Affirmative Action and Career Consequences: Evidence from India

Lakshita Sharma*

Job Market Paper

November 15, 2026

Abstract

This paper studies how increasing women's representation in elite engineering programs affects their labor market outcomes along two margins: (a) first jobs at elite firms and (b) early-career promotions. I examine this question in the context of India's 2018 Supernumerary Seats Scheme, a gender-based affirmative action policy that added female-only seats at the Indian Institutes of Technology (IITs) until women made up 20% of each program. Programs with fewer women before the reform added more seats and were more exposed to the policy. Using LinkedIn career histories and a novel classification of elite firms built with a large language model, I exploit this variation in exposure across programs in a difference-in-differences design. I document three main findings. First, in more exposed programs, the number of women entering the labor market roughly doubled, and elite firms hired about 60% of these additional women without hiring fewer men. Second, women in these programs were 21% more likely to begin their careers at an elite firm. Third, women from these programs who started at non-elite firms were more likely to be promoted within two years. These findings are consistent with latent demand for women among elite firms and with human capital accumulation. Together, they suggest that gains from gender-based affirmative action can extend beyond education into the labor market.

JEL Codes: I23, I28, J16, J24, J71, M51

*Graduate Student, Dept of Applied Economics and Management, Cornell University. Email: ls822@cornell.edu. I am deeply grateful to Michael Waldman, Daniela Scur, and Nicolas Bottan for their guidance and support. I also thank seminar participants at Cornell University and participants at the 2026 Fall Research Conference of the Association for Public Policy Analysis and Management (APPAM) and the 2026 Northeast Universities Development Consortium (NEUDC) Conference for helpful comments and suggestions. All errors are my own.

1 Introduction

The gender gap in the labor market remains large, both in earnings and in access to leadership positions (Goldin, 2014; Blau and Kahn, 2017), and it is more pronounced in developing countries (Jayachandran, 2015). A key driver of this gap is the type of degree individuals pursue. Field of study generates large differences in labor market returns, with STEM fields yielding among the highest returns (Altonji et al., 2012; Kirkeboen et al., 2016; Sloane et al., 2021). However, women remain underrepresented in these fields, accounting for only 35% of STEM graduates worldwide, a share that has remained largely unchanged over the past decade (UNESCO, 2024).

Affirmative action (AA), long used to address historical inequalities by race, caste, and socioeconomic status, is increasingly used to address women's underrepresentation in higher education.[1] Despite its widespread adoption, AA remains a contentious issue. Proponents argue it corrects historical disadvantage, while critics contend it undermines meritocracy by placing beneficiaries in programs for which they are less prepared.[2] Most existing evidence concerns policies targeting race, caste, or socioeconomic status, and even there the findings remain mixed (Arcidiacono and Lovenheim, 2016).[3] Since the effects of AA may vary with the group targeted and the design of the policy, these results may not transfer to gender-based policies.

In this paper, I evaluate the labor market consequences of a gender-based affirmative action policy at India's most selective engineering institutions, the Indian Institutes of Technology (IITs). The IITs play a role similar to Ivy Plus universities in the United States, whose graduates are far more likely to reach top income positions (Zimmerman, 2019; Chetty et al., 2026; Abramitzky et al., 2024). However, access to the IITs has been highly unequal along gender lines. Before 2018, women made up only 10% of admitted students (Sengupta et al., 2025). To address this gap, the Government of India introduced the Supernumerary Seats Scheme (SSS) in 2018. The policy required every IIT program to raise its female share to 20% by creating additional seats for women. I use this reform to address two questions. First, how does increasing women's representation in elite engineering education affect women's

[1] Such policies exist in countries including the United States, India, Brazil, and South Africa (Sowell, 2004).

[2] For arguments and evidence in favor of AA, see Chan and Eyster (2003), Fryer et al. (2008), Ellison and Pathak (2021), and Akhtari et al. (2024). For arguments and evidence against, see Sander (2004), Ferman and Assunção (2005), and Grau (2018).

[3] For policies based on race, see Arcidiacono and Lovenheim (2016) and Bleemer (2022); for caste, see Bertrand et al. (2010), Bagde et al. (2016), and Frisancho and Krishna (2016); and for socioeconomic status, see Barahona et al. (2023) and Oliveira et al. (2024).

access to jobs at elite firms? Second, how does it affect their early careers, as measured by promotions?

The effect of increasing women's representation on women's labor market outcomes is theoretically ambiguous. On the one hand, women may build more of the skills employers value when more women study in their program, for example through their peers (Mouganie and Wang, 2020; Busso and Frisancho, 2021), and employers with unmet demand for women may hire more of them. On the other hand, women's outcomes may worsen if the additional women are less prepared than their classmates (Sander, 2004; Arcidiacono and Lovenheim, 2016), or if employers respond through statistical discrimination (Phelps, 1972; Coate and Loury, 1993). Therefore, whether increasing women's representation improves or worsens their outcomes is an empirical question.

To answer these questions, I use variation across programs in how much the reform increased women's representation. Since every program had to reach the same 20% target, programs with fewer women before the reform had to add more seats for women, relative to their size. For example, Mechanical Engineering at IIT Delhi, where women made up 2% of the 2017 cohort, added many seats for women, while Computer Science at IIT Madras, already at 16%, added few. I measure a program's exposure as the number of seats it added for women, relative to its size before the reform, and refer to programs above the median as High Exposure programs and to the rest as Low Exposure programs. By 2020, the reform raised women's share from about 6 to 20% in High Exposure programs, and from about 15 to 20% in Low Exposure programs. Using a difference in differences design, I compare how women's outcomes changed after the reform in High Exposure programs, relative to Low Exposure programs. Because Low Exposure programs also added seats for women, the comparison identifies the effect of a larger increase in women's representation, not the effect of the policy as a whole.[4]

To follow graduates from admission into their early careers, I bring together three sources of data. The main dataset contains career histories for 25,915 graduates admitted between 2015 and 2020 to 6 legacy IITs, constructed by Revelio Labs from public LinkedIn profiles. Second, I use records published by the authority that conducts the Joint Entrance Examination (JEE) Advanced, a national exam that alone determines admission to the IITs. These records report the number of seats added to each program and the examination rank of every admitted student. Third, I construct a classification of elite firms, the highest paying employers

[4]The career data do not show whether a woman was admitted only because of the new seats, so the estimates are average effects on all women in a program. However, in most program and cohort pairs after the reform, every woman in a female-only seat could have entered the program only because of the reform.

recruiting IIT graduates. To do so, I use a large language model to extract these firms from newspaper coverage of IIT placements.[5]

The analysis focuses on three outcomes that follow graduates through the early career, namely entry into the labor market, a first job at an elite firm, and promotion within two years of the first job. Labor market entry matters since women admitted under the reform could have chosen further study instead of work. A first job at an elite firm is the main outcome, since these firms offer the highest paying positions available to IIT graduates. Finally, promotions capture whether these placements translate into career progress once women start working.

I first estimate the effects at the program level. The reform roughly doubled the number of women entering the labor market from High Exposure programs, an increase of about 5 women per program and cohort. Elite firms hired about 60% of these additional women. The number of men elite firms hired from the same programs did not change.

I then turn to each woman's likelihood of an elite first job. The women admitted under the reform had worse JEE Advanced ranks than the women admitted before it. If rank captures what employers value, each woman's likelihood of an elite first job should fall, and by more in High Exposure programs, which added more of these women relative to their size. The results show that women in High Exposure programs became 7 percentage points, or 21%, more likely to begin their careers at an elite firm, relative to women in Low Exposure programs, while their likelihood of entering the labor market did not change. This difference comes mainly from Low Exposure programs. In these programs, more women graduated after the reform, but elite firms hired about as many of them as before, so each woman's likelihood of an elite first job fell. In High Exposure programs, the number of women hired by elite firms rose roughly in line with the number of women graduating.

Next, I examine women's early careers. If elite firms had lowered their hiring bar to hire more women, women from High Exposure programs should be promoted less often once employed.[6] The results do not show the broad decline a lower hiring bar would predict. Women from High Exposure programs who started at non-elite firms became 15.7 percentage points, or 39%, more likely to be promoted within two years of their first job, mostly by moving to a more senior position at another firm, while men show no such change. Women who started at elite firms were promoted less often, but this decline does not come from promotions within their firm, where a lower hiring bar should show. These patterns suggest the gains for women

[5] Section 3 describes the classification, and Appendix A.3 details how the firms are extracted from newspaper reports and how the classification is validated.

[6] The hiring bar is the minimum level of skill a candidate must show in a firm's tests and interviews to receive an offer. A lower hiring bar means elite firms reduced this threshold after the reform, so women who would have fallen below it before the reform now received offers.

from High Exposure programs extend beyond elite firms.

Finally, I find evidence consistent with two mechanisms working together, namely latent demand and human capital accumulation. Latent demand refers to elite firms wanting to hire more women than the IITs produced before the reform. To examine it, I compare the number of women that elite firms hired from each program before the reform with a gender-blind benchmark, i.e., the number they would have hired had they ignored gender. I find that for every 100 women that elite firms would have hired under this benchmark, they hired about 134. This ratio was similar in High and Low Exposure programs, and the difference between the two is not statistically significant. This is consistent with common latent demand for women, i.e., elite firms' unmet demand for women being similar across programs. Hence, once the reform increased the number of women, elite firms could hire more of them. A back-of-the-envelope calculation suggests latent demand could account for about 85% of the increase in the number of women hired by elite firms.

However, while common latent demand could account for most of the increase in the number of women hired by elite firms, it would not by itself predict a difference between High and Low Exposure programs in women's likelihood of an elite first job. A second possible mechanism is human capital accumulation, in which women in High Exposure programs built more of the skills employers value during their degree. Within a program, the teaching and curriculum are unlikely to have changed with the reform. What did change was women's peers, and they changed the most in High Exposure programs, where women had far fewer female classmates before the reform. Since students tend to form friendships and study groups with classmates of the same gender (Currarini et al., 2009; Friebel et al., 2021), having more female classmates could have helped these women build more skills. Consistent with this, the gains in elite hiring are concentrated in the programs with the fewest women before the reform. Women who started at non-elite firms were also promoted more often, which is consistent with human capital accumulation via peer effects.

The identifying assumption is that, absent the reform, outcomes in High and Low Exposure programs would have evolved in the same way. Consistent with this assumption, an event study shows no systematic difference between the two groups before the reform in the number of women hired by elite firms. A series of robustness checks shows the estimates are stable across specifications. The increase in the number of women hired by elite firms is statistically significant in every specification, including Poisson models, a continuous measure of exposure, and comparisons within the same field or the same IIT. The estimate for women's likelihood of an elite first job remains positive in every specification, ranging from 4.7 to 7.0 percentage points, although it is not statistically significant in all of them. The results also do not appear

to be explained by the signal a more selective program sends or by elite firms recruiting heavily from a few departments.

My paper contributes to two strands of literature. First, it adds to the literature on the effects of affirmative action in higher education on labor market outcomes. A growing body of work studies policies based on race, caste, and socioeconomic status (Bertrand et al., 2010; Frisancho and Krishna, 2016; Francis-Tan and Tannuri-Pianto, 2018; Bleemer, 2022; Machado et al., 2023; Barahona et al., 2023; Oliveira et al., 2024). However, the evidence on gender-based policies is limited to their effects on access to higher education and enrollment (Najam, 2024; Sengupta et al., 2025). The closest paper to mine is Gupta (2024), which studies the same policy using a correspondence study and finds no gender gap in callbacks for IIT graduates, while women from lower ranked colleges received fewer callbacks after the policy. I add to this literature in two ways. First, while most of this literature studies earnings, I study access to elite jobs and early careers, as measured by promotions. Second, I study a supernumerary policy, which added seats for women without removing seats from other candidates. Such policies are relatively less studied in the literature, which mostly examines policies that reserve a share of existing seats.

Second, the paper contributes to the literature on how elite institutions shape access to top paying careers. Graduates of highly selective institutions hold a disproportionate share of top positions (Zimmerman, 2019; Chetty et al., 2026). However, these gains accrue mainly to men from advantaged backgrounds, and social ties among college peers from similar backgrounds appear to play an important role (Zimmerman, 2019; Michelman et al., 2022). Much of this literature estimates the return to elite admission by comparing applicants just above and just below the admission cutoff. I study a different margin, namely how women's outcomes in an elite program change with its gender composition. My results suggest the gender composition of a program, and not only admission to it, shapes women's access to the highest paying jobs. In doing so, I also add to work on the gender gap in high paying STEM jobs (Goldin, 2014; Blau and Kahn, 2017; Kahn and Ginther, 2017; Sloane et al., 2021) and on how the gender composition of peers affects women in STEM (Mouganie and Wang, 2020; Busso and Frisancho, 2021; Zölitz and Feld, 2021; Bostwick and Weinberg, 2022). This work studies women's choices and persistence during their education, and my results suggest these effects can extend into the labor market.

The paper is organized as follows. Section 2 provides background on admission to the IITs, the Supernumerary Seats Scheme, the placement market, and other changes during the period. Section 3 describes the data. Section 4 presents the empirical strategy, including how to interpret the estimates and how the reform changed who was admitted. Section 5 presents

the results on first jobs and early careers, together with the robustness checks. Section 6 examines the mechanisms, and Section 7 concludes.

2 Context

2.1 Admission to the IITs

The Indian Institutes of Technology (IITs) are the highest ranked engineering institutions in India.[7] The first 7 IITs, located in Kharagpur, Bombay, Kanpur, Madras, Delhi, Guwahati, and Roorkee, are known as the legacy IITs. The Ministry of Education has since expanded the network to 23 institutes, although the newer IITs are generally not regarded as comparable to the legacy ones (Figure A1).

Admission to the IITs is determined solely by a student's rank on the Joint Entrance Examination (JEE) Advanced, a national examination in physics, chemistry, and mathematics.[8] Each year, roughly 1.5 million students compete for about 16,000 seats. Candidates who qualify receive a rank on the Common Rank List (CRL), which orders candidates of all social categories by their score.[9] I refer to this rank as the JEE Advanced rank. It is a measure of ability at admission, though an imperfect one, since it reflects a single examination taken before college.[10] Candidates who qualify then submit their ranked preferences over pairs of institutes and programs, for example Civil Engineering at IIT Bombay. A centralized procedure, run by the Joint Seat Allocation Authority (JoSAA), assigns each student to a single pair.[11] I refer to each such pair as an admission program. Within each program, a share of seats is reserved for disadvantaged social categories, and the remaining seats form the open category, for which all candidates are eligible (Joint Seat Allocation Authority, 2018). Each category has its own closing rank, the rank of the last student admitted, so I compare ranks only within the same category.

[7] https://www.topuniversities.com/university-rankings/rankings-by-location/india/2020

[8] Candidates must also complete high school with at least a 75% grade (65% for SC/ST candidates), a threshold that is not difficult to meet for students preparing for the JEE.

[9] Appendix A.2 explains which candidates appear on the CRL and which appear only on the rank lists of reserved categories.

[10] A lower rank number denotes a higher score. Throughout the paper, I call a rank with a lower number a better rank and a rank with a higher number a worse rank.

[11] Candidates submit their preferences after learning their own rank and while knowing the likely cutoffs for each pair, so strategic reporting of preferences is not a major concern.

2.2 The Supernumerary Seats Scheme

Before the reform, women were underrepresented at every stage of admission to the IITs. They made up roughly 20% of the students who registered for the entrance examination, 12.5% of those who qualified, and under 10% of those admitted (Sengupta et al., 2025). To address this gap, the Government of India introduced the Supernumerary Seats Scheme (SSS) across all 23 IITs in 2018. The scheme aimed to raise the female share of each undergraduate program and was phased in gradually. Women were to make up 14% of each program's cohort admitted in 2018, 17% of the cohort admitted in 2019, and 20% by the cohort admitted in 2020. Figure 1 shows how the female share of admitted students changed at the 6 IITs in my sample. The share remained close to 10% between 2014 and 2017. From 2018 onward, it rose with the target, reached 20% in 2020, and has remained at this level since. Across the 6 IITs, the number of women admitted more than doubled, from 584 in 2015 to 1,347 in 2020.[12]

Importantly, the additional seats were supernumerary, meaning they expanded each program without removing any seat available to existing candidates. After the reform, the seats in each program were divided into gender-neutral seats, open to all candidates, and female-only seats. The female-only seats were divided across the open and reserved categories following the same reservation norms as the gender-neutral seats (Joint Seat Allocation Authority, 2018). Therefore, the reform changed the gender composition of each program but not its composition by social category. Women were considered for the female-only seats first, according to their rank and preferences. This means the women in female-only seats were a mix of women who would have been admitted without the reform and women admitted only because of the new seats. The number of female-only seats was set to bring women's share of each program to the target. Once these seats were filled, the remaining women could still be admitted through gender-neutral seats, where they competed with men on the basis of rank. Women could exceed the target share in programs where some of them also obtained gender-neutral seats, although this happened in only a few programs.

2.3 The IIT Placement Market

Most IIT graduates find their first job through campus placement, a process similar across the IITs and other elite Indian institutes (Shukla, 2022). Each IIT runs a centralized placement process through its Training and Placement Cell. The cell invites firms to recruit on campus over several weeks in the final year of study. Before the season begins, firms announce the

[12] Author's calculations from the admission reports of the JEE authority.

roles they are hiring for, the compensation they offer, and the departments eligible for each role. Firms then shortlist eligible students for each role, and shortlisted students from different programs compete in a common pool of interviews.

Each firm is assigned a day in the placement season, and the day reflects how attractive its jobs are. The earliest slots, known as Day 0 and Day 1, go to the firms offering the highest compensation and with the longest relationship with the institute. In this paper, I define elite firms as the firms recruiting on Day 0/Day 1. These include trading firms such as Jane Street, Tower Research, and Graviton, and technology firms such as Google, Apple, and Microsoft. Offers from a given day are released the same night, and a student who gets an offer leaves the process. Therefore, firms recruiting earlier choose from a larger pool of students than firms recruiting later.

The program plays a central role in this market for three reasons. First, firms open roles to specific departments, not to the institute as a whole, without a fixed number of positions for each department. A student's program determines which roles she can compete for. Second, the program is the group of classmates with whom a student is most likely to study and prepare for recruitment. Third, the program is the level at which the SSS added seats. Employers observe a candidate's program but not whether a woman entered through a supernumerary seat.

Firms decide how many offers to make each season based on their own hiring needs, not on the number of students graduating. As a result, admitting more students to a program did not by itself create more elite positions. For elite firms to hire more women from a program, they had to either add positions or hire fewer of the other graduates they would have hired.

2.4 Other Changes during the Period

Two other changes took place in the years I study. Both were common to High and Low Exposure programs, which suggests that they do not explain the differences I estimate between the two groups.

First, in 2019 and 2020, the IITs added seats for a new 10% reservation for the Economically Weaker Section (EWS), candidates outside the existing reserved categories whose family income falls below a set threshold.[13] These seats were added to every program in proportion to its size and divided into gender-neutral and female-only seats like the seats of the other

[13] Ministry of Human Resource Development, Office Memorandum of 17 January 2019 on the implementation of the EWS reservation in Central Educational Institutions.

categories. They made each program larger but left the share of seats reserved for women unchanged, so there is no reason to expect them to have affected High and Low Exposure programs differently.

Second, the cohorts admitted under the reform entered the labor market during a boom in technology hiring in 2022 and the slowdown that followed (NASSCOM, 2022, 2024; Business Today, 2022). These swings affected all graduates in a cohort, and since I compare High and Low Exposure programs within the same cohort, they are unlikely to drive my estimates, although I cannot rule out that they affected some fields more than others.

3 Data

I bring together three sources of data. The main dataset contains career histories of IIT graduates from LinkedIn. In addition to these career histories, I use reports and rank lists published by the authority that conducts the JEE Advanced, and a classification of elite firms I construct from newspaper coverage of IIT placements. Table 1 summarizes each source and how it is linked to the LinkedIn career histories.

3.1 Career Histories

For the main analysis, I use the universe of public LinkedIn profiles, which Revelio Labs aggregates into structured career histories (Revelio Labs, 2026). For each individual, the data report the institution attended, degree, field, graduation year, and gender, as well as the sequence of positions held, with employer names, job titles, and dates. The first job is the first employment spell on each profile, after screening out positions at educational institutions, so further study, teaching assistantships, and research positions are not counted as a first job. Each first employer is assigned to one of five broad industries (technology, finance, consulting, core engineering, and other) using its six digit NAICS code. Following how IIT placements classify recruiters, I treat online retail and ride hailing firms such as Amazon, Flipkart, and Uber as technology firms. These data measure each graduate's entry into the labor market, first employer, and promotions. Not every graduate has a LinkedIn profile, and I examine whether the reform changed who is observed in Section 4.4.

3.2 JEE Reports and Rank Lists

The JEE authority publishes two kinds of data each year.[14] The first is a report on the seats in every IIT program. The second is the Common Rank List of the students who took up IIT seats, which gives each student's JEE Advanced rank, category, and program. Only the 2015 list also reports each student's name and gender. From the reports, I measure the size of each program and its exposure to the reform. For each program and year, the reports give the number of seats filled, which I use as the size of the program's cohort. From 2018, they also report the number of supernumerary seats added to each program. Each program's exposure to the reform is constructed from these two counts, as the supernumerary seats added by 2020 relative to the size of its 2017 cohort.

The rank lists are used in two ways. First, I use the lists for 2018 to 2020 to describe the women who entered after the reform. These lists do not report gender. However, the JEE reports give the closing rank of the gender-neutral seats in each program and category.[15] Combined with this closing rank, the lists identify the ranks of women who entered only because of the reform.

Second, I use the 2015 list to examine how JEE Advanced rank related to elite hiring before the reform. Following other studies of exam based admissions in India (Bertrand et al., 2010; Bagde et al., 2016), I use the rank as a measure of ability at entry. The rank is likely correlated with the skills firms value, since the examination tests analytical and quantitative ability, but it may not capture the skills students acquire during the degree or the soft skills firms assess at placement, such as communication and interview performance. Since the 2015 list reports each student's name and gender, I link it to LinkedIn profiles by name. The linked sample contains 2,028 graduates, of whom about 100 are women, and being found on LinkedIn is not related to rank or gender (Table B1, column 2). Because 2015 is the only cohort for which I observe both rank and career, this is the only analysis that relates a graduate's rank to career outcomes.

3.3 Elite Firms

Each year, national newspapers in India report on campus placement at the IITs, including which firms recruit on the first days and the offers they make. IIT placements receive

[14] JEE reports can be accessed at `https://jeeadv.ac.in/reports.html`.

[15] The closing rank is the JEE Advanced rank of the last student admitted to a given set of seats. Since seats are filled in order of rank, every student admitted to these seats had a rank at least as good as the closing rank, and a student with a worse rank could not have been admitted to them.

this coverage because their outcomes are widely read as a signal of the job market for engineering graduates at other institutes. Since there is no public record of which firms recruit on Day 0/Day 1, I construct one from this coverage, using newspaper reports on the placement seasons for students graduating from 2015 to 2025. The firms named in each report are extracted with a large language model. To limit reporting errors, a firm enters the classification only if at least two independent reports name it as a Day 0/Day 1 recruiter. The resulting classification contains 121 firms in technology, quantitative finance, consulting, core engineering, and research. As a validation, it matches 80% of the Day 0/Day 1 firms in an internal placement office record from one legacy IIT. Appendix A.3 describes how the firms are extracted from the newspaper reports and how the classification is validated.

3.4 Sample

The analysis covers undergraduate students admitted between 2015 and 2020 to 6 legacy IITs, namely Bombay, Delhi, Kharagpur, Madras, Guwahati, and Roorkee.[16] Throughout the paper, I refer to a cohort by its year of admission, and the policy first applied to the 2018 cohort. Students in four year programs graduate four years after admission, while students in five year dual degree programs graduate one year later. Since 83% of graduates in the sample complete their degree in four years, I take the year a cohort entered the labor market to be its admission year plus four. Thus, the 2018 cohort mostly entered the labor market in 2022, and the cohorts admitted from 2015 to 2020 mostly entered between 2019 and 2024 (Figure B1). In the figures and tables, this year is shown in brackets below each admission cohort.

The sample is restricted to programs for which the JEE Advanced is the only route of entry. In addition, graduates often describe their field on LinkedIn more loosely than the admission system does. To address this, I pool closely related programs into broad fields based on curriculum overlap and common job profiles, and I combine the four year and dual degree variants of the same discipline (Table B2). Thus, a program in the analysis is a pair of an IIT and a field, which can combine several admission programs. The final sample contains 69 programs and 25,915 graduates, of whom 3,750 are women.

[16] IIT Kanpur is excluded because of inconsistencies in how its JEE reports record female-only seats, so its exposure to the reform cannot be measured.

3.5 Outcomes

Labor market entry. The analysis studies three binary outcomes, measured at three stages of the early career. First, I code a graduate as entering the labor market if her first job begins in the year she graduates, whether four or five years after admission. Since campus placement ends before students graduate, I treat such a job as a hire through campus placement. The indicator equals 0 for graduates who continue into further study, whose profiles record no job, or who begin working in a later year.

Elite first job. The main outcome is an indicator equal to 1 if a graduate's first employer is one of the 121 elite firms. It is measured in two samples. In the sample of all graduates, I code it as 0 for graduates who do not enter the labor market, so it measures each graduate's likelihood of starting her career at an elite firm. In the sample of labor market entrants, it measures the likelihood of an elite first job among graduates who entered the labor market. Summing these indicators within each program and cohort gives the number of labor market entrants and the number hired by elite and non-elite firms.

Promotion. To measure progress after the first job, I compare each graduate's first job with her next position, if it begins within two years. The next position can be a new title at the same firm or a job at a different firm. A graduate is promoted if the title of her next position is more senior than the title of her first job, for example from software engineer to senior software engineer, or from Software Development Engineer (SDE) 1 to SDE 2. A next position at the same or a lower level counts as no promotion, whether it is a new title at the same firm, such as a lateral move to another team, or a job at a different firm. A promotion is internal if it takes place at the same firm, and external if it comes with a move to a different firm, so the two add up to all promotions. As a measure of mobility, I also code whether the next position is at a different firm, with or without a promotion. These outcomes are measured among labor market entrants who record a next position within two years. Graduates whose profile shows no new position, at the same firm or elsewhere, are not in this sample. Appendix B.4 describes how I identify next positions and the seniority ladder I use to rank titles, including the rules for titles it cannot rank on its own.

4 Empirical Strategy

4.1 Exposure to the Reform

The SSS did not expand every program by the same amount. Because each program had to reach the target without removing any gender-neutral seat, the number of seats added to a program depended on how many women it had admitted before the reform. I measure a program's exposure to the reform as

$$Exposure_p = \frac{Seats_p^{SSS}}{Enrollment_{p,2017}}, \tag{1}$$

where $Seats_p^{SSS}$ is the number of supernumerary seats added to program p by 2020, when the policy was fully phased in, and $Enrollment_{p,2017}$ is the size of its 2017 cohort, the last cohort admitted before the reform. I classify programs above the median as High Exposure and the remaining programs as Low Exposure. This gives 34 High Exposure and 35 Low Exposure programs. Dividing programs at the median makes the comparison easy to interpret. Since it discards part of the variation in exposure and depends on a particular cutoff, I also estimate the main specifications with exposure measured continuously.

Figure 2 plots each program's exposure against its female share in 2017.[17] Programs that admitted almost no women before the reform added the most seats relative to their size, while programs already close to the target added few. Figure 3 shows the target was binding. By 2020, women's share of seats had reached the target in almost every program, regardless of its starting point. For example, the female share of Mechanical Engineering at IIT Delhi rose from 2 to 20% between 2017 and 2020, while that of Computer Science at IIT Madras moved from 16 to 20%. Programs had different female shares in 2017 for reasons that are probably not random, such as their field and their IIT. However, the target was set nationally and was the same for every program, so how many seats a program added depended mainly on its female share before the reform. Exposure thus came from a national rule applied to each program's female share before the reform, and not from choices made by a program, and I use this variation to identify the effects of the reform.

[17] Figure B2 plots exposure for each of the 69 programs, ranked from lowest to highest.

4.2 Difference in Differences

Main specification. I use a difference in differences design to study how increasing women's representation affected graduates' outcomes. My main specification is

$$Y_{ipc} = \beta \left(High_p \times Post_c \right) + \mu_p + \gamma_c + \varepsilon_{ipc}, \tag{2}$$

where Y_{ipc} is an outcome for graduate i admitted to program p in cohort c, $High_p$ equals 1 for High Exposure programs, and $Post_c$ equals 1 for cohorts admitted in 2018 or later. Program fixed effects μ_p, one for each IIT and field, absorb permanent differences across programs, including differences in the firms recruiting from them. Cohort fixed effects γ_c absorb shocks common to all students admitted in the same year, such as changes in overall elite hiring. The coefficient of interest is β, which captures the change in outcomes after the reform in High Exposure programs relative to Low Exposure programs.

I estimate equation (2) at the graduate level for individual outcomes and at the program and cohort level for counts, such as the number of elite hires, separately for women and men. Standard errors are clustered by program, the level at which exposure is assigned. With only 69 clusters, conventional clustered standard errors can understate uncertainty, so I also report wild cluster bootstrap p values.

Identification. The main identifying assumption for the causal interpretation of β is that outcomes in High and Low Exposure programs would have evolved in the same way in the absence of the reform. Characteristics of a program that change over time and are correlated with the outcomes would be a threat to identification. To assess this concern, I estimate an event study specification of equation (2). Instead of interacting $High_p$ with $Post_c$, I interact $High_p$ with a set of cohort dummies as follows,

$$Y_{ipc} = \sum_{k \neq 2017} \beta_k \left(\mathbf{1}[c = k] \times High_p \right) + \mu_p + \gamma_c + \varepsilon_{ipc}, \tag{3}$$

where $\mathbf{1}[c = k]$ is an indicator for admission cohort k. The 2017 cohort is omitted, so each coefficient measures the difference between High and Low Exposure programs relative to the last cohort admitted before the reform. The coefficients for the 2015 and 2016 cohorts serve as a test of parallel trends before the reform, and the coefficients for the 2018 to 2020 cohorts estimate the effect of the reform on each cohort. If trends are parallel before the reform, I expect the coefficients for the 2015 and 2016 cohorts to be close to zero and statistically insignificant. This would provide suggestive evidence that the two groups would also have

followed parallel trends after 2017 in the absence of the reform.

4.3 Interpreting the Estimates

What the estimates measure. Since both High and Low Exposure programs added seats for women, β is the effect of a larger increase in women's representation. This effect has two parts. The first is a change in composition, since the reform changed which women were admitted to each program. The second is a change in what happened to women after admission, namely the conditions under which they studied and were hired. The LinkedIn data do not show which women entered through the female-only seats, so β compares all women in a program after the reform with all women before it, and it includes both parts. This is the effect of the policy on a program, since a program cannot add seats for women without changing which women it admits. Section 6.3 examines the role of composition.

Spillovers. The same elite firms recruit from High and Low Exposure programs. Before the reform, about 75% of the elite firms hiring from the sample programs hired from both groups, and these firms accounted for 94 to 97% of elite hires. The market remained shared after the reform (Table A1). If these firms hired women from High Exposure programs in place of women from Low Exposure programs, the comparison group would itself be affected by the reform, and β would overstate the effect. Two patterns suggest this is not a major concern. First, elite hiring across these IITs increased after the reform. Second, the number of women hired by elite firms from Low Exposure programs remained roughly stable. I examine both in Section 5.3. Men in the same programs could also be affected through competition for the same positions, and the estimates for men measure these spillovers.

4.4 High and Low Exposure Programs before the Reform

Table 2 compares High and Low Exposure programs before the reform, using the JEE reports (Panel A) and the LinkedIn sample (Panels B and C). As expected from the allocation rule, High Exposure programs had far fewer women. In the 2017 cohort, women made up 5.8% of the cohort in High Exposure programs, compared with 14.5% in Low Exposure programs, and High Exposure programs were larger, admitting 89 students on average, compared with 67 (Table 2, Panel A). Admission to High Exposure programs was slightly more competitive

for both women and men, although the differences are not statistically significant.[18] The LinkedIn sample follows the same pattern, with women making up 7.6% of graduates in High Exposure programs and 14.7% in Low Exposure programs (Table 2, Panel B).

Since the analysis relies on graduates observed on LinkedIn, I examine whether the reform changed who is observed on LinkedIn. I do not find a significant change in LinkedIn coverage between the two groups (Table C1 and Figure C1), and I report further robustness checks in Section 5.5 to show the results are not driven by women missing from LinkedIn. Panel C of Table 2 reports labor market outcomes. In both groups, about 70% of graduates entered the labor market in the year they graduated. Since High Exposure programs were larger, more firms hired from them, and elite firms hired about twice as many men from them, 17.6 per cohort compared with 8.9. However, as a share of each program's male graduates, elite hiring was similar, at 28% in High Exposure programs and 24% in Low Exposure programs. Elite firms also hired a similar number of women from the two groups, about 2 per cohort. In both groups, women were more likely than men from the same program to start at an elite firm, by 10.6 percentage points in High Exposure programs and by 8.3 in Low Exposure programs.

The main takeaway from Table 2 is that High and Low Exposure programs differ considerably in size and female share, while they are similar in selectivity and in the share of graduates hired by elite firms. These differences in levels are not necessarily a problem, as long as outcomes in the two groups follow parallel trends.

4.5 How the Reform Changed Who Was Admitted

Before turning to labor market outcomes, I describe how the reform changed the women admitted to each program. The reform increased the number of women in every program, mostly by admitting women who could not have entered the program otherwise, and these women had worse ranks. Figure 4 shows the female share of students in High and Low Exposure programs. From 2018 onward, the share rose in both groups with the target and converged to 20% by 2020 (Figure 4, panel a). As a result, women's share rose by about 14 percentage points in High Exposure programs, compared with about 5 in Low Exposure programs. The LinkedIn sample follows the same pattern (Figure 4, panel b).

Who filled the female-only seats. The female-only seats could have gone to women who would have been admitted to the program in any case, so I first establish which women were

[18] In 2015, the average JEE Advanced rank of women in open seats was 2,806 in High Exposure programs and 3,405 in Low Exposure programs, and for men it was 2,366 and 2,711.

new to each program. I refer to women who could not have entered their program without the reform as marginal, and to women in female-only seats who would have been admitted even without it as inframarginal.

The rank lists for 2018 to 2020 do not report gender, but they report each admitted student's rank. From the JEE reports, I also know two ranks for each program and category. The first is the closing rank of the gender-neutral seats, the rank of the last student admitted through them, and the second is the opening rank of the female-only seats, the rank of the best-ranked woman admitted to them. Men could enter a program only through the gender-neutral seats. I therefore infer that any student with a rank worse than the gender-neutral closing rank is a woman in a female-only seat, and that she is marginal.

This identifies marginal women, but not inframarginal women. A woman with a rank better than the gender-neutral closing rank cannot be told apart from a man in the lists. I therefore define inframarginality at the level of the program-cohort, a program in a given admission year, and not of the individual woman. If the best-ranked woman in the female-only seats has a rank worse than the gender-neutral closing rank, every woman in these seats is marginal, and I call the program-cohort marginal-only. Otherwise, at least one of these women could have entered through a gender-neutral seat, and I call it a program-cohort with inframarginal women. Most post-reform program-cohorts were marginal-only, 157 of 207, and the share was similar in High and Low Exposure programs (Table D1, Panel A). Hence, in most programs and years, the women in female-only seats could not have entered the program without the reform. Overall, the reform changed which women entered each program, and it did so in a similar way in High and Low Exposure programs.

JEE Rank of admitted women. Since most women in female-only seats could not have entered their program otherwise, they also had worse JEE Advanced ranks than the students these programs had admitted before. As the target rose, the median closing rank of female-only seats worsened from 6,381 in 2018 to 9,373 in 2020, far worse than the closing rank of gender-neutral seats, which stayed between 3,650 and 4,298 (Table 3). The full distribution of ranks of students admitted to open seats shifted in the same direction, and the median rank worsened from 2,121 in 2015 to 3,300 in 2020 (Figure D1, panel a).

The marginal women added to High Exposure programs did not have worse ranks than those added to Low Exposure programs. In every year, the distributions of ranks of marginal women in the two groups largely overlap (Figure D1, panel b). Their medians are also close, at 4,245, 5,706, and 6,981 in High Exposure programs in 2018, 2019, and 2020, compared with 4,933, 5,818, and 6,310 in Low Exposure programs. Hence, the two groups differed mainly

in how many marginal women they admitted, not in the ranks of these women. However, since High Exposure programs added more of these women relative to their size, and had admitted women with better ranks before the reform, the average rank of women worsened more in High Exposure programs. If rank captures what employers value, women's labor market outcomes should worsen after the reform, and by more in High Exposure programs.

JEE Rank and elite hiring. The prediction above rests on rank capturing something elite firms value. I examine this in the 2015 cohort, the only cohort for which I observe both a graduate's rank and career (Table 4). Within a program, graduates with worse ranks were less likely to start at an elite firm. A graduate ranked 1,000 places below a classmate was 1.8 percentage points less likely to do so (column 1). Rank is thus informative about elite hiring, although the relationship is modest. Estimated separately by gender, the relationship holds for men, while for women the estimate is smaller (column 2). The estimate for women is imprecise because only about 100 women are linked, although it could also reflect rank mattering less for the hiring of women.

5 Results

This section presents the effects of the reform on women's careers, in the order a graduate's career unfolds. I first show whether elite firms hired the additional women, then how each woman's likelihood of starting at an elite firm changed, and then how women progressed once employed. I end the section with robustness checks.

5.1 Number of Women Hired by Elite Firms

Table 5 and Table 6 report the estimates of β in equation (2) for the number of graduates from each program and cohort. Compared with Low Exposure programs, the number of women graduating from High Exposure programs increased by 6.4 per program and cohort (Table 5, Panel A, column 2), and the number entering the labor market increased by 4.8, roughly doubling the pre-reform level (Table 6, Panel A, column 2). Most of the additional women who graduated therefore entered the labor market. Of the 4.8 additional women entering the labor market, elite firms hired 2.8 and non-elite firms hired 1.9 (Table 6, Panels B and C, column 2). Hence, elite firms hired about 60% of the additional women who entered the labor market, and the number of women they hired from High Exposure programs more

than doubled.[19]

Figure 5 shows the event study estimates of β_k in equation (3), for women in blue and for men in red. For women, the coefficients before the reform are close to zero in all four panels, consistent with parallel trends. From 2018, the first cohort admitted under the reform, the number of women graduating (panel a), entering the labor market (panel b), and hired by elite firms (panel c) rises clearly. For men, the number hired by elite firms did not change, since the coefficients in panel (c) are close to zero in every cohort and the difference in differences estimate is not statistically significant (Table 6, Panel B, column 3). The number of men graduating from High Exposure programs rose only in the 2020 cohort (panel a), and most of these additional men appear to have been hired by non-elite firms (panel d). This increase could reflect the EWS seats, which were added for both men and women in 2019 and 2020. For women, the increase already appears in the 2018 cohort, a year before the EWS seats were created, so these seats are unlikely to be the main reason for it.

5.2 Likelihood of an Elite First Job

The additional women had worse ranks than the women admitted before the reform. If rank captures what employers value, each woman's likelihood of an elite first job should fall after the reform, and by more in High Exposure programs, which added more of these women relative to their size. Table 7 shows the effects of the reform at the graduate level, reporting the estimates of β in equation (2) for women in Panel B and for men in Panel C. For both women and men, the likelihood of entering the labor market did not change (column 1). For an elite first job, the coefficient implies women in High Exposure programs became 7.0 percentage points, or 21% relative to the pre-reform mean, more likely to begin their careers at an elite firm, and the estimate is statistically significant at the 10% level (Panel B, column 2). Among women who entered the labor market, the effect is 8.4 percentage points (Panel B, column 3). For men, the likelihood of an elite first job did not change (Panel C, column 2).

The raw numbers before and after the reform show where this effect comes from. In High Exposure programs, the number of women hired by elite firms rose roughly in proportion to the number of women. As a result, each woman's likelihood of an elite first job remained close to its level before the reform, as it did for men (Figure E1). In Low Exposure programs, the number of women also rose, but the number hired by elite firms remained about the same (Figure E2, panel c). A similar number of elite hires was shared among more women, so each

[19] Since the number of women hired from a program is a small count, I also estimate these regressions with a Poisson pseudo maximum likelihood model, and the results are similar.

woman's likelihood of an elite first job declined. Hence, the effect mainly reflects this decline for women in Low Exposure programs.

Figure 6 shows the estimates of β_k in equation (3). For an elite first job, the coefficients for women are positive in every cohort after the reform, although not individually significant (Figure 6, panel b). Before the reform, the coefficients are close to zero, except for a negative coefficient in 2016.[20] For labor market entry, the coefficients after the reform are close to zero (Figure 6, panel a). Before the reform, the coefficient for women in 2015 is positive, and the pre-reform coefficients are jointly significant ($p = 0.018$), so I interpret the estimate for labor market entry with caution.

5.3 Displacement

The gains for women in High Exposure programs could have come at the expense of other graduates, since women and men from High and Low Exposure programs compete for the same elite positions. Within the 6 IITs, I do not find evidence of such displacement. The number of men hired by elite firms from High Exposure programs did not change, and the number of women they hired from Low Exposure programs remained roughly stable after the reform (Figure E2, panel c). Total elite hires from High Exposure programs rose by 3.2 per program and cohort, close to the 2.8 additional women hired (Table 6, Panel B, column 1). The raw totals for the 6 IITs show the same pattern, with more women hired after the reform and no decline in the number of men hired (Table E1). I do not observe the positions elite firms opened, only the graduates they hired. However, these patterns are suggestive of elite firms adding positions for graduates of the IITs, and not of women replacing other IIT graduates. Since elite firms hired more IIT graduates in total, the women hired from High Exposure programs are also less likely to have come at the expense of women from Low Exposure programs.

I do not find this increase in the hiring of women elsewhere. Across all other institutes in India, the number of women hired by the same elite firms did not show a similar increase. This suggests the additional positions are specific to women from the IITs, and part of the gains for IIT women may have come at the expense of women from other institutes. Before the reform, firms with demand for women could meet part of it only by hiring women from less selective institutes. Once the reform increased the number of IIT women, they could hire them instead. To assess this, I compare the 6 IITs descriptively with the Birla Institute of Technology and Science (BITS), which was not covered by the reform. At BITS, elite hires of

[20] The estimates are similar when I exclude the 2016 cohort.

women fell by more than elite hires of men after 2022, while elite hires of IIT women nearly doubled.[21] This pattern is consistent with Gupta (2024), who finds women from lower ranked colleges received fewer callbacks after the policy, while IIT graduates faced no gender gap.

5.4 Early Careers

I next turn to whether women from High Exposure programs kept pace after their first job. Employers learn about workers' productivity over time and reward it through promotions (Farber and Gibbons, 1996; Altonji and Pierret, 2001). Promotions therefore show how women performed once employed. I estimate equation (2) for the promotion outcomes. Since these outcomes are measured only among graduates who record a next position, the estimates would be hard to interpret if the reform changed who records one. The reform did not change women's likelihood of recording a next position within two years or of entering this sample (Table F1, Panel A, columns 2 and 6).[22] Because titles and the speed of promotion differ across industries, all regressions include fixed effects for the industry of the first employer.

All women who entered the labor market. Table 8 shows the effects of the reform on the promotions of all graduates who entered the labor market, with women in Panel A and men in Panel B. If women from High Exposure programs had fallen behind after their first job, they should be promoted less often. Instead, the coefficient for promotion is positive, 5.4 percentage points, although statistically insignificant (Panel A, column 1). Internal and external promotions show the same pattern (Panel A, columns 2 and 3). For men, all estimates are small and statistically insignificant (Panel B).

This average may hide different patterns for women who started at elite and at non-elite firms, so I separate the two groups. Separating them also tests whether elite firms lowered their hiring bar to hire more women. A lower hiring bar has two implications. First, the women hired by elite firms after the reform should be less productive than those hired before it, so they should be promoted less often within their firm. Second, the strongest women would now start at elite firms, so the women who still start at non-elite firms should be weaker than before, and they too should be promoted less often. Under a lower hiring bar,

[21] BITS is the leading private engineering institute in India and the closest to the IITs in selectivity and recruiters. Averaged over 2022 to 2024, elite hires of women at BITS were about 13% lower than over 2019 to 2021, and elite hires of men about 7% lower (Table E1 and Figure E3). Since these years also saw a slowdown in hiring, which may have affected less selective institutes more, this comparison is descriptive.

[22] The number of programs, and hence of clusters, differs across samples. Some programs have no women in a given group, for example no women who started at an elite firm and record a next position, and programs with a single graduate in a sample are dropped by the fixed effects.

women from High Exposure programs should be promoted less often in both groups, relative to women from Low Exposure programs.

Women who started at elite firms. Women from High Exposure programs who started at elite firms became 12.7 percentage points less likely to be promoted, compared with women from Low Exposure programs, and the estimate is statistically significant at the 10% level (Table 9, Panel A, column 1). This decline does not come from promotions within the firm, where a lower hiring bar should show. The coefficient for internal promotions is −2.6 percentage points and statistically insignificant (Panel A, column 2), and the event study coefficients are close to zero in every cohort (Figure 7, panel d). The decline came mostly from external promotions, which fell by 10.1 percentage points, although the estimate is statistically insignificant (Panel A, column 3). The event study coefficients for external promotions are negative in every cohort after the reform (Figure 7, panel f).

One possible explanation for the decline in external promotions could be lower mobility. For a woman at an elite firm, an external promotion often means leaving one of the highest paying employers. Before the reform, about 24% of women who started at elite firms moved to another firm within two years. After the reform, women from High Exposure programs became 7.8 percentage points less likely to move, a decline of about a third, although the estimate is statistically insignificant (Table 9, Panel A, column 4). The fall in external promotions is spread across elite and non-elite destinations (Table 10, Panel A, columns 5 and 6), so these women appear to have moved less often, and not to different firms. Men who started at elite firms were promoted as often as before, but they became more mobile.[23]

Women who started at non-elite firms. Women from High Exposure programs who started at non-elite firms became 15.7 percentage points, or 39% relative to the pre-reform mean, more likely to be promoted, compared with women from Low Exposure programs, and the estimate is statistically significant (Table 11, Panel A, column 1). The increase came mostly from external promotions, which rose by 11.3 percentage points and are statistically significant at the 10% level (Panel A, column 3). Internal promotions also rose, but the coefficient is statistically insignificant. In the event study for all promotions, the pre-reform coefficients are positive but not jointly significant ($p = 0.214$), and the post-reform coefficients

[23]Men who started at elite firms became 6.2 percentage points more likely to move to another firm and 4.7 percentage points more likely to receive an external promotion (Table 9, Panel B, columns 4 and 3). Their external promotions increased to firms that had recently hired a man from the same program (Table 10, Panel B, column 2), consistent with referral networks among male graduates of the same program. For women, I do not find a similar pattern.

rise in each cohort (Figure 7, panel a). For external promotions, the pre-reform coefficients are close to zero, and the coefficients are positive in every cohort after the reform (Figure 7, panel e).[24]

This increase does not seem to have come from more frequent moves. The coefficient for moving to another firm is 4.0 percentage points and statistically insignificant, so these women changed employers about as often as before, but their moves more often came with a more senior title, mostly at other non-elite firms (Table 11, Panel A, column 4, and Table 12, Panel A, columns 5 and 6).[25] Men who started at non-elite firms show no change in promotions or moves (Table 11, Panel B). Taken together, the promotion results do not show the broad decline a lower hiring bar would predict. Women from High Exposure programs who started at non-elite firms were promoted more often after the reform, while the decline for women who started at elite firms does not come from promotions within their firm. These patterns suggest the gains for women from High Exposure programs may extend beyond elite firms.

5.5 Robustness

I consider two main concerns about the comparison between High and Low Exposure programs, and then briefly report other checks. The first concern is signalling. More selective programs carry more prestige, so their graduates may send a stronger signal to employers. For example, a field such as Mechanical Engineering, which admits students with better ranks than several other fields, may carry more prestige with employers. If High Exposure programs were more selective, the women the reform added to them would carry this stronger signal, and elite firms could have hired them for this reason and not because of the increase in women's representation. I measure a program's selectivity by the mean JEE Advanced rank of the students it admitted in 2015, so a better mean rank indicates a more selective program. Exposure is only weakly related to selectivity (Figure 8), so High Exposure programs were not systematically more selective. To test the concern directly, I add selectivity, interacted with $Post_c$, to equation (2), so programs of different selectivity can follow different paths after the reform. With this control, women in High Exposure programs became 6.8 percentage points more likely to begin their careers at an elite firm, compared with 7.0 without it, and selectivity itself is not related to the change in women's likelihood of an elite first job

[24] For internal promotions, the pre-reform coefficients are positive, although not jointly significant ($p = 0.288$), so I interpret the estimate for internal promotions with caution (Figure 7, panel c).

[25] Unlike the elite market, the non-elite market changed after the reform, as the number of non-elite firms hiring from these programs rose from about 640 per cohort before the reform to about 1,000 by 2020 (Table A2). These firms may differ in how they promote. However, men who started at non-elite firms faced the same change in firms, and they show no change in promotions.

(Table G1, column 2).

If selectivity drove the gains, women's likelihood of an elite first job should also have risen more in more selective programs within each group. I therefore estimate, separately within High Exposure programs and within Low Exposure programs, how the change in women's likelihood of an elite first job after the reform varied with program selectivity. In neither group did women in more selective programs gain more (Table G2, columns 1 and 3). Hence, the gains for women do not appear to come from the signal a selective program sends.

The second concern is that elite firms recruit heavily from a few departments. Firms open each role to specific departments, and technology firms in particular hire mostly from Computer Science and Electrical Engineering. If these departments were more exposed to the reform, and elite firms expanded hiring from them after 2018, women in High Exposure programs would have gained because of their department, not because of the increase in women's representation. I address this concern in two ways. First, I compare programs in the same field across IITs, using field by cohort fixed effects, which absorb any change in hiring from a department in a given year. With these fixed effects, women in High Exposure programs became 6.1 percentage points more likely to begin their careers at an elite firm, compared with 7.0 in the main specification (Table G3, Panel A, column 2).[26]

Second, I divide elite firms by how widely they recruited before the reform. I call an elite firm generalist if, in the cohorts admitted from 2015 to 2017, it hired at least two graduates from each of more than three fields, and specialist otherwise.[27] A generalist firm recruits across many departments, so its hiring of women from a program does not depend on which department the program belongs to. If the gains reflected department targeting, they should come mainly from specialist firms. Instead, of the 2.8 additional women hired by elite firms from each High Exposure program and cohort, 2.2 were hired by generalist firms (Table G4, Panel A, column 2). In the same way, women's likelihood of an elite first job rose by 6.6 percentage points at generalist firms and did not change at specialist firms (Table G5, Panel A, columns 2 and 3).

The results are also robust to other specifications. When I compare programs within the same field or the same IIT in each cohort, exclude the 2016 cohort, or measure exposure

[26] As a further check, I control directly for a program's ties to elite firms before the reform, measured by the share of its men hired by elite firms or by the number of elite firms recruiting from it. With these controls, the estimate falls to 4.8 and 4.4 percentage points and is no longer statistically significant (Table G1, columns 3 and 4). This suggests part of the gains is in programs from which elite firms already recruited heavily. One possible explanation could be elite firms hiring the additional women through the recruiting relationships they already had with a program.

[27] For example, Goldman Sachs hired graduates of 15 fields before the reform. Firms first observed after the reform are counted as specialist, since I do not observe whom they recruited before it.

continuously, women's likelihood of an elite first job rises by between 4.7 and 7.0 percentage points, although the estimate is not statistically significant in all of them (Table G3, Panel A). The increase in the number of women hired by elite firms is statistically significant in a Poisson model (Table G6, Panel B), in each of these specifications, and when I weight programs by their size before the reform (Table G7, Panel A). Comparing women with men from the same program gives the same pattern. Relative to men, the number of women hired by elite firms from each High Exposure program and cohort rose by 2.5 more (Table G8, column 3), and the gap in the likelihood of an elite first job moved in women's favor by 6.6 percentage points more than in Low Exposure programs (Table G9, Panel B, column 3). Finally, I bound the estimate under different assumptions about women missing from LinkedIn. It remains close to 7 percentage points if the missing women had the same elite rate as observed women, and it disappears only if almost none of them obtained an elite job (Table C2).

6 Mechanisms

The previous sections show a larger increase in women's representation had three effects. Elite firms hired more women without hiring fewer men, women's likelihood of an elite first job rose in High Exposure programs relative to Low Exposure programs, and women from High Exposure programs who started at non-elite firms were promoted more often. Two mechanisms are consistent with these results. The first is latent demand for women among elite firms, which could account for most of the increase in the number of women hired. The second is human capital accumulation, possibly through peers, which is consistent with women's higher likelihood of an elite first job in High Exposure programs and with the rise in promotions. A change in the composition of admitted women could also explain the results, but the evidence does not suggest it is the main driver.

6.1 Latent Demand

One possible explanation could be latent demand, in which elite firms want to hire more women than the IITs supply. Before the reform, few women graduated from the IITs, so the number of women hired from them by elite firms may have been limited by supply rather than by demand, and press reports describe recruiters complaining that the IITs produce too few women graduates (The Economic Times, 2012). The additional women had worse ranks, and rank predicts elite hiring (Section 4.5). However, rank is an imperfect measure of

the skills elite firms value, which they assess through their own tests and interviews. Hence, women with worse ranks could still meet these firms' hiring bar, and elite firms could hire more of the women the reform added without necessarily lowering it.

I look for evidence of latent demand in hiring before the reform. If elite firms wanted more women, then before the reform they should have hired women at a higher rate than men from the same program, who were admitted from a similar distribution of entrance ranks. To make this comparison, I compute the number of women that elite firms would have hired from each program and cohort if every labor market entrant from the program had the same likelihood of an elite first job. I call this number the gender-blind benchmark. I measure how far actual hiring departs from it with the ratio R of the number of women actually hired by elite firms to the benchmark, summed over programs and cohorts (Appendix H.1 gives the formulas). Under gender-blind hiring, R equals 1 in expectation, and a ratio above 1 means women who entered the labor market were hired at a higher rate than men who entered from the same program. For example, if women make up 10% of a program's entrants and elite firms hire 10 of its graduates, the benchmark is 1 woman, and if elite firms in fact hired 2 women, the ratio is 2.

In every cohort before the reform, elite firms hired between 12 and 14 women for every 10 the benchmark implies (Figure 9, panel a). Pooling the three cohorts, the ratio is 1.34, and it is statistically different from 1 (Table H1, Panel A).[28] This pattern is consistent with elite firms wanting to hire more women than the IITs produced. Once the reform increased the number of women graduating, elite firms could hire more of them without necessarily lowering their hiring bar.

However, latent demand alone would not predict the rise in women's likelihood of an elite first job in High Exposure programs relative to Low Exposure programs. Before the reform, elite firms hired women at a similar rate relative to the benchmark in the two groups (Table H1, Panel B), which is suggestive of a common latent demand for women. If the reform worked through a common latent demand alone, elite firms would have hired the additional women at the same rate in the two groups, and each woman's likelihood of an elite first job would have changed in the same way. Latent demand among elite firms is also unlikely to account for the more frequent promotions of women who started at non-elite firms, since these promotions do not depend on hiring by elite firms. This suggests demand for women may not be the

[28] Following Miller et al. (2022), I also examine whether this pattern came from a few firms, such as those with targets for women, by comparing how women were spread across elite firms with random assignment. In High Exposure programs, women were spread across firms much as random assignment would predict, while in Low Exposure programs they went to a smaller set of firms (Figure H1). Hence, at least in High Exposure programs, the pattern does not appear to come from a few firms.

only mechanism behind the results.

6.2 Human Capital Accumulation

Another possible mechanism could be human capital accumulation via peer effects, in which women build more of the skills employers value during their degree because they have more female classmates. The teaching, curriculum, and elite recruiters of a program are unlikely to have changed with the reform, and the program fixed effects absorb the features of a program that do not change over time. What the reform did change was the number of female classmates, and it changed the most in High Exposure programs. Before the reform, a woman in a High Exposure program had about 5 women in her cohort, compared with about 10 in a Low Exposure program (Table 2, Panel A).

Female classmates could matter because students tend to form friendships with their classmates (Marmaros and Sacerdote, 2006; Mayer and Puller, 2008) and with peers of the same gender (Currarini et al., 2009; Friebel et al., 2021). Earlier studies also find the share of women among a student's peers affects women's choices and persistence in STEM fields (Mouganie and Wang, 2020; Busso and Frisancho, 2021; Zölitz and Feld, 2021; Bostwick and Weinberg, 2022). With about 5 women in her cohort, a woman in a High Exposure program may have had few classmates with whom to study and prepare for placement. The reform gave these women a larger group of female classmates. Women in Low Exposure programs already had a larger group before the reform, so additional female classmates may have added little.[29]

Two results are consistent with peer effects. First, the gains are largest in the programs with the fewest women before the reform, where additional female classmates should matter the most. Table 13 splits High Exposure programs at the median of their 2017 female share. In the programs below the median, women became 11.4 percentage points more likely to obtain an elite first job than women in Low Exposure programs, an increase of 35% (column 1). In the programs at or above the median, the coefficient is close to zero, and the difference between the two is statistically significant. For men, neither coefficient is statistically significant (column 2). Second, the gains are not limited to hiring by elite firms. Women from High Exposure programs who started at non-elite firms were promoted more often after the reform (Section 5.4), and demand for women among elite firms is unlikely to account for this result.

[29] Female classmates could also help after graduation, if women who join a firm refer younger women from their program (Machado et al., 2022). I do not find clear evidence of this channel. Women from High Exposure programs became more likely to start at an elite firm that had hired a woman from their program in the previous cohort, but the difference with men is not statistically significant (Table H2).

The peer channel assumes that students form their social circles within their program and rely on them when preparing for placement. I do not observe friendships or study groups in the data, and I have no survey of my own, so I draw on two outside sources. The first is the 2026 senior survey run by Insight, the student media body of IIT Bombay. Respondents most often named their program (34%) as what their social circle had in common, and about three quarters of the 110 respondents asked about placements described their friends as helpful or supportive (Figure H2).[30] The second is a set of interviews published by the Board for Student Publications of IIT Delhi. Women admitted before the reform described having few or no female classmates in their program, and the article concludes that the reform made it easier for women to find peers to study with (Board for Student Publications, IIT Delhi, 2021).[31] This evidence is anecdotal, but it is consistent with the two assumptions. The evidence in this subsection is thus consistent with peer effects among women being one channel through which the reform could have raised women's human capital.

6.3 Composition of Admitted Women

The estimates include a change in the composition of admitted women, and this change is part of the reform. Most women in female-only seats could not have entered their program without the reform, so the reform re-sorted women across programs, and the women in each program after the reform differ from those before it. This means composition is at play in both High and Low Exposure programs. For my estimates, however, composition would explain the gains only if the reform brought stronger women into High Exposure programs than into Low Exposure programs, and based on what I observe, the evidence does not point in this direction.

First, the women the reform brought into the two groups had similar ranks. In every year, the marginal women admitted to High and Low Exposure programs had similar JEE Advanced ranks (Figure D1, panel b), and a similar share of cohorts in the two groups included inframarginal women (Table D1, Panel A). I do not find stronger women re-sorting toward High Exposure programs, or Low Exposure programs losing their best-ranked women. In addition, High Exposure programs added more marginal women relative to their size, so the average rank of women worsened more in these programs. By this measure, the change

[30] The survey results are available at **https://seniorsurvey2026.insightiitb.org/** (Insight, IIT Bombay, 2026). The survey covers one IIT, and respondents chose whether to take part.

[31] The article does not report how many women were interviewed or how they were selected, and some names were changed. It covers one IIT.

in composition did not favor High Exposure programs.

Second, the gains do not appear to come from inframarginal women, who would have been admitted even without the reform. Table 14 separates marginal-only cohorts, in which no woman in a female-only seat could have entered the program without the reform, from cohorts with inframarginal women. In marginal-only cohorts, women from High Exposure programs became 9.3 percentage points more likely to obtain an elite first job than women from Low Exposure programs (Panel A, column 2). In cohorts with inframarginal women, the difference is 1.9 percentage points and statistically insignificant. This suggests the gains are not driven by stronger women taking the female-only seats.

The remaining concern is selection on unobservable characteristics, that is, characteristics the JEE Advanced rank does not capture, such as motivation, ambition, or family background. The female-only seats may have drawn women who differ in these characteristics toward High Exposure programs, and I do not observe them, so part of the estimates may reflect such differences. Overall, composition is part of what the estimates measure, but the evidence does not suggest it is the main driver of the estimates.

6.4 Discussion

Taken together, the results are consistent with latent demand and human capital accumulation via peer effects working together. Latent demand could account for most of the increase in the number of women hired by elite firms, and a back-of-the-envelope calculation shows how much. Before the reform, elite firms hired 51% of the women who entered the labor market. The reform added 4.8 more women entering the labor market per program and cohort in High Exposure programs than in Low Exposure programs. Hiring these additional women at the pre-reform rate would mean 2.4 more women hired by elite firms, compared with the estimated increase of 2.8. Hence, hiring at the pre-reform rate could account for about 85% of the estimated increase (Table H3). The remaining 15% may reflect human capital accumulation via peer effects, consistent with the evidence in this section. However, it may also reflect a change in the composition of admitted women through selection on unobservable characteristics, such as motivation or family background, which their JEE Advanced rank does not capture. I refer to human capital accumulation in broad terms, since determining which skills women built would require data on grades, interview performance, or study groups, which I do not observe.

7 Conclusion

This paper studies how increasing women's representation in elite engineering programs affects their careers, using the Supernumerary Seats Scheme at the IITs. I find the reform roughly doubled the number of women entering the labor market from High Exposure programs, and elite firms hired about 60% of these additional women without hiring fewer men from the same programs. Women in High Exposure programs became 21% more likely to begin their careers at an elite firm, relative to women in Low Exposure programs. Women from High Exposure programs who started at non-elite firms were also promoted more often. The results are consistent with latent demand for women among elite firms, together with human capital accumulation via peer effects.

These findings suggest gender-based affirmative action in elite higher education can widen women's access to the highest paying jobs. Since differences in access to high paying jobs account for a large part of the gender gap in earnings (Blau and Kahn, 2017), such policies may help narrow this gap. The design of the policy may also matter. Adding seats, instead of reserving existing ones, raised women's representation without reducing men's elite hiring, although part of the gains may have come at the expense of women from other institutes.

One limitation qualifies the interpretation of these results. The women admitted under the reform may differ from earlier women in ways their entrance rank does not capture, so part of the gains in High Exposure programs may reflect who entered each program, and not only human capital accumulation. This limitation concerns why women in High Exposure programs kept pace, not the finding that elite firms hired more women from the IITs without hiring fewer men from the same programs. Future work could examine whether these gains persist into later careers, including wages and leadership positions.

References

Abramitzky, R., Kowalski, J. K., Pérez, S., and Price, J. (2024). The GI Bill, standardized testing, and socioeconomic origins of the US educational elite over a century. NBER Working Paper, National Bureau of Economic Research.

Akhtari, M., Bau, N., and Laliberté, J.-W. (2024). Affirmative action and precollege human capital. *American Economic Journal: Applied Economics*, 16(1):1–32.

Altonji, J. G., Blom, E., and Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics*, 4:185–223.

Altonji, J. G. and Pierret, C. R. (2001). Employer learning and statistical discrimination. *The Quarterly Journal of Economics*, 116(1):313–350.

Arcidiacono, P. and Lovenheim, M. (2016). Affirmative action and the quality-fit trade-off. *Journal of Economic Literature*, 54(1):3–51.

Bagde, S., Epple, D., and Taylor, L. (2016). Does affirmative action work? Caste, gender, college quality, and academic success in India. *American Economic Review*, 106(6):1495–1521.

Barahona, N., Dobbin, C., and Otero, S. (2023). Affirmative action in centralized college admissions systems. Working paper.

Bertrand, M., Hanna, R., and Mullainathan, S. (2010). Affirmative action in education: Evidence from engineering college admissions in India. *Journal of Public Economics*, 94(1–2):16–29.

Blau, F. D. and Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865.

Bleemer, Z. (2022). Affirmative action, mismatch, and economic mobility after California's Proposition 209. *Quarterly Journal of Economics*, 137(1):115–160.

Board for Student Publications, IIT Delhi (2021). What effect has the IIT supernumerary scheme had? A look at IIT Delhi. The Wire Science, 11 March 2021. `https://science.thewire.in/education/what-effect-has-the-iit-supernumerary-scheme-had-a-look-at-iit-delhi/`. Republished from the Board for Student Publications, IIT Delhi. Accessed November 2026.

Bostwick, V. K. and Weinberg, B. A. (2022). Nevertheless she persisted? Gender peer effects in doctoral STEM programs. *Journal of Labor Economics*, 40(2):397–436.

Business Today (2022). IIT Madras records highest number of campus placements in 2021–22. `https://www.businesstoday.in/jobs/story/iit-madras-records-highest-number-of-campus-placements-in-2021-22-344075-2022-08-08`.

Busso, M. and Frisancho, V. (2021). Good peers have asymmetric gendered effects on female educational outcomes: Experimental evidence from Mexico. *Journal of Economic Behavior & Organization*, 189:727–747.

Chan, J. and Eyster, E. (2003). Does banning affirmative action lower college student quality? *American Economic Review*, 93(3):858–872.

Chetty, R., Deming, D. J., and Friedman, J. N. (2026). Diversifying society's leaders? the determinants and causal effects of admission to highly selective private colleges. *The Quarterly Journal of Economics*, 141(1):51–145.

Coate, S. and Loury, G. C. (1993). Will affirmative-action policies eliminate negative stereotypes? *The American Economic Review*, 83(5):1220–1240.

Currarini, S., Jackson, M. O., and Pin, P. (2009). An economic model of friendship: Homophily, minorities, and segregation. *Econometrica*, 77(4):1003–1045.

Ellison, G. and Pathak, P. A. (2021). The efficiency of race-neutral alternatives to race-based affirmative action: Evidence from Chicago's exam schools. *American Economic Review*, 111(3):943–975.

Farber, H. S. and Gibbons, R. (1996). Learning and wage dynamics. *The Quarterly Journal of Economics*, 111(4):1007–1047.

Ferman, B. and Assunção, J. (2005). Affirmative action in university admission and high school students' proficiency. Working paper, Pontifical Catholic University of Rio de Janeiro.

Francis-Tan, A. and Tannuri-Pianto, M. (2018). Black movement: Using discontinuities in admissions to study the effects of college quality and affirmative action. *Journal of Development Economics*, 135:97–116.

Friebel, G., Lalanne, M., Richter, B., Schwardmann, P., and Seabright, P. (2021). Gender differences in social interactions. *Journal of Economic Behavior & Organization*, 186:33–45.

Frisancho, V. and Krishna, K. (2016). Affirmative action in higher education in India: Targeting, catch up, and mismatch. *Higher Education*, 71(5):611–649.

Fryer, Jr., R. G., Loury, G. C., and Yuret, T. (2008). An economic analysis of color-blind affirmative action. *Journal of Law, Economics, and Organization*, 24(2):319–355.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119.

Grau, N. (2018). The impact of college admissions policies on the academic effort of high school students. *Economics of Education Review*, 65:58–92.

Gupta, R. (2024). Equity conundrum: Unintended consequences of college-level affirmative action on the labor market. Working paper, University of Virginia. SSRN 4763745.

Insight, IIT Bombay (2026). The senior survey 2026. `https://seniorsurvey2026.insight iitb.org/`.

Jayachandran, S. (2015). The roots of gender inequality in developing countries. *Annual Review of Economics*, 7:63–88.

Joint Seat Allocation Authority (2018). Business rules for joint seat allocation for the academic programs offered by the IITs, NITs, IIEST, IIITs and other-GFTIs for the academic year 2018–19. https://josaa.nic.in.

Kahn, S. and Ginther, D. (2017). Women and STEM. NBER Working Paper 23525, National Bureau of Economic Research.

Kirkeboen, L. J., Leuven, E., and Mogstad, M. (2016). Field of study, earnings, and self-selection. *The Quarterly Journal of Economics*, 131(3):1057–1111.

Machado, C., Reyes, G., and Riehl, E. (2022). Alumni job networks at elite universities and the efficacy of affirmative action. IZA Discussion Paper 15026, IZA Institute of Labor Economics.

Machado, C., Reyes, G., and Riehl, E. (2023). The direct and spillover effects of large-scale affirmative action at an elite Brazilian university. arXiv preprint 2305.02513.

Marmaros, D. and Sacerdote, B. (2006). How do friendships form? *The Quarterly Journal of Economics*, 121(1):79–119.

Mayer, A. and Puller, S. L. (2008). The old boy (and girl) network: Social network formation on university campuses. *Journal of Public Economics*, 92(1–2):329–347.

Michelman, V., Price, J., and Zimmerman, S. D. (2022). Old boys' clubs and upward mobility. *Quarterly Journal of Economics*, 137(2):845–909.

Miller, C., Peck, J., and Seflek, M. (2022). Missing women, integration costs, and big push policies in the Saudi labor market. *American Economic Journal: Applied Economics*, 14(2):51–77.

Mouganie, P. and Wang, Y. (2020). High-performing peers and female STEM choices in school. *Journal of Labor Economics*, 38(3):805–841.

Najam, R. (2024). Closing the gap: Effect of a gender quota on women's access to education in Afghanistan. *Economics of Education Review*, 99:102509.

NASSCOM (2022). Strategic review 2022: India set for the rising techade as industry revenues soar past $200 billion. Press release, NASSCOM.

NASSCOM (2024). Technology sector in India 2024: Strategic review. Report, NASSCOM.

Oliveira, R., Santos, A., and Severnini, E. (2024). Bridging the gap: Mismatch effects and catch-up dynamics under a Brazilian college affirmative action program. *Economics of Education Review*, 98:102501.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *The American Economic Review*, 62(4):659–661.

Revelio Labs (2026). Individual position and education histories, India. Revelio Labs, Inc., New York, NY. Dataset. https://www.reveliolabs.com. Accessed November 2026.

Sander, R. H. (2004). A systemic analysis of affirmative action in American law schools. *Stanford Law Review*, 57(2):367–483.

Sengupta, N., Munshi, R., and Kaur, R. (2025). A foot in the door: Evaluating the supernumerary seats scheme for girls in the IITs. *Higher Education*, pages 1–26.

Shukla, S. (2022). Making the elite: Top jobs, disparities, and solutions. *arXiv preprint arXiv:2208.14972*.

Sloane, C. M., Hurst, E. G., and Black, D. A. (2021). College majors, occupations, and the gender wage gap. *Journal of Economic Perspectives*, 35(4):223–248.

Sowell, T. (2004). *Affirmative Action around the World: An Empirical Study*. Yale University Press, New Haven.

The Economic Times (2012). IIMs, IITs fail to impress India Inc on gender diversity; recruiters complain of lesser women graduates. https://economictimes.indiatimes.com/jobs/iims-iits-fail-to-impress-india-inc-on-gender-diversity-recruiters-complain-of-lesser-women-graduates/articleshow/12153661.cms.

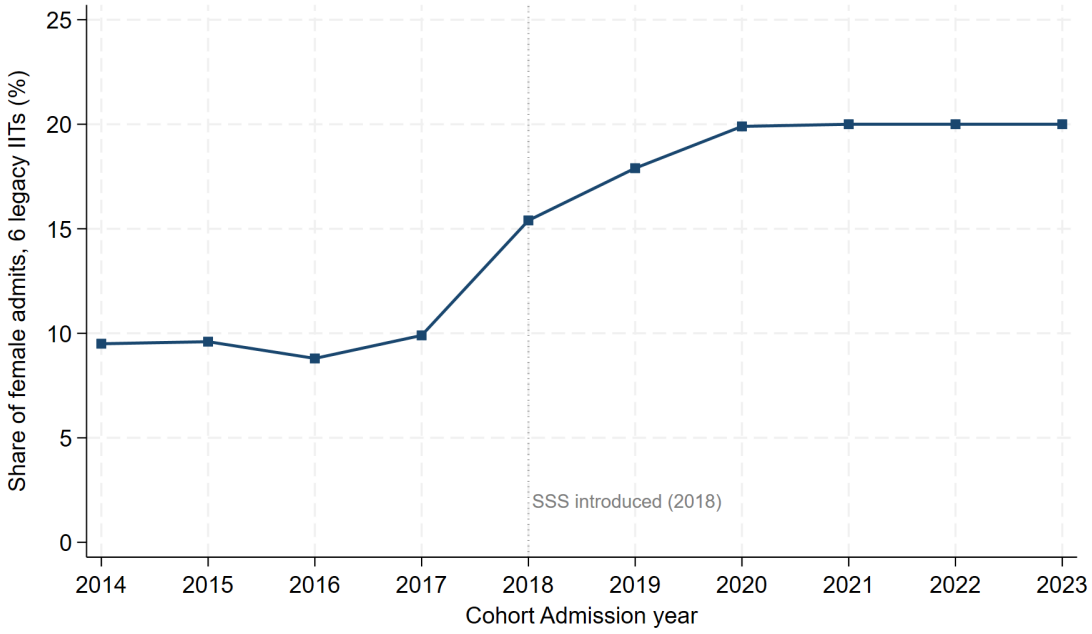
UNESCO (2024). Global education monitoring report 2024, gender report: Technology on her terms. Technical report, Global Education Monitoring Report Team, UNESCO, Paris.

Zimmerman, S. D. (2019). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review*, 109(1):1–47.

Zölitz, U. and Feld, J. (2021). The effect of peer gender on major choice in business school. *Management Science*, 67(11):6963–6979.

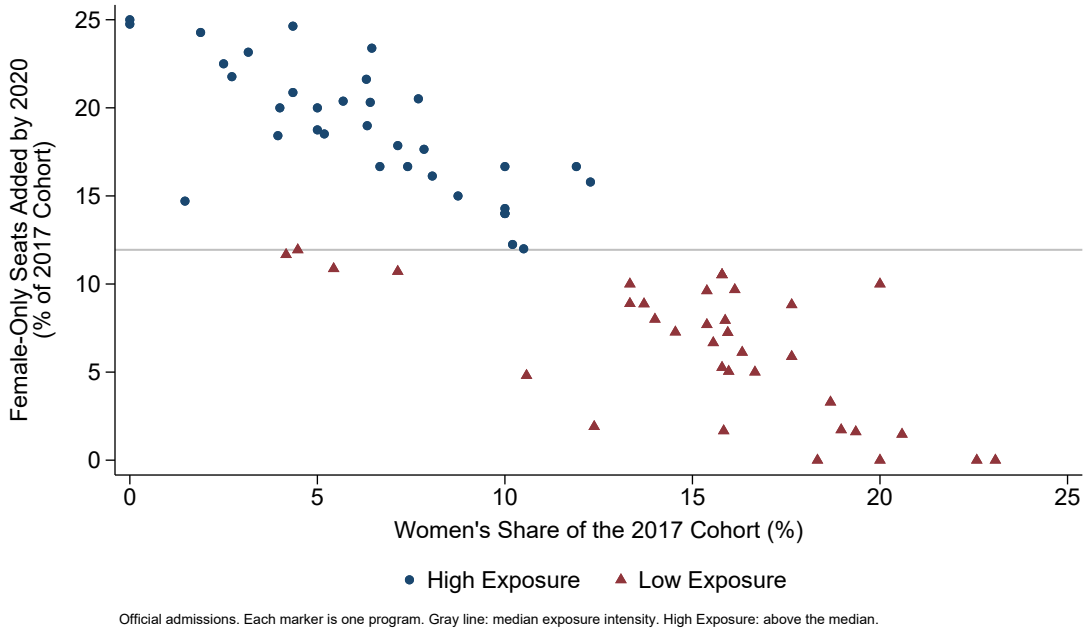
Figures

Figure 1: Female Share of Admitted Students at the 6 IITs, 2014 to 2023



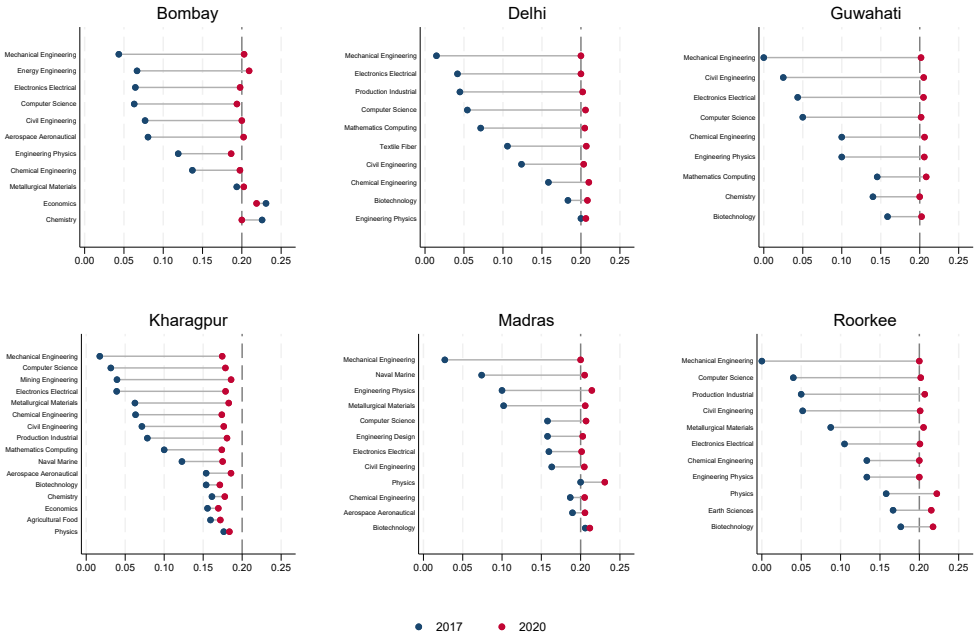
Notes: The figure shows the share of women among students admitted to undergraduate programs at the 6 IITs in the sample (Bombay, Delhi, Guwahati, Kharagpur, Madras, and Roorkee), by admission year. The vertical line marks the introduction of the Supernumerary Seats Scheme in 2018.

Figure 2: Exposure to the Reform and Female Share in 2017



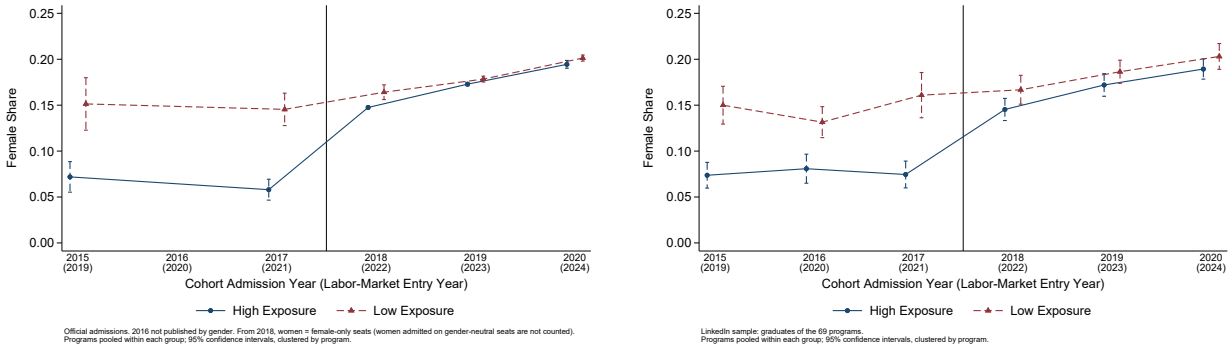
Notes: Each marker is a program (IIT and field). The horizontal axis is the female share of the program's 2017 admission cohort in the JEE reports. The vertical axis is exposure in equation (1), the female-only seats added by 2020 as a share of 2017 enrollment. The horizontal line marks the median, which separates High Exposure programs (above) from Low Exposure programs (below).

Figure 3: Share of Seats Offered to Women by Program, 2017 and 2020



Notes: The figure shows the share of seats offered to women in each program at the 6 IITs in the sample, in 2017 and 2020. The vertical line marks the 20% target every program had to reach by 2020.

Figure 4: Female Share of Students, by Exposure

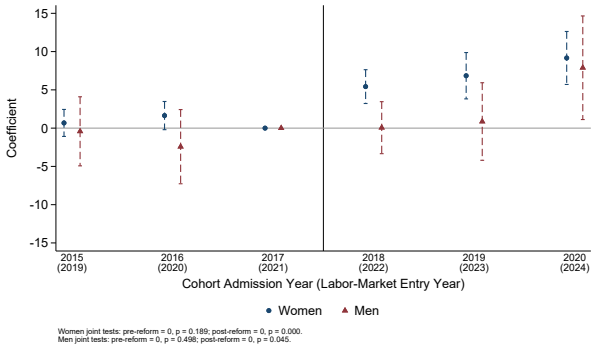


(a) Admission records

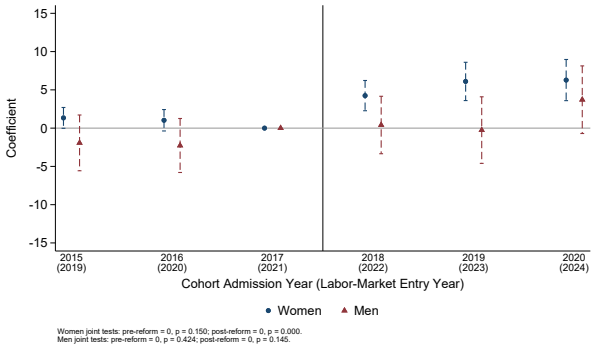
(b) LinkedIn sample

Notes: Panel (a) shows the female share of admitted students by admission cohort in High and Low Exposure programs, from the JEE reports, pooling programs within each group. Admissions by gender are not published for 2016. From 2018, women are counted from the female-only seats, so women admitted through gender-neutral seats are not included. Panel (b) shows the female share of graduates observed on LinkedIn, by admission cohort, in the same 2 groups of programs. Vertical bars show 95% confidence intervals clustered by program.

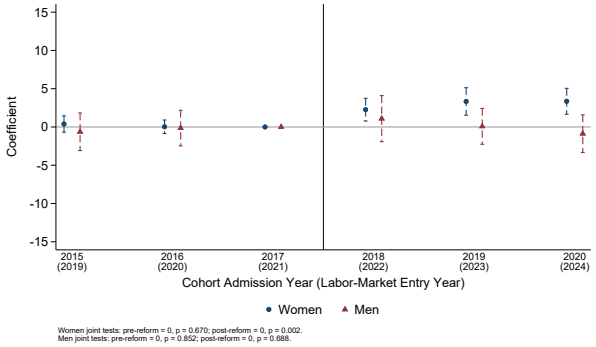
Figure 5: Event Studies: Number of Graduates, Labor Market Entrants, and Hires



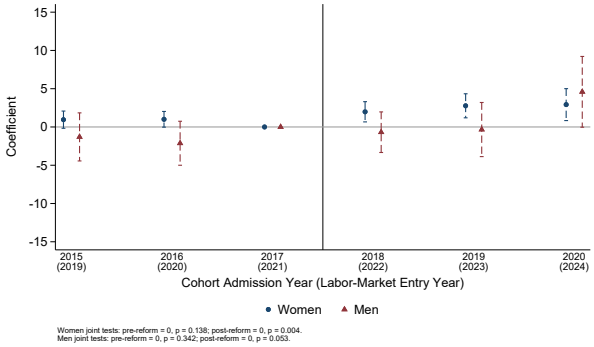
(a) Graduates



(b) Labor market entrants



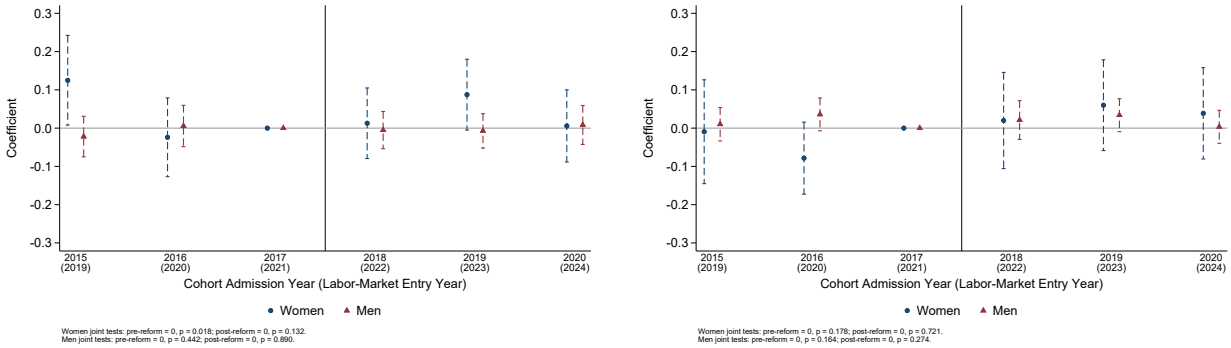
(c) Elite hires



(d) Non-elite hires

Notes: The figure plots the coefficients from equation (3), estimated separately for women (blue) and men (red) at the program and cohort level. The outcomes are the number of graduates observed on LinkedIn (a), the number entering the labor market (b), and the number whose first job is at an elite firm (c) or at a non-elite firm (d). The 2017 cohort is the omitted category. Regressions include program and cohort fixed effects. Vertical bars show 95% confidence intervals clustered by program. The joint tests in each panel test whether the pre-reform and the post-reform coefficients are 0.

Figure 6: Event Studies: Labor Market Entry and an Elite First Job

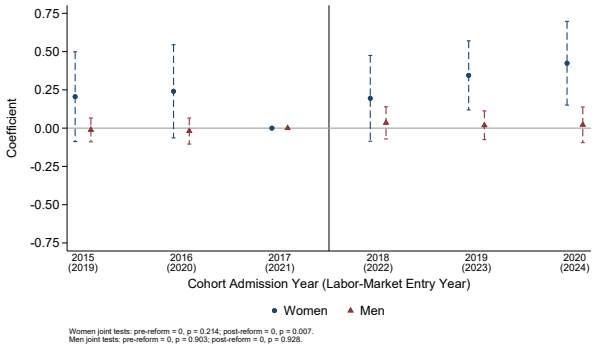


(a) Labor market entry

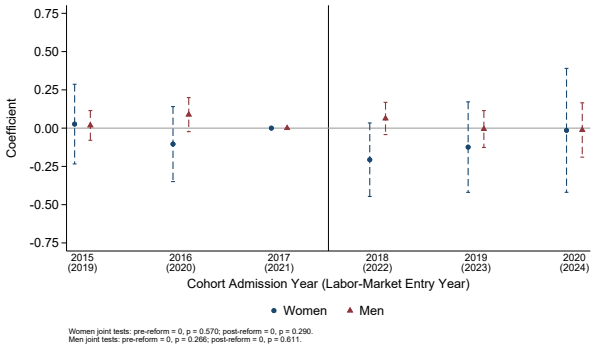
(b) Elite first job

Notes: The figure plots the coefficients from equation (3), estimated at the graduate level separately for women (blue) and men (red). The outcomes are indicators for entering the labor market (a) and for a first job at an elite firm (b), the latter coded 0 for graduates who do not enter the labor market. The 2017 cohort is the omitted category. Regressions include program and cohort fixed effects. Vertical bars show 95% confidence intervals clustered by program.

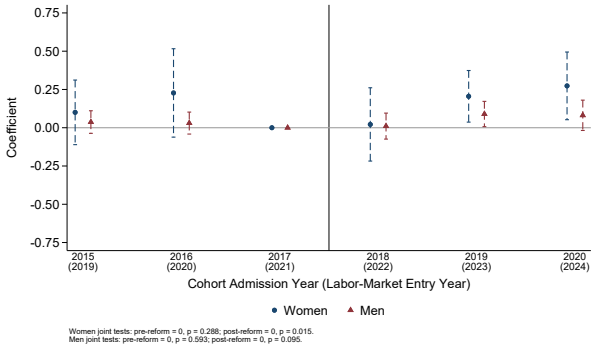
Figure 7: Event Studies: Promotion within 2 Years



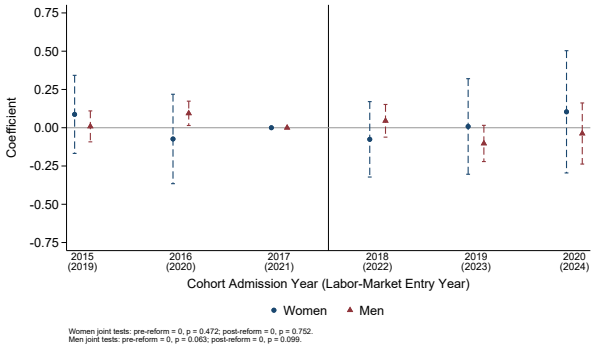
(a) Promoted, started at a non-elite firm



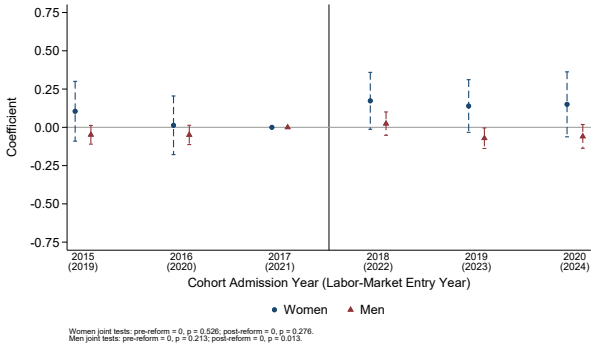
(b) Promoted, started at an elite firm



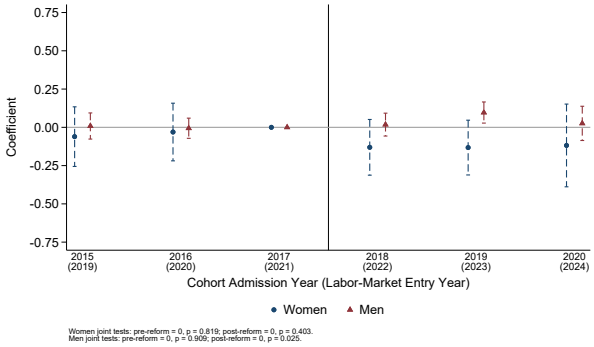
(c) Internal promotion, started at a non-elite firm



(d) Internal promotion, started at an elite firm



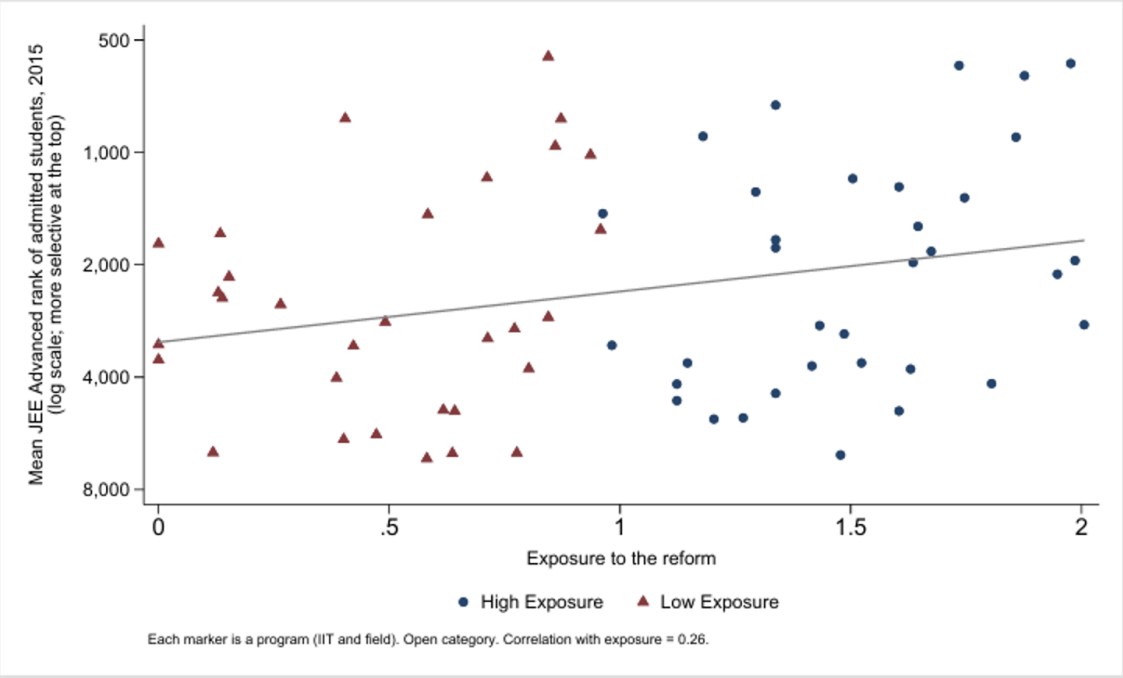
(e) External promotion, started at a non-elite firm



(f) External promotion, started at an elite firm

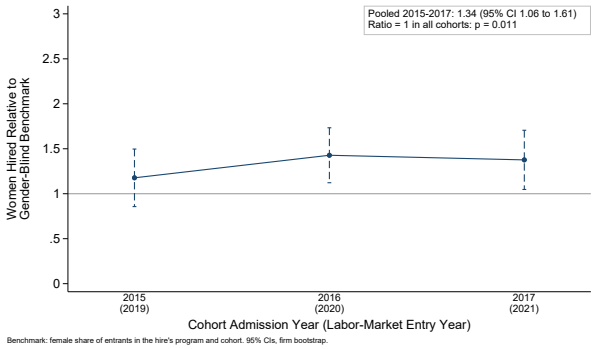
Notes: The figure plots the coefficients from equation (3), estimated separately for women (blue) and men (red) who entered the labor market and record a next position. The outcomes are promotion within 2 years of starting the first job (a and b), promotion within the same firm (c and d), and promotion through a move to a different firm (e and f), for graduates who started at a non-elite firm (left) and at an elite firm (right). Regressions include program, cohort, and first job industry fixed effects. The 2017 cohort is the omitted category. Vertical bars show 95% confidence intervals clustered by program.

Figure 8: Exposure to the Reform and Program Selectivity

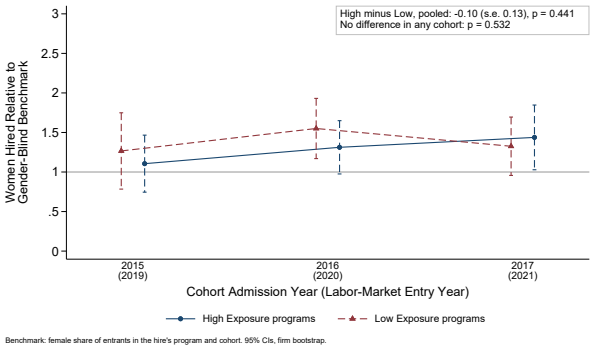


Notes: Each marker is a program (IIT and field). The vertical axis is the mean JEE Advanced rank of students admitted to open seats in 2015, on a log scale, with more selective programs at the top. The horizontal axis is exposure, the female-only seats added by 2020 relative to 2017 enrollment, rescaled so 1 equals the gap between the average High and the average Low Exposure program. The line shows a linear fit. The figure covers the 65 programs whose students in the 2015 Common Rank List could be assigned to a program.

Figure 9: Women Hired by Elite Firms Relative to the Gender-blind Benchmark, Before the Reform



(a) All programs



(b) High and Low Exposure programs

Notes: Panel (a) shows, for each cohort admitted before the reform, the number of women hired by elite firms divided by the number expected under gender-blind hiring, pooling all programs. Panel (b) shows the same ratio separately for High and Low Exposure programs. Gender-blind hiring assigns each program and cohort's elite hires to women in proportion to women's share of the program's labor market entrants. A ratio of 1 means women were hired at the same rate as men from the same program. Vertical bars show 95% confidence intervals from a firm bootstrap. The box in panel (b) reports the pooled difference between High and Low Exposure programs and a joint test of no difference in any cohort.

Tables

Table 1: Data Sources and How They Link

Source	Unit	Years	What it gives	How it links to LinkedIn
LinkedIn profiles (Revelio Labs)	Graduate	Admission cohorts 2015 to 2020	Institution, field, gender, employers, job titles, and dates	Main dataset
JEE reports	Program and year	2015 to 2020	Seats filled by program; supernumerary seats added from 2018; opening and closing ranks from 2018	By program and cohort
Common Rank Lists	Student	2015, 2018 to 2020	JEE Advanced rank, social category, and program; name and gender in 2015 only	By name for the 2015 cohort; by program and cohort for 2018 to 2020
Newspaper coverage of placements	Firm	Labor market years 2015 to 2025	121 elite firms recruiting on Day 0/Day 1	By the name of the first employer

Notes: The table lists the data sources, the unit each describes, the years covered, what each provides, and how each is linked to the LinkedIn career histories. A program is an IIT and field. Appendix B.1 describes how the 2015 Common Rank List is linked to LinkedIn profiles.

Table 2: Programs Before the Reform, by Exposure

	Low Exposure		High Exposure		Diff
	Mean	SD	Mean	SD	(H − L)
	(1)	(2)	(3)	(4)	(5)
Panel A: Official admissions, 2017 cohort					
Cohort size	67	32	89	45	22**
Women	9.7	5.2	5.1	3.8	−4.5***
Women's share of cohort (%)	14.5	4.7	5.8	3.1	−8.7***
JEE Advanced rank, 2015 cohort					
Women	3405	2025	2806	2151	−599
Men	2711	1806	2366	1565	−345
Panel B: LinkedIn sample, 2015–2017 (per cohort)					
Cohort size	43.0	34.2	68.4	45.4	25.4**
Women's share of cohort (%)	14.7	5.2	7.6	3.0	−7.1***
Coverage (LinkedIn / Official cohort size)	0.57	0.31	0.73	0.26	0.16**
Panel C: Labor market, 2015–2017 (per cohort)					
Labor market entrants (% of cohort)	68.9	8.3	70.4	8.6	1.5
Women's share of labor-market entrants (%)	14.5	6.6	7.6	3.0	−6.9***
Elite hires, women	2.1	2.2	2.0	2.0	−0.1
Elite hires, men	8.9	12.3	17.6	20.3	8.7**
Women's share of elite hires (%)	18.8	12.0	10.3	5.9	−8.6***
Hired by an elite firm, women (% of women)	32.6	15.9	38.5	12.1	5.8
Hired by an elite firm, men (% of men)	24.3	15.2	27.8	16.7	3.5
Women − men (pp)	8.3**	14.6	10.6***	17.6	2.3
Elite firms hiring from the program	6.6	6.5	10.5	8.8	3.9**
All firms hiring from the program	22.3	15.6	34.0	19.5	11.8***
Elite hires by industry (%)					
Finance	34.2	16.0	33.1	13.9	−1.1
Consulting	8.2	12.7	4.4	8.1	−3.9
Technology	47.1	26.8	51.8	22.2	4.7
Programs	35		34		

Notes: The table reports program-level descriptive statistics for the analysis sample in the pre-reform cohorts, admitted in 2015–2017. A program is an IIT–field pair. *High Exposure* refers to programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median; *Low Exposure* refers to the remaining programs. Columns (1)–(4) report means and standard deviations across programs; shares pool the three cohorts within a program, and group means weight programs by the denominator of the share. Column (5) reports the High-minus-Low difference in means, with stars from a regression on a High Exposure indicator with heteroskedasticity-robust standard errors. Panel A uses official admission records for the 2017 cohort, except the JEE Advanced rank, which is the mean rank on the 2015 common rank list of Open-category students admitted to the program (1 = best, so a higher number means lower ability), by the gender reported in the list, with group means weighting programs by the number of these students; the 2015 list is the only one that reports gender; Panels B and C use the LinkedIn sample, and counts are averages per admission cohort. Labor-market entrants are graduates whose first job begins in the year of graduation. *Hired by an elite firm* is the number of graduates whose first job is at an elite firm divided by all graduates in the LinkedIn sample; graduates who do not enter the labor market count as not hired. Industry shares are computed over the program's elite hires. *Women − men* is the difference between the shares of women and of men hired by an elite firm, in percentage points; stars in columns (1) and (3) test whether the gap is zero, and stars in column (5) test whether it differs between High and Low Exposure programs, with standard errors clustered by program. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Median Program Closing Rank, Gender-neutral and Female-only Seats

Year	Gender-neutral closing rank	Female-only closing rank
2015	3,989	—
2018	3,650	6,381
2019	4,044	7,919
2020	4,298	9,373

Notes: The table reports the median across programs of the closing rank of gender-neutral and female-only seats in the open category, at the 6 IITs in the sample. The closing rank is the JEE Advanced rank of the last student admitted. A higher rank number is a worse rank. Female-only seats were introduced in 2018, so there is no female-only closing rank in 2015. For 2015, I compute the closing rank from the Common Rank List, and for 2018 to 2020 I take it from the JEE reports.

Table 4: JEE Advanced Rank and Elite First Jobs Before the Reform, 2015 Cohort

	Elite job (=1)			
	(1)	(2)	(3)	(4)
JEE Advanced rank (thousands)	-0.0179***	-0.0194***	-0.0090***	-0.0107***
	(0.0022)	(0.0023)	(0.0029)	(0.0029)
Wild bootstrap p-value	0.000	0.000	0.004	0.001
Female		-0.001		-0.003
		(0.054)		(0.053)
Wild bootstrap p-value		0.989		0.952
Female × JEE Advanced rank		0.0157*		0.0146*
		(0.0084)		(0.0083)
Wild bootstrap p-value		0.093		0.113
JEE Advanced rank, slope for women		-0.0037		0.0040
		(0.0079)		(0.0078)
Wild bootstrap p-value		–		–
Mean of outcome	0.295	0.295	0.295	0.295
Observations	2,028	2,028	2,028	2,028
Clusters	63	63	63	63
School × field FE	Yes	Yes	Yes	Yes
Open / Reserved category FE	No	No	Yes	Yes

Notes: The table reports regressions of an indicator for an elite first job on JEE Advanced rank for graduates admitted in 2015, before the reform, whose names in the 2015 Common Rank List were linked to the LinkedIn sample. Graduates who did not enter the labor market are coded as 0. Rank is measured in thousands of places, with 1 the best rank, so a negative coefficient means better ranked graduates were more likely to obtain an elite first job. In columns (2) and (4), the coefficient on JEE Advanced rank is the slope for men, the coefficient on Female × JEE Advanced rank is the difference between the slopes of women and men, and the slope for women is their sum. Columns (3) and (4) add fixed effects for the open (General) and reserved (OBC-NCL, SC, and ST) categories. All regressions include program fixed effects, so they compare graduates within the same program. Coefficients on rank are reported to 4 decimal places. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. The bootstrap p value is not reported for the slope for women, which is a sum of two coefficients (–). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of the Reform on the Number of Graduates

	# Graduates (1)	# Women (2)	# Men (3)	Women's share (4)
Panel A: Unweighted				
Post × High Exposure	10.258***	6.375***	3.883*	0.052***
	(3.062)	(1.218)	(2.128)	(0.016)
Wild bootstrap p-value	0.001	0.000	0.071	0.002
Control mean, Low Exposure, 2015–2017	42.981	6.333	36.648	0.160
Observations	414	414	414	414
Clusters	69	69	69	69
Panel B: Weighted by pre-reform program size				
Post × High Exposure	11.666***	7.421***	4.245	0.052***
	(4.291)	(1.583)	(3.060)	(0.010)
Wild bootstrap p-value	0.011	0.000	0.186	0.000
Control mean, Low Exposure, 2015–2017	69.422	9.620	59.802	0.145
Observations	414	414	414	414
Clusters	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the number of graduates in the LinkedIn sample from each program and admission cohort. Columns (1) to (3) report the number of all graduates, women, and men, and column (4) reports women's share. Panel B weights each program by its average number of graduates per cohort before the reform. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a program and admission cohort, and every program appears in every cohort. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of the Reform on Labor Market Entry and Elite Hires

	# All (1)	# Women (2)	# Men (3)	Women's share (4)
Panel A: # Labor-market entrants				
Post × High Exposure	7.443***	4.754***	2.689	0.057**
	(2.416)	(0.979)	(1.679)	(0.022)
Wild bootstrap p-value	0.002	0.000	0.115	0.009
Control mean, Low Exposure, 2015–2017	29.629	4.305	25.324	0.156
Observations	414	414	414	414
Clusters	69	69	69	69
Panel B: # Elite hires				
Post × High Exposure	3.203**	2.847***	0.356	0.099**
	(1.278)	(0.665)	(0.845)	(0.038)
Wild bootstrap p-value	0.013	0.000	0.679	0.013
Control mean, Low Exposure, 2015–2017	10.971	2.067	8.905	0.204
Observations	414	414	414	414
Clusters	69	69	69	69
Panel C: # Non-elite hires				
Post × High Exposure	4.239**	1.907***	2.332*	0.019
	(1.698)	(0.618)	(1.318)	(0.024)
Wild bootstrap p-value	0.016	0.003	0.082	0.457
Control mean, Low Exposure, 2015–2017	18.657	2.238	16.419	0.122
Observations	414	414	414	414
Clusters	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the number of graduates from each program and admission cohort who entered the labor market (Panel A), whose first job was at an elite firm (Panel B), and whose first job was at a non-elite firm (Panel C). Columns (1) to (3) report the number of all graduates, women, and men, and column (4) reports women's share, which is set to 0 in program-cohorts with no graduates in that category. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. A labor market entrant is a graduate whose first job begins in the year of graduation. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a program and admission cohort, and every program appears in every cohort. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of the Reform on the Likelihood of Labor Market Entry and an Elite First Job

		Elite job (=1)	
	Labor-market entry (=1)	All graduates	Labor-market entrants
	(1)	(2)	(3)
Panel A: All graduates			
Post × High Exposure	0.006	0.022*	0.032**
	(0.013)	(0.013)	(0.016)
Wild bootstrap *p*-value	0.639	0.094	0.046
Control mean, Low Exposure, 2015–2017	0.689	0.255	0.370
Observations	25,915	25,915	18,067
Clusters	69	69	69
Panel B: Women			
Post × High Exposure	0.004	0.070*	0.084*
	(0.029)	(0.037)	(0.048)
Wild bootstrap *p*-value	0.905	0.082	0.108
Control mean, Low Exposure, 2015–2017	0.680	0.326	0.481
Observations	3,750	3,750	2,618
Clusters	69	69	67
Panel C: Men			
Post × High Exposure	0.004	0.003	0.008
	(0.014)	(0.013)	(0.016)
Wild bootstrap *p*-value	0.776	0.800	0.606
Control mean, Low Exposure, 2015–2017	0.691	0.243	0.352
Observations	22,165	22,165	15,447
Clusters	69	69	69
School × field FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on graduates' likelihood of entering the labor market (column 1) and of obtaining a first job at an elite firm (columns 2 and 3). Column (2) includes all graduates, with those who did not enter the labor market coded as 0, and column (3) includes only labor market entrants. Panel A pools women and men, and Panels B and C estimate the model separately for women and men. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. A labor market entrant is a graduate whose first job begins in the year of graduation. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017, among the graduates included in each column. An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Promotions and Moves: All Graduates Who Entered the Labor Market

	All labor-market entrants			
	Promoted (=1)	Internal (=1)	External (=1)	Moved (=1)
	(1)	(2)	(3)	(4)
Panel A: Women				
Post × High Exposure	0.054	0.039	0.014	-0.065
	(0.044)	(0.047)	(0.042)	(0.055)
Wild bootstrap p-value	0.234	0.421	0.737	0.254
Control mean, Low Exposure, 2015–2017	0.386	0.262	0.124	0.346
Observations	1,365	1,365	1,365	1,365
Clusters	65	65	65	65
Panel B: Men				
Post × High Exposure	0.027	0.010	0.017	-0.010
	(0.018)	(0.019)	(0.015)	(0.026)
Wild bootstrap p-value	0.145	0.611	0.279	0.723
Control mean, Low Exposure, 2015–2017	0.400	0.274	0.125	0.369
Observations	9,278	9,278	9,278	9,278
Clusters	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
First-job industry FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the early careers of all labor market entrants, pooling graduates whose first job was at an elite firm (Table 9) and at a non-elite firm (Table 11). The sample includes labor market entrants who record a next position within 2 years of the start of their first job, excluding next positions in further study, research, or a career break and next positions that begin more than 6 months after the first job ends. Promoted equals 1 if the title of the next position ranks above the title of the first job on the seniority ladder in Table B3. Internal and external promotions are promotions at the same firm and at a different firm, and they add up to column (1). Moved equals 1 if the next position is at a different firm, with or without a promotion. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. All regressions include fixed effects for the industry of the first employer. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effect of the Reform on Promotions and Moves: Graduates Who Started at Elite Firms

	Graduates who started at an elite firm			
	Promoted (=1) (1)	Internal (=1) (2)	External (=1) (3)	Moved (=1) (4)
Panel A: Women				
Post × High Exposure	-0.127*	-0.026	-0.101	-0.078
	(0.072)	(0.083)	(0.061)	(0.087)
Wild bootstrap p-value	0.092	0.749	0.140	0.400
Control mean, Low Exposure, 2015–2017	0.364	0.283	0.081	0.243
Observations	632	632	632	632
Clusters	59	59	59	59
Panel B: Men				
Post × High Exposure	-0.004	-0.052	0.047**	0.062*
	(0.026)	(0.032)	(0.020)	(0.034)
Wild bootstrap p-value	0.869	0.148	0.038	0.091
Control mean, Low Exposure, 2015–2017	0.425	0.322	0.104	0.293
Observations	3,400	3,400	3,400	3,400
Clusters	63	63	63	63
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
First-job industry FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the early careers of graduates whose first job was at an elite firm. The sample includes labor market entrants who record a next position within 2 years of the start of their first job, excluding next positions in further study, research, or a career break and next positions that begin more than 6 months after the first job ends. Promoted equals 1 if the title of the next position ranks above the title of the first job on the seniority ladder in Table B3. Internal and external promotions are promotions at the same firm and at a different firm, and they add up to column (1). Moved equals 1 if the next position is at a different firm, with or without a promotion. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. All regressions include fixed effects for the industry of the first employer. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Where External Promotions Go: Graduates Who Started at Elite Firms

	Graduates who started at an elite firm					
	External	Promoted move to a firm with...			Promoted move to...	
	promotion (=1)	an own-gender graduate (=1)	other-gender graduates only (=1)	no graduate (=1)	an elite firm (=1)	a non-elite firm (=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Women						
Post × High Exposure	-0.101	-0.027	0.005	-0.079	-0.038	-0.063
	(0.061)	(0.018)	(0.029)	(0.059)	(0.027)	(0.060)
Wild bootstrap p-value	0.140	0.198	0.883	0.243	0.185	0.375
Control mean, Low Exposure, 2015–2017	0.081	0.006	0.023	0.052	0.035	0.046
Observations	632	632	632	632	632	632
Clusters	59	59	59	59	59	59
Panel B: Men						
Post × High Exposure	0.047**	0.034***	0.004*	0.010	0.032***	0.015
	(0.020)	(0.009)	(0.002)	(0.016)	(0.011)	(0.016)
Wild bootstrap p-value	0.038	0.001	0.097	0.576	0.022	0.360
Control mean, Low Exposure, 2015–2017	0.104	0.032	0.001	0.070	0.039	0.065
Observations	3,400	3,400	3,400	3,400	3,400	3,400
Clusters	63	63	63	63	63	63
School × field FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
First-job industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table decomposes the external promotions of graduates whose first job was at an elite firm by the firm they moved to. Column (1) reports external promotion, as in Table 9. Columns (2) to (4) split it by whether the new firm had given a first job to a graduate of the same program (IIT and field) of the mover's gender (column 2), only to graduates of the program of the other gender (column 3), or to no graduate of the program (column 4), from the mover's own admission cohort or the cohort 1 year above. Columns (5) and (6) split it by whether the new firm is elite or non-elite. Each set of columns adds up to column (1), and so do the coefficients. Firms are matched by name. The sample is described in Table 9. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effect of the Reform on Promotions and Moves: Graduates Who Started at Non-elite Firms

	Graduates who started at a non-elite firm			
	Promoted (=1)	Internal (=1)	External (=1)	Moved (=1)
	(1)	(2)	(3)	(4)
Panel A: Women				
Post × High Exposure	0.157**	0.044	0.113*	0.040
	(0.075)	(0.069)	(0.061)	(0.087)
Wild bootstrap p-value	0.040	0.523	0.081	0.662
Control mean, Low Exposure, 2015–2017	0.407	0.242	0.165	0.445
Observations	729	729	729	729
Clusters	63	63	63	63
Panel B: Men				
Post × High Exposure	0.036	0.033	0.004	-0.030
	(0.028)	(0.023)	(0.018)	(0.031)
Wild bootstrap p-value	0.213	0.170	0.848	0.348
Control mean, Low Exposure, 2015–2017	0.386	0.249	0.137	0.410
Observations	5,876	5,876	5,876	5,876
Clusters	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
First-job industry FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the early careers of graduates whose first job was at a non-elite firm. The sample and outcomes are defined as in Table 9. Internal and external promotions add up to column (1). Moved equals 1 if the next position is at a different firm, with or without a promotion. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. All regressions include fixed effects for the industry of the first employer. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Where External Promotions Go: Graduates Who Started at Non-elite Firms

	Graduates who started at a non-elite firm					
	External	Promoted move to a firm with...			Promoted move to...	
	promotion (=1)	an own-gender graduate (=1)	other-gender graduates only (=1)	no graduate (=1)	an elite firm (=1)	a non-elite firm (=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Women						
Post × High Exposure	0.113*	0.014	0.005	0.094	0.019	0.094*
	(0.061)	(0.014)	(0.014)	(0.059)	(0.023)	(0.056)
Wild bootstrap p-value	0.081	0.338	0.755	0.124	0.433	0.111
Control mean, Low Exposure, 2015–2017	0.165	0.016	0.005	0.143	0.038	0.126
Observations	729	729	729	729	729	729
Clusters	63	63	63	63	63	63
Panel B: Men						
Post × High Exposure	0.004	0.014**	-0.004	-0.007	-0.001	0.004
	(0.018)	(0.007)	(0.003)	(0.016)	(0.007)	(0.017)
Wild bootstrap p-value	0.848	0.054	0.115	0.691	0.942	0.807
Control mean, Low Exposure, 2015–2017	0.137	0.021	0.001	0.116	0.019	0.119
Observations	5,876	5,876	5,876	5,876	5,876	5,876
Clusters	69	69	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
First-job industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table decomposes the external promotions of graduates whose first job was at a non-elite firm by the firm they moved to. Column (1) reports external promotion, as in Table 11. Columns (2) to (4) split it by whether the new firm had given a first job to a graduate of the same program (IIT and field) of the mover's gender (column 2), only to graduates of the program of the other gender (column 3), or to no graduate of the program (column 4), from the mover's own admission cohort or the cohort 1 year above. Columns (5) and (6) split it by whether the new firm is elite or non-elite. Each set of columns adds up to column (1), and so do the coefficients. Firms are matched by name. The sample is described in Table 11. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Elite First Jobs, by Female Share of High Exposure Programs in 2017

	Elite job (=1)	
	Women	Men
	(1)	(2)
Post × High Exposure, by 2017 female share:		
Below median	0.114**	-0.001
	(0.044)	(0.014)
Wild bootstrap p-value	0.039	0.939
At or above median	0.003	0.012
	(0.039)	(0.018)
Wild bootstrap p-value	0.939	0.546
Equality test, p-value	0.032	0.492
Control mean, Low Exposure, 2015–2017	0.326	0.243
Observations	3,750	22,165
Clusters	69	69
School × field FE	Yes	Yes
Cohort FE	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the likelihood of an elite first job, splitting High Exposure programs at the median of the female share of their 2017 cohort in the JEE reports. Each row reports the coefficient on Post × High Exposure for High Exposure programs below the median or at or above it, estimated in a single regression in which Low Exposure programs are the comparison group for both. The equality test reports the p value from a test that the 2 coefficients are equal. The outcome includes all graduates, with those who did not enter the labor market coded as 0, and the model is estimated separately for women (column 1) and men (column 2). The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Elite First Jobs in Marginal-only Cohorts and Cohorts with Inframarginal Women

	Labor-market entry (=1) (1)	Elite job (=1) (2)
Panel A: Women		
Post × High Exposure, marginal-only cohorts	0.020	0.093**
	(0.033)	(0.035)
Wild bootstrap *p*-value	0.561	0.015
Post × High Exposure, cohorts with inframarginal women	-0.032	0.019
	(0.036)	(0.051)
Wild bootstrap *p*-value	0.392	0.726
Difference, inframarginal − marginal-only	-0.052	-0.074*
	(0.037)	(0.040)
Wild bootstrap *p*-value	0.176	0.108
Post × Cohort with inframarginal women	0.044	0.069**
	(0.032)	(0.034)
Wild bootstrap *p*-value	0.201	0.102
Control mean, Low Exposure, 2015–2017	0.680	0.326
Observations	3,750	3,750
Clusters	69	69
Panel B: Men		
Post × High Exposure, marginal-only cohorts	0.005	0.010
	(0.015)	(0.013)
Wild bootstrap *p*-value	0.740	0.426
Post × High Exposure, cohorts with inframarginal women	0.002	-0.011
	(0.020)	(0.024)
Wild bootstrap *p*-value	0.926	0.664
Difference, inframarginal − marginal-only	-0.003	-0.021
	(0.022)	(0.025)
Wild bootstrap *p*-value	0.893	0.451
Post × Cohort with inframarginal women	-0.010	-0.006
	(0.015)	(0.018)
Wild bootstrap *p*-value	0.511	0.746
Control mean, Low Exposure, 2015–2017	0.691	0.243
Observations	22,165	22,165
Clusters	69	69
School × field FE	Yes	Yes
Cohort FE	Yes	Yes

Notes: The table reports estimates separately for marginal-only cohorts and cohorts with inframarginal women. Each program and post-reform cohort is classified by its own year. In a marginal-only cohort, every woman in a female-only seat had a rank worse than the gender-neutral closing rank of her program and category, and in a cohort with inframarginal women, at least 1 of them had a better rank. The first 2 rows compare High and Low Exposure programs within each type of cohort, and the third row reports their difference, the coefficient on Post × High Exposure × Cohort with inframarginal women. The fourth row compares cohorts with inframarginal women with marginal-only cohorts within Low Exposure programs. Program-cohorts with no female-only seat are excluded. Column (1) is an indicator for entering the labor market, equal to 1 if the graduate's first job begins in the year of graduation. Column (2) is an indicator for an elite first job and includes all graduates, with those who did not enter the labor market coded as 0. Panels A and B are estimated separately for women and men. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Institutional Context and the Placement Market

This appendix describes the IITs, the rank lists of the JEE Advanced, how I construct the classification of elite firms, and the elite and non-elite placement markets.

A.1 The IITs

Figure A1 shows where the 23 IITs are located. The 7 legacy IITs are the oldest and most selective.

Figure A1: Location of the IITs



Notes: The figure shows the locations of the 23 IITs. The 7 legacy IITs are shown in red.

A.2 Rank Lists

The JEE Advanced produces several rank lists. To appear on the Common Rank List (CRL), a candidate must score above a minimum set for the CRL. Candidates from reserved categories, Other Backward Classes, Scheduled Castes, Scheduled Tribes, and, from 2019, the Economically Weaker Section, face a lower minimum, and each reserved category has its own rank list. A reserved category candidate who scores above the CRL minimum appears on both the CRL and her category list. A reserved category candidate who scores between

her category's minimum and the CRL minimum appears only on her category list, so she has no CRL rank. Open seats are filled in order of CRL rank, and reserved seats are filled in order of rank within each category. Since I compare ranks only within the open category, every student in these comparisons has a CRL rank.

A.3 Elite Firm Classification

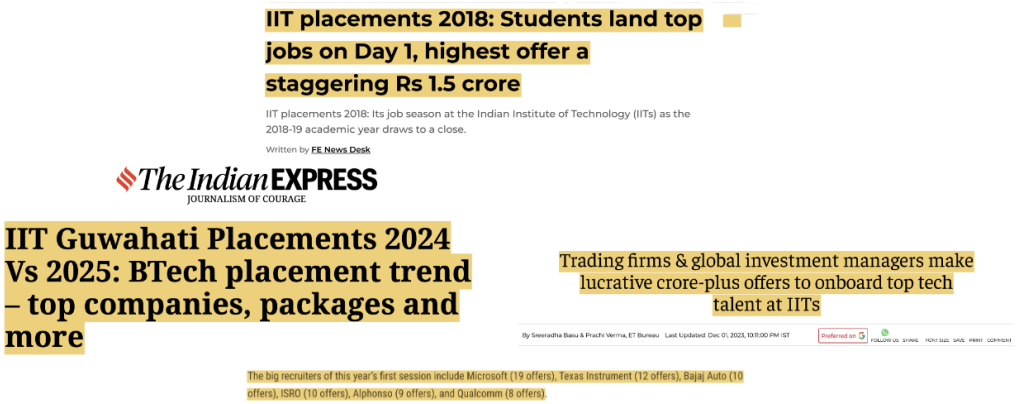
This subsection describes the steps behind the classification of elite firms in Section 3. I first collect newspaper reports published between 2015 and 2025 using search terms such as "IIT placement", "IIT campus placements", and "IIT highest packages". I keep only the reports that name at least one of the 6 IITs in my sample.

Using a large language model, I then extract every firm mentioned in these reports together with the sentence in which it appears. I read each sentence in the original report and keep a firm only if the sentence places it on the first days of placement. Reports describe this day in several ways, such as "Day 0", "Day 1", "the first day", or "the first session". For example, one report states, "The big recruiters of this year's **first session** include Microsoft (19 offers), Texas Instruments (12 offers), Bajaj Auto (10 offers), ISRO (10 offers) etc." I drop mentions unrelated to Day 0/Day 1 recruitment, such as a firm recruiting later in the season or a report of salaries.

Finally, I keep a firm only if at least two independent reports name it as a Day 0/Day 1 recruiter, where independent means the reports are not republished copies of the same story. This rule guards against errors in a single report and against one story being counted several times. Figure A2 shows examples of these reports. The final classification contains 121 firms. To classify each graduate's first job, I standardize employer names in the LinkedIn data and match them to these firms.

To validate the classification, I compare it with an internal record from the placement office of one legacy IIT. The record lists every firm that recruited at this IIT and the day of its interviews, for three placement seasons. Of the firms the record assigns to Day 0/Day 1, 80% also appear in my classification. A perfect overlap is not expected, since firms do not recruit at every IIT and the record covers a single institute.

Figure A2: Examples of News Coverage of Day 0/Day 1 Placements



Notes: The figure shows examples of newspaper coverage of the first days of IIT placements, of the kind used to construct the elite firm classification.

A.4 Structure of the Placement Market

Table A1 describes the elite firms that hired graduates of the sample programs in each cohort, including the number of firms, their hires, and the share of hires accounted for by firms hiring from both High and Low Exposure programs. Table A2 reports the same statistics for non-elite firms. About 89 elite firms hired from the sample programs in each pre-reform cohort, and about 101 in the 2018 cohort. In every cohort, technology firms made up about 40% of elite firms, and consulting and core engineering firms about 10% each, while the share of finance firms rose from about 34% before the reform to about 40% after it.

Table A1: Structure of the Elite Placement Market by Admission Cohort

	Pre-reform			Post-reform		
Cohort admission year	2015	2016	2017	2018	2019	2020
(Labor-market entry year)	(2019)	(2020)	(2021)	(2022)	(2023)	(2024)
Firms and hires						
Distinct firms	89	88	89	101	101	89
Total hires	959	1062	1129	1314	1251	1170
Hires per firm	10.8	12.1	12.7	13.0	12.4	13.1
Common employers						
Firms hiring from High & Low Exposure (% of firms)	75.3	75.0	75.3	69.3	70.3	82.0
Share of hires (%)	94.5	96.9	94.5	94.0	93.6	96.4
Firms present pre- and post-reform (% of firms)	93.3	94.3	95.5	92.1	92.1	94.4
Share of hires (%)	97.6	98.8	97.7	99.2	99.0	98.4
Hires from departments the firm used pre-reform (%)	74.9	75.1	72.5	77.1	77.5	76.4
Industry composition of firms (%)						
Technology	39.3	44.3	40.4	37.6	36.6	39.3
Finance	34.8	31.8	36.0	40.6	39.6	40.4
Consulting	11.2	10.2	10.1	9.9	10.9	10.1
Core engineering	10.1	9.1	11.2	9.9	10.9	9.0
Other	4.5	4.5	2.2	2.0	2.0	1.1

Notes: The table reports, by admission cohort and the year most of the cohort entered the labor market (in brackets), the number of elite firms hiring graduates of the sample programs, their hires, the share of firms and hires accounted for by firms hiring from both High and Low Exposure programs, the share accounted for by firms present both before and after the reform, the share of hires from departments the firm recruited from before the reform, and the industry mix of elite firms.

Table A2: Structure of the Non-elite Placement Market by Admission Cohort

	Pre-reform			Post-reform		
Cohort admission year	2015	2016	2017	2018	2019	2020
(Labor-market entry year)	(2019)	(2020)	(2021)	(2022)	(2023)	(2024)
Firms and hires						
Distinct firms	636	622	649	663	841	1004
Total hires	1605	1608	1664	1799	2139	2367
Hires per firm	2.5	2.6	2.6	2.7	2.5	2.4
Common employers						
Firms hiring from High & Low Exposure (% of firms)	21.4	22.0	25.6	23.8	20.8	19.4
Share of hires (%)	59.3	59.8	62.4	63.0	59.7	55.2
Firms present pre- and post-reform (% of firms)	37.3	44.9	48.8	45.7	32.5	24.0
Share of hires (%)	66.5	70.3	75.5	71.5	60.4	46.7
Hires from departments the firm used pre-reform (%)	50.1	52.3	50.2	53.3	49.5	44.2
Industry composition of firms (%)						
Technology	42.3	46.0	44.8	43.7	40.7	44.1
Finance	10.8	10.9	13.9	15.2	15.7	14.0
Consulting	7.5	7.6	6.5	7.1	7.0	7.9
Core engineering	15.4	10.8	11.9	11.3	13.9	15.3
Other	23.4	24.6	23.0	22.6	22.7	18.6

Notes: The table reports the same statistics as Table A1 for non-elite firms.

B Data Construction

This appendix describes how I link the 2015 Common Rank List to LinkedIn, the sample timeline, how I pool admission programs into fields, how I code next positions and promotions, and how exposure varies across programs.

B.1 Linking the 2015 Common Rank List to LinkedIn

Some students in the 2015 Common Rank List are listed without a name. I link the named students to profiles in the LinkedIn sample of the same program by name, keeping matches with a similarity score of at least 0.66. The linked graduates come from 63 programs. Better ranked students were slightly less likely to be named in the list (Table B1, column 1), while among named students, being found on LinkedIn is not related to rank or gender (Table B1, column 2).

Table B1: Linking the 2015 Common Rank List to LinkedIn

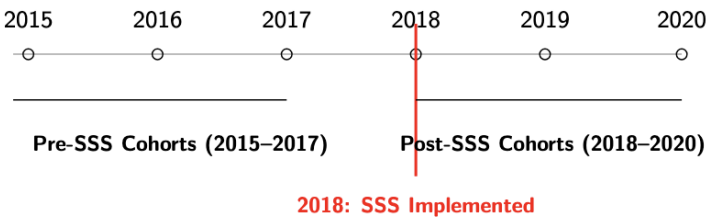
	Named in the list (=1) All admitted students (1)	Found on LinkedIn (=1) Named students (2)
JEE Advanced rank (thousands)	0.0062***	-0.0047
	(0.0012)	(0.0037)
Wild bootstrap p-value	0.000	0.234
Female	-0.029	-0.031
	(0.019)	(0.031)
Wild bootstrap p-value	0.143	0.329
Mean of outcome	0.808	0.585
Observations	4,287	3,466
Clusters	64	64
School × field FE	Yes	Yes
Open / Reserved category FE	Yes	Yes

Notes: The table examines whether linking the 2015 Common Rank List to the LinkedIn sample depends on rank or gender. Column (1) regresses an indicator for being named in the list on JEE Advanced rank and an indicator for women, among all students admitted to the 6 IITs in 2015. Column (2) regresses an indicator for being found on LinkedIn on the same variables among named students. A student is found if her name matches a profile in the LinkedIn sample of the same program with a similarity score of at least 0.66. Rank is measured in thousands of places, with 1 the best rank, so a negative coefficient means better ranked students were more likely to be named or found. Both regressions include program fixed effects. Coefficients on rank are reported to 4 decimal places. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Sample and Timeline

Figure B1 shows each admission cohort in the sample, the year most of its graduates entered the labor market, and whether it was admitted before or after the reform.

Figure B1: Study Timeline



Notes: The figure shows each admission cohort in the sample and the year most of its graduates entered the labor market, four years after admission. Cohorts admitted from 2015 to 2017 were admitted before the reform, and cohorts admitted from 2018 to 2020 after it.

B.3 Field Pooling

Table B2 lists the admission programs combined into each field. For example, Electrical Engineering and Electronics and Communication Engineering form a single field.

Table B2: Classification of JEE Advanced Programs into Broad Fields

Field	JEE Advanced programs included
Aerospace & Aeronautical	Aerospace Engineering
Agricultural & Food	Agricultural and Food Engineering
Architecture	Architecture
Biotechnology	Bio Technology; Biochemical Engineering and Biotechnology; Biological Engineering; Biological Sciences; Biotechnology and Biochemical Engineering
Chemical Engineering	Chemical Engineering
Chemistry	Chemical Science and Technology; Chemistry
Civil Engineering	Civil Engineering; Civil Engineering with any of the listed specialization
Computer Science	Computer Science and Engineering
Earth Sciences	Applied Geology; Exploration Geophysics; Geological Technology; Geophysical Technology
Economics	Economics
Electronics & Electrical	Electrical Engineering; Electrical Engineering (Power and Automation); Electrical Engineering with M. Tech in Microelectronics; Electronics and Communication Engineering; Electronics and Electrical Communication Engineering; Electronics and Electrical Engineering
Energy Engineering	Energy Engineering with M. Tech in Energy Systems Engineering
Engineering Design	Engineering Design; Quality Engineering Design and Manufacturing
Engineering Physics	Engineering Physics
Instrumentation	Instrumentation Engineering
Manufacturing	Manufacturing Science and Engineering
Mathematics & Computing	Applied Mathematics; Mathematics and Computing
Mechanical Engineering	Mechanical Engineering
Metallurgy & Materials	Metallurgical and Materials Engineering
Mining	Mining Engineering; Mining Safety Engineering
Naval & Marine	Naval Architecture and Ocean Engineering
Physics	Physics
Polymer	Polymer Science and Engineering
Production & Industrial	Industrial and Systems Engineering; Production and Industrial Engineering
Textile	Textile Technology

Notes: The table reports the JEE Advanced programs combined into each broad field, including their dual degree variants. Architecture is excluded from the estimation sample.

B.4 Next Positions and Promotions

This subsection describes how I identify next positions and how I rank job titles to code promotions.

Next position. The next position is the first position on a profile after the first job, whether at the same firm or at a different one. I keep it only if it begins within two years of the start of the first job. When a next position has no start date, but the first job has an end date and the next employer is named, I take the end of the first job as the start of the next. I exclude next positions in further study, research, or a career break, which I identify from the employer, such as universities, research institutes, the IITs, and the IIMs, or from the title, such as PhD, master's, MBA, research fellow, gap year, sabbatical, or civil services preparation. I also exclude next positions that begin more than six months after the first job ends, since the period between the two jobs is not observed. For the latest cohorts, the two year window may not be fully observed when the data were collected, so fewer graduates in these cohorts record a next position. This affects High and Low Exposure programs in the same cohorts.

Coding promotions. The ladder in Table B3 places a title at the level of the seniority word it contains, such as junior, senior, manager, or director. Titles with no seniority word, such as software engineer or analyst, are at level 3, and the word senior moves a title up one level. Within two years of graduation, the relevant steps are at the bottom of the ladder, from intern or trainee, to junior or entry titles, to titles with no seniority word, and then to senior or lead titles. For four kinds of titles, the seniority words give the wrong answer, so I apply the following rules.

1. *Numbered grades.* Some firms grade the same job with numbers instead of seniority words. Software Development Engineer (SDE) 1 and SDE 2 fall on the same level of the ladder, but a change from SDE 1 to SDE 2 is a promotion.

2. *Associate.* In technology firms, associate denotes an entry role, so associate software engineer is at level 2. In consulting and finance firms, associate is the role above analyst, so a change from analyst to associate is a promotion.

3. *Trainee to a different kind of job.* A change from management trainee to software developer at another firm moves up the ladder but reflects a different kind of job. I

code such a change as a promotion only if it happens within the same firm or the same line of work.

4. *Management titles without a seniority word.* A change from a non-management job into a title such as head of operations is a promotion.

I code the few remaining pairs of titles by hand.

Table B3: Seniority Ladder

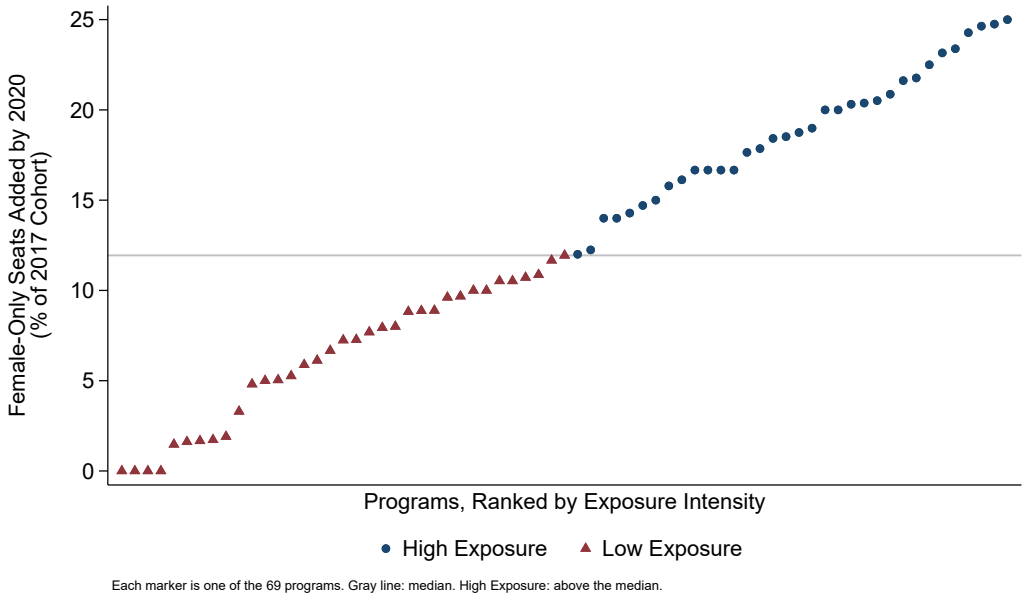
Level	Category	Example titles
1	Intern and trainee	Intern, management trainee
2	Junior and entry	Junior engineer, associate software engineer
3	No seniority word	Software engineer, analyst
4	Senior and lead	Senior engineer, team lead
5	Manager	Manager, product manager
6 to 8	Director, vice president, executive	Director, vice president, chief executive officer

Notes: The table reports the seniority ladder used to code promotions, with example titles at each level. Levels 6 to 8 are shown together.

B.5 Exposure to the Reform

Figure B2 shows how exposure varies across the 69 programs.

Figure B2: Exposure Intensity across Programs



Notes: Each marker is 1 of the 69 programs, ranked by exposure in equation (1), the female-only seats added by 2020 as a share of 2017 enrollment. The horizontal line marks the median. High Exposure programs lie above it.

C LinkedIn Coverage

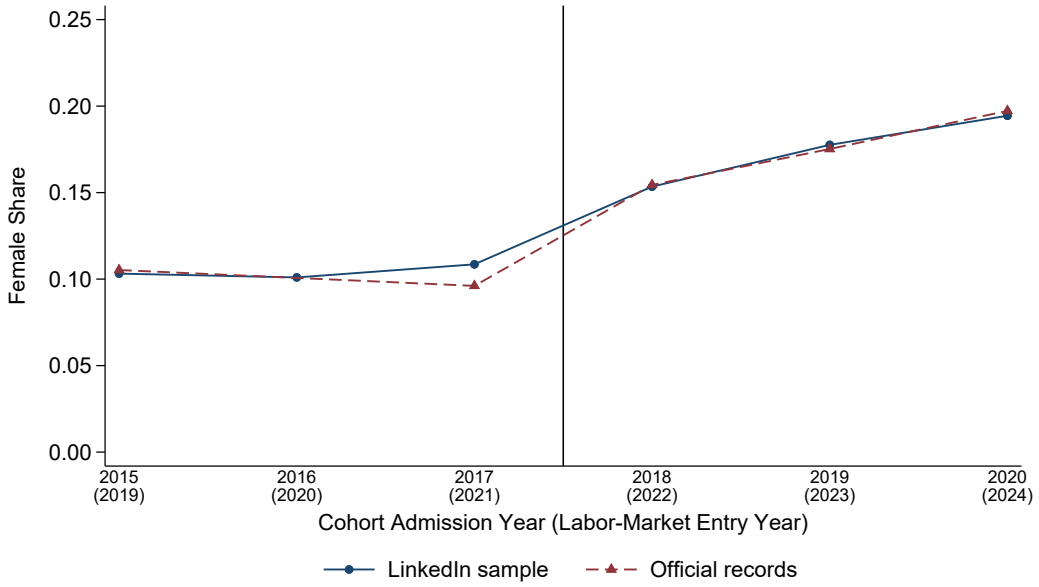
This appendix reports the checks on LinkedIn coverage discussed in Section 4.4 and Section 5.5. Table C1 reports the estimates of equation (2) with coverage as the outcome, for all students and for women, and Figure C1 compares the female share of the LinkedIn sample with the female share in the JEE reports. Table C2 reports the bounds on women's likelihood of an elite first job.

Table C1: LinkedIn Coverage, by Exposure

	(1)	(2)
Panel A: Share of admitted students observed on LinkedIn		
Post × High Exposure	-0.012	0.012
	(0.026)	(0.027)
Wild bootstrap p-value	0.664	0.662
Control mean, Low Exposure, 2015–2017	0.572	0.594
Observations	414	378
Clusters	69	63
Panel B: Share of admitted women observed on LinkedIn		
Post × High Exposure	-0.179	0.052
	(0.149)	(0.147)
Wild bootstrap p-value	0.256	0.718
Control mean, Low Exposure, 2015–2017	0.710	0.764
Observations	339	307
Clusters	69	63
School × field FE	Yes	Yes
Cohort FE	Yes	No
Field × cohort FE	No	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on LinkedIn coverage, the number of graduates observed on LinkedIn divided by the number of students admitted according to the JEE reports, for each program and admission cohort. Panel A uses all students and Panel B uses women. Panel B excludes the 2016 cohort, for which admissions by gender were not published. From 2018, the official count of women is the number of female-only seats, so it excludes women admitted to gender-neutral seats. Column (2) replaces cohort fixed effects with field × cohort fixed effects. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. An observation is a program and admission cohort. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C1: Female Share of Students, Official Records and LinkedIn Sample



Notes: The figure shows the female share of admitted students by admission cohort in the JEE reports and among graduates observed on LinkedIn, pooling all programs.

Table C2: Bounds on Women's Likelihood of an Elite First Job under Differential Coverage

	Assumed drop in women's coverage		
Missing women's elite rate	0.179 (est.)	0.100	0.229
No adjustment	0.070	0.070	0.070
Same as observed women	0.069*	0.070*	0.069*
	(0.037)	(0.037)	(0.037)
Same as men in the program-cohort	0.049	0.057	0.044
	(0.037)	(0.037)	(0.037)
Program's pre-reform women's rate	0.073**	0.072**	0.074**
	(0.033)	(0.035)	(0.032)
None elite (worst case)	0.003	0.029	-0.012
	(0.035)	(0.036)	(0.035)
Effect gone if missing women's rate $\leq$	never	never	0.05
Not significant (10%) if rate $\leq$	0.29	0.26	0.30

Notes: The table reports how the estimated effect of the reform on women's likelihood of an elite first job changes if women missing from LinkedIn in High Exposure programs after the reform are added back. Each column assumes a drop in women's coverage in these program-cohorts. Column (1) uses the point estimate in Table C1, Panel B, and columns (2) and (3) use alternative values. Each row assumes an elite rate for the women added back, equal to the rate among observed women, the rate among men in the same program and cohort, the program's pre-reform rate for women, or 0. The last 2 rows report the elite rate of the missing women below which the estimate falls to 0 or is no longer significant at the 10% level. An observation is a program and admission cohort, weighted by the number of women. Standard errors are clustered by program. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Admitted Students

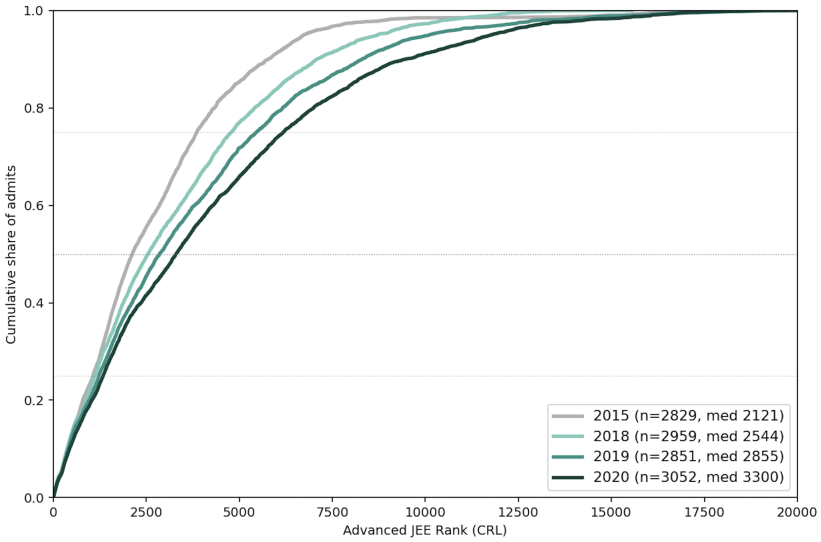
This appendix reports the classification of post-reform cohorts into marginal-only cohorts and cohorts with inframarginal women, and the rank distributions of admitted students, discussed in Section 4.5.

Table D1: Marginal-only Cohorts and Cohorts with Inframarginal Women

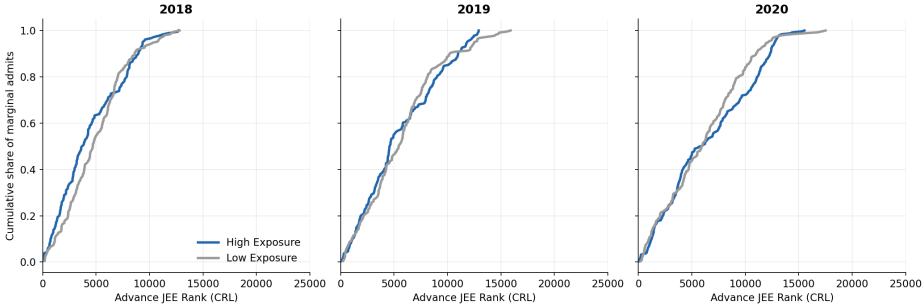
	Low Exposure		High Exposure	
	Marginal-only	Inframarginal	Marginal-only	Inframarginal
	(1)	(2)	(3)	(4)
Panel A: # Program-cohorts				
2018	20	15	24	10
2019	28	7	28	6
2020	30	5	27	7
2018–2020	78	27	79	23
Panel B: # Women per program-cohort, LinkedIn sample				
2018	6.7	8.7	9.5	15.0
2019	9.4	11.7	13.9	19.5
2020	11.0	16.4	16.6	28.4
2018–2020	9.3	10.9	13.5	20.3
2015–2017 (all programs)	6.7		5.2	

Notes: The table reports the number of post-reform program-cohorts of each type (Panel A) and the average number of women per program-cohort in the LinkedIn sample (Panel B), in Low and High Exposure programs. In a marginal-only cohort, every woman in a female-only seat had a rank worse than the gender-neutral closing rank of her program and category. In a cohort with inframarginal women, at least 1 of them had a rank better than this closing rank and would have been admitted without the reform. Each cohort is classified by its own year using the opening and closing ranks in the JEE reports. Program-cohorts with no female-only seat in a given year are excluded. The last row reports the average number of women per program-cohort before the reform, in all programs in each group.

Figure D1: JEE Advanced Ranks of Admitted Students



(a) All admitted students, by year



(b) Marginal women, by exposure

Notes: Panel (a) shows the cumulative distribution of JEE Advanced ranks from the Common Rank Lists of all students admitted to open seats in the sample programs, in 2015, 2018, 2019, and 2020. Cohorts admitted in 2019 and 2020 include the seats added for the EWS quota. Panel (b) shows the cumulative distribution of JEE Advanced ranks of marginal women in the open category, women admitted to female-only seats with ranks worse than their program's gender-neutral closing rank, in High and Low Exposure programs, separately for 2018, 2019, and 2020. A higher rank number is a worse rank. The legends report the number of students and the median rank in each group.

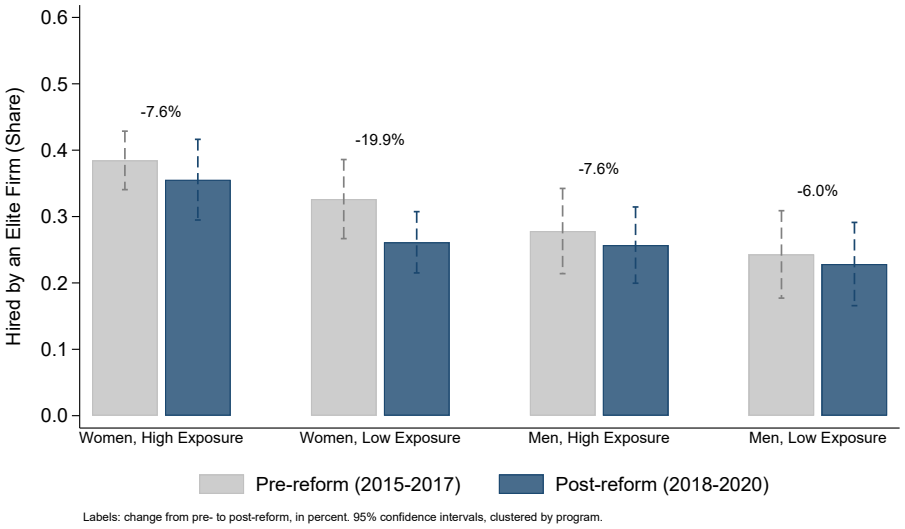
E First Jobs: Additional Results

This appendix reports the raw outcomes behind the difference in differences estimates for first jobs and the comparison of elite hiring at the 6 IITs and BITS.

E.1 Raw Outcomes

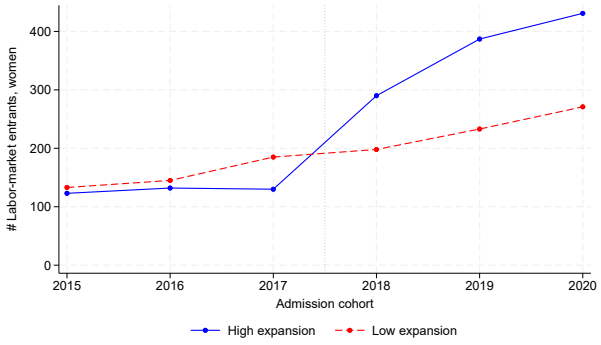
Figure E1 shows the raw share of graduates whose first job was at an elite firm before and after the reform, and Figure E2 shows the raw number of labor market entrants and hires behind the difference in differences estimates.

Figure E1: Share of Graduates Hired by an Elite Firm, Before and After the Reform

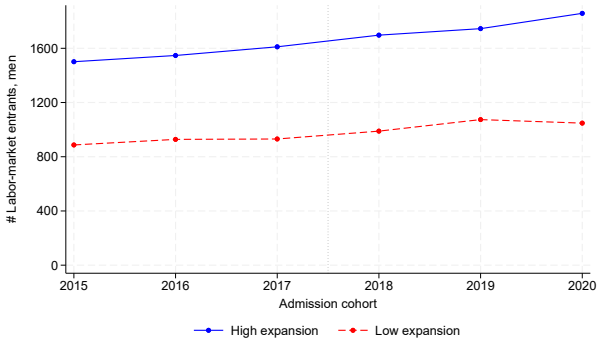


Notes: The figure shows the raw share of women and men whose first job is at an elite firm, in High and Low Exposure programs, for the cohorts admitted before (2015 to 2017) and after (2018 to 2020) the reform. Labels report the change from before to after the reform, in %. Graduates who do not enter the labor market count as not hired. Vertical bars show 95% confidence intervals clustered by program.

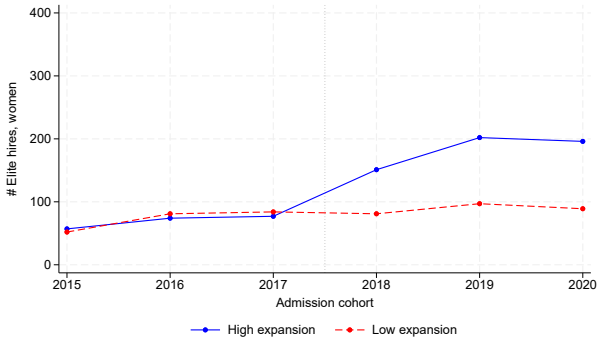
Figure E2: Raw Number of Labor Market Entrants and Hires, by Exposure



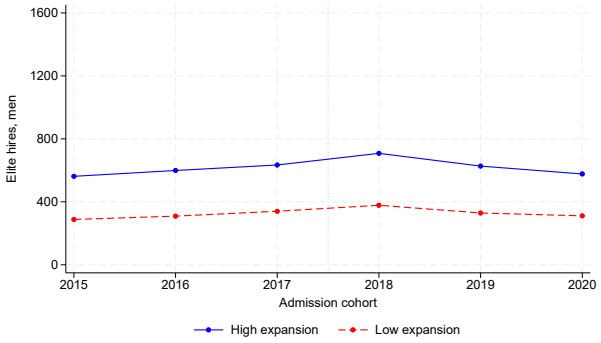
(a) Labor market entrants, women



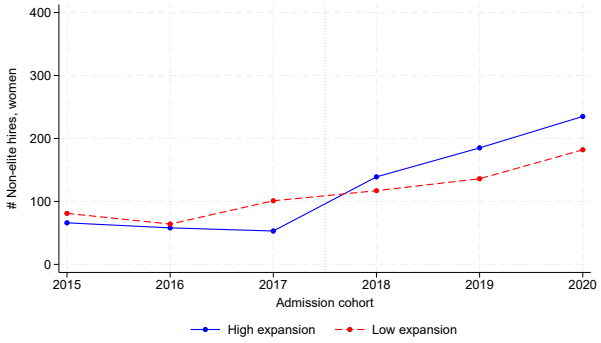
(b) Labor market entrants, men



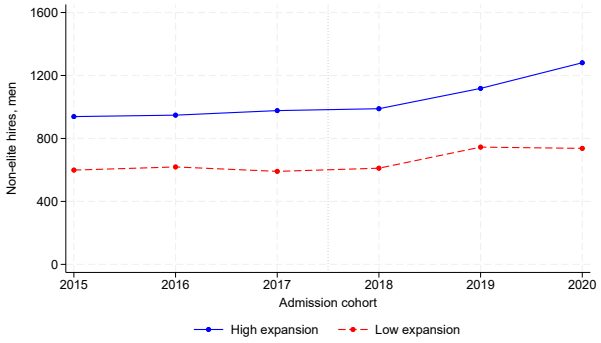
(c) Elite hires, women



(d) Elite hires, men



(e) Non-elite hires, women



(f) Non-elite hires, men

Notes: The figure shows the raw number of women and men from High and Low Exposure programs who enter the labor market (a and b), whose first job is at an elite firm (c and d), and whose first job is at a non-elite firm (e and f), by admission cohort, summed over the programs in each group.

E.2 Comparison with BITS

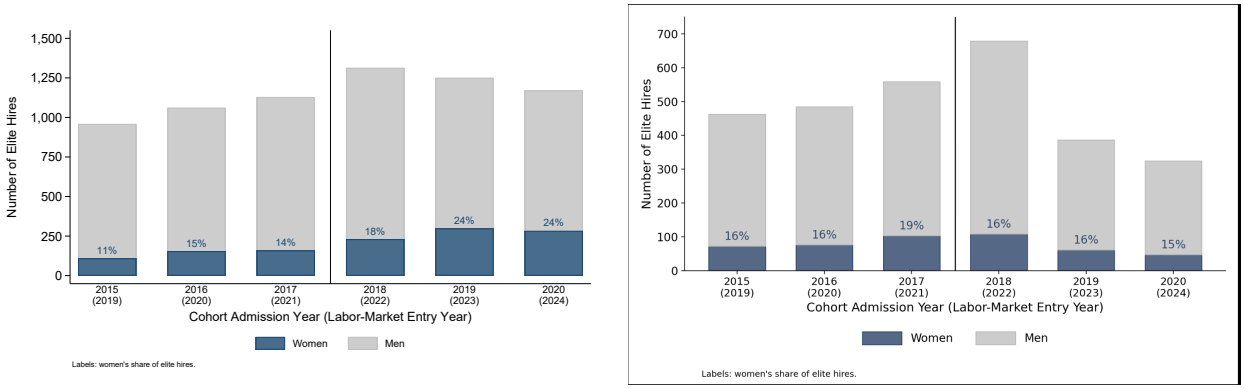
Table E1 and Figure E3 compare elite hiring at the 6 IITs with elite hiring at BITS, which was not covered by the reform.

Table E1: Elite Hires of New Graduates at the 6 IITs and BITS, Before and After 2022

	6 IITs in sample		BITS	
	Before	After	Before	After
Elite hires, all	1,050	1,245	501	462
Elite hires, women	141	273	83	72
Elite hires, men	909	972	418	390
Women's share of elite hires (%)	13.4	21.9	16.6	15.6

Notes: The table reports the average number of graduates per year whose first job was at an elite firm in the year they graduated, by institute and gender. Before refers to the years 2019 to 2021, and after to 2022 to 2024. For the 6 IITs, each admission cohort is assigned to its admission year plus four, the year most of its graduates entered the labor market, so the first cohort admitted under the reform corresponds to 2022. For the 6 IITs in the sample, total elite hires are from Table A1, and hires of women and men are computed from women's share of elite hires in Figure E3(a). For BITS, the counts are computed from the yearly counts in Figure E3(b). BITS was not covered by the reform. Elite firms are defined as in Section 3.

Figure E3: Elite Hires of New Graduates at the 6 IITs and BITS



(a) 6 IITs in sample

(b) BITS

Notes: The figure plots the number of graduates of the 6 IITs in the sample (a) and of BITS (b) whose first job was at an elite firm in the year they graduated, split into women and men. For the 6 IITs, the horizontal axis shows each admission cohort and, in brackets, the year most of its graduates entered the labor market. For BITS, it shows the year of graduation. Labels report women's share of elite hires. BITS was not covered by the reform. The vertical line marks 2022, the year the first cohort admitted under the reform mostly entered the labor market. Elite firms are defined as in Section 3.

F Early Careers: Additional Results

This appendix reports the margins that determine the early career sample in Section 5.4.

Table F1: Margins That Determine the Early Career Sample

	Started at elite firm (=1) (1)	Next position within 2 years (=1) (2)	Study, research or break (=1) (3)	Gap > 6 months (=1) (4)	Title pair not rankable (=1) (5)	In early-career sample (=1) (6)
Panel A: Women						
Post × High Exposure	0.084*	-0.016	-0.015	0.005	0.000	-0.027
	(0.048)	(0.043)	(0.022)	(0.013)	(0.000)	(0.041)
Wild bootstrap p-value	0.108	0.719	0.524	0.730	–	0.525
Control mean, Low Exposure, 2015–2017	0.481	0.661	0.058	0.033	0.000	0.787
Observations	2,618	2,618	2,618	2,618	2,618	2,618
Clusters	67	67	67	67	67	67
Panel B: Men						
Post × High Exposure	0.008	-0.014	-0.001	-0.008*	-0.000	-0.007
	(0.016)	(0.019)	(0.006)	(0.004)	(0.000)	(0.018)
Wild bootstrap p-value	0.606	0.486	0.872	0.060	0.807	0.734
Control mean, Low Exposure, 2015–2017	0.352	0.663	0.053	0.026	0.000	0.781
Observations	15,447	15,447	15,447	15,447	15,447	15,447
Clusters	69	69	69	69	69	69
School × field FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table examines whether the reform changed who enters the early career sample. The sample includes all labor market entrants. Each column is an indicator for one margin, starting at an elite firm (column 1), recording a next position within 2 years of the start of the first job (column 2), moving into further study, research, or a career break (column 3), starting the next position more than 6 months after the first job ends (column 4), holding a pair of titles the seniority ladder cannot rank (column 5), and being in the early career sample (column 6). Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them, except where the outcome takes the same value for almost all graduates (–). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Robustness

This appendix reports the robustness checks discussed in the main text, in the order they are discussed.

G.1 Program Selectivity

Table G1 adds program characteristics measured before the reform, each interacted with Post, to equation (2). Table G2 estimates how the change in the likelihood of an elite first job after the reform varied with the same characteristics, separately within Low Exposure programs and within High Exposure programs.

Table G1: Elite First Jobs, Controlling for Program Characteristics Before the Reform

	Baseline	Adding Post × program measure		
		JEE Advanced rank	Men hired by elite firms	Elite firms recruiting
	(1)	(2)	(3)	(4)
Panel A: Women, elite job (=1)				
Post × High Exposure	0.070*	0.068*	0.048	0.044
	(0.037)	(0.037)	(0.033)	(0.034)
Wild bootstrap p-value	.	.	.	.
Post × program measure (z-score)		0.007	0.053***	0.034**
		(0.017)	(0.016)	(0.013)
Wild bootstrap p-value		.	.	.
Control mean, Low Exposure, 2015–2017	0.326	0.325	0.326	0.326
Observations	3,750	3,713	3,750	3,750
Clusters	69	65	69	69
Panel B: Women, elite job at a generalist firm (=1)				
Post × High Exposure	0.066*	0.066*	0.045	0.039
	(0.033)	(0.034)	(0.028)	(0.030)
Wild bootstrap p-value	.	.	.	.
Post × program measure (z-score)		0.001	0.048***	0.035***
		(0.014)	(0.013)	(0.012)
Wild bootstrap p-value		.	.	.
Control mean, Low Exposure, 2015–2017	0.256	0.255	0.256	0.256
Observations	3,750	3,713	3,750	3,750
Clusters	69	65	69	69
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on women's likelihood of an elite first job (Panel A) and of a first job at a generalist elite firm (Panel B), adding to equation (2) a program characteristic measured before the reform, interacted with Post. Column (1) is the baseline specification. Column (2) adds the mean JEE Advanced rank of students admitted to open seats in 2015, column (3) the share of men hired by an elite firm in the cohorts admitted from 2015 to 2017, and column (4) the number of elite firms hiring from the program per cohort over the same years. Each characteristic is standardized across programs, and the JEE Advanced rank enters as minus its logarithm, so a higher value indicates a more selective program. Column (2) covers the 65 programs with a 2015 rank. A generalist elite firm is an elite firm that hired at least 2 graduates from each of more than 3 fields in the cohorts admitted from 2015 to 2017. Graduates who did not enter the labor market are coded as 0. Post equals 1 for cohorts admitted from 2018 to 2020, and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G2: Change in Elite First Jobs by Program Characteristics, Within Low and High Exposure Programs

	Elite job (=1)			
	Low Exposure		High Exposure	
	Women (1)	Men (2)	Women (3)	Men (4)
Post × JEE Advanced rank (z-score)	0.003	-0.004	0.012	-0.017**
	(0.021)	(0.009)	(0.027)	(0.008)
Wild bootstrap p-value	.	.	.	.
Post × share of men hired by elite firms (z-score)	0.015	-0.018*	0.085***	-0.022***
	(0.022)	(0.009)	(0.018)	(0.006)
Wild bootstrap p-value	.	.	.	.
Post × number of elite firms recruiting (z-score)	-0.002	-0.012	0.052***	-0.022***
	(0.022)	(0.011)	(0.015)	(0.006)
Wild bootstrap p-value	.	.	.	.
Clusters	35	35	34	34
School × field FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes

Notes: The table reports how women's and men's likelihood of an elite first job changed after the reform in programs with different characteristics before the reform, separately within Low Exposure programs (columns 1 and 2) and within High Exposure programs (columns 3 and 4). Each cell is the coefficient on a program characteristic, standardized across programs and interacted with Post, from a separate regression. The characteristics are the mean JEE Advanced rank of students admitted to open seats in 2015, entered as minus its logarithm so a higher value indicates a more selective program, the share of men hired by an elite firm in the cohorts admitted from 2015 to 2017, and the number of elite firms hiring from the program per cohort over the same years. Graduates who did not enter the labor market are coded as 0. All regressions include program and cohort fixed effects. Post equals 1 for cohorts admitted from 2018 to 2020. An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.2 Alternative Specifications: Likelihood of an Elite First Job

In Table G3, each column changes one feature of the baseline specification. Column (2) replaces cohort fixed effects with field by cohort fixed effects, so High and Low Exposure programs are compared within the same field, which also absorbs any change in hiring specific to a field in a given year, such as a technology boom that favored some fields. Column (3) compares programs within the same IIT using IIT by cohort fixed effects. The remaining columns exclude the 2016 cohort and replace the High Exposure indicator with exposure in equation (1), rescaled so the coefficient compares the average High Exposure program with the average Low Exposure program.

Table G3: Likelihood of Labor Market Entry and an Elite First Job, Alternative Specifications

	Coefficient on Post × High Exposure				
	(1)	(2)	(3)	(4)	(5)
Panel A: Women					
Entered the labor market (=1)	0.004	−0.020	−0.001	−0.021	−0.000
	(0.029)	(0.034)	(0.032)	(0.033)	(0.026)
	[0.905]	[0.600]	[0.970]	[0.516]	[0.993]
Elite first job, all graduates (=1)	0.070*	0.061*	0.062	0.050	0.047
	(0.037)	(0.036)	(0.047)	(0.042)	(0.033)
	[0.082]	[0.148]	[0.258]	[0.253]	[0.185]
Elite first job, entrants (=1)	0.084*	0.079*	0.068	0.070	0.056
	(0.048)	(0.045)	(0.055)	(0.053)	(0.040)
	[0.108]	[0.151]	[0.280]	[0.210]	[0.188]
Observations, all graduates	3,750	3,745	3,750	3,356	3,750
Observations, entrants	2,618	2,604	2,618	2,347	2,618
Panel B: Men					
Entered the labor market (=1)	0.004	0.008	0.024	0.010	−0.003
	(0.014)	(0.018)	(0.019)	(0.016)	(0.011)
	[0.776]	[0.700]	[0.249]	[0.526]	[0.792]
Elite first job, all graduates (=1)	0.003	0.014	−0.000	0.014	0.001
	(0.013)	(0.014)	(0.013)	(0.014)	(0.012)
	[0.800]	[0.370]	[0.996]	[0.319]	[0.935]
Elite first job, entrants (=1)	0.008	0.023**	−0.004	0.019	0.009
	(0.016)	(0.012)	(0.016)	(0.017)	(0.016)
	[0.606]	[0.066]	[0.806]	[0.292]	[0.589]
Observations, all graduates	22,165	22,164	22,165	18,657	22,165
Observations, entrants	15,447	15,445	15,447	13,048	15,447
School × field FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes			Yes	Yes
Field × cohort FE		Yes			
IIT × cohort FE			Yes		
Excludes 2016 cohort				Yes	
Continuous exposure					Yes

Notes: Each cell reports the coefficient on Post × High Exposure from a separate regression, with standard errors clustered by program in parentheses and wild cluster bootstrap p values in brackets. An observation is a graduate, admission cohorts 2015 to 2020. Entered the labor market equals 1 if the graduate's first job begins in the year of graduation. Elite first job (all graduates) equals 1 if the first job is at an elite firm, with graduates who did not enter the labor market coded as 0. Elite first job (entrants) is the same outcome among graduates who entered the labor market. School × field fixed effects are the program fixed effects in equation (2). Column (1) is the baseline specification. Columns (2) and (3) replace cohort fixed effects with field × cohort or IIT × cohort fixed effects, so High and Low Exposure programs are compared within the same field or the same IIT in each cohort. Column (4) drops the 2016 admission cohort. Column (5) replaces High Exposure with the female-only seats added by 2020 relative to 2017 enrollment, rescaled so 1 equals the gap between the average High and the average Low Exposure program. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.3 Generalist and Specialist Elite Firms

Table G4 and Table G5 divide elite firms into generalist firms, which recruited from many fields before the reform, and specialist firms, and estimate the effect of the reform on elite hires at each type of firm.

Table G4: Elite Hires, by Type of Elite Firm

	# Elite hires	By type of elite firm	
	All elite firms	Generalist	Specialist
	(1)	(2)	(3)
Panel A: # Women			
Post × High Exposure	2.847***	2.243***	0.604**
	(0.665)	(0.513)	(0.242)
Wild bootstrap p-value	0.000	0.000	0.012
Control mean, Low Exposure, 2015–2017	2.067	1.619	0.448
Observations	414	414	414
Clusters	69	69	69
p-value, generalist = specialist		0.001	
Panel B: # Men			
Post × High Exposure	0.356	-0.578	0.934
	(0.845)	(0.742)	(0.614)
Wild bootstrap p-value	0.679	0.453	0.137
Control mean, Low Exposure, 2015–2017	8.905	5.410	3.495
Observations	414	414	414
Clusters	69	69	69
p-value, generalist = specialist		0.162	
School × field FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the number of graduates from each program and admission cohort whose first job was at an elite firm, for all elite firms (column 1), generalist elite firms (column 2), and specialist elite firms (column 3). A generalist elite firm hired at least 2 graduates from each of more than 3 fields in the cohorts admitted from 2015 to 2017. All other elite firms, including those first observed after the reform, are specialist, so columns (2) and (3) add up to column (1). The p value at the bottom of each panel tests whether the coefficients in columns (2) and (3) are equal. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a program and admission cohort, and every program appears in every cohort. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G5: Likelihood of an Elite First Job, by Type of Elite Firm

	Elite job (=1)	By type of elite firm	
	All elite firms	Generalist	Specialist
	(1)	(2)	(3)
Panel A: Women			
Post × High Exposure	0.070*	0.066*	0.004
	(0.037)	(0.033)	(0.022)
Wild bootstrap p-value	0.082	0.067	0.845
Control mean, Low Exposure, 2015–2017	0.326	0.256	0.071
Observations	3,750	3,750	3,750
Clusters	69	69	69
p-value, generalist = specialist		0.154	
Panel B: Men			
Post × High Exposure	0.003	-0.008	0.011
	(0.013)	(0.012)	(0.010)
Wild bootstrap p-value	0.800	0.523	0.326
Control mean, Low Exposure, 2015–2017	0.243	0.148	0.095
Observations	22,165	22,165	22,165
Clusters	69	69	69
p-value, generalist = specialist		0.304	
School × field FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on graduates' likelihood of a first job at any elite firm (column 1), at a generalist elite firm (column 2), and at a specialist elite firm (column 3). Generalist and specialist elite firms are defined as in Table G4, so columns (2) and (3) add up to column (1). Graduates who did not enter the labor market are coded as 0. The p value at the bottom of each panel tests whether the coefficients in columns (2) and (3) are equal. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.4 Alternative Specifications: Number of Labor Market Entrants and Hires

Table G6 estimates the count regressions with a Poisson pseudo maximum likelihood model, which suits small counts. Table G7 repeats the specifications of Table G3 for the counts, and adds a column that weights programs by their size before the reform.

Table G6: Labor Market Entrants and Hires: Poisson Estimates

	# All (1)	# Women (2)	# Men (3)
Panel A: # Labor-market entrants			
Post × High Exposure	0.061	0.641***	-0.003
	(0.040)	(0.119)	(0.037)
Control mean, Low Exposure, 2015–2017	29.629	4.305	25.324
Observations	414	414	414
Clusters	69	69	69
Panel B: # Elite hires			
Post × High Exposure	0.097	0.769***	-0.021
	(0.065)	(0.149)	(0.059)
Control mean, Low Exposure, 2015–2017	11.636	2.333	9.444
Observations	402	390	402
Clusters	67	65	67
Panel C: # Non-elite hires			
Post × High Exposure	0.045	0.574***	0.013
	(0.047)	(0.157)	(0.047)
Control mean, Low Exposure, 2015–2017	18.657	2.238	16.419
Observations	414	414	414
Clusters	69	69	69
School × field FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Notes: The table reports Poisson pseudo maximum likelihood estimates of the effect of the reform on the number of graduates from each program and admission cohort who entered the labor market (Panel A), whose first job was at an elite firm (Panel B), and whose first job was at a non-elite firm (Panel C). A coefficient β implies a proportional change of $e^{\beta} - 1$. The specification otherwise follows Table 6. Programs with a count of 0 in every cohort are dropped, since they do not contribute to the Poisson estimates, so the number of observations and the control mean in Panel B differ from Table 6. An observation is a program and admission cohort. Standard errors clustered by program are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G7: Number of Labor Market Entrants and Hires, Alternative Specifications

	Coefficient on Post × High Exposure					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Women						
Number entering the labor market	4.754***	1.831	5.372***	4.874***	5.816***	4.573***
	(0.979)	(1.167)	(0.989)	(1.002)	(1.347)	(0.732)
	[0.000]	[0.118]	[0.000]	[0.000]	[0.000]	[0.000]
Number hired by elite firms	2.847***	2.045**	3.029***	2.792***	4.127***	2.638***
	(0.665)	(0.829)	(0.673)	(0.707)	(1.065)	(0.503)
	[0.000]	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]
Number hired by non-elite firms	1.907***	−0.214	2.343***	2.082***	1.690*	1.935***
	(0.618)	(0.592)	(0.627)	(0.620)	(0.916)	(0.561)
	[0.003]	[0.727]	[0.000]	[0.002]	[0.084]	[0.002]
Observations	414	378	414	345	414	414
Panel B: Men						
Number entering the labor market	2.689	0.468	3.281**	2.254	2.426	3.053**
	(1.679)	(2.392)	(1.548)	(1.755)	(2.637)	(1.160)
	[0.115]	[0.840]	[0.037]	[0.209]	[0.397]	[0.013]
Number hired by elite firms	0.356	0.213	0.419	0.414	−0.225	0.734
	(0.845)	(1.206)	(0.823)	(0.905)	(1.517)	(0.740)
	[0.679]	[0.857]	[0.622]	[0.656]	[0.884]	[0.332]
Number hired by non-elite firms	2.332*	0.255	2.863**	1.840	2.651	2.319**
	(1.318)	(1.510)	(1.271)	(1.346)	(1.966)	(1.128)
	[0.082]	[0.867]	[0.028]	[0.177]	[0.198]	[0.051]
Observations	414	378	414	345	414	414
School × field FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes			Yes	Yes	Yes
Field × cohort FE		Yes				
IIT × cohort FE			Yes			
Excludes 2016 cohort				Yes		
Weighted by pre-reform size					Yes	
Continuous exposure						Yes

Notes: Each cell reports the coefficient on Post × High Exposure from a separate regression, with standard errors clustered by program in parentheses and wild cluster bootstrap p values in brackets. An observation is a program and admission cohort, 2015 to 2020. The dependent variables are the number of women (Panel A) or men (Panel B) from the program and cohort who entered the labor market, that is, whose first job begins in the year of graduation, the number whose first job was at an elite firm, and the number whose first job was at a non-elite firm. School × field fixed effects are the program fixed effects in equation (2). Column (1) is the baseline specification. Columns (2) and (3) replace cohort fixed effects with field × cohort or IIT × cohort fixed effects, so High and Low Exposure programs are compared within the same field or the same IIT in each cohort. Column (4) drops the 2016 admission cohort. Column (5) weights each program by its average number of graduates per cohort before the reform. Column (6) replaces High Exposure with the female-only seats added by 2020 relative to 2017 enrollment, rescaled so 1 equals the gap between the average High and the average Low Exposure program. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G.5 Women Compared with Men

Table G8 and Table G9 compare the change for women with the change for men from the same program, separately within High and Low Exposure programs.

Table G8: Number of Graduates, Entrants, and Hires: Women Compared with Men

	High Exposure (Women − Men) (1)	Low Exposure (Women − Men) (2)	Triple difference (1) − (2) (3)
# Graduates			
Post × Female	0.186	-2.305**	
	(1.256)	(1.055)	
Wild bootstrap p-value	0.883	0.030	
Post × Female × High Exposure			2.491
			(1.630)
Wild bootstrap p-value			0.130
Pre-reform mean, women	5.225	6.333	6.333
Observations	408	420	828
Clusters	34	35	69
# Labor-market entrants			
Post × Female	0.637	-1.429*	
	(1.093)	(0.741)	
Wild bootstrap p-value	0.558	0.062	
Post × Female × High Exposure			2.066
			(1.311)
Wild bootstrap p-value			0.119
Pre-reform mean, women	3.686	4.305	4.305
Observations	408	420	828
Clusters	34	35	69
# Elite hires			
Post × Female	2.196***	-0.295	
	(0.724)	(0.408)	
Wild bootstrap p-value	0.002	0.469	
Post × Female × High Exposure			2.491***
			(0.825)
Wild bootstrap p-value			0.003
Pre-reform mean, women	2.010	2.067	2.067
Observations	408	420	828
Clusters	34	35	69
# Non-elite hires			
Post × Female	-1.559	-1.133*	
	(1.025)	(0.570)	
Wild bootstrap p-value	0.133	0.055	
Post × Female × High Exposure			-0.425
			(1.164)
Wild bootstrap p-value			0.720
Pre-reform mean, women	1.676	2.238	2.238
Observations	408	420	828
Clusters	34	35	69
School × field × gender FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	No
Cohort × exposure FE	No	No	Yes

Notes: The table compares the change in the number of women with the change in the number of men within each group of programs. Columns (1) and (2) report the coefficient on Post × Female from regressions estimated separately in High and Low Exposure programs, which measures the change after the reform in the number of women minus the number of men. Column (3) reports the coefficient on Post × Female × High Exposure from the pooled regression, which equals column (1) minus column (2). The outcomes are the number of graduates, labor market entrants, elite hires, and non-elite hires. The pre-reform mean is the mean number of women in the programs of each column, and in Low Exposure programs for column (3). An observation is a program, admission cohort, and gender. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G9: Labor Market Entry and Elite First Jobs: Women Compared with Men

	High Exposure (Women − Men) (1)	Low Exposure (Women − Men) (2)	Triple difference (1) − (2) (3)
Panel A: Labor-market entry (=1)			
Post × Female	0.013	0.014	
	(0.023)	(0.022)	
Wild bootstrap p-value	0.577	0.525	
Post × Female × High Exposure			-0.001
			(0.032)
Wild bootstrap p-value			0.977
Pre-reform mean, women	0.705	0.680	0.680
Observations	15,933	9,982	25,915
Clusters	34	35	69
Panel B: Elite job (=1)			
Post × Female	0.019	-0.047*	
	(0.032)	(0.023)	
Wild bootstrap p-value	0.548	0.044	
Post × Female × High Exposure			0.066*
			(0.039)
Wild bootstrap p-value			0.113
Pre-reform mean, women	0.385	0.326	0.326
Observations	15,933	9,982	25,915
Clusters	34	35	69
School × field × gender FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	No
Cohort × exposure FE	No	No	Yes

Notes: The table compares the change in women's outcomes with the change in men's within each group of programs. Columns (1) and (2) report the coefficient on Post × Female from regressions estimated separately in High and Low Exposure programs, which measures the change after the reform in the gap between women and men. Column (3) reports the coefficient on Post × Female × High Exposure from the pooled regression, which equals column (1) minus column (2). Panel A uses labor market entry, and Panel B uses an elite first job among all graduates, with those who did not enter the labor market coded as 0. The pre-reform mean is the mean for women in the programs of each column, and in Low Exposure programs for column (3). An observation is a graduate. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Mechanisms: Additional Results

This appendix reports additional evidence for the mechanisms in Section 6 and the back-of-the-envelope calculation in Section 6.4.

H.1 Latent Demand

Table H1 reports the number of women hired by elite firms before the reform relative to the gender-blind benchmark, pooled and by cohort (Panel A), by exposure (Panel B), and splitting High Exposure programs by whether women made up less than 5% of their 2017 cohort (Panel C). Figure H1 compares how the women hired were spread across elite firms with random assignment.

Under gender-blind hiring, every labor market entrant from a program has the same likelihood of an elite first job, E_{pc}/N_{pc}, where E_{pc} is the number of graduates of program p in cohort c hired by elite firms and N_{pc} is the number of its labor market entrants. The expected number of women hired, the gender-blind benchmark, is then

$$B_{pc} = \frac{E_{pc}}{N_{pc}} \times N_{pc}^{W} = E_{pc} \times s_{pc}, \tag{4}$$

where N_{pc}^{W} is the number of women among the entrants and s_{pc} is their share. I measure how far actual hiring departs from the benchmark with the ratio

$$R = \frac{\sum_{p,c} A_{pc}}{\sum_{p,c} B_{pc}}, \tag{5}$$

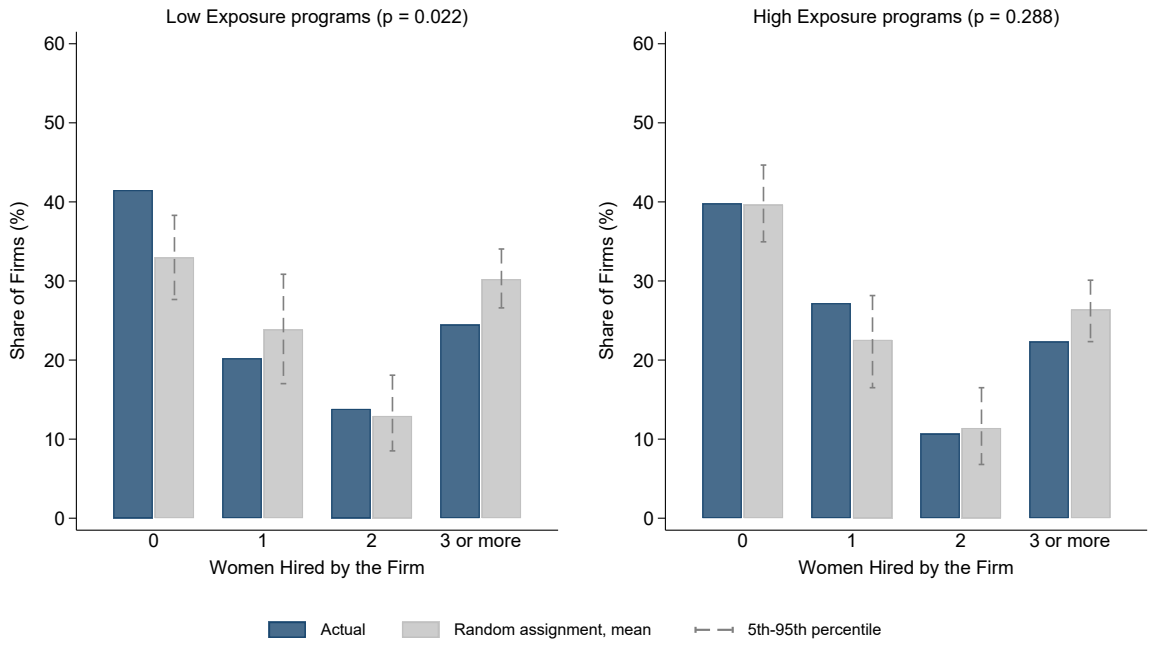
where A_{pc} is the number of women actually hired by elite firms.

Table H1: Women Hired Relative to the Gender-blind Benchmark, Before the Reform

	Estimate	95% CI	p-value
Panel A: Women hired relative to the gender-blind benchmark			
Pooled, 2015–2017	1.34	[1.06, 1.61]	0.015
Cohort 2015 (2019)	1.18	[0.86, 1.50]	0.278
Cohort 2016 (2020)	1.43	[1.12, 1.73]	0.006
Cohort 2017 (2021)	1.38	[1.05, 1.71]	0.025
Joint test, ratio = 1 in all cohorts	$\chi^2(3) = 11.13$		0.011
Panel B: High vs Low Exposure, pooled 2015–2017			
Low Exposure programs	1.39	[1.07, 1.70]	0.015
High Exposure programs	1.29	[1.00, 1.57]	0.046
Difference, High minus Low	-0.10	[-0.35, 0.15]	0.441
Clustered by program	-0.10	(0.15)	0.501
Joint test, no difference in any cohort	$\chi^2(3) = 2.20$		0.532
Panel C: By 2017 female share, pooled 2015–2017			
Low Exposure programs	1.39	[1.07, 1.70]	0.015
High Exposure, 2017 female share $\geq 5\%$	1.36	[1.04, 1.68]	0.027
High Exposure, 2017 female share $< 5\%$	1.10	[0.74, 1.47]	0.589
Difference, $< 5\%$ minus $\geq 5\%$	-0.26	[-0.65, 0.13]	0.194
Difference, $< 5\%$ minus Low	-0.28	[-0.58, 0.01]	0.060

Notes: The table reports the number of women hired by elite firms divided by the number expected under gender-blind hiring, for cohorts admitted 2015 to 2017. Gender-blind hiring assigns each program and cohort's elite hires to women in proportion to women's share of the program's labor market entrants. Confidence intervals and p values are from a firm bootstrap and test whether the ratio equals 1, or whether the difference equals 0. The year most of each cohort entered the labor market, its admission year plus four, is in brackets. Panel C splits High Exposure programs by whether the female share of their 2017 cohort was below 5%.

Figure H1: Number of Women Hired per Elite Firm, Before the Reform



Notes: The figure shows, for cohorts admitted 2015 to 2017, the share of elite firms hiring 0, 1, 2, or 3 or more women from a program, in Low and High Exposure programs. Dark bars show the actual shares. Light bars show the mean share when the women hired from each program and cohort are reassigned at random across that program and cohort's elite hires, holding the number of women fixed, over 1,000 draws. Whiskers show the 5th to 95th percentiles of the reassigned shares. The p values test whether the actual distribution equals the reassigned one.

H.2 Human Capital Accumulation

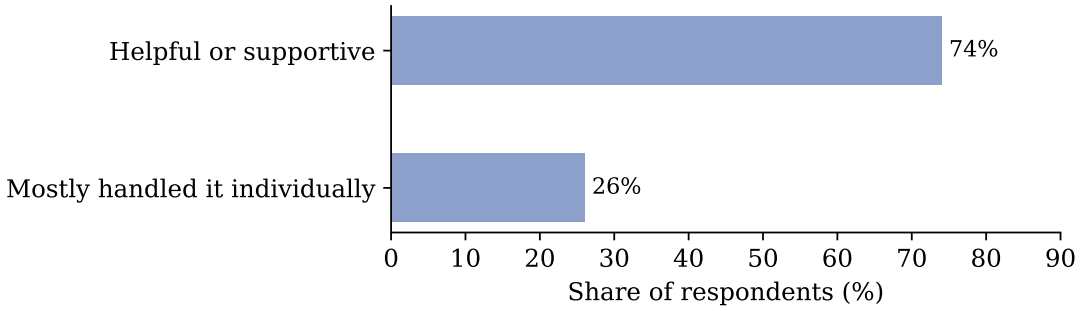
Table H2 examines whether women started at elite firms that had hired a graduate of their program in the previous cohort. Figure H2 reports the responses on friends during placements from the IIT Bombay senior survey cited in the main text.

Table H2: Elite First Jobs at Firms That Hired from the Same Program in the Previous Cohort

	Elite job (=1) at a firm that hired, from the same program in the previous cohort ($t-1$), at least one...		
	Graduate	Woman	Man
	(1)	(2)	(3)
Panel A: Women			
Post × High Exposure	0.026	0.070*	0.033
	(0.042)	(0.037)	(0.041)
Wild bootstrap p-value	0.546	0.079	0.450
Control mean, Low Exposure, 2015–2017	0.216	0.096	0.179
Observations	2,369	2,369	2,369
Clusters	67	67	67
Panel B: Men			
Post × High Exposure	0.029	0.026*	0.016
	(0.020)	(0.013)	(0.020)
Wild bootstrap p-value	0.180	0.062	0.470
Control mean, Low Exposure, 2015–2017	0.195	0.066	0.174
Observations	13,133	13,133	13,133
Clusters	69	69	69
p-value, women = men	0.95	0.23	0.69
School × field FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Notes: The table reports difference in differences estimates of the effect of the reform on the likelihood that a labor market entrant's first job was at an elite firm that had given a first job to at least 1 graduate of the same program (IIT and field) from the previous admission cohort, whether any graduate (column 1), a woman (column 2), or a man (column 3). Firms are matched by name. The sample includes labor market entrants admitted from 2016 to 2020, since the 2015 cohort has no previous cohort in the data. The last row tests whether the coefficient is the same for women and men, using a pooled regression with program × gender and cohort × gender fixed effects. Each coefficient is the coefficient on Post × High Exposure in equation (2), where Post equals 1 for cohorts admitted from 2018 to 2020 and High Exposure equals 1 for programs in which the female-only seats added by 2020, relative to 2017 enrollment, were above the median. The control mean is the mean in Low Exposure programs for cohorts admitted from 2015 to 2017. Standard errors clustered by program are in parentheses, and wild cluster bootstrap p values are reported below them. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure H2: Friends and Placements: Responses from the IIT Bombay Senior Survey, 2026



Notes: The figure reports responses from the 2026 senior survey run by Insight, the student media body of IIT Bombay, an online survey of graduating students at IIT Bombay. Respondents chose whether to take part, so they may not represent all graduating students. The figure shows the answers of the 110 respondents asked to describe their friends during placements. Source: `https://seniorsurvey2026.insightiitb.org/` (Insight, IIT Bombay, 2026).

H.3 Back-of-the-Envelope Calculation

This subsection describes the back-of-the-envelope calculation in Section 6.4. The calculation asks how much of the estimated increase in the number of women hired by elite firms would arise if elite firms had hired the additional women at the rate at which they hired women before the reform. Table H3 reports each step. Before the reform, elite firms hired 51% of the women who entered the labor market. Applying this rate to the 4.75 additional women entering the labor market gives 2.4 additional women hired by elite firms, which is 85% of the estimated increase of 2.85.

Table H3: Share of the Increase in Women Hired by Elite Firms Accounted for by Hiring at the Pre-reform Rate

Per program and cohort	
(1) Pre-reform share of women entering the labor market hired by elite firms	0.51
(2) Additional women entering the labor market, High relative to Low Exposure	4.75
(3) Additional women hired by elite firms at the pre-reform rate, (1) × (2)	2.4
(4) Additional women hired by elite firms, estimated	2.85
(5) Share accounted for by hiring at the pre-reform rate, (3)/(4)	0.85

Notes: Row (1) is the pre-reform mean number of women hired by elite firms divided by the pre-reform mean number of women entering the labor market, averaged over High and Low Exposure programs (Table G8). Rows (2) and (4) are the estimates in Table 6, Panels A and B, column 2.