getting bigger check raises than the females."

In addition, women also reported they were often treated unfairly compared to their male counterparts. Many women felt they were often criticized for attributes that are not related to their work performance such as being "too emotional" or "not assertive enough." For example, a respondent described: "I was in a discussion with some sales leaders, and we are trying to have a [...] discussion about where the problems are in the sales organization or what needs to be done. And after that meeting, [...] there were questions about the tone I was taking in that meeting. Which I don't fundamentally have proof that it was based on a sexist assumption. *But I don't know too many men who are chastised for their tone coming out of leadership-level meetings where we're just trying to have a business discussion.*"

Second, 40% of women were challenged by the lack of flexibility and time-demanding nature of their jobs. For example, one woman explained that the travel demands of her job were difficult for her children, despite the support of her husband's parents, her own parents, and two nannies: "Having to [travel], it took a toll on the kids. We had a lot of infrastructure, like my parents were available, and my husband's parents were available, and we had a lot of support and two nannies. [...] But my two older kids were already completely insane, because my travel affected them."

Third, 37% of female graduates mentioned difficulties in networking. For example, a female alumna said, "In the group I was at, it seemed like the in-crowd was a group of middle aged men who had similar interests and lived near each other and worked together for a long time. It was frustrating to see when younger men would come in, who were all also good at their jobs, but it seemed a little easier for them just being able to develop those relationships with the leaders, and have those advocates. So even though I had strong female advocate and some great male managers, I always felt like I had to fight for it a bit more than a couple other men."

Lastly, 35% of women were challenged by the lack of family-friendly policies. In several cases, the companies where women worked offered no official maternity leave policies or had policies on paper but no official procedures in place. For example, a female alumna mentioned that, when she came back from maternity leave, she found out that the firm "had divided [her] job into three roles" and was told to "figure out what [her] role is the day [she] got back from maternity leave."

Overall, the women in our interviews faced considerable and gender-specific challenges in their post-MBA careers. Everyone we interviewed agreed that they faced additional difficulties that men in similar careers did not, suggesting that female peers may have a comparative advantage in helping women navigate these challenges given their shared experiences.

M.2 Potential Mechanisms Highlighted in Interviews

After investigating the challenges that women face, we explore mechanisms through which female peers support women's career advancement.

M.2.1 Emotional Support

One of the most frequent forms of support that women mention in our interviewers is emotional support from other female peers. More specifically, 82% of our interviewees talk about how women create an "organic community" and support each other by "sharing stories" and "experience." For example, a female MBA alumna from the class of 2011 said, "There's [a] shared lived experience[...] We are women in industry who are finding the same challenges and factors that are influencing our advancement, regardless of industry[...] We can understand those things and how we navigate them make sense to me."

M.2.2 Information

In addition to emotional support, 64% of women mention that female peers help them in their careers by providing two types of information. The first type of information relates to general advice, such as how to effectively negotiate or what would represent a fair compensation. For example, a female alumna from class 2010 said, "I've only talked to female friends about a total compensation package, although I should probably be talking to male friends too [...] I'm more comfortable having those equity conversations with [women]."

Second, female peers provide useful gender-specific information. In some instances, this information relates to firm benefits and culture. For example, a female graduate from the class of 2015 said, "If I receive an offer, I'm comfortable talking to a [female] friend [...] I'd ask how maternity leave works or generally what the female community looks like and what the support is. *I probably wouldn't ask those questions [to a hiring manager] in the off chance the person uses this as a red flag.*" In other cases, female peers provide general information on how to balance work-life responsibilities and female-related policies. For example, they provide advice on what kinds of firm attributes women should focus on when searching for a job and how to take advantage of family-related policies. A female alumna from the class of 2015 said, "I was one of the first people at an earlier stage company [...] to actually have kids [...] and so they had no idea what parental leave looks like [...]. I had to write up a document that scopes who to contact and how to leave my projects to other people. *I talked* *to several females from the [MBA] community who had already gone through this cycle, just to learn exactly how they left things.*"

The information we obtained from our interviews is consistent with the literature. Female peers have been shown to provide private career information that may be more relevant for women than for men (Yang et al., 2019). In male-dominated settings, women may provide more credible and gender-specific information about topics such as navigating job cultures, managing relationships, and balancing work-family responsibilities (Sandberg and Scovell, 2013; Saloner, 1985). This is particularly true regarding firm-level information such as firm culture, hiring and promotion strategies, and family-friendly policies.

M.2.3 Job Referrals and Work-Related Opportunities

Sixty percent of women mentioned referrals as a critical form of support that they received from their business school peers, especially during the first years post MBA. For example, a female alumna from the class of 2009 said, "Early on getting out of school, one of my first good jobs out of business school I got through a classmate...in the first [few] years, there was a lot more leaning on classmates in the network to find potential hires." Although in many occasions women mentioned receiving referrals by both male and female peers, referrals from female peers seem to become more relevant when women search specifically for firms with a more female-friendly environment—such as firms with female leadership. This suggests that female peers may have a comparative advantage in referrals to specific types of firms.

M.2.4 Ambition and Self-Confidence

Twenty-two percent of our respondents mention that female peers increased their ambition and boosted their self-confidence by representing motivational figures. For example, a female MBA alumna from the class of 2008 said, "I think [having more female peers] does also motivate [me]. [...] When I see all the different people I graduated [from this MBA program] with, especially the females, and I see what they're doing, and how they're juggling their lives, or like the career path they've gone on, it is a little more motivating. Oh, wow! They've done this, and like, maybe I could do this, too, and like they made this, and that's totally possible. So I do think not only being able to rely on them for advice, but just seeing where they are is a motivational factor, too."

The literature has identified self-confidence and ambitions as possible drivers of the gender gap in male-dominated fields and managerial positions (Carlana, 2019; Rosenthal et al., 1996;

Rosenthal, 1995; Kirkpatick and Locke, 1991). Given that we do not have any measure of self-confidence and ambition in our current datasets, we collect survey data on these outcomes to test this channel more directly.

M.2.5 Role Models

In addition to ambition and self-confidence, 16% of interviewees mention that their female MBA peers act as role models and that their successes are "inspirational" for their career progression. For example, an alumna from class 2006 said, "I know personally for me that my fellow women inspire me... When they achieve, it helps [and] gives me hope. And whereas when I look at men[...] it's kind of almost like a given [...], yeah, they're going to be successful. They're dudes."

M.2.6 Improved Academic Environment

Finally, 9% of women mention that having more female peers in sections contributes to a "less intimidating" and "safer environment" during the MBA. This academic environment helps women feel more comfortable when participating in class and asking questions. For example, a female MBA alumna from the class of 2015 said, "I feel like having a good group of women with whom you could be in small groups just makes it *less intimidating* [to ask questions]. I think that it's just a safer environment, and so I think if you have that, from the beginning, like in your study groups [...], *it would just be a skill that you would learn in life.*"

N Back of the Envelope Calculations

In this section, we use our main results to provide an estimate on how gender compositions of MBA peers can play a key role in the reduction of the gender gap in leadership positions.

Given 60 students per section, 34% of female students per section, and a total of 144 unique section-by-class peer groups between 2000 and 2018, the total number of female students between 2000 and 2018 is given by $144 \times 60 \times 0.34 \approx 2938$. From our summary statistics, we know that 39% of female graduates are senior managers, for a total of 1,146 ($=2938 \times 0.39$) female senior managers. We compare the real distribution of female share across sections in our data with a counterfactual where all sections are assumed to have 34% of female students. We then compute the differential effect of female peers between the baseline allocation and the new allocation.

To do that, we use the coefficients from the one-knot spline in Table F.1. In this table, we find that female peers have a positive but non-significant effect in sections with a share of female students above the median (34%). To compute our lower bound, we interpret this coefficient as zero marginal effect. This leads to 42 additional female senior managers, or an average of two additional female senior managers per graduating class. Instead, for our upper bound, we assume that the effect of female peers above the 34% cutoff is equal to the value of the coefficient. This leads to 96 additional female senior managers, or an average of five additional female senior managers per graduating class. Note that, for classes with an overall female share below 34%, we assume that female students are allocated such that a section reaches 34% female share before starting to fill out the following section, until all female students in the class are allocated.