Equity Conundrum: Unintended Consequences of College-Level Affirmative Action on the Labor Market

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Abstract

Gender-based affirmative action policies in top-ranked STEM institutions aim to enhance women's representation in both higher education and the labor force. While these policies can promote diversity, they may also increase statistical discrimination in hiring practices as colleges lower admission standards to increase female enrollment. This paper examines this trade-off and investigates how expanding seats for women in premier Indian engineering colleges affects gender discrimination in hiring. I conduct a large-scale correspondence study that randomizes gender, college type, and year of entry and induces variation in policy exposure within the experimental design. The results indicate no significant male-female callback gap at top colleges before or after the policy; however, women from lower-ranked colleges face disadvantages. Specifically, the policy implementation led to a 52% drop in the female callback probability, increasing male-female callback gap by 2 percentage points in these colleges. To further shed light on actual employment outcomes, I analyze data scraped from LinkedIn profiles, revealing consistent evidence that supports my findings. I propose a model of statistical discrimination that incorporates affirmative action for women at top colleges, aligning with the observed trends in hiring practices.

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1 Introduction

Despite efforts to promote gender equality, women's representation in STEM jobs remains disproportionately low worldwide. This is a significant concern for policymakers (Global Gender Gap Report 2023). The gender gap in STEM exacerbates the gender wage gap, hampers economic growth, and leads to biased products and services. It could stem from both supply-side factors—such as gender stereotypes, lack of confidence in math, and the absence of role models—and demand-side factors, including taste-based and statistical discrimination.

College-level affirmative action (AA) policies aim to address such gaps and improve female representation in both higher education and the labor force. Although these policies could improve outcomes for beneficiaries, they may backfire if firms believe that relaxing admissions criteria to fill reserved seats lowers the quality of the protected group,[1] thus increasing statistical discrimination against women and exacerbating gender gaps.

In this paper, I investigate whether college-level AA policies impact discrimination against the beneficiary group, measured by callbacks to job applications. To this end, I leverage the supernumerary reservation policy introduced by premier Indian engineering colleges (the IITs) in 2018, which reserved additional seats for female candidates in order to increase female representation to a minimum of 14%[2] in undergraduate engineering classes, and ultimately increase the number of women in the STEM labor force.

Admission to Indian engineering programs is determined by a common entrance exam, with the highest-achieving students attending highly selective and prestigious IITs. Private sector firms that offer high-paying STEM jobs frequently recruit from IIT campuses and are often aware of institutional policies. Due to a very low proportion of females in IITs—8%—the supernumerary seat policy that was introduced in 2018 doubled the percentage of women enrolling thereafter to 16%, without displacing males or females already

[1]Protected groups are those who are legally protected from discrimination based on a common characteristic such as race, religion, sex, age, disability, genetic information, military or veteran status, citizenship, or immigration status.

[2]This proportion was gradually increased to 17% in 2019 and 20% in 2020.

entering IITs (Gupta 2023). I examine the impact of this policy on male-female callback gaps for job applicants at firms that recruit from IIT campuses.

The policy can have ambiguous effects on the callback of females at IITs, because it may have minimal impact on average ability. Also, firm beliefs about the distribution of women entering through the reserved category can also affect women attending colleges ranked just below the IITs. To illustrate this theoretically, I extend the canonical model of statistical discrimination (Phelps 1972) for discrete ability types in which firms use gender and college rankings as signals of productivity. Using this framework, I examine the implications of a supernumerary policy that enables some females to move from lower- to higher-ranked institutions such as the IITs. Depending on firms' perceptions of the average ability of females admitted through these seats, and the resulting shifts in the ability distribution relative to firms' quality thresholds, female callback rates at one or both types of institutions may decrease. If the average ability of supernumerary females is comparable to that of IITs, callbacks for females at these colleges will remain stable, but may decline at lower-ranked colleges. Conversely, if supernumerary females have lower average ability, callback rates for females at IITs will drop, without affecting those at lower-ranked institutions.

I use a correspondence study that embeds variation in policy exposure to empirically answer the research question. I sent 8-12 similar CVs of engineers to jobs posted by firms that recruit from elite engineering colleges, randomizing three parameters: gender (male or female); year of college entry (pre-policy: 2016 and 2017, or post-policy: 2018); and college type (IIT or elite non-IIT). The applications targeted firms that regularly hire from IITs and are likely to be aware of the policy.[3] I submitted 5,236 applications across 616 jobs in two waves.[4] The correspondence study enables me to compare the male-female callback gap between pre- and post-policy cohorts, controlling for gender, cohort, and other resume characteristics, using a difference-in-differences framework. I perform

[3] I interviewed hiring managers who visited IIT campuses for recruitment to confirm this.

[4] The first wave was conducted in June-September 2023 and the second wave in February-April 2024.

this analysis separately for applicants from IITs, who were directly affected by the AA policy, and for applicants from non-IITs, who may have been indirectly affected. I further estimate the change in male-female callback gaps at IITs relative to non-IITs, using a regression with triple interactions to compare all subgroups.

The key finding is that there is no significant male-female callback gap before the policy in either college type, nor is there any evidence of a change in this gap after the policy at IITs, but the policy led to a significant reduction in callback rates for females at non-IITs by 2 percentage points (or 52%) relative to males. These results suggest that the supernumerary policy does not induce discrimination for candidates at top institutions, but indirectly increases it for candidates at lower-ranked institutions. Triple interaction estimates show that post-policy, IIT females are 3 percentage points (or 75%) more likely to receive a callback than non-IIT females relative to males. Predicted callback rates indicate that post-policy, non-IIT women would need to submit 14.4 more applications than IIT women to receive a callback, whereas pre-policy, both groups required a similar number of applications. Overall, there is no impact of the policy on women, since I do not find a significant difference in the male-female callback gap between pre- and post-policy cohorts across all colleges. Supernumerary seats are drawing high-ability women from lower-ranked to top-ranked institutions.[5] Consequently, the likelihood of receiving callbacks for females in top institutions remains unchanged, but has decreased in lower-ranked institutions. A higher number of high-ability women at IITs prompts firms to substitute IIT females instead of non-IIT females, and as a result the overall callback rates for females across all colleges remain unaffected.

A potential concern is that years of experience can be valued differently for male and female candidates and affect the male-female callback gap in the post-policy cohort. To test this, I run placebo regressions using only pre-policy cohorts and find no significant

[5]There is evidence in the experimental literature that adding gender-based affirmative action to a tournament can induce more high-ability women to enter the competition (Niederle, Segal, and Vesterlund 2013). Similarly, adding seats in IITs allows more high-ability women, who would have otherwise enrolled in a lower-ranked college, to compete and enter these colleges.

differences in the male-female callback gap between the two pre-policy cohorts in either college type. The triple interaction is also insignificant which rules out alternative explanations such as younger non-IIT females being perceived as less aspirational or less likely to get callbacks due to social norms, for instance, marriage market concerns could be driving the results.

To determine differences in actual hiring outcomes, I scraped the LinkedIn profiles of 6,980 engineering graduates in India. Extracted profiles represent 43% of students who graduated from IITs and elite non-IIT colleges between 2020 and 2023. Using parallel regressions, I find that non-IIT females in the post-policy cohort are 7.2 percentage points (or 13.6%) less likely to be employed at firms[6] included in the correspondence study sample within 6 months of graduation compared to non-IIT males. Triple interaction indicates that IIT females graduating in the post-policy cohort are 13.4 percentage points (or 26%) more likely to be employed at these firms within the first 6 months after graduation than non-IIT females relative to males. Importantly, I do not find significant differences in the duration of time employed after graduation, which alleviates concern that the results are driven by differences in aspirations, labor force participation, or marriage market outcomes between younger IIT and non-IIT women. These findings are robust when I use proportion of individuals covered in the data out of the total cohort size (coverage rate) as weights. Coverage rates are similar across colleges and cohorts and therefore, it is unlikely that selection in the data is driving these findings which corroborates the results from the correspondence study.

Study findings show that AA policies do not harm beneficiaries at top competitive institutions and support efforts to improve access to elite colleges, but they can have distributional consequences because they increase discrimination and job search costs for the protected group graduating from lower-ranked colleges. That said, these are short-run effects, since the pool of engineering applicants may respond to the policy and change over time. Moreover, even though AA doesn't hurt female callbacks in top colleges, it

[6] High-paying firms which hire elite engineering college graduates

may improve matching of high-ability female candidates to suitable jobs and influence the search costs of firms. In order to comment on the impact of policy on overall welfare, studying other longer-term outcomes, such as wages, firm-level and employee productivity, likelihood of getting promoted, marriage market, and migration indicators, is necessary.

This is the first paper in the AA literature to examine labor market outcomes for both direct beneficiaries and non-beneficiaries within a protected group. Prior research has focused on the impact on beneficiaries within the protected group (Deshpande and Weisskopf 2014; Bagde, Epple, and Taylor 2016; Khanna 2020; Bleemer 2022; Prakash 2020; Howard and Prakash 2012) and on the displaced within the non-protected groups (Bertrand, Hanna, and Mullainathan 2010). Another strand of research on AA has focused on discriminatory attitudes toward beneficiary groups through intergroup contact, either as part of integration policies or randomized experiments. In contrast, this paper focuses on firm perceptions as measured by callbacks (Van Laar et al. 2005; Boisjoly et al. 2006; Carrell, Hoekstra, and West 2019; Mousa 2020; Lowe 2021; Barnhardt 2009; Rao 2019; Corno, La Ferrara, and Burns 2022, Glover, Pallais, and Pariente 2017).

This paper contributes to the literature on gender discrimination studied from a labor demand perspective using correspondence studies (Bertrand and Mullainathan 2004; Petit 2007; Bertrand and Duflo 2017). To my knowledge, this is the first correspondence study to examine gender discrimination in high-skilled STEM jobs, and also the first to integrate a gender policy within a correspondence study. Prior research has focused on low-skilled jobs and highlighted sex-stereotyping and firm-level heterogeneity (Riach and Rich 2002; Riach and Rich 2006; Rich 2014; Kline, Rose, and Walters 2022; Adamovic and Leibbrandt 2023; Birkelund et al. 2022). While correspondence studies have been combined with policies to analyze racial discrimination (Brandon et al. 2023; Agan and Starr 2018), my study differs by not only looking at gender discrimination but also randomizing policy exposure within the experiment, rather than running correspondence studies before and after the policy change. Also, it provides new evidence from a developing context in which research on gender discrimination remains scarce (Banerjee et al. 2009; Zhou, Zhang, and Song 2013).

This paper examines a college-level quota for women in elite STEM colleges - a policy with potential implications for the gender gap in STEM and the gender wage gap (Kahn and Ginther 2018; Shapiro and Williams 2012; Funk and Parker 2018; Rogers et al. 2021; Reuben, Sapienza, and Zingales 2014; Exley and Kessler 2022). Although the labor market effects of gender quotas have been studied in various job domains, including law enforcement (Miller and Segal 2019; Sukhtankar, Kruks-Wisner, and Mangla 2022); corporate boards (Matsa and Miller 2013); and politics (Beaman et al. 2009), most research on college-level quotas focuses on racial or ethnic groups. I address this gap by analyzing how college-level gender reservations affect labor market outcomes for women in STEM.

The rest of the paper is organized as follows. Section 2 explains the empirical context and the policy. Section 3 outlines the conceptual framework. Section 4 describes the research design and the correspondence study. Section 5 presents summary statistics, and Section 6 outlines the empirical methodology and tests the identifying assumptions. Section 7 discusses the main results from the correspondence study and Section 8 presents the findings from LinkedIn employment data. Section 9 concludes.

2 Context, Policy & Background

2.1 Indian Labor Market & STEM Education

Women are underrepresented in STEM careers across the world with only 29% holding STEM jobs (Global Gender Gap Report 2023). Female representation in STEM jobs in India stands at only 14% - which is quite low in comparison to the world. Despite producing 43% female STEM graduates, Engineering and Technology graduates are highly male-dominated with only 29% women pursuing these degrees (All India Survey of Higher Education 2020-21).

2.2 Elite Engineering Institutions

The Indian Institutes of Technology (IITs) are public engineering and research institutions in India, recognized as the highest-ranked colleges in the country for engineering courses. Admission to these B.Tech programs requires students to pass a highly competitive entrance examination, covering subjects taught in the Science track during Grades 11 and 12. The highest scorers are admitted to one of the IITs based on their exam rank and declared preferences for field and location. Each year, approximately 1.5 million students take the exam and apply for around 16,000 available seats across all IITs. IITs attract students from the top tier of the ability distribution, with acceptance rates ranging from 0.5% to 2%, lower than those of prestigious U.S. universities like MIT. CEOs of leading U.S. companies such as Google, IBM, and Deloitte are among IIT graduates. In 2005, the U.S. House of Representatives honored IIT graduates for their contributions to American society. Engineering aspirants who do not gain admission to IITs often enroll in non-IIT colleges, which are typically second choices due to their lack of the "IIT brand", which is valuable for signaling and connecting with the well-established IIT alumni network (Choudhury, Ganguli, and Gaulé 2023). Among non-IITs, there are other prestigious institutions like the Birla Institute of Technology and Science (BITS), Netaji Subhash University of Technology (NSUT), Delhi Technological University (DTU), and Vellore Institute of Technology (VIT), which offer similar degrees, ensure promising careers and boast a 100% placement record[7]. About 40% of the firms that recruit at top IIT campuses also visit and hire from these non-IIT colleges, according to information on the college websites. Since admission processes at these institutions are based on exam ranks and cutoffs, engineering aspirants who attend elite non-IITs are often very similar in ability to those admitted to IITs and are closer to the cutoff ranks.

[7] Ministry of Education, Govt. of India, releases NIRF rankings of major public and private national institutes. The rankings of the first 100 institutes is available at https://www.nirfindia.org/2023/EngineeringRanking.html. This paper uses some specific elite institutes from this list which are mentioned in Table 7 along with the NIRF 2023 rankings. Rankings by Indian Institutional Ranking Framework (IIRF) is considered a more authentic source released by Education Post and are available at https://iirfranking.com/ranking/top-engineering-colleges-in-india.

2.3 Supernumerary Seat Policy at IITs

Applications and admissions to undergraduate engineering programs are highly male-dominated, with the gender gap being particularly pronounced in IITs. In 2016, only 19% of applicants and 12.5% of candidates who cleared the entrance exam were women (Gupta 2020). Before 2018, these institutes would admit, on average, only 38 girls (out of 439 students) per cohort, resulting in a gender ratio of just 8.7%. To address this disparity, the Supernumerary Seat policy was introduced in IITs in 2018, reserving additional seats for women to ensure a certain proportion of female students in each undergraduate engineering class. The policy increased the gender ratio by 11 percentage points and the proportion of women by 8.7 percentage points (Gupta 2023). Based on average enrollment numbers, the absolute number of girls in a cohort rose from 759 to 2,070 — an increase of about 1,300 girls per cohort. The policy also boosted the proportion of women taking the exam by 10.5% and qualifying the exam by 15.3%.

The policy led to program expansion for girls without altering the admission procedure for boys. It did not displace boys or girls who were already qualified for IITs. Instead, it brought more girls into IITs while maintaining the merit-based criteria, as female candidates still had to clear the entrance exam to gain admission. Prior to the policy, a candidate's exam rank determined their eligibility for admission to IITs. With the policy in place, seats at IITs were divided into two categories: gender-neutral and female-only supernumerary seats. Admission was first granted to gender-neutral seats based on exam rank. Once these seats were filled, female candidates were admitted to supernumerary seats, also based on exam rank, to increase the gender ratio. The cutoff marks needed for admission through the female-only seats were likely lower, and the cutoff rank was likely higher than those for gender-neutral seats. The closing or cut-off ranks for 2017 and 2018 are provided in Appendix Table A.1. In 2017, the last person admitted to an IIT had a rank of 14,983, which was the same for both girls and boys. In 2018, the last person admitted to the regular seats had a rank of 12,216. However, the last female admitted had a rank of 16,035, made possible by the additional seats reserved exclusively for women. Without the supernumerary policy, women ranked below 12,216 would not have qualified for admission to the IITs. Thus, the policy opened doors to IITs for girls who would have otherwise likely attended elite non-IITs.

The supernumerary policy was not introduced in non-IITs and did not directly affect admissions at these colleges. However in the short-run, it would have influenced the quality and ranking of students within the ability distribution who enter these colleges, leading to effects on the outcomes of students at these institutions. Out of the candidates taking the IIT entrance exam, approximately 15% are women (as per 2017 exam report). The top 100 colleges in NIRF rankings include the IITs and the elite non-IITs. These colleges have an average cohort size of 700 which means that 53,900 candidates graduate from elite non-IITs. 15% females at these colleges implies that out of 53,900 candidates, 8,085 are women. The introduction of roughly 1,500 supernumerary seats at IITs means that approximately the top 18-20% (=1500/8085) of the female distribution in elite non-IITs could potentially qualify for the IITs.

2.4 Qualitative Interviews with Hiring Managers

In December 2023, I conducted qualitative interviews with seven hiring managers who visited IIT campuses for recruitment. I asked them about their views on the impact of the supernumerary policy on the academic quality of female candidates. None of the managers believed that the policy would significantly affect the average quality of the female candidate pool from IITs. They were all familiar with the admission process and understood that the selection of students is still merit-based, even though the policy lowers the required cutoff to enter IITs. They shared the opinion that the top performers in the entrance exam who make it to IITs have similar productivity, and lowering the cutoff slightly should not significantly change that.

Moreover, the managers viewed the policy as a program expansion and expressed that "*it will naturally reduce the need to hire from lower-ranked colleges*" and "*if there are more capable girls, this policy will have an effect across the board*". They also noted that "*girls in IITs are studying with capable peers, which helps in the IT sector where demand for girls is high as it improves the quality of the crowd*". One hiring manager pointed out that graduating from IIT signals higher capability, and the policy has made hiring female candidates easier, stating that "*now firms can hire more capable people who have entered college on merit, there are more girls to choose from, there are more options*" — suggesting that firms do use high-ranked colleges as a screening device.

3 Conceptual Framework

I derive a simple model of statistical discrimination using discrete ability types where firms use college and gender as signals of skill. This model has been extended from the canonical model of statistical discrimination (Phelps 1972) to analyze the impact of a supernumerary policy. The purpose of this section is to provide a theoretical way to interpret how the policy changes the quality distribution at different types of colleges, thereby changing firms' beliefs about expected skill which has implications for statistical discrimination.

3.1 Model Setup

3.1.1 Employees

A potential employee belongs to either of the two groups - male (M) or female (F) and their skill can be of two types[8] - high type (μ_H) and low type (μ_L) where $\mu_H > \mu_L$. Their skill is assumed to be equal to the value of their marginal product when employed. The unconditional likelihood that the employee has a particular skill type is equal ($= \frac{1}{2}$). This distribution is same for both males (M) and females (F)[9].

[8]The model can be extended to a type distribution.

[9]This assumption implies that males and females have the same expected skill. The model can be extended for different average skills and this assumption is not crucial for model implications.

3.1.2 College Admissions

There are three college types - higher ranked (θ_H), medium-ranked (θ_M) and lower-ranked (θ_L). Higher-ranked colleges are the most selective and attract high-type candidates with the highest probability. Therefore, the likelihood of getting admission in a better ranked college is greater for a person with higher skill. College of graduation acts a signal of skill, albeit with some noise. Moreover, the signal can be differently informative for males and females. For males, the likelihood that a potential employee is of high type conditional on graduating from college θ_i is $P(\mu_H/\theta_i) \equiv p_i$ where $i \in \{H, M, L\}$. Since higher ranked colleges are more likely to admit candidates with higher skill level, $p_H > p_M > p_L$. Further, I assume that both higher-ranked and medium-ranked colleges are elite with a higher likelihood of observing high-type candidates than in the population i.e. $p_H > p_M > \frac{1}{2} > p_L$. Similarly, for females, the likelihood that she is of high type conditional on graduating from college with ranking θ_i is q_i where $i \in \{H, M, L\}$[10] and $q_H > q_M > \frac{1}{2} > q_L$. If $p_i = q_i \ \forall \ i \in \{H, M, L\}$, then the signal is equally informative about the skill levels of both males and females.

3.1.3 Representative STEM Employer

A representative employer does not observe the skill level of potential candidates with certainty but observes group identity and a noisy signal of productivity - college of graduation - to form a belief about the employee's skill type. Employer considers an employee for a job if their expected skill conditional on observable characteristics is greater than a minimum skill level $\underline{\mu}$. For my purposes, I focus on high-skilled jobs at elite companies requiring higher than average skill and therefore, hire from colleges where expected skill of candidates is greater than the population average. Therefore, I assume[11] $\underline{\mu} > \frac{\mu_H + \mu_L}{2}$. I also assume that this threshold does not respond to any policy changes at the college

[10] $\sum p_i = 1$ and $\sum q_i = 1 \ \forall i$

[11] This assumption helps me to examine changes in callbacks for jobs that are hiring candidates from colleges with high rankings. If the threshold is too low or too high, policy changes are not very interesting as then either firms always hire candidates or never hire them irrespective of the policy.

level and is determined by the skill standards demanded by the tasks that the candidate is expected to fulfill at the job[12].

3.1.4 Expected Skill of Employee

The employer updates their beliefs about the expected skill of an employee using the observable information - group identity (gender) and college type.

$$E(\mu/\theta_i, M) = P(\mu_H/\theta_i).\mu_H + P(\mu_L/\theta_i).\mu_L = p_i\mu_H + (1 - p_i)\mu_L \equiv s_i$$
$$E(\mu/\theta_i, F) = P(\mu_H/\theta_i).\mu_H + P(\mu_L/\theta_i).\mu_L = q_i\mu_H + (1 - q_i)\mu_L \equiv f_i$$

Since $p_H > p_M > p_L$, $q_H > q_M > q_L$ and $\mu_H > \mu_L$, for a given group identity, expected skill increases as college ranking improves.

Case 1: If $p_i = q_i$, i.e. if college signal is equally informative for males and females, then both males and females will be considered to have equal expected skill for the same college type, i.e. $s_i = f_i \;\; \forall \;\; i$.

Case 2: Suppose the college signal is more informative for females and they are better sorted into colleges by ability[13]. With this assumption, $q_i > p_i$ for high- and medium-ranked colleges and $q_L < p_L$[14]. Females are considered having higher expected skill than males for elite (higher- and medium- ranked) colleges and vice-versa for the lower-ranked college. This implies that $s_i < f_i \;\; \forall \;\; i \in \{H, M\}$ and $s_L > f_L$.

These cases are illustrated in Figure 1. The left panel shows the first case. With the level of $\underline{\mu}$ shown in the figure, all male and female candidates from college θ_H receive a callback for the job whereas candidates from θ_M and θ_L do not receive a callback. The

[12] As an example, jobs may require candidates to have certain coding skills which they will not change with changing policies at colleges.

[13] Women are historically disadvantaged in STEM fields/careers and only very high-ability women are able to break the social norms barriers and make it to the very top while for the men, such barriers are limited. Human capital formation required to qualify for highest ranked STEM colleges involves parental investments and significant years of additional coaching which is often not undertaken for girls. I, therefore, assume that college acts as a more informative signal for women than the men.

[14] $\sum p_i P(\theta_i) = \sum q_i P(\theta_i) = \mu_H = \frac{1}{2}$ where $P(\theta_i)$ is the unconditional probability of getting admission in college with ranking θ_i and is assumed to be same for males and females.

right panel show the second case where college is a more informative signal for women. If $f_M > \underline{\mu} > s_M$ and $s_H > \underline{\mu}$, females from colleges θ_H and θ_M receive a callback and males from only college θ_H receive a callback. College θ_M females do better than the counterpart males relative to that of college θ_H, in terms of callback.

In general, females in college i receive a callback if $q_i \mu_H + (1 - q_i)\mu_L > \underline{\mu}$ or $q_i > \frac{\underline{\mu} - \mu_L}{\mu_H - \mu_L} \equiv \mu^*$. To demonstrate the impact of the supernumerary policy, I assume unequally informative signals to begin with as described in Case 2 above where $q_H > q_M > \mu^*$.[15]

3.2 Impact of Supernumerary Policy

I will now describe the implications of a supernumerary policy introduced at the higher-ranked colleges in a context where eligibility of engineering college admission is determined by the subject choice being 'Science' track in high school, a decision which is made two years before entering college. In the short run, the supply of engineering aspirants is unaffected by the policy change. A supernumerary policy which adds seats at top ranked colleges will impact the skill distribution at not just those colleges but also in the colleges ranked below.

Suppose the supernumerary policy, introduced in higher-ranked college, adds seats for females in order to increase their proportion in college θ_H by m (where $m > \frac{q_H - \mu^*}{\mu^*}$). If x proportion of the supernumerary women are of high-type (i.e. have skill μ_H), the new likelihood of observing a high-type female in college θ_H changes from q_H to q'_H where $q'_H = \frac{q_H + mx}{1+m}$.

Similarly, the policy also affects the skill distribution in college θ_M with the seat expansion in college θ_H, as women who would have otherwise joined college θ_M are now able to enrol in college θ_H. For simplicity, I assume no change in skill distribution in college θ_L (i.e. q_L remains the same). Assuming, the proportion of women in college θ_M

[15]Supernumerary policy only affects ability distributions of women at elite colleges and does not affect that of the men. Therefore, the exact same impact of the policy can be illustrated within the first case as well. The model predictions on the change in callbacks of females relative to the males remains the same.

falls by n (where $\frac{q_M-\mu^*}{1-\mu^*} < n < 1$), the new likelihood of observing a high-type female in college M changes from q_M to q'_M where $q'_M = \frac{q_M-nx}{1-n}$. After the policy, the new expected skill of females given the college signal will now depend on the employers' beliefs about x and the resulting changes in q_H and q_M.[16]

Let $x_1^* = \mu^* - \frac{q_H-\mu^*}{m}$ and $x_2^* = \mu^* + \frac{q_M-\mu^*}{n}$. It follows that the impact on callback of females in the two college types after the supernumerary policy depends on where the proportion of high-type supernumerary women lies relative to other parameters of the model (x_1^* and x_2^* in particular). I compare the new probability of observing high type candidate in these colleges (q'_M and q'_H) with μ^* to derive the following propositions (details are in Appendix section A.1.1):

Proposition 1: If $0 < x < x_1^*$, $q'_H < \mu^*$, i.e. there is a high proportion of low-type women who are able to enrol in college θ_H rather than joining θ_M, decreasing the likelihood of observing high-type women in college θ_H. As shown in Figure 2a, f_H falls below $\underline{\mu}$. Expected skill of college θ_M females is still greater than $\underline{\mu}$. This results in an increase in gender gap in callbacks for college θ_H but no impact for college θ_M as women in only top-ranked college stop getting callbacks.

Proposition 2: If $x_1^* < x < x_2^*$, proportion of high-type women in both colleges remain high after the policy such that the expected skill of females is greater than $\underline{\mu}$ and we observe no impact on callbacks of females in either colleges (Figure 2b). For $x < \frac{(1+m)q_M-(1-n)q_H}{m+n}$, females from college θ_H are associated with lower expected skill than those in college θ_M whereas for $x > \frac{(1+m)q_M-(1-n)q_H}{m+n}$, opposite holds.

Proposition 3: If $x_2^* < x < 1$, $q'_M < \mu^*$, a large proportion of high-type women enrol in college θ_H rather than joining college θ_M, reducing the likelihood of observing high-type women in college θ_M. As shown in Figure 2c, f_M falls below $\underline{\mu}$ whereas expected skill

[16]The model assumes that there is no addition of men and women within middle ranked colleges to displace the seats that open up after the policy. If we relax that assumption, the model implications will be similar. In that case, both lower-quality men and women will move from the bottom part of distribution. However, additional women will be disproportionately worse in quality than the men within middle ranked colleges and therefore, any impact on the men's quality in these colleges should be small and insignificant.

of college θ_H females is still greater than $\underline{\mu}$. This results in an increase in gender gap in callbacks for college θ_M but no impact for college θ_H as women only in the medium-ranked college stop receiving callbacks.

3.2.1 Model: Summary & Welfare Impacts of the Policy

Employer's beliefs and perceptions about what the average ability of women in supernumerary seats is, relative to the pre-policy average ability in colleges, is essential and determine the impact on callbacks. A high proportion of high-ability females within these seats do not impact callbacks in the high-ranked colleges but affects the ability distribution in the medium-ranked colleges and callbacks of female from these colleges fall. On the other hand, if the proportion of high-ability females within these seats is low, callbacks in the medium-ranked colleges is unaffected but average ability, and therefore callbacks, in high-ranked colleges falls.

While the policy helps supernumerary women associate themselves with a college of better ranking, it can have ambiguous effects. Similarly, the corresponding impact on other women also depends on model parameters and therefore overall impact of the policy is ambiguous. If the policy benefits some, it can hurt others at the same time. Even if callbacks are unaffected, changes in expected skill can change expected wages of females and impact welfare. Moreover, these are short-run effects. If the pool of candidates aspiring to enter the elite engineering colleges responds to the policy, long-run impacts may vary. The focus of this framework has been on engineering students and firms who form a small share of the market. I, therefore, do not anticipate general equilibrium effects.

4 Research Design - Correspondence Study

I conducted a correspondence study to assess the effect of the supernumerary policy on gender discrimination. I restricted the correspondence study to companies that specifically hire graduates from IITs and other elite non-IITs, as these companies are likely to be aware of college policies due to their close ties and connections with these institutions through annual on-campus recruitment. Notably, 85% of the hiring managers I interviewed during the IIT recruitment drive indicated that they were aware of the policy and the year it was introduced.

I began by compiling a list of firms that recruit from elite engineering colleges in India.[17]. I then filtered jobs available on these firms' websites that required engineers with 1+ years of experience. The jobs were categorized into three broad roles: software, data, and consulting.[18] I further classified the jobs into two tiers — Tier 1 and Tier 2 — based on a tier classification list of companies and job roles that I obtained from one elite engineering college.[19]

One challenge in creating CVs was determining how to indicate that a candidate was exposed to the supernumerary policy when she entered college. To signal policy exposure, I used the year an individual entered and graduated college in the CVs. Any explicit indication of affirmative action exposure could have raised suspicion among recruiters or induced biases in their callback decisions. The policy timeline is clearly delineated in Figure 3: cohorts unexposed to the policy graduated in 2021 or earlier, while the first cohort exposed to the policy graduated in 2022. The timing of my correspondence study aligns well with this timeline, as it allowed me to submit CVs of both pre-policy and post-policy candidates to the same entry-level jobs. Additionally, the recent implementation of the policy provided an opportunity to identify discrimination rooted in firms' pre-existing biases and beliefs about supernumerary beneficiaries. To ensure the CVs appeared as authentic and credible as possible, I used actual IIT graduates' CVs as references.

[17] This information is available on college websites and their annual reports.

[18] Examples of these roles include AI Engineer, Data Scientist, Machine Learning Engineer, Business Analyst, Business Development, Consultant, Software Developer, Full Stack Developer, Java Developer, Python Developer, Backend or Frontend Developer, Web Developer, Applications Developer (Android or iOS), Financial Analyst, Risk Analyst, and Hardware Engineer.

[19] Colleges use this classification based on how competitive the job is and on the compensation-bracket the job falls in.

4.1 Randomization in CVs

I randomized three parameters within each job : (1) Year of Entry: 2016[20] or 2017 (pre-policy years) or 2018 (post-policy year); (2) Gender - Male or Female; (3) College Type - AA (IITs) or Non-AA (Non-IITs)[21]. This randomization resulted in 8 (= 2 X 2 X 2) combinations: (a) Female AA Pre; (b) Male AA Pre; (c) Female Non-AA Pre; (d) Male Non-AA Pre; (e) Female AA Post; (f) Male AA Post; (g) Female Non-AA Post; and (h) Male Non-AA Post.

I randomly selected a college-degree combination from a list for each CV profile (i.e., Software, Consulting, or Data). Other characteristics, such as College CGPA, school name, and high school percentages, were also randomly chosen from a common list applicable to all job categories. The lists of some of these characteristics are provided in Appendix Tables A.12-A.13, and Appendix Figure A.1 shows a sample CV of a female software engineer. Other sections of the CV, such as Extracurricular Activities, Scholastic Achievements, and Positions of Responsibility (included only for consulting roles), were randomly selected from a large pool of CV points, independent of any other characteristics. For consulting CVs, I also included Business Case study participation in the common pool of points. Data and Software CVs featured an additional Technical Skills section, which was kept consistent across all CVs.

Each CV included an experience section, comprising one current job and one previous internship. I categorized all internships based on the engineering major they most closely relate to, and the internship was then randomly selected from the corresponding pool for that CV's engineering major. Work experience was similarly classified by job category, and then randomly chosen from the relevant pool corresponding to the job category of the CV. Additionally, I randomized the LaTeX template used to create each CV. The entire CV creation process was coded in Python, allowing for automatic generation of CVs in

[20] This year was added in the second wave only.

[21] Within the IITs, I kept IIT Delhi, IIT Kanpur and IIT Indore. Within the Non-IITs, the colleges kept were NSIT, BITS, IIIT Hyderabad, IIIT Delhi, VIT, SRM Chennai

LaTeX with randomized characteristics.

Balance Amongst CVs: I demonstrate balance across the 444 CVs (48 from the first wave and 396 from the second wave) in Appendix Tables A.3 - A.5. The balance is shown across each broad parameter used for randomization — gender, college type, and year of entry. However, the CVs are not fully balanced concerning some work experience characteristics, as these were selected based on the job category and engineering major. Therefore, I control for these characteristics in my analysis.

4.2 Job Applications

The study was carried out in two waves: the first and the second wave was conducted in June-September 2023 and February-April 2024, respectively.

In the first wave, I created 8 CVs for each of the 6 job profile-tier combinations, resulting in a total of 48 CVs. I applied the same set of 8 CVs (based on profile-tier combination) to each job I identified during the first wave. These 8 CVs represented every possible combination of the two genders, two college types and two years of entry.

In the second wave, I focused solely on Tier 1 jobs. I created 12 CVs[22] corresponding to every possible combination of two genders, two college types and three cohorts. 12 CVs were created for each of the three job profiles, totaling 36 CVs. Additionally, each week of the second wave, I generated a new set of 36 CVs and applied them to jobs available that week. In total, I created 396 CVs during the second wave.

I applied CVs to jobs within the relevant categories at companies that recruit from elite engineering colleges. To avoid repetition of contact details, each CV sent for a particular job included a unique phone number and email address. In the first wave, 48 CVs were applied to 396 jobs, while in the second wave, 396 CVs were applied to 220 jobs. Out of the total 616 jobs, 295 were software roles, 201 were data roles, and 120 were consulting roles. Additionally, 518 jobs were categorized as Tier 1, and 98 as Tier 2. In total, 5,236

[22]The maximum number of applications was increased from 8 to 12 in the second wave in order to include one more cohort in my sample of CVs and control for years of experience.

job applications were successfully completed.

During the correspondence study, some job postings expired before all CVs could be applied. In the first wave, all 8 CVs were sent to 302 jobs, and in the second wave, all 12 CVs were sent to 201 jobs[23]. Appendix Table A.2 provides details on the number of jobs for which a specific number of successful applications were sent. Callbacks were monitored via email and phone.

5 Summary Statistics

The overall callback rate in the study is 3.4%. The low callback rate can be attributed to several factors. First, firms often rely on referrals and recruitment networks for hiring, as online job applications can be difficult to verify (Fernando, Singh, and Tourek 2023). Second, most STEM job seekers have LinkedIn profiles and use online job platforms for applications. Since the resumes I created were for fictitious individuals who do not have a LinkedIn presence, their applications were even harder to verify, limiting me to job application channels outside of these networks. Third, the study was conducted while the economy was still recovering post-COVID. During this period, employees at top technology firms were being laid off, the labor market was highly competitive, jobs were scarce, and callback or response rates were lower than usual[24].

5.1 Average Callback Rates

Table 1 presents the callback rate by the three broad parameters on which the CVs were randomized within each job. The male callback rate is 3.2%, and the female callback rate is 3.6%, but the difference is statistically insignificant, indicating no gender callback gap in the overall sample. Most of the correspondence study literature also do not find significant evidence of gender callback gap. For instance, a recent paper by Kline, Rose, and Walters

[23]I control for total applications in my analysis

[24]Source: https://www.cnbc.com/2024/02/02/why-it-feels-so-hard-to-get-a-job-right-now.html

2022, which focused on low-skilled jobs, found that some U.S. firms discriminate against men while others discriminate against women, resulting in no overall gender discrimination. Another recent study by Adamovic and Leibbrandt 2023 found evidence of gender discrimination against women in male-dominated jobs in Australia. A summary of previous correspondence studies on gender discrimination in male-dominated jobs is provided in Appendix Table A.14. In this paper, I focus on male-dominated and high-skilled jobs and do not find evidence of gender callback gap, at least in the Indian context.

The callback rate for candidates who graduated from IITs is 3.8%, while for those from non-IITs, it is 3%; however, this difference is also statistically insignificant. Additionally, the callback rate for the pre-policy cohort is 3.6%, which is higher than the post-policy cohort's rate of 3.1%, but this difference is statistically insignificant as well.

Figure 5 and Appendix Table A.8 show the callback rates for each job profile. Jobs in software roles show a statistically significant preference for female candidates over male candidates and for IIT graduates over non-IIT graduates, with the differences significant at the 5% level. Consulting roles, on the other hand, prefer candidates from older cohorts, indicating a preference for applicants with more years of experience.

6 Empirical Methodology

In an ideal scenario, the first difference in callback rates between females graduating before 2022 and those graduating in or after 2022 would provide a direct measure of the supernumerary policy's effect. However, since these two cohorts differ, this estimate may also capture cohort effects.[25] Since the policy was only introduced for females, I compare the difference in callback rates between males and females, exploiting the fact that the policy did not displace male candidates — *new* supernumerary seats were created and reserved specifically for female candidates. This allows me to compare the male-female

[25] For example, if younger cohorts have lower levels of experience which employer does not prefer, then the difference will capture the effect of lower experience *and* the effect of the policy.

callback gap before and after the policy for IIT candidates. I also perform the same analysis for non-IIT candidates to estimate how the supernumerary policy affects colleges ranked just below the IITs. To do this, I employ a difference-in-differences regression to estimate the policy's effect within the two types of colleges.

The identifying assumption is that, in the absence of the policy, the male-female callback gap would remain constant across cohorts graduating at different times (i.e., there would be no change in gender preferences), conditional on other observable characteristics. If employer prefers a specific gender, then a difference-in-differences estimation will identify the impact of the policy as long as that preference is constant across cohorts i.e. different levels of experience do not impact gender preferences. Any change, therefore, in the male-female callback gap in the post-policy cohorts will be attributed to the policy. Moreover, the correspondence study allows me to create a comparable counterfactual candidate, ensuring that any differences in the male-female callback gap between pre- and post-policy cohorts can be attributed to statistical discrimination based on firms' beliefs about changing ability distributions within colleges, rather than differences in individual candidates. I test the identifying assumption for both college types in Section 6.1.

The estimating equation for the difference-in-differences estimate is as follows and the coefficient of interest is γ:

$$y_{ijt} = \alpha_0 + \gamma F_i \,.\, P_t + \alpha_1 P_t + \alpha_2 F_i + \rho X_i + \mu_j + W_i + \epsilon_{ijt} \tag{1}$$

The outcome y_{ijt} takes value 1 if a candidate i with entry year t received a callback (on phone or e-mail) from job j and 0 otherwise, P_t is dummy for post year of entry (2022), F_i is a dummy if female, and μ_j represent the job specific controls such as job profile, job tier and total applications sent to a job. Standard errors are clustered at the job level since errors can be correlated within a job. Although resume characteristics were randomized within each job, I applied the same set of CVs across multiple jobs within a category. Additionally, some job categories had more available openings than others, causing certain

CV sets to be applied more frequently, which created an imbalance in the overall sample, despite the initial balance of the CVs. To address this, I control for specific resume characteristics (X_i), such as the resume template, work-experience location, whether the work-experience firm is large, internship experience at a multinational firm, class 12th percentage, and school location. I also control for the number of years of experience of each individual to account for the effect of the policy, independent of age or experience level. Furthermore, I include wave dummies (W_i) in the regression to account for any potential differences across the waves of the study.

I estimate the magnitude of the policy impact taking into account the distributional consequences by comparing the post-policy change in the gender callback gap between the IIT and non-IIT females using a triple difference regression. The estimation equation is provided below, with the coefficient of interest being δ, which estimates the difference in the impact of the policy between IIT and non-IIT females, relative to the males.

$$y_{ijct} = \alpha + \delta\, F_i \,.\, P_t \,.\, A_c + \beta_1\, F_i \,.\, P_t + \beta_2\, A_c.\, F_i + \beta_3\, P_t \,.\, A_c + \beta_4\, P_t + \beta_5\, F_i + \beta_6\, A_c + \rho\, X_i + \mu_j + W_i + \epsilon_{ijct} \quad (2)$$

The outcome y_{ijct} takes value 1 if a candidate i of college c and entry year t received a callback (on phone or e-mail) from job j and 0 otherwise, P_t is dummy for post year of entry (2022), F_i is a dummy if female, and A_c is a dummy for college being IIT. The specification includes the same controls as in Equation (1) and standard errors are clustered at the job level.

The triple difference estimate can be biased if employers value experience of IIT females differently than that of non-IIT females, relative to the males. For example, suppose firms prefer IIT female *more* over non-IIT female if experience is low, than they would in the older cohorts with higher experience. Firm may prefer this if they believe that non-IIT female is more likely to quit working and get married. In this case, our triple difference estimate will be upward biased. Therefore, the identifying assumption for the triple difference estimate to be unbiased would that be no factors other than the policy drive post-policy differences in the gender callback gap between the IITs and non-IITs. I test this assumption by running a triple difference regression on the pre-policy cohorts which is discussed in Section 6.1.

6.1 Verifying Parallel Trends: Placebo Regression

To test the parallel trends assumption, I conduct a placebo check by re-running the DID and triple difference regressions using data only from pre-policy cohort candidates. In this placebo test, I re-define the *Post* variable (P) such that it takes the value 1 if the candidate entered in 2017 and 0 if the candidate entered in 2016. The estimating equation for the DID and the triple difference is provided below, where γ' captures the change in the male-female callback gap between the 2017 and 2016 entering cohorts within the two college types and, δ' captures the difference in the male-female callback gap between the 2017 and 2016 entering cohorts across IITs and non-IITs. If the parallel trends assumption holds, we should not reject the null hypothesis that these coefficients are significantly different from 0, as neither of these cohorts was exposed to the policy.

$$y = \alpha_0 + \gamma' \, F \, . \, P + \alpha_1 \, P + \alpha_2 \, F + \rho \, X_i + \mu_j + \epsilon \tag{3}$$

$$\begin{aligned} y = \beta_0 + \delta' \, F \, . \, P \, . \, A + \beta_1 \, F \, . \, P + \beta_2 \; A. \, F + \beta_3 \, P \, . \, A + \\ \beta_4 \, P + \beta_5 \, F + \beta_6 \, A + \rho \, X_i + \mu_j + \epsilon \end{aligned} \tag{4}$$

I test whether the parallel trends assumption holds by conducting a placebo check and estimating Equation (3). The results are presented in Table 6. The DID estimate corresponding for the IITs in Column 1 is insignificant and, most importantly, has a negative sign (opposite to the main results). This suggests that there were no trends favoring female candidates over male candidates in the recent cohorts. The DID estimate for non-IITs in Column 2 is very small in magnitude and imprecise, further suggesting no pre-trends in the female/male callback ratio in earlier cohorts. The triple difference estimate, corresponding to Equation (4) and presented in Column 1, is similar in magnitude as the main result but notice that it is in the opposite direction and is insignificant. This indicates that the female/male callback ratio was moving in parallel across the two college types before the policy, and there are no pre-existing trends that could potentially influence the results. These results alleviate concerns that the findings could be driven by differences in experience levels among younger cohorts, which might be valued differently in IITs versus non-IITs, or between men and women. If this were the case, we would observe significant estimates in both the double and triple difference regressions.

7 Results

7.1 Main Results

I use a linear probability model to estimate the difference-in-differences (DID) Equation (1), and the results are presented in Table 3.[26] The first column shows the results for IIT graduates. The coefficient on *Female* is small in magnitude and statistically insignificant, suggesting no evidence of gender discrimination in callback rates for pre-policy graduates. The DID estimate (coefficient on *FemaleXPost*), which captures the change in gender callback gap after the policy's introduction, is very small and insignificant. Thus, I conclude that there is no significant difference between male and female callback rates among IIT graduates, and the callbacks for IIT females are not affected relative to IIT males after the introduction of the supernumerary policy. The second column estimates the same specification for non-IIT graduates. Similar to the IIT results, I do not find evidence of gender discrimination in the pre-policy cohorts. However, the DID estimate in this case

[26] I also estimate corresponding Probit and Logit models and the results are reported in Appendix Table A.10.

is negative and statistically significant at the 10% level, indicating that when the policy was introduced at IITs, the male-female callback gap increased within elite non-IITs by 2 percentage points, or the female callback rate at non-IITs decreased by 52% relative to the pre-policy cohort. In the third column, I estimate the same specification for the combined IIT and non-IIT sample. The overall change in the gender gap after the policy is negative but statistically insignificant, indicating that, in aggregate, likelihood of getting a callback has not changed for the females, relative to the males. This result suggests that supernumerary seats are being filled by females who would have otherwise gone to non-IITs, and the firms are responding to their job applications instead of those from the non-IITs. These results together mean that high-ability females are filling up the supernumerary seats affecting the callbacks of non-IIT females who are now perceived to have a lower expected skill, leading to a substitution effect where firms call back females at IITs entering via the policy instead of females in the non-IITs.

Table 4 presents the results of the triple difference regression (Equation 2), which I estimate using linear probability, probit, and logit models, reporting the marginal effects. The coefficient on *Female* is positive and significant, indicating that non-IIT females in cohorts unexposed to the policy are 0.9 to 1 percentage point more likely to receive a callback than males. The coefficient on $Female \times IIT$ is negative and significant in both the probit and logit models, suggesting that the female/male callback ratio is lower in IITs compared to non-IITs by approximately 1 percentage point. The positive and significant coefficient on IIT shows that IIT males are about 1 percentage point more likely to receive a callback than their non-IIT counterparts in the pre-policy cohort.

The baseline results align with my model setup where (1) males have a higher callback probability if they are graduating from a better-ranked college and (2) the college signal is more informative for females because of which females in medium-ranked colleges receive a callback, while males don't, whereas both females and males at top-ranked colleges receive callbacks. As a result, females have a relative advantage over males in terms of callbacks in middle-ranked colleges compared to higher-ranked colleges.

Consistent with the DID results in Table 3, the coefficient on $Female \times Post$ indicates that non-IIT females are 2 to 2.7 percentage points (or 52%) less likely to receive a callback relative to males if they entered college in a post-policy year. This suggests that non-IIT females in cohorts exposed to the policy experienced a drop in their callback rate. The coefficient of interest, $Female \times IIT \times Post$, represents the triple difference estimate, which ranges from 2.7 to 3.6 percentage points. This differential effect for IIT females is positive, large, and statistically significant, indicating that post-policy IIT females are at a relative advantage compared to non-IIT females. While the callback rate for IIT females remains unaffected by the policy, the callback rate for non-IIT females has declined relative to their male counterparts. These findings imply that affirmative action is not putting women in IITs at a disadvantage. In fact compared to the pre-policy female callback rate of 3.8%, the callback rate for IIT females is approximately 75% higher than that of non-IIT females after the policy.

7.2 Predicted Callback Probability & Policy Impact

I estimate the predicted callback rates of the 8 groups using the Probit model (Table 4 Column 2). I find that IIT women graduating in the post-policy period need to submit 5 fewer applications compared to those graduating in the pre-policy period. In contrast, non-IIT women graduating in the post-policy period need to submit 9 more applications than their pre-policy counterparts, suggesting an increase in search costs for non-IIT women. For men, IIT graduates from the post-policy period need to submit about 1 additional application compared to those from the pre-policy period, while non-IIT graduates need to submit 14 fewer applications compared to their pre-policy counterparts. These findings are summarized in Table 5, along with 95% confidence intervals.

According to the pre-policy predicted callback rates, non-IIT women needed to submit 1 fewer application than IIT women, but now they would need to submit approximately

14.4 more applications compared to IIT women. Non-IIT males, who previously needed to submit about 12 more applications than IIT males, would now need to submit 15 fewer applications relative to IIT men.

The magnitude of discrimination as indicated by the correspondence study is large. It is plausible that a competitive labor market in which labor supply exceeds demand aggravated it. Discrimination falls in tight labor markets and increases when labor supply is high and/or demand is low (Baert et al. 2015). Having a large pool of applicants not only allows employers to choose preferred demographic characteristics, but it also increases their search costs such that they may resort to using other characteristics to rank applicants (Autor 2001; Botelho and Abraham 2017). Therefore, gender gap between differently ranked colleges may be more prominent in such competitive markets resulting in large magnitude of bias.

7.3 Sub-Sample Analysis and Heterogeneity

I perform sub-sample analyses on various job and firm characteristics to understand the heterogeneous response to the policy on callback rates. I estimate the triple difference regression across different sample splits, with the coefficients plotted in Figure 6 and Figure 7. As shown in Figure 6(a), the results are primarily driven by software and data profiles. These job profiles are more technical, involving mathematical and coding skills, and may therefore require a different skill set compared to consulting roles.

I also split the sample based on whether the listed job provides above or below median compensation, as shown in Figure 6(b). Although I do not have actual compensation details for each job, I estimate approximate compensation using data from websites like AmbitionBox and Glassdoor. The median annual compensation for the jobs I applied to is INR 1,200,000 (approximately USD 75,000, adjusted for purchasing power parity). For jobs offering above-median compensation, I find a positive but insignificant impact on callbacks for IIT females relative to non-IIT females exposed to the policy. Since IITs are higher-ranked, they tend to attract higher-paying jobs, which may have stricter callback criteria based on the expected skill level. It is possible that the skill levels of non-IIT females were below the threshold for these jobs even before the policy, and as a result, the policy had little effect in this context. The relative advantage for IIT females after the policy is more pronounced within lower-paying jobs. In the pre-policy period, non-IIT females had a relative advantage for these jobs, but this dynamic reversed after the policy. These lower-paying jobs likely have more relaxed callback criteria, and they may have initially called back candidates from both IITs and non-IITs. The policy significantly influenced callbacks for non-IIT females in these roles. However, the coefficients from the triple difference regression for the two sample splits are not significantly different.

I also split my sample based on job location (Figure 6(c)). The results show that jobs located in the South of India prefer IIT females over non-IIT females after the policy. This effect is likely driven by the concentration of software and technology jobs headquartered in cities like Bangalore and Hyderabad, which are major hubs in South India. While there is some preference for IIT females in the Western part of the country as well, the effect is insignificant.

I also perform heterogeneity analysis based on company-specific characteristics. In terms of company size, large firms[27] prefer IIT females over non-IIT females, and the triple difference estimate is statistically significant. However, the results are imprecise for smaller firms. Nevertheless, the two coefficients are not statistically different (Figure 7(a)). Additionally, I split the sample based on whether the owner of the Indian entity of the company is an IIT alumnus or not. The triple difference coefficient is positive and similar in magnitude across both types of firms, but it is imprecise (Figure 7(b)).

I also split the sample based on whether a firm is a multinational corporation (MNC) or not (Figure 7(c)). A company is defined as multinational if it has multiple international locations, indicating an international presence. The effect is large and statistically

[27]A large firm is defined as one with more than 500 employees. I gather company size and other firm-specific characteristics using information provided on LinkedIn pages of the companies.

significant within non-MNC companies, while it is insignificant in MNCs, although the two coefficients are not statistically significantly different. Most non-MNC companies hiring in India are likely Indian-owned, with little or no presence outside India. I expect Indian-owned companies, particularly those with Indian-origin decision-makers or board members, to be more influenced by policies introduced in Indian institutions. In contrast, MNCs may have policies set by international managers that follow standard operating procedures across different countries, which could explain the lack of a significant effect in these firms.

Lastly, I conduct a sub-sample analysis based on whether the firm is a start-up (Figure 7(d)). A start-up is defined as a company founded after 2005. I find that both startups and non-startups show a relative preference for IIT females, but the individual estimates are imprecise. Therefore, I do not have sufficient evidence to conclude whether the result is driven by startups or non-startups.

8 Employment Data from LinkedIn

While the correspondence study helps identify hiring preferences, actual hiring outcomes are not directly observable. Whether callbacks translate into eventual hires remains an open question that the correspondence study cannot address. To explore this further, I use a large professional networking platform, LinkedIn, to obtain profiles of engineers who graduated from elite engineering colleges in India between 2020 and 2023 (those who entered between 2016 and 2019). This process involved first visiting each college's LinkedIn page and searching for alumni who started or ended their college studies in specific years. I then extracted the profile URLs of the visible alumni. Through this method, I collected approximately 14,000 URLs. The data was obtained using a LinkedIn scraping tool, *Proxycurl*[28]. By utilizing the *Proxycurl* API and the extracted URLs, I

[28]Proxycurl's LinkDB stands out with its extensive database and powerful APIs for detailed data extraction from LinkedIn profiles. I conducted the data extraction process in June 2024 using the tool's People API.

scraped data available on each profile page, including the name, education (college, field of study, degree obtained, start and end dates), and past and current employment (company name, role, description, start and end dates). After removing profiles with incomplete data and those who pursued higher education (such as a Master's or PhD directly after B.Tech), I was left with 6,980 profiles for analysis. I then assigned gender to each profile using a publicly available dataset[29] that matches Indian names to gender. For profiles that did not match, I manually visited each LinkedIn page and assigned gender based on the name and profile picture.

Causal interpretation of the comparisons and differences in outcomes obtained from LinkedIn profiles is challenging. In particular, active LinkedIn users may represent a self-selected sample, and this selection may vary across different cohorts. To test this concern, I imputed coverage rates (equal to the number of individuals of a particular cohort divided by the total cohort size as reported in the college's annual reports) corresponding to each combination of gender, college and entry year. I, then, conducted a triple difference (corresponding to the main one) using coverage rate as the dependent variable. The results are reported in Table 11. There are no significant differences in the proportion of cohort size covered in the LinkedIn sample by *IIT*, older cohorts (*Post*), older/younger females (*Female X Post*), females graduating from IITs (*Female X IIT*), older IIT cohorts (*Post X IIT*) or older IIT females (*Female X Post X IIT*). This reassures that even if there is any selection amongst the people active on LinkedIn, it is not significantly different across colleges or cohorts and should not lead to any differences that I may find in other outcomes. However, evaluating the impact of the supernumerary policy is not straightforward, as non-beneficiaries may not serve as a good counterfactual for beneficiaries, given potential differences between the two groups. Despite the limitations for conducting causal analysis, I utilize this data to provide suggestive evidence that supports the findings of the correspondence study and to refute alternative theories that could potentially explain the results.

[29]Link for the dataset: https://www.kaggle.com/datasets/shubhamuttam/indian-names-by-gender

Policy & Gender Ratio: I extracted data from LinkedIn for six colleges — three IITs and three non-IITs — which cover 85% of the sample used in my correspondence study. Table 7 provides a breakdown of LinkedIn and correspondence study data by college. Approximately 43% of students who entered these colleges between 2016 and 2019 are included in the LinkedIn data. The table also indicates the proportion of students covered in the LinkedIn data for each college. Figure 8 shows the proportion of females in the LinkedIn data by college type and entry year. The supernumerary policy was introduced for the cohort entering IITs in 2018. As illustrated in the figure, there is a noticeable increase in the proportion of IIT females on LinkedIn after 2017, rising from 14% to 19%. In contrast, the proportion of non-IIT females remains relatively stagnant, hovering around 17%, with no clear trend.

8.1 Outcomes from LinkedIn

I examine various labor market outcomes based on the 6,980 LinkedIn profiles. Of these, 4,724 profiles provide the name of the firm where the individual had their first job. To compare these outcomes with the results from my correspondence study, I focus primarily on whether an individual's first job is at one of the companies included in my correspondence study sample. If the first job is at one of these firms, I assign the outcome *Ever Employed in sample firm* as 1, and 0 otherwise. If these firms prefer IIT females over non-IIT females after the policy, relative to males, I expect to see a similar pattern in the employment data. These firms are elite employers that recruit from both IIT and non-IIT campuses for immediate placements after graduation, making LinkedIn data a good indicator of placement outcomes.

I also examine the start date of the first job to assess whether the job began within 6 months of graduation, which I define as the outcome *Employed in sample firm within 6 months*. I refrain from analyzing second and later jobs for two reasons: (a) hiring for those roles depends on the experience gained from the first job, which is difficult to control for, and (b) post-policy cohorts are less likely to have a second job currently, leaving the analysis underpowered for meaningful comparisons.

However, I do analyze the number of jobs (*Number of Distinct Jobs*) an individual has held as a proxy for job switching. For this outcome, I include profiles that do not report the name of the firm. Additionally, I explore labor force participation outcomes in order to determine whether the candidates differ in terms of being employed (in any firm) in the labor force which could be driving differences in employment outcomes. Using the start and end dates of jobs, I calculate the number of years spent working and create two labor force participation outcomes: (1) *proportion of time employed since graduation till date*, which is the number of years worked divided by the total number of years since graduation, and (2) *proportion of time employed since graduation & before higher education*, which is the number of years worked divided by the total number of years from graduation until the start of any higher education (such as a Master's or PhD), if applicable. Table 8 provides summary statistics for the outcomes described above.

8.1.1 Findings: Employment Outcomes

Table 9 provides the estimates from the triple difference regression (Equation (2)) for employment-related outcomes. The positive and statistically significant coefficient on $Female \times IIT \times Post$ suggests that IIT females graduating in the post-policy cohort are 14 percentage points more likely to be employed by one of the companies included in my correspondence study sample compared to non-IIT females, relative to males. The magnitude of the coefficient seems pretty large and it translates to 26% higher likelihood of IIT females to be employed in the sample firm than non-IIT females after the policy. This suggests that 52% higher likelihood for IIT females getting a callback results in 26% higher likelihood of being hired and employed in these firms. The coefficient on $Female \times Post$ is large, negative, and significant for the second outcome — whether an individual started their first job at one of the companies within 6 months of graduation. This outcome likely reflects college recruitment patterns, as college graduates typically begin working at the firm where they were hired within three months of finishing college. The evidence strongly suggests that non-IIT females in the post-policy cohort are 7.2 percentage points (or 13.6%) less likely to be hired by one of these companies during college placements compared to non-IIT males.

Furthermore, the negative and statistically significant coefficient on $Female \times Post$ in the last column suggests that non-IIT females graduating in the post-policy cohort are more likely to have held multiple jobs and therefore switch employers more frequently than those graduating before, relative to males. If firms adjust their hiring policies at specific colleges following the introduction of the policy, it may leave students at those colleges dissatisfied with their first job, prompting more frequent job switches. While the triple difference coefficient is insignificant, its negative direction suggests that IIT females in the post-policy cohort are relatively less likely to switch jobs compared to non-IIT females, relative to males. These findings strengthen the results from my correspondence study, indicating that companies visiting elite engineering colleges and aware of the policy are now more likely to call back and hire females from IITs compared to non-IITs. As an additional robustness check, I repeat my analysis using coverage rates as weights. The results remain unchanged as reported in Appendix Table A.15.

I also assess the impact of the policy on wages by scraping publicly available salary data based on company name and job role for 1,569 profiles using a reliable website. This information is available only for selective software and analyst job roles. I use the salary estimates to create 10 wage decile bins. Each job is assigned a wage score between 1 to 10 based on the wage decile bin. For example, jobs in the top 10 percentile are assigned a wage score of 10, and those in the bottom 10 percentile are assigned a score of 1. I estimate Equation (2) for the wage score measure, and the results are presented in Appendix Table A.11. In the pre-policy cohort, females have higher wage score than males by 0.37. However, non-IIT females in the post-policy cohort have lower wage score compared to males, with a difference of 0.52. The positive coefficient on the triple difference suggests that IIT females are more likely to be employed in higher-paying firms than non-IIT females relative to males, but the coefficient is not statistically significant, indicating no significant differential effect of the policy on the salary standards for IIT females.

8.1.2 Findings: Labor Force Participation Outcomes

The effects on time spent working or being employed are presented in Table 10. The triple or double-difference estimates are not significant, suggesting that the policy has not affected the likelihood of employment or the time spent working. These results are not surprising and, in fact, cast doubt on alternative explanations for my findings.

First, the insignificant $Female \times Post$ coefficient suggests that females graduating in the post-policy cohort are no less likely to spend time working or have lower career aspirations than older cohorts. Any impact on hiring or callback outcomes for post-policy females is unlikely to be driven by changes in their labor supply decisions or firms perceiving them having lower likelihood of working.

Second, the insignificant coefficients on $Female \times IIT$ and $Female \times IIT \times Post$ suggest that non-IIT and IIT women spend similar amount of time working or participating in the labor force, which refutes explanations related to social norms, marriage markets, or differing aspirations between the two groups. This implies that any differences in callbacks or employment outcomes between IIT and non-IIT women are less likely to be driven by firms' assumptions about their future labor force participation. In simple words, differences in employment outcomes are being observed between similar groups, with similar aspirations and similar likelihood to work.

Thus, it is plausible that the differences in callback rates observed in the correspondence study, along with the differences in employment outcomes suggested by the LinkedIn data, are driven by the supernumerary policy, which may be altering firms' beliefs about the relative productivity of IIT females.

9 Conclusion

This paper estimates the impact of affirmative action policies, introduced at top institutions in the form of additional seats reserved for females, on firms' discriminatory behavior against the beneficiary group using a correspondence study embedded in a policy change environment. There is no evidence of gender discrimination before the policy at either top- or lower-ranked institutions, and no change in gender discrimination was found at top-ranked institutions after the policy. This result is important because it suggests that discrimination is less likely to persist at competitive STEM institutions.

However, the findings also indicate that affirmative action can have unintended consequences at lower-ranked colleges where such policies were not introduced: Affirmative action for women at top institutions increased gender discrimination in hiring at lower-ranked institutions. Although these policies aim to provide better opportunities for minority groups, they can also induce discriminatory attitudes toward the same group in other institutions. There is thus a trade-off between the benefits of increased access at top institutions and the potential loss of job opportunities at lower-ranked institutions.

This paper is limited in its ability to estimate the overall welfare changes arising from the policy and to determine what an optimal policy might look like in order to maximize aggregate welfare. Additional data on wages and productivity are essential in order to determine the impact on overall welfare. Moreover, supernumerary females probably do not benefit in terms of callbacks, but may benefit by being alumni of top colleges in terms of promotions, migration, marriage market outcomes, etc. Analysis of these outcomes will provide more insights about the overall impact of the policy. Importantly, these policies may affect the applicant pool and ability distribution, and potentially lead to different long-term outcomes. The paper thus highlights short-term effects, and leaves the long-term impact of this policy for future research.

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10 Figures & Tables

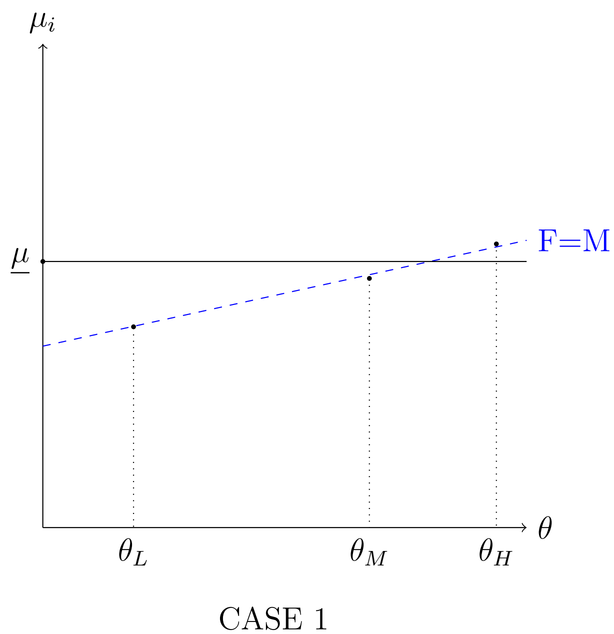


FIGURE 1

Note: This figure illustrates two different cases of signal informativeness in the base model. Case 1 corresponds to equally informative signals for both genders. In this case, expected productivity for both males and females is same at a given college. Case 2 corresponds to a more informative college signal for women as they are better sorted by ability. Females are associated with a higher productivity in the high- and medium-ranked colleges, whereas they are associated with a lower productivity in the low-ranked college.

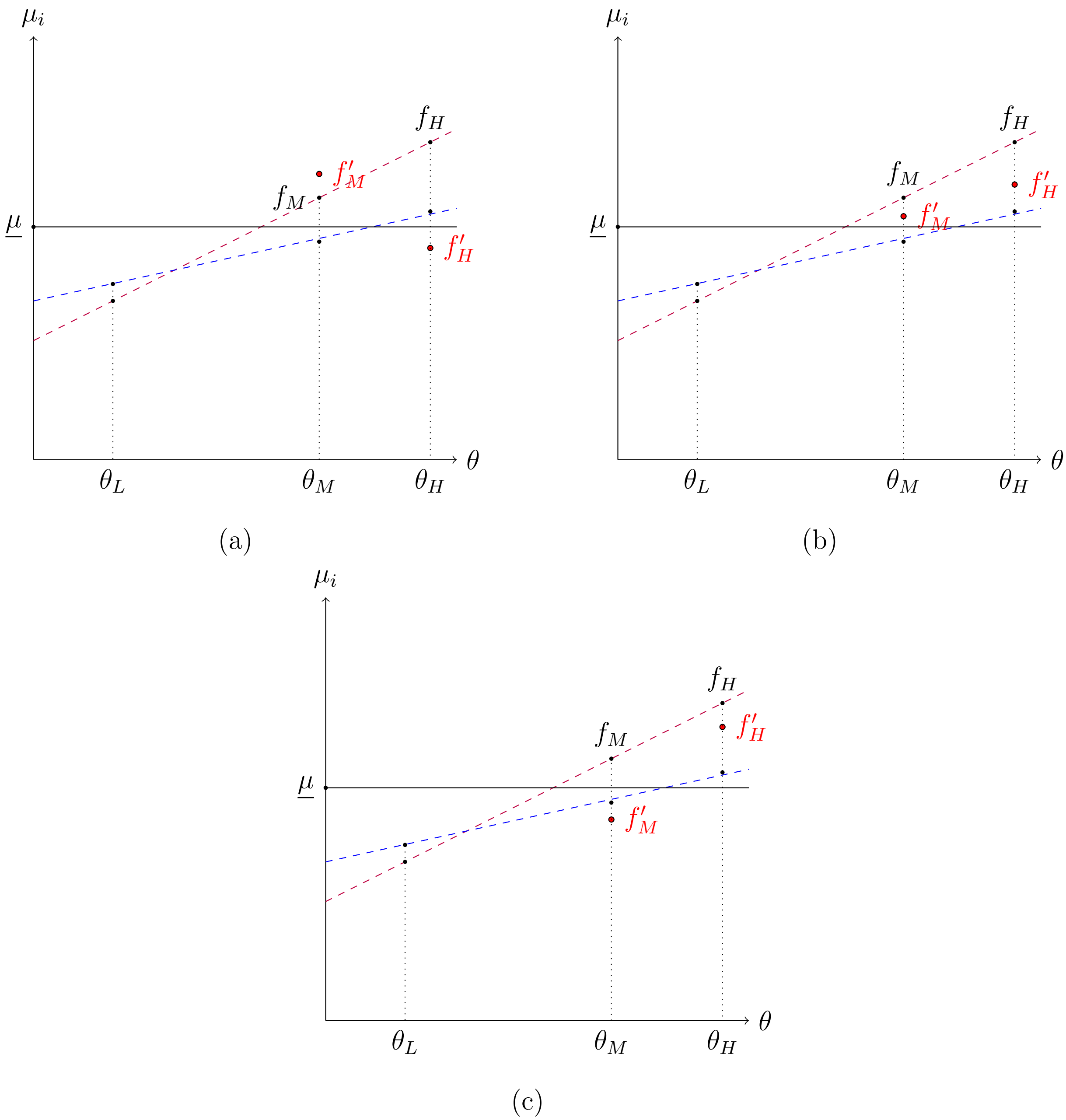
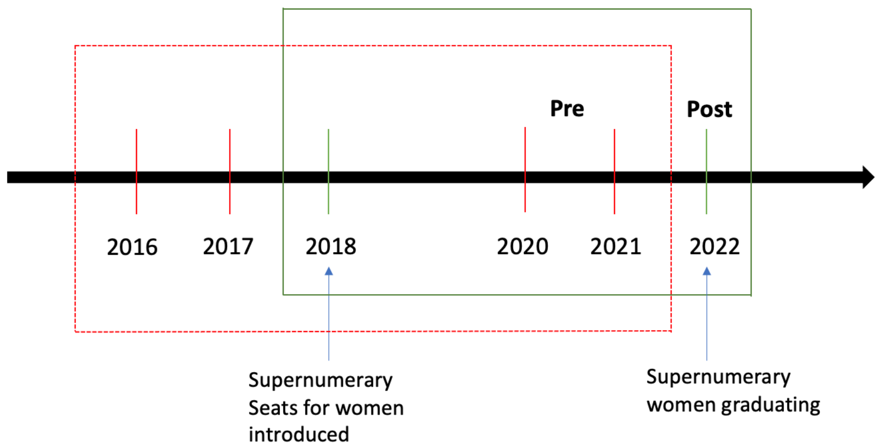
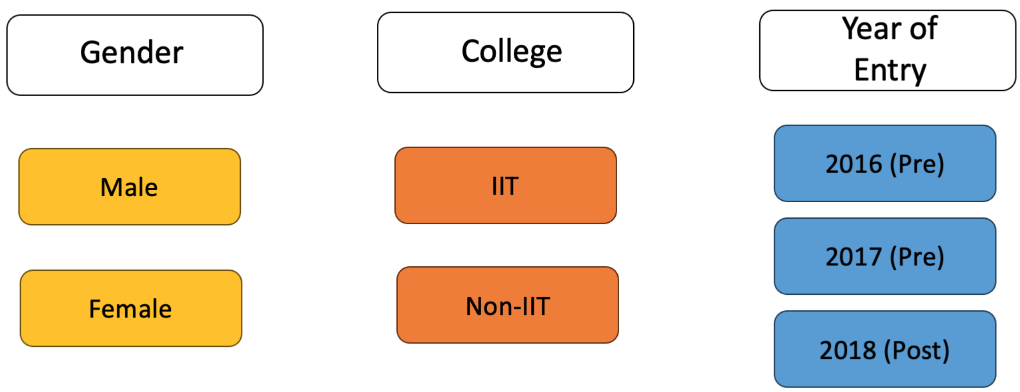


FIGURE 2

Note: This figure illustrates the impact of supernumerary seat policy on high- and medium-ranked college when college signal is more informative for females. In panel (a) proportion of high-type supernumerary females is low such that productivity in the medium-ranked college increases and in the high-ranked college falls below the threshold, in panel (b) productivity in both the medium-ranked and high-ranked college falls but it is still above the threshold such that callback is unaffected at both colleges, and in panel (c) proportion of high-type supernumerary females is large enough such that productivity in medium-ranked college falls below the threshold while the productivity in high-ranked college falls but their callbacks are unaffected.



(a) Policy Timeline



(b) Randomization within each job

FIGURE 3

Note: Panel (a) shows the timeline of the supernumerary seat policy. The first cohort exposed to the policy entered college in 2018 and graduated in 2022. This is the post-cohort in my analysis and two cohorts before it are the pre-cohorts. Panel (b) depicts the randomization of CVs within each job. 12 CV combinations (2X2X3) based on gender, college and year of entry, as depicted, were sent to each job.

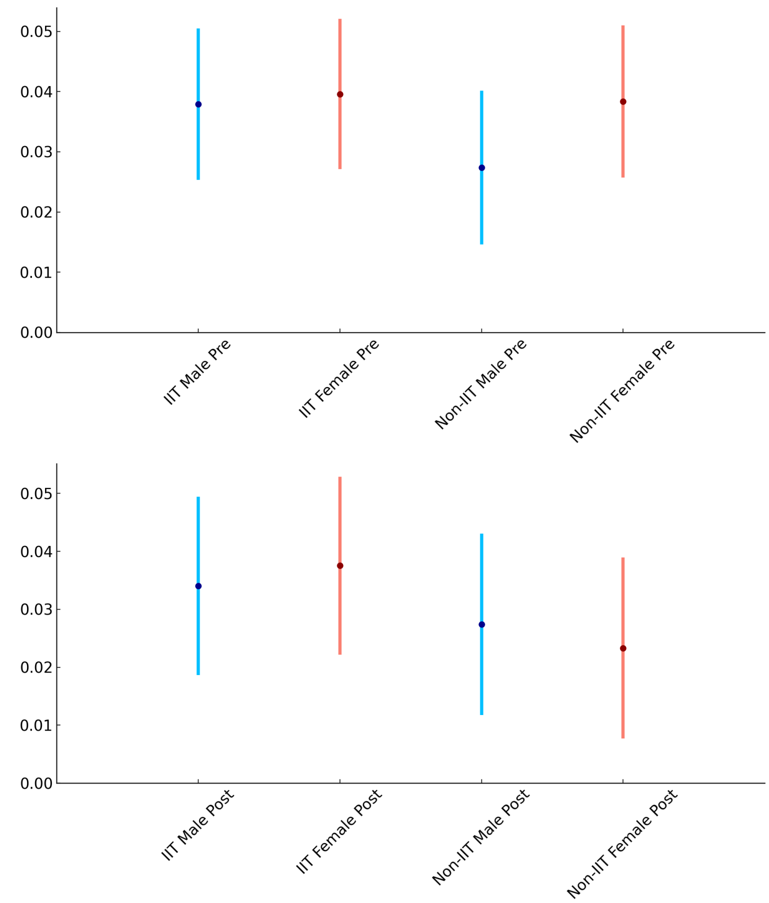
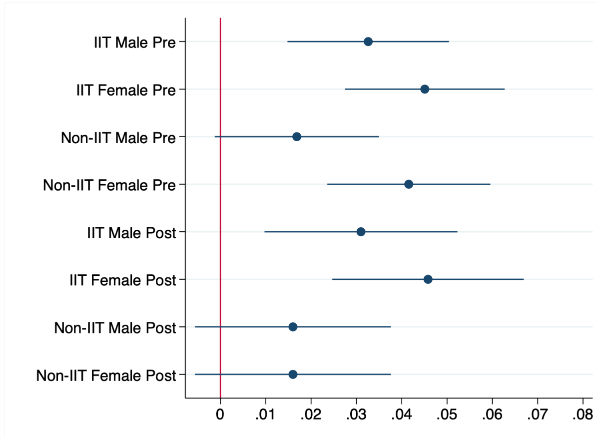
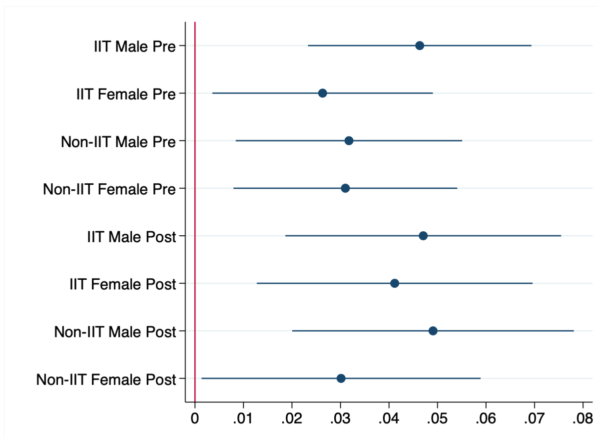


FIGURE 4

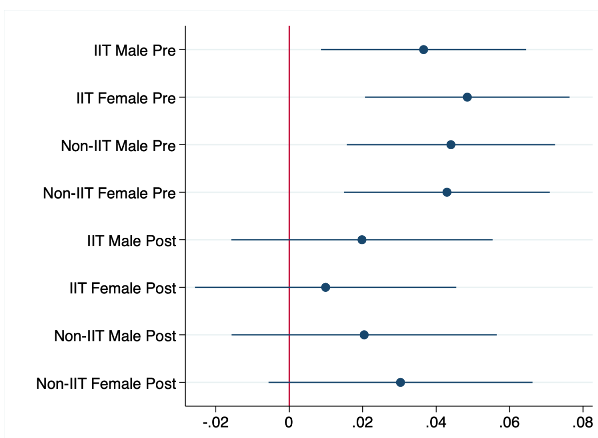
Note: This figure plots the overall callback rates from the correspondence study for each group along with their 95% confidence intervals, with the top panel showing it for the pre-cohorts and the bottom panel showing it for the post-cohorts. The average callback rate for each group is the coefficient in a simple regression (without constant) of callbacks on the corresponding dummy for each group. Confidence intervals are constructed using the standard errors of those coefficients.



Software



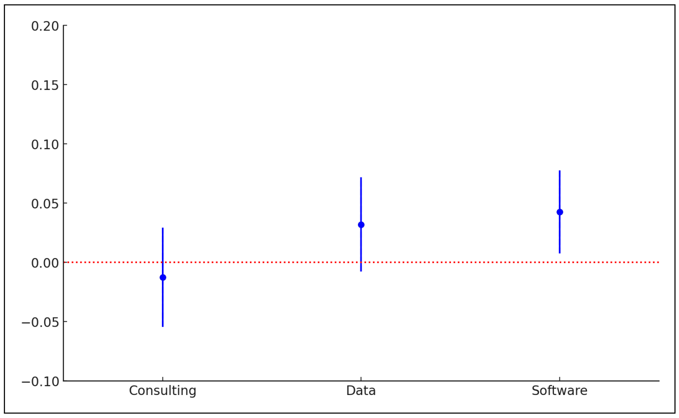
Data



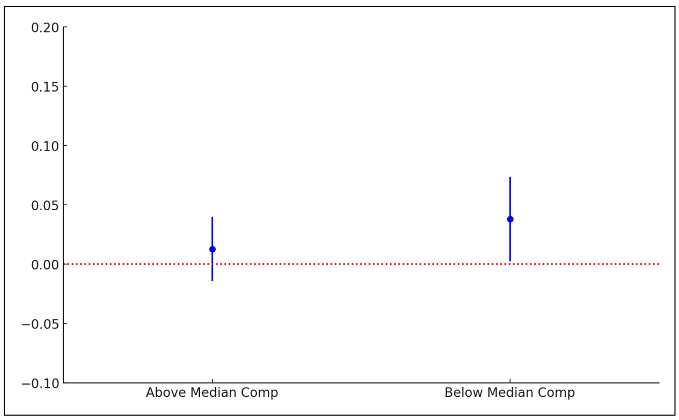
Consulting

FIGURE 5

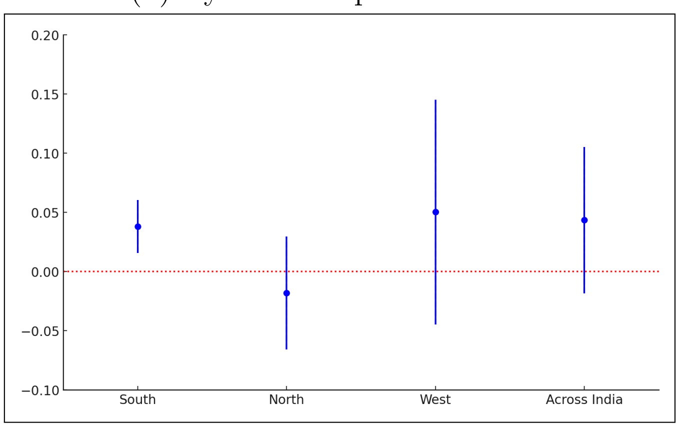
Note: This figures plots the overall callback rates from the correspondence study for each group along with their 95% confidence intervals within each job profile. The average callback rate for each group is the coefficient in a simple regression (without constant) of callbacks on the corresponding dummy for each group within a job profile. Confidence intervals are constructed using the standard errors of those coefficients.



(a) By Job Profile



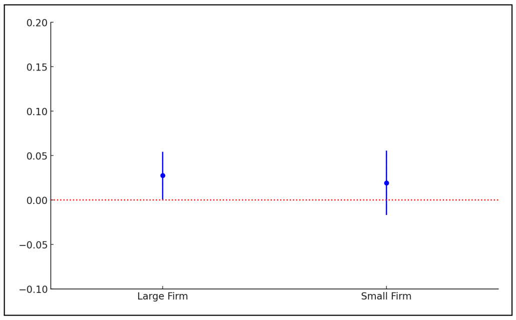
(b) By Job Compensation



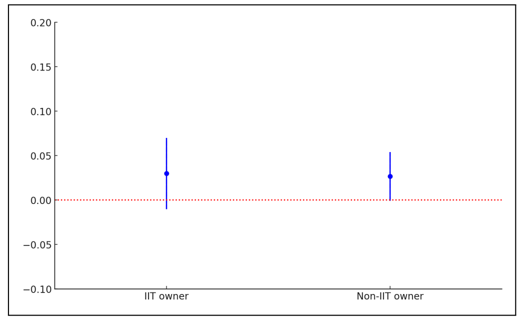
(c) By Job Location

Figure 6: Heterogeneity by Job Characteristics

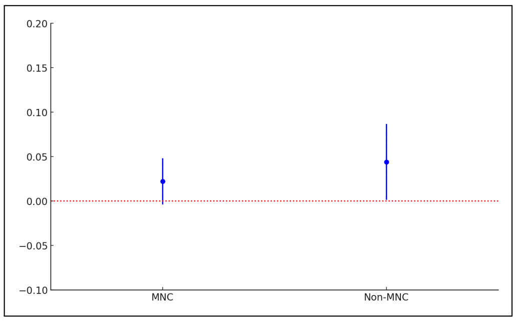
Note: This figure shows the triple difference coefficients (along with 90% confidence intervals) when I split my correspondence study sample by different job characteristics. Standard Errors are clustered at the job level and same controls are used as in the main regression to estimate the coefficient. Chow test indicate that coefficient for Data and Software profiles is statistically different from that of Consulting profile at the 5% level.



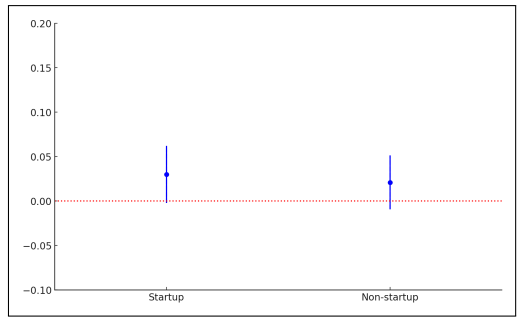
(a) By Firm Size



(b) By Owner of Firm



(c) By Firm being Multi-national



(d) By Firm being Startup

FIGURE 7: Heterogeneity by Firm Characteristics

Note: This figure shows the triple difference coefficients (along with 90% confidence intervals) when I split my correspondence study sample by different firm characteristics. Standard Errors are clustered at the job level and same controls are used as in the main regression to estimate the coefficient. Chow test indicates no statistically significant difference between the coefficients in any firm characteristic.

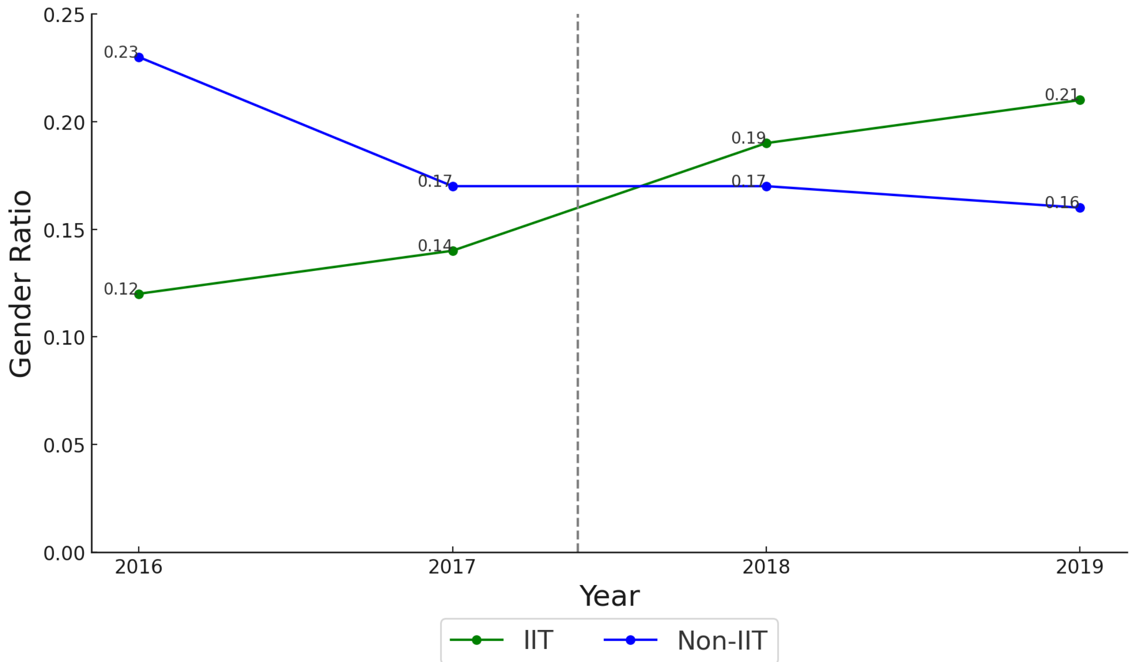


Figure 8

Note: This figures plots the proportion of females for a given cohort and college type in the LinkedIn profiles. IIT cohorts entering in 2018 and 2019 were exposed to the policy. There is a jump in proportion of females for IIT cohorts after 2017 in Linkedin whereas that seems to be stagnant after 2016 for the non-IIT cohorts.

Table 1: Callback Rates

	(1)	N_1	(2)	N_2	Diff	P-val
By Gender	Male		Female			
Callback	0.032	2598	0.036	2638	-0.004	0.461
By College Type	Non-IIT		IIT			
Callback	0.030	2575	0.038	2661	-0.008	0.124
By Year of Entry	Pre		Post			
Callback	0.036	3148	0.031	2088	0.005	0.304

Note: This table shows the overall callback rate of the correspondence study by the three broad parameters on which the CVs were randomized. There is no statistically significant difference between callback rates of male and female, non-IIT and IIT, and pre-policy and post-policy cohort resumes.

Table 2: Callback Rates of the eight groups

	Callback Rate
IIT Male	0.0379
IIT Female	0.0396
Non-IIT Male	0.0274
Non-IIT Female	0.0384

(a) Cohorts graduating in 2020 or 2021

	Callback Rate
IIT Male	0.0340
IIT Female	0.0375
Non-IIT Male	0.0274
Non-IIT Female	0.0233

(b) Cohorts graduating in 2022

Note: This table shows the raw callback rates of the correspondence study for each of the 8 sub-groups. Panel (a) corresponds to the pre-policy cohort resumes and panel (b) corresponds to the post-policy cohort resumes.

Table 3: DID estimate for two college-types

Callback (LPM)	IIT	Non-IIT	Overall
Female X Post	0.00196	-0.0212*	-0.00701
	(0.00975)	(0.0113)	(0.00659)
Female	3.83e-05	0.00866	0.00409
	(0.00671)	(0.00634)	(0.00401)
Post	0.0168	0.00537	0.00615
	(0.0132)	(0.0143)	(0.0100)
Control Mean	0.040	0.038	0.039
Observations	2,661	2,575	5,236
R-squared	0.033	0.034	0.026

Note: This table provides the coefficients of Equation (1) estimated using a linear probability model from the correspondence study data, separately for IIT and non-IIT resumes in column 1 and 2 respectively. Column 3 uses the full sample for DID estimation. The outcome variable is whether a job application received a callback. The regression includes controls for resume characteristics - location of school, resume template, work experience location, a dummy for a large work-ex, dummy for MNC internship, Class XII % age, Total applications sent to job, job tier, job profile, wave and years of experience. Standard Errors reported in parenthesis, are clustered at the job level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 4: Triple Difference Regression

Callback	LPM	Probit	Logit
Female X IIT X Post	0.0278**	0.0318**	0.0361**
	(0.0139)	(0.0153)	(0.0168)
Female X Post	-0.0212**	-0.0241**	-0.0271**
	(0.00907)	(0.0108)	(0.0115)
Female X IIT	-0.0106	-0.0132*	-0.0149*
	(0.00765)	(0.00784)	(0.00822)
Post X IIT	-0.0117	-0.0156	-0.0155
	(0.00946)	(0.0102)	(0.0107)
Female	0.00930*	0.0113*	0.0117*
	(0.00548)	(0.00598)	(0.00635)
Post	0.0121	0.0148	0.0138
	(0.0116)	(0.0122)	(0.0126)
IIT	0.00816	0.0122*	0.0124*
	(0.00623)	(0.00665)	(0.00723)
Control Mean	0.038	0.038	0.038
Observations	5,236	5,236	5,236
R-squared	0.027	0.0597	0.0598

Note: This table provides the coefficients of Equation (2) estimated using a linear probability model and marginal effects estimated for the Probit and Logit Models from the correspondence study data. The outcome variable is whether a job application received a callback. The regression includes controls for resume characteristics - location of school, resume template, work experience location, a dummy for a large work-ex, dummy for MNC internship, Class XII % age, Total applications sent to job, job tier, job profile, wave and years of experience. Standard Errors reported in parenthesis, are clustered at the job level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 5: Impact of Supernumerary on Additional applications to get a callback

Group	Additional Applications	95% CI
Non-IIT women	9.16	[7.97,10.35]
IIT women	-5.25	[-5.92, -4.58]
Non-IIT men	-14.3	[-15.24, -13.36]
IIT men	0.65	[-0.17, 1.47]

Note: This table summarizes the additional applications that each group will need to fill in order to get a callback after the policy. This is calculated by taking the difference of the inverse of the pre- and post-policy predicted callback rates (from the Probit model estimates of Equation (2)). The negative sign implies that the group will have to submit fewer applications than before. The last column shows the 95% confidence interval for these numbers (calculated using the Delta method).

Table 6: Placebo Regression - Triple Difference and DID

Callback (LPM)	IIT	Non-IIT	All
Female X IIT X Placebo Post			-0.0237
			(0.0221)
Female X Placebo Post	-0.0210	-0.00995	0.00102
	(0.0157)	(0.0154)	(0.0143)
Placebo Post X IIT			0.00398
			(0.0132)
Female X IIT			0.000708
			(0.0180)
Female	0.0140	0.0139	0.00839
	(0.0146)	(0.0107)	(0.0107)
Placebo Post	-0.0174*	-0.00608	-0.0115
	(0.0102)	(0.0108)	(0.00958)
IIT			0.00719
			(0.0101)
Observations	1,599	1,549	3,148
R-squared	0.040	0.051	0.036

Note: This table provides the coefficients of Equation (3) and the corresponding DID specification for the two college types separately only for the pre-cohort resumes in the correspondence study data. This regression excludes the data of 2022 graduating cohort (post-policy). The outcome variable is whether a job application received a callback. *Placebo Post* is a dummy for graduating year being 2021. The regression includes controls for resume characteristics - location of school, resume template, work experience location, a dummy for a large work-ex, dummy for MNC internship, Class XII % age, Total applications sent to job, job tier, job profile and wave. Standard Errors reported in parenthesis, are clustered at the job level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 7: Decomposition of Data by College (in % terms) & NIRF Rankings

	Correspondence Study	LinkedIn Data	NIRF Rankings 2023	% of LinkedIn profiles out of total cohort size
BITS Pilani	0.14	0.16	25	0.28
IIT Delhi	0.19	0.21	2	0.40
IIT Kanpur	0.25	0.22	4	0.56
IIT Indore	0.06	0.09	14	0.58
IIIT Hyderabad	0.08	0.04	55	0.29
NSUT Delhi	0.12	0.28	60	0.48
IIIT Delhi	0.10	0.00	75	-
SRM Chennai	0.03	0.00	28	-
VIT	0.03	0.00	11	-

Note: This table compares the proportion of data for each college in my correspondence study and Linkedin Data sample. LinkedIn data constitutes of colleges which form 85% of my correspondence study sample. National Institutional Ranking Framework (NIRF) is a ranking methodology adopted by the Ministry of Education, Government of India, to rank institutions of higher education in India. This table also shows the NIRF rankings for each of those colleges. The last column shows the percentage of the total cohort size for a given college covered in the LinkedIn sample. Overall, 43% of graduates at these colleges who entered between 2016-2019 are present in the data.

Table 8: LinkedIn Data: Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Ever employed in sample firm	.519	.499	0	1
Employed in sample firm within 6 months	.490	.499	0	1
Number of Distinct Jobs	.861	.766	0	5
Prop of time employed since graduation	.570	.437	0	1
Prop of time employed before higher education	.615	.433	0	1

Note: This table shows summary statistics of the main outcomes that I study from the LinkedIn Data. The number of observations is 4,724 for the first three outcomes and 6,980 for the last three outcomes.

Table 9: LinkedIn Data: Employment Outcomes

	Ever Employed in sample firm	Employed in sample firm within 6 months	Number of Distinct Jobs
Female X IIT X Post	0.142**	0.134**	-0.0842
	(0.0675)	(0.0642)	(0.101)
Female X Post	-0.0528	-0.0720**	0.158**
	(0.0384)	(0.0301)	(0.0671)
Female X IIT	-0.0326	-0.0238	0.0532
	(0.0365)	(0.0388)	(0.0967)
Post X IIT	-0.0554	-0.0448	-0.0339
	(0.0561)	(0.0613)	(0.129)
Female	0.0714**	0.0805***	-0.171**
	(0.0268)	(0.0181)	(0.0654)
Post	0.0270	0.0533	-0.492***
	(0.0343)	(0.0390)	(0.0912)
IIT	0.0607	0.0614	0.00454
	(0.0456)	(0.0516)	(0.0823)
Constant	0.478***	0.435***	1.132***
	(0.0290)	(0.0333)	(0.0502)
Control Mean	0.53	0.50	1
Observations	4,724	4,724	6,980
R-squared	0.005	0.007	0.106

Note: This table estimates Equation (2) for the employment outcomes in the LinkedIn data. There are no controls in these regressions. The outcome variable in the first column is whether an individual's first job is in one of the companies which were in my correspondence study sample; in the second column is whether the first job is in one of those companies and job started within 6 months of graduation (or same year as graduation year). The third dependent variable is the number of distinct companies where an individual worked after graduation (and before higher education, if any). Standard Errors clustered at cohort level are reported in parentheses.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 10: LinkedIn Data: Labor Force Participation Outcomes

	Prop of time employed since graduation	Prop of time employed before higher education
Female X IIT X Post	0.00800	0.0395
	(0.0465)	(0.0421)
Female X Post	0.0513	0.0147
	(0.0322)	(0.0257)
Female X IIT	-0.00542	-0.0350
	(0.0364)	(0.0303)
Post X IIT	-0.00949	-0.00609
	(0.0839)	(0.0820)
Female	-0.0859***	-0.0487***
	(0.0219)	(0.0117)
Post	-0.158**	-0.225***
	(0.0659)	(0.0602)
IIT	-0.00856	-0.0115
	(0.0362)	(0.0175)
Constant	0.667***	0.746***
	(0.0335)	(0.0111)
Control Mean	0.60	0.71
Observations	6,980	6,760
R-squared	0.035	0.070

Note: This table estimates Equation (2) for the labor force participation outcomes in the LinkedIn data. There are no controls in these regressions. The dependent variable in the first column is the number of years worked out of the total years that has passed after college till date; and in the second column is the number of years worked out of the total years that has passed after college excluding any years where individual is pursuing higher education. Standard Errors clustered at cohort level are reported in parentheses.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 11: LinkedIn Data: Sample Coverage

	Coverage Rate
Female X IIT X Post	-0.103
	(0.117)
Female X IIT	0.0170
	(0.108)
Post X IIT	0.104
	(0.0905)
Female X Post	-0.151
	(0.0915)
Female	0.264***
	(0.0869)
Post	-0.0663
	(0.0661)
IIT	0.0555
	(0.0520)
Constant	0.413***
	(0.0465)
Observations	6,980
R-squared	0.396

Note: This table estimates Equation (2) for the coverage rate in the LinkedIn data. There are no controls in these regressions. The dependent variable is the proportion of candidates covered in the LinkedIn data out of the total cohort size for each corresponding $genderXcollegeXentryyear$ combination. Standard Errors clustered at cohort level are reported in parentheses.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Appendix

A.1 Model

A.1.1 Derivations of Propositions

The propositions are derived by comparing the new probability of observing high type females from each college with μ^*.

Females in college θ_H will receive callback if $q'_H > \mu^*$.

i.e.

$$\frac{q_H + mx}{1+m} > \frac{\underline{\mu} - \mu_L}{\mu_H - \mu_L}$$

$$\implies x > \mu^* - \frac{q_H - \mu^*}{m} \equiv x_1^*$$

Females in college θ_M will receive callback if $q'_M > \mu^*$.

i.e.

$$\frac{q_M - nx}{1-n} > \frac{\underline{\mu} - \mu_L}{\mu_H - \mu_L}$$

$$\implies x < \mu^* + \frac{q_M - \mu^*}{n} \equiv x_2^*$$

A.1.2 Social Welfare Function

Employee's true productivity is revealed once he/she is hired and works for the firm. Suppose, a fixed wage w_L is promised at the time when employee is hired. If the employee turns out to be high-type, a bonus payment of B is disbursed at the end of the year. I can therefore write the yearly wage in the following manner:

$$w = \begin{cases} w_L + B\ (\equiv w_H) & \text{if } \mu = \mu_H \\ w_L & \text{if } \mu = \mu_L \end{cases}$$

Assuming all individuals getting a callback get hired and are paid wages according to their type, I can write an aggregate welfare function W as:

$$W = q_H w_H + (1 - q_H)w_L + q_M w_H + (1 - q_M)w_L + p_H w_H + (1 - p_H)w_L$$

The welfare function under the policy would change to W_p:

$$W_p = \mathbb{1}_{\{x>x_1^*\}}(q'_H w_H + (1 - q'_H)w_L) + \mathbb{1}_{\{x<x_2^*\}}(q'_M w_H + (1 - q'_M)w_L) + p_H w_H + (1 - p_H)w_L$$

where $q'_H = \frac{q_H+mx}{1+m}$ and $q'_M = \frac{q_M-nx}{1-n}$. An optimal policy will try to maximise W_p conditional on the constraint that it is higher than the original social welfare, i.e. $W_p > W$.

A.1.3 An Alternative Quota Policy

In this section, I extend the model to discuss the implications of an alternative (non-supernumerary) quota policy which displaces the non-beneficiaries in institutions that introduce affirmative action. In this case, the ability distribution of men will also be impacted in both top and middle-ranked colleges.

Suppose the proportion of females in college θ_i before any quota is w_i and therefore, that of the males is $1 - w_i$. When a quota for females is implemented it reserves certain number of seats for them and displaces the males who would have otherwise occupied those seats. Let the quota increase seats of females in top-colleges such that the proportion of women in class (out of all the women) increase by m. For example, if there were 10 females in a class of 100 to begin with, a 20% quota will increase their proportion by $m = 1 \equiv \frac{(20-10)}{10}$. The proportion of males (out of the total males) reduce to $1 - \frac{mw_H}{1-w_H} \equiv 1 - m^*$.

Going back to our basic setup, if x proportion of the additional females are of high-type, the likelihood of observing a high-type female in college θ_H changes from q_H to q'_H where $q'_H = \frac{q_H+mx}{1+m}$. Now, if y proportion of the displaced males are of high-ability, then the likelihood of observing a high-type male in college θ_H also changes from p_H to p'_H

where $p'_H = \frac{p_H - m^* y}{1-m^*}$.

Similarly, in college ranked θ_M that don't introduce quota, the likelihood of observing high-type female changes from q_M to q'_M where $q'_M = \frac{q_M - nx}{1-n}$ where n is the reduction in proportion of females due to quota in top colleges.[30] Males who are unable to qualify for admission in top colleges due to female reservation now occupy the vacant seats at middle-ranked colleges. Therefore, the likelihood of observing high-ability males in middle-ranked college also changes from p_M to p'_M where $p'_M = \frac{p_M + n^* y}{1+n^*}$ and $n^* = \frac{n w_M}{1-w_M}$.

The implications of such a policy depends on the relative change in ability distribution of males and females in both college types. Males in college θ_i receive callback from the representative employer if $p_i > \mu^*$. Specifically, males in college θ_M receive a callback if $y > \mu^* + \frac{\mu^* - p_M}{n^*} \equiv y_1^*$ and males in college θ_H receive a callback if $y < \mu^* + \frac{p_H - \mu^*}{m^*} \equiv y_2^*$.

Let us define gender gap in college i as callback of males minus callback of female graduates of college i. In the base case, both males and females receive callback and therefore the gender gap in college H is 0, whereas in college M, only females receive callback and the gender gap is -1.

CASE 1A: $x < x_1^*$ & $y < y_1^*$

In the middle-ranked college, females still receive a callback and males don't. There is no change in gender gap compared to the base setup. In the top-ranked colleges, females stop getting callbacks whereas males keep on receiving callbacks increasing a gender gap to 1 from 0.

CASE 1B: $x < x_1^*$ & $y_1^* < y < y_2^*$

In the middle-ranked college, females still receive a callback and males also start receiving callbacks which increases gender gap increases to 0 from -1. In the top-ranked colleges, females stop getting callbacks whereas males keep on receiving callbacks increasing a gender gap to 1 from 0.

CASE 1C: $x < x_1^*$ & $y > y_2^*$

[30] Now females in middle-ranked colleges reduce not just because some of them move to top-colleges but also because they get displaced by the additional males displaced from top-colleges.

In the middle-ranked college, females still receive a callback and males also start receiving callbacks which increases gender gap increases to 0 from -1. In top-ranked colleges, both males and females stop receiving callbacks and gender gap remains 0.

CASE 2A: $x_1^* < x < x_2^*$ & $y < y_1^*$

In the middle-ranked college, females still receive a callback and males don't. There is no change in gender gap compared to the base setup. In top-colleges, both males and females still receive a callback and therefore the gender gap remains 0.

CASE 2B: $x_1^* < x < x_2^*$ & $y_1^* < y < y_2^*$

In the middle-ranked college, females still receive a callback and males also start receiving callbacks which increases gender gap increases to 0 from -1. In top-ranked college, both males and females still receive a callback and therefore the gender gap remains 0.

CASE 2C: $x_1^* < x < x_2^*$ & $y > y_2^*$

In the middle-ranked college, females still receive a callback and males also start receiving callbacks which increases gender gap increases to 0 from -1. In top-ranked college, females still receive a callback but males stop receiving and therefore the gender gap falls from 0 to -1.

CASE 3A: $x > x_2^*$ & $y < y_1^*$

In the middle-ranked college, females stop getting callback and males don't get a callback either which increases gender gap from -1 to 0. In top-ranked college, both males and females still receive a callback and therefore gender gap remains 0.

CASE 3B: $x > x_2^*$ & $y_1^* < y < y_2^*$

In middle-ranked college, female stop getting callback but males start getting callback which increases gender gap from -1 to 1. In top-ranked college, both males and females still receive a callback and therefore gender gap remains 0.

CASE 3C: $x > x_2^*$ & $y > y_2^*$

In middle-ranked college, female stop getting callback but males start getting callback which increases gender gap from -1 to 1. In top-ranked college, females still receive a callback but males don't and gender gap falls from 0 to -1.

A.2 Tables & Figures

Table A.1: IIT Exam Closing Ranks

Entry Year	Cut-off Rank (Gender-Neutral)	Corresponding Marks	Cut-off Rank (Female-Only)	Corresponding Marks
2017	14,983	163/366	-	-
2018	12,216	122/360	16,035	110/360

Note: Data Source: IIT Exam Reports. This table estimates shows the cut-off rank and marks for the IIT entrance exam for two years (2017 is before policy and 2018 is post-policy). Cut-off is determined by the rank/score of the last person taking admission.

Table A.2

No of successful applications per job	No of jobs
1	18
2	17
3	13
4	35
5	8
6	17
7	5
8	302
9	0
10	0
11	0
12	201

Note: This table gives the number of jobs where a certain number of successful applications were done in the correspondence study (combined for the two waves). Total applications per job varied because certain job links would expire in the middle of the study.

Table A.3: Balance by Gender

Variable	Male	Female	Diff	P-value
CGPA	8.19	8.22	-0.02	0.27
Class XIIth %	93.39	93.44	-0.05	0.70
School in North	0.73	0.76	-0.04	0.39
School in West	0.27	0.24	0.04	0.39
Work-Ex in MNC firm	0.68	0.77	-0.09**	0.03
Work-Ex in Large firm	0.80	0.87	-0.08**	0.03
Work Ex Location				
Bangalore	0.17	0.22	-0.05	0.19
Delhi/NCR	0.61	0.58	0.03	0.50
Mumbai	0.22	0.20	0.02	0.64
Intern in MNC/Non-Indian University	0.93	0.95	-0.02	0.44
Intern in Industry	0.93	0.94	-0.01	0.70
Resume Template				
Resume 1	0.25	0.23	0.02	0.66
Resume 2	0.25	0.27	-0.02	0.59
Resume 3	0.26	0.23	0.03	0.51
Resume 4	0.24	0.26	-0.02	0.58
Observations	222	222		

Note: This table shows balance between male and female resumes used in the study for various resume characteristics.

Table A.4: Balance by College Type

Variable	Non-IIT	IIT	Diff	P-value
CGPA	8.21	8.20	0.01	0.56
Class XIIth %	93.39	93.44	-0.05	0.72
School in North	0.79	0.69	0.10**	0.02
School in West	0.21	0.31	-0.10**	0.02
Work-Ex in MNC firm	0.73	0.72	0.01	0.75
Work-Ex in Large firm	0.82	0.86	-0.04	0.25
Work Ex Location				
Bangalore	0.17	0.22	-0.05	0.19
Delhi/NCR	0.61	0.57	0.04	0.39
Mumbai	0.22	0.21	0.01	0.82
Intern in MNC/Non-Indian University	0.94	0.94	0.00	1.00
Intern in Industry	0.92	0.95	-0.03	0.24
Resume Template				
Resume 1	0.24	0.25	-0.01	0.83
Resume 2	0.29	0.23	0.06	0.16
Resume 3	0.22	0.28	-0.06	0.12
Resume 4	0.26	0.24	0.01	0.74
Observations	222	222		

Note: This table shows balance between IIT and Non-IIT resumes used in the study for various resume characteristics.

Table A.5: Balance by Year of Entry

Variable	Pre	Post	Diff	P-value
CGPA	8.22	8.18	0.03	0.11
Class XIIth %	93.36	93.50	-0.14	0.31
School in North	0.72	0.79	-0.07	0.11
School in West	0.28	0.21	0.07	0.11
Work-Ex in MNC firm	0.74	0.71	0.02	0.58
Work-Ex in Large firm	0.81	0.88	-0.07*	0.07
Work Ex Location				
Bangalore	0.16	0.26	-0.09**	0.02
Delhi/NCR	0.61	0.56	0.04	0.37
Mumbai	0.23	0.18	0.05	0.22
Intern in MNC/Non-Indian University	0.94	0.92	0.02	0.38
Intern in Industry	0.95	0.91	0.04*	0.09
Resume Template				
Resume 1	0.25	0.24	0.01	0.83
Resume 2	0.25	0.27	-0.02	0.72
Resume 3	0.22	0.29	-0.07*	0.09
Resume 4	0.28	0.20	0.08*	0.07
Observations	288	156		

Note: This table shows balance between pre-policy and post-policy cohort resumes used in the study for various resume characteristics.

Table A.6: Overall Callback Rate of Gender X College Type group

	Callback Rate
IIT Male	0.0364
IIT Female	0.0388
Non-IIT Male	0.0274
Non-IIT Female	0.0324

Note: This table shows the overall callback rate in the correspondence study for each gender-college category.

Table A.7: Callback Rates by Year of Entry

Variable		N		N	Diff
By Gender	Male		Female		
Pre-period	0.0327	1558	0.0390	1590	-0.0063
Post-period	0.0308	1040	0.0305	1048	0.0002
By College Type	Non-IIT		IIT		
Pre-period	0.033	1549	0.039	1599	-0.006
Post-period	0.0253	1026	0.0358	1062	-0.0104

Note: This table shows the overall callback rate in the correspondence study for each gender-cohort and college-cohort category.

Table A.8: Callback Rates by Job Profiles

Variable		N		N	Diff	P-Value
By Gender	Male		Female			
Software	0.024	1232	0.038	1250	-0.014**	0.045
Data	0.043	844	0.031	860	0.011	0.218
Consulting	0.033	522	0.036	528	-0.003	0.761
By College Type	Non-IIT		IIT			
Software	0.024	1217	0.039	1265	-0.015**	0.033
Data	0.035	839	0.039	865	-0.005	0.604
Consulting	0.037	519	0.032	531	0.005	0.683
By Year of Entry	Pre		Post			
Software	0.034	1462	0.027	1020	0.007	0.343
Data	0.034	1035	0.042	669	-0.008	0.391
Consulting	0.043	651	0.020	399	0.023**	0.047

Note: This table shows the overall callback rate of the correspondence study by the three broad parameters on which the CVs were randomized for different job profiles.

Table A.9: Two-sided t-tests between each pair of group

(1)	Callback Rate	(2)	Callback Rate	Difference
IIT Male Pre	0.0379	IIT Male Post	0.0340	0.004
		IIT Female Pre	0.0396	-0.002
		IIT Female Post	0.0375	0.000
		Non-IIT Male Pre	0.0274	0.011
		Non-IIT Male Post	0.0274	0.011
		Non-IIT Female Pre	0.0384	0.000
		Non-IIT Female Post	0.0233	0.015
IIT Male Post	0.0340	IIT Female Pre	0.0396	-0.006
		IIT Female Post	0.0375	-0.003
		Non-IIT Male Pre	0.0274	0.007
		Non-IIT Male Post	0.0274	0.007
		Non-IIT Female Pre	0.0384	-0.004
		Non-IIT Female Post	0.0233	0.011
IIT Female Pre	0.0396	IIT Female Post	0.0375	0.002
		Non-IIT Male Pre	0.0274	0.012
		Non-IIT Male Post	0.0274	0.012
		Non-IIT Female Pre	0.0384	0.001
		Non-IIT Female Post	0.0233	0.016
IIT Female Post	0.0375	Non-IIT Male Pre	0.0274	0.010
		Non-IIT Male Post	0.0274	0.010
		Non-IIT Female Pre	0.0384	-0.001
		Non-IIT Female Post	0.0233	0.014
Non-IIT Male Pre	0.0274	Non-IIT Male Post	0.0274	0.000
		Non-IIT Female Pre	0.0384	-0.011
		Non-IIT Female Post	0.0233	0.004
Non-IIT Male Post	0.0274	Non-IIT Female Pre	0.0384	0.011
		Non-IIT Female Post	0.0233	0.004
Non-IIT Female Pre	0.0384	Non-IIT Female Post	0.0233	0.015

Note: This table shows the differences between each pairwise sub-group and its significance level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A.10: DID: Probit & Logit Models

Callback	Probit	Probit	Logit	Logit
Female X Post	0.00348	-0.0210*	0.00469	-0.0234*
	(0.0117)	(0.0110)	(0.0125)	(0.0121)
Female	-0.000993	0.0112*	-0.00272	0.0116*
	(0.00752)	(0.00609)	(0.00806)	(0.00681)
Post	0.0170	0.00288	0.0179	0.00241
	(0.0144)	(0.0144)	(0.0147)	(0.0149)
Control Mean	0.040	0.038	0.040	0.038
Observations	2,661	2,575	2,661	2,575
Sample	IIT	Non-IIT	IIT	Non-IIT

Note: This table provides the marginal effects of Equation (1) estimated using probit and logit model from the correspondence study data, separately for IIT and non-IIT resumes. The outcome variable is whether a job application received a callback. The regression includes controls for resume characteristics - location of school, resume template, work experience location, a dummy for a large work-ex, dummy for MNC internship, Class XII % age, Total applications sent to job, job tier, job profile, wave and years of experience. Standard Errors reported in parenthesis, are clustered at the job level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A.11: LinkedIn Data: Wage Score

	Wage Score
Female X IIT X Post	0.0969
	(0.802)
Female X Post	-0.517**
	(0.235)
Female X IIT	-0.0709
	(0.522)
Post X IIT	0.121
	(0.461)
Female	0.373***
	(0.116)
Post	0.555
	(0.342)
IIT	-0.363
	(0.378)
Constant	5.234***
	(0.265)
Observations	1,569
R-squared	0.012

Note: This table estimates Equation (2) for wage score as ranked using approximate wages of 1,569 individuals in the LinkedIn data. There are no controls in these regressions. The dependent variable in the first column is a wage score measure which takes values from 1 to 10, where 1 is assigned to the jobs paying wages that fall in the bottom 10 percentile and 10 assigned to jobs paying wages that fall in the highest 10 percentile. Wages for each profile are scraped using the company name and job designation of the individual from a website called *Levels.fyi*. Standard Errors clustered at cohort level are reported in parentheses.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A.12: Names

Male Names					
AAKARSH	KUNAL	BHUVAN	ASHISH	PIYUSH	HARDIK
ABHAY	KUSH	CHANDAN	AYUSH	PRANJAL	HARSH
ABHISHEK	LAKSHAY	CHETAN	BHASKAR	PRASHANT	HARSHIT
ADITYA	MANISH	CHINMAY	BHAVESH	PUNEET	HIMANSHU
AJAY	MAYANK	CHIRAG	RAGHAV	SHANTANU	INDRAJEET
AMAN	MOHIT	DEEPAK	RAHUL	SHASHANK	JAY
AMANDEEP	MUKESH	DEVANSH	RAJA	SHIVAM	KAPIL
ANIL	NIKHIL	DEVESH	RAJESH	SHIVOM	KARAN
ANIRUDH	NIKUNJ	DINESH	RITIK	SHUBHAM	UTKARSH
ANKIT	NISHANT	DIVANSHU	ROHAN	SIDHARTH	VANSH
ANKUR	NITIN	EKANSH	SAGAR	SOMESH	YASH
ANSHUMAN	PARAS	GAGANDEEP	SAHIL	SURAJ	
ANUP	PARIKSHIT	GANESH	SARTHAK	SAURABH	
ANURAG	PAWAN	GAURAV	TANVIR	TUSHAR	
Female Names					
ADITI	KAVYA	REENA	DEVIKA	NUPUR	SHRUTI
AKSHARA	LEENA	REETIKA	DEVYANI	OJASVITA	SIMRAN
AKSHITA	MAHIMA	RIDHI	DIVYA	PALAK	SOMYA
AMITA	MANSI	RISHIKA	EKTA	PARUL	SUGANDHA
ANISHA	MEDHA	RITU	GAURI	PAYAL	SURBHI
ANKITA	MEETA	RITWIKA	GEETIKA	POONAM	TANVI
ANSHIKA	MEGHA	RIYA	HARSHITA	PREETI	TANYA
ARUSHI	MIKISHA	SAKSHI	IRA	PRIYA	VAMIKA
ASHIMA	NEHA	SALONI	ISHA	PRIYANKA	VANSHIKA
AVIKA	NIDHI	SANCHITA	ISHITA	PRIYANSHI	VIDYA
AYUSHI	NIHARIKA	SANYA	JYOTI	RADHIKA	VRINDA
BHAVYA	NIKITA	SAUMYA	KALIKA	RAKHI	
DEEPALI	NISHA	SHIKHA	KANIKA	YASHI	
DEEPIKA	NISHTHA	SHREYA	RASHI	YASHIKA	
Last Names					
AGARWAL	BHATIA	CHHABRA	KURSIJA	SETH	KHANDELWAL
AGGARWAL	BHATTACHARYA	CHOPRA	MADAN	SETHI	KOHLI
AHUJA	JAIN	DHINGRA	MAHAJAN	SHARMA	TRIVEDI
ANEJA	JINDAL	GARG	MEHRA	SINGHAL	UPADHYAY
ARORA	BINDAL	GOEL	MISHRA	SINGLA	ROY
BAKSHI	CHATURVEDI	GOYAL	MITTAL	SONI	SACHDEVA
BANSAL	CHAUHAN	GROVER	MUKHERJI	SOOD	SAHNI
BATRA	CHAWLA	GUPTA	PATEL	TRIPATHI	
RASTOGI	RAWAT	KALRA	KAPOOR	SAXENA	

Note: This table shows the sample of Indian names from which I randomly selected the names for the correspondence study. All last names belong to upper-caste.

Table A.13: Other CV characteristics

Tier	Job Profile	Type of College	College Name	Degree Type
Tier 1	Consulting	AA	Indian Institute of Technology, Delhi	B.Tech in Chemical Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Delhi	B.Tech in Mechanical Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Delhi	B.Tech in Civil Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Delhi	B.Tech. in Biochemical Engineering and Biotechnology
Tier 1	Consulting	AA	Indian Institute of Technology, Kanpur	B.Tech in Chemical Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Kanpur	B.Tech in Mechanical Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Kanpur	B.Tech in Civil Engineering
Tier 1	Consulting	AA	Indian Institute of Technology, Kanpur	B.Tech in Biological Sciences and Bio-Engineering
Tier 1	Consulting	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Manufacturing Processes and Automation Engineering
Tier 1	Consulting	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Mechanical Engineering
Tier 1	Consulting	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Civil Engineering
Tier 1	Consulting	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Mechanical Engineering
Tier 1	Consulting	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Chemical Engineering
Tier 2	Consulting	AA	Indian Institute of Technology, Indore	B.Tech in Mechanical Engineering
Tier 2	Consulting	AA	Indian Institute of Technology, Indore	B.Tech in Civil Engineering
Tier 2	Consulting	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Mechanical Engineering
Tier 2	Consulting	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Chemical Engineering
Tier 2	Consulting	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Civil Engineering
Tier 2	Consulting	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Biotechnology
Tier 1	Software	AA	Indian Institute of Technology, Delhi	B. Tech in Computer Science & Engineering
Tier 1	Software	AA	Indian Institute of Technology, Delhi	B.Tech. in Electrical Engineering
Tier 1	Software	AA	Indian Institute of Technology, Kanpur	B.Tech in Computer Science & Engineering
Tier 1	Software	AA	Indian Institute of Technology, Kanpur	B.Tech. in Electrical Engineering
Tier 1	Software	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Computer Engineering
Tier 1	Software	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Electronics and Communication Engineering
Tier 1	Software	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Computer Science Engineering
Tier 1	Software	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Electrical and Electronics Engineering
Tier 1	Software	Non-AA	International Institute of Information Technology, Hyderabad	B.Tech in Computer Science and Engineering
Tier 1	Software	Non-AA	International Institute of Information Technology, Hyderabad	B.Tech in Electronics and Communication Engineering
Tier 1	Software	Non-AA	Indraprastha Institute of Information Technology, Delhi	B.Tech in Computer Science and Engineering
Tier 1	Software	Non-AA	Indraprastha Institute of Information Technology, Delhi	B.Tech in Electronics and Communication Engineering
Tier 2	Software	AA	Indian Institute of Technology, Indore	B. Tech in Computer Science & Engineering
Tier 2	Software	AA	Indian Institute of Technology, Indore	B.Tech. in Electrical Engineering
Tier 2	Software	Non-AA	SRM Institute of Science and Technology, Chennai	B. Tech in Computer Science & Engineering
Tier 2	Software	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Electrical and Electronics Engineering
Tier 1	Data	AA	Indian Institute of Technology, Delhi	B. Tech in Computer Science & Engineering
Tier 1	Data	AA	Indian Institute of Technology, Delhi	B.Tech. in Electrical Engineering
Tier 1	Data	AA	Indian Institute of Technology, Kanpur	B.Tech in Computer Science & Engineering
Tier 1	Data	AA	Indian Institute of Technology, Kanpur	B.Tech. in Electrical Engineering
Tier 1	Data	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Computer Engineering
Tier 1	Data	Non-AA	Netaji Subhash Institute of Technology, Delhi	B.Tech in Electronics and Communication Engineering
Tier 1	Data	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Computer Science Engineering
Tier 1	Data	Non-AA	Birla Institute of Technology & Sciences, Pilani	B.E. Hons in Electrical and Electronics Engineering
Tier 1	Data	Non-AA	International Institute of Information Technology, Hyderabad	B.Tech in Computer Science and Engineering
Tier 1	Data	Non-AA	International Institute of Information Technology, Hyderabad	B.Tech in Electronics and Communication Engineering
Tier 1	Data	Non-AA	Indraprastha Institute of Information Technology, Delhi	B.Tech in Computer Science and Engineering
Tier 1	Data	Non-AA	Indraprastha Institute of Information Technology, Delhi	B.Tech in Electronics and Communication Engineering
Tier 2	Data	AA	Indian Institute of Technology, Indore	B. Tech in Computer Science & Engineering
Tier 2	Data	AA	Indian Institute of Technology, Indore	B.Tech. in Electrical Engineering
Tier 2	Data	Non-AA	SRM Institute of Science and Technology, Chennai	B. Tech in Computer Science & Engineering
Tier 2	Data	Non-AA	SRM Institute of Science and Technology, Chennai	B.Tech in Electrical and Electronics Engineering

Tier	Minimum College CGPA	Maximum College CGPA	Minimum Marks (Grade 12)	Maximum Marks (Grade 12)	Grade 10 CGPA
Tier 1	8	8.5	91	96	10
Tier 2	7.25	7.75	91	96	10

Note: The above tables show the list for other characteristics (college name, degree, College CGPA, Class 10 and 12 grades) which were used in randomization.

Table A.14: Gender Discrimination in Other Studies

Study	**Research Question**	**Estimates**
Neumark (1996)	High-price jobs in US	0.58
Riach and Rich (2006)	Engineers in England	0.5
Petit (2007)	High-skilled jobs in France	0.58
Bravo et al (2007)	Newspaper job applications in Chile	0
Zhou et al (2013)	Software engineers in China	0
Albert et al (2018)	All jobs in Spain (find occupational segregation)	0
Yavorsky (2019)	Male-dominated jobs in 5 US states	0
Birkelund et al (2021)	Male-dominated jobs in 6 western countries	0
Ahmed et al (2021)	Male-dominated jobs in Sweden	0
Kline et al (2022)*	Low-skilled jobs, find high heterogeneity within US firms	0.23
Adamovic et al (2023)	Male-dominated jobs in Australia	0.33

Note: This tables shows a list of gender discrimination estimates in seminal papers that conducted a correspondence study.

*Estimate provided for the high-end jobs that discriminate against women.

Table A.15: LinkedIn Results using Coverage Rates as Weights

	Ever Employed in sample firm	Employed in sample firm within 6 months	Number of Distinct Jobs
Female X IIT X Post	0.151**	0.136**	-0.0307
	(0.0629)	(0.0605)	(0.104)
Female X Post	-0.0487	-0.0654***	0.153**
	(0.0288)	(0.0232)	(0.0686)
Female X IIT	-0.0363	-0.0182	0.00151
	(0.0312)	(0.0341)	(0.0984)
Post X IIT	-0.0633	-0.0514	-0.0407
	(0.0553)	(0.0604)	(0.129)
Female	0.0646***	0.0697***	-0.163**
	(0.0171)	(0.0118)	(0.0674)
Post	0.0344	0.0613	-0.492***
	(0.0351)	(0.0402)	(0.0917)
IIT	0.0565	0.0535	-0.00868
	(0.0485)	(0.0542)	(0.0829)
Constant	0.473***	0.432***	1.145***
	(0.0323)	(0.0374)	(0.0546)
Observations	4,724	4,724	6,980
R-squared	0.005	0.007	0.104

Note: Main results are repeated using coverage rates as weights

SOMYA MEHRA

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Education

Indian Institute of Technology, Kanpur *2017-2021*
B.Tech in Computer Science & Engineering *CGPA: 8.18/10*

Central Model School *2017*
CBSE *92.8%*

Central Model School *2015*
CBSE *GPA: 10/10*

Work experience

Samsung Research Institute *July 2021 - Present*
Software Engineer *Noida, India*

- Worked with the Enterprise Device Management Team to implement Confidential Action Functionality for Remote Control Admin
- Researched about the existing mechanisms like SurfaceFlinger for compositing mobile display surface from multiple layers
- Designed ways to block screen content on the display while being visible on EDM's RC Server; made an API for the same

Meesho *May 2020 - July 2020*
Intern *Bangalore, India*

- Administered a pilot project to introduce a new mentorship programme consisting of 200+ mentors and 1000+ resellers
- Formulated a plan for new growth opportunities by rectifying existing consumer problems post mobile application activation
- Enhanced and improvised existing Meesho Pathshala, decreasing churn rate by 22.4% and complaint issue by 13.6%

Extracurricular activities

- Badminton: Participated in Inter College Championship
- Runner-Up, Social Entrepreneurship Challenge: among 500+ college teams; judged on social impact
- Lead Vocalist, Inaugural Ceremony, Inter-College Competition in College Fest

Scholastic Achievements

- KVPY Scholar: Awarded scholarship to top 1000 students by Department of Science and Technology, Govt. of India
- International Math Qualifier: Got 597 international rank in International Math Qualifier conducted by NFO

Technical skills

Programming Languages	R, Java, C/C++, Python
Development Tools	React, CSS, JavaScript, Linux, Git, HTML

Figure A.1

Note: This is a sample CV of a female software engineer who graduated from IIT Kanpur in 2021.