BRIDGING THE GENDER GAP: AFFIRMATIVE ACTION, SOCIAL NORMS, AND WOMEN EMPOWERMENT

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(ABSTRACT)

My dissertation comprises three independent yet thematically related chapters on development, gender and labor economics. The first two chapters focus on the impact of college-based affirmative action policies on women in STEM. The first chapter examines the upstream effects by studying labor market outcomes and gender discrimination in hiring, while the second investigates downstream effects on the subject choice girls make at the high-school level. The third chapter focuses on the role social norms play within households in developing countries which has consequences on domestic violence faced by married women.

The first chapter, **"Equity Conundrum: Unintended Consequences of College-Level Affirmative Action on the Labor Market"**, examines the impact of affirmative action (AA) policies on discrimination in hiring against the beneficiary group. 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. I investigate 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.

The second chapter, titled **"Fixing the Leaky Pipeline: Affirmative Action in Local Elite Colleges and Subject Choice"**, examines the same policy's impact on girls' educational outcomes in school. Women are largely underrepresented in STEM careers associated with higher labor market returns. This gender gap is even more stark in a context where societal biases are prevalent and female role models are lacking. I investigate the impact of an affirmative action policy implemented in an elite educational institution in India that ensures additional seats specifically for women in undergraduate STEM courses. After the policy was implemented, the proportion of women enrolling increased by 100%, proportion of women taking the college entrance exam increased by 10% and those qualifying the exam increased by 15%. Using nationally representative data, I employ a triple difference strategy and find a 27% increase in the probability of studying science courses after Grade 10 amongst younger girls exposed to this policy, suggesting a 6% increase in the expected earnings of women.

In the third chapter, co-authored with Sheetal Sekhri and Pooja Khosla, titled **"Em-**

powering to Conform: Age at Marriage, Social Norms, and Violence Against Women", we deliver a theoretical model of domestic violence which proposes that delayed age of marriage aids women in complying to socially desirable behavior expected by the husband rather than challenging the dis-empowering norms. The theory predicts that delaying the age of marriage would reduce domestic violence, but individual wealth of the wife would offset this effect. We corroborate the model by leveraging two rounds of nationally representative health surveys from India and differences in societal and marriage practices among Hindus and Muslims, finding causal empirical support for our theory. Using age of menarche as an instrument, we find that one year delay in age of marriage reduces emotional violence by 18%, less severe physical violence by 26% and severe physical violence by 39%. These findings are stronger amongst Hindu women and gets muted for Muslims who typically have higher wealth at the time of marriage. Our paper highlights that fear of violence can undermine empowering policies when there is widespread acceptance of beating social norms.

Dedication

This dissertation is dedicated to my husband and our parents.

Acknowledgments

Doing a PhD means climbing a mountain of questions, only to discover the summit is still higher each morning.

This dissertation would not have come to its final shape without the support of my faculty advisors, peers, family and other countless people who have provided me feedback on the way while supporting me through the PhD journey.

I would like to begin by expressing my deepest gratitude to my committee members who have invested their precious time and energy in training and mentoring me. The chair of my committee, Sheetal Sekhri, has been an amazing mentor in shaping my research interests and portfolio providing me opportunities to grow as a researcher and has supported me through challenging times of Covid. Amalia Miller and Gaurav Chiplunkar have always been available to provide important critical feedback while supporting and encouraging me to answer big and broader research questions. Emma Harrington has been extremely kind providing me essential feedback during my research and helpful comments on my writing and presentation. The technical expertise and important advice of my committee members has always pushed me to advance the frontiers of my knowledge. I feel fortunate to have obtained immense support and guidance from them. Uncountable moments of distress and despair were turned to moments of comfort and hope whenever I talked to them, especially when my research was at a standstill. Without them, it would have been impossible for me to overcome all the challenges I faced during my PhD journey.

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Chapter 1

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

1.1 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 entering IITs (R. 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

[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.

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 this analysis separately for applicants from IITs, who were directly affected by the AA policy, and for applicants from non-IITs, who

[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.

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

[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.

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 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 45% of students who graduated from IITs and elite non-IIT colleges between 2020 and 2023. Using parallel regressions that involve triple interactions, I find that IIT females graduating in the post-policy cohort are 13.4 percentage points (or 26%) more likely to be employed at the firms[6] included in the correspondence study sample within the first 6 months after graduation than non-IIT females relative to males. In contrast, non-IIT females in the post-policy cohort are 7.2 percentage points (or 13.6%) less likely to be employed at these firms within 6 months of graduation compared to non-IIT 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 corroborate the correspondence study results.

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

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

short-run effects, since the pool of engineering applicants may respond to the policy and change over time. Finally, other longer-term outcomes, such as wages, productivity, likelihood of getting promoted, marriage market, and migration indicators, are necessary in order to comment about the impact of the policy on overall welfare.

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, M. Hoekstra, and West 2019; Mousa 2020; Lowe 2021; Barnhardt 2009; G. 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; J. R. Shapiro and A. M. 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 1.2 explains the empirical context and the policy. Section 1.3 outlines the conceptual framework. Section 1.4 describes the research design and the correspondence study. Section 1.5 presents summary statistics, and Section 1.6 outlines the empirical methodology and tests the identifying assumptions. Section 1.7 discusses the main results from the correspondence study and Section 1.8 presents the findings from LinkedIn employment data. Section 1.9 concludes.

1.2 Context, Policy & Background

1.2.1 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).

1.2.2 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.

1.2.3 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 (N. 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

[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 1.7 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.

percentage points and the proportion of women by 8.7 percentage points (R. 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 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.

1.2.4 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.

1.3 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.

1.3.1 Model Setup

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

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

is equal ($=\frac{1}{2}$). This distribution is same for both males (M) and females (F)[9].

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.

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

[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.

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

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

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

[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.

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

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 1.1. 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 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]

[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.

[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.

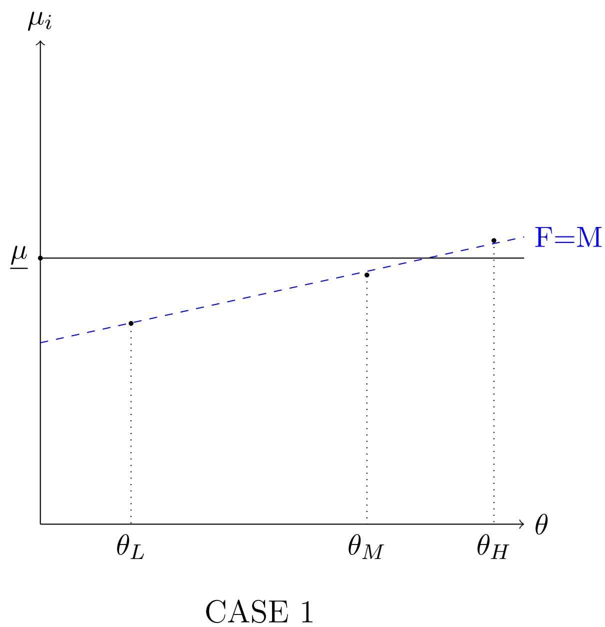


Figure 1.1: Relationship of Expected Skill & College Rankings in the base model

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.

1.3.2 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 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.

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 Section A.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 1.2(a), 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 1.2(b)). 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 1.2(c), f_M falls below $\underline{\mu}$ whereas expected skill 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.

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

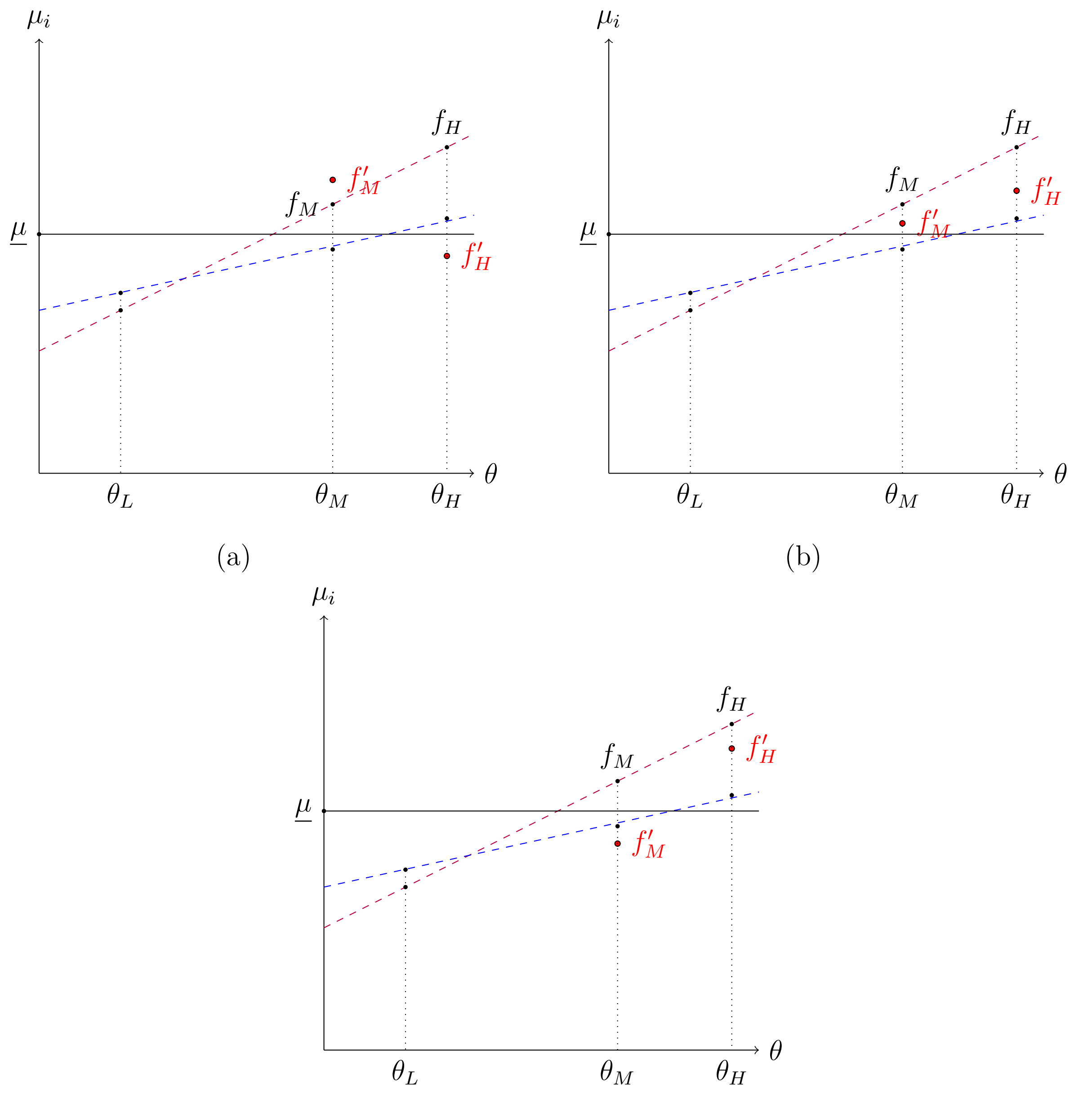


Figure 1.2: Impact of Supernumerary Policy on Expected Skill

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.

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.

1.4 Research Design

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.

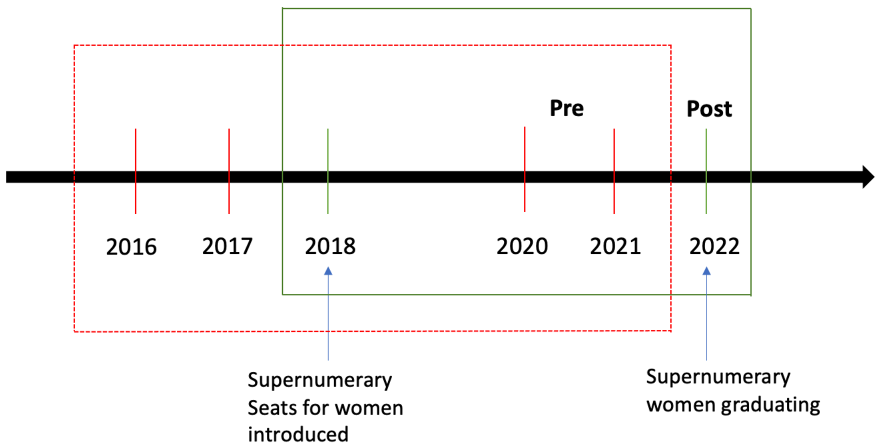
I began by compiling a list of firms that recruit from elite engineering colleges in India.[16]. I then filtered jobs available on these firms' websites that required engineers with 1+ years of experience. The jobs were categorized into three broad roles: software, data, and consulting.[17] I further 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.[18]

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 1.3: 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.

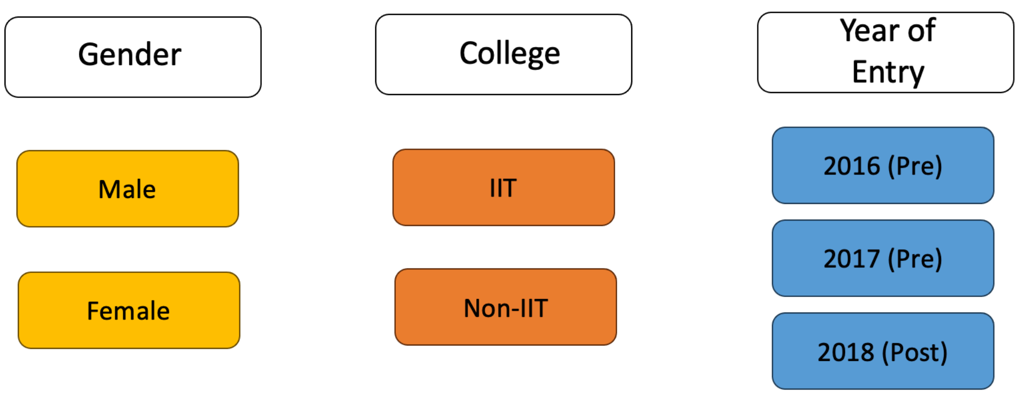
[16]This information is available on college websites and their annual reports.

[17]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.

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



(a) Policy Timeline



(b) Randomization within each job

Figure 1.3: Randomization in CVs

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.

1.4.1 Randomization in CVs

I randomized three parameters within each job : (1) Year of Entry: 2016[19] 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)[20]. 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 Table A.12 and Figure A.1, and Figure A.2 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

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

[20]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

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 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 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.

1.4.2 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[21] 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.

[21] 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.

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 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[22]. 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.

1.5 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

[22] I control for total applications in my analysis

was highly competitive, jobs were scarce, and callback or response rates were lower than usual[23].

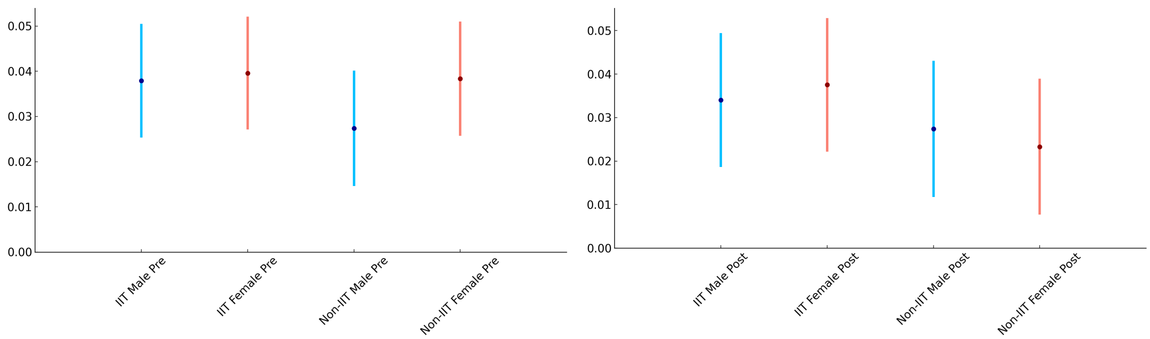


Figure 1.4: Average Callback Rates

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.

1.5.1 Average Callback Rates

Table 1.1 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 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

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

in Australia. A summary of previous correspondence studies on gender discrimination in male-dominated jobs is provided in Table A.13. 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.

Table 1.1: 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.

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 1.5 and 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

Table 1.2: Callback Rates of the eight groups

(a) Cohorts graduating in 2020 or 2021

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

(b) Cohorts graduating in 2022

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

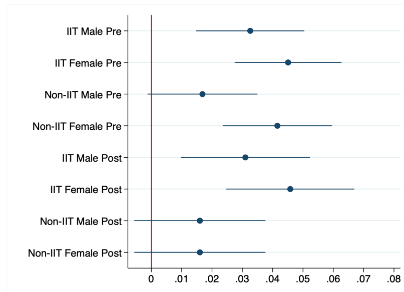
Note: This table shows the raw callback rates of the correspondence study for each of the 8 sub-groups. Panel (a) corresponds to the pre-policy cohort resumes and panel (b) corresponds to the post-policy cohort resumes.

cohorts, indicating a preference for applicants with more years of experience.

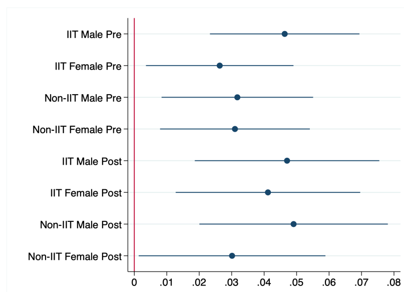
1.6 Empirical Methodology

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.[24] 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 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.

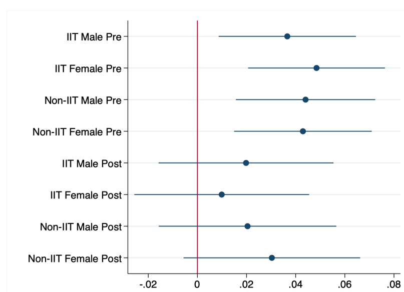
[24] For example, if younger cohorts have lower levels of experience which employer does not prefer, then the difference will capture the effect of lower experience *and* the effect of the policy.



Software



Data



Consulting

Figure 1.5: Average Callback Rates by Job Profile

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.

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 1.6.1.

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

$$y_{ijt} = \alpha_0 \,+\, \gamma\, F_i \,.\, P_t \,+\, \alpha_1\, P_t \,+\, \alpha_2\, F_i \,+\, \rho\, X_i \,+\, \mu_j \,+ W_i + \,\epsilon_{ijt} \tag{1.1}$$

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.

$$\begin{aligned} y_{ijct} &= \alpha + \delta F_i \cdot P_t \cdot A_c + \beta_1 F_i \cdot P_t + \beta_2 A_c \cdot F_i + \beta_3 P_t \cdot A_c \\ &\quad + \beta_4 P_t + \beta_5 F_i + \beta_6 A_c + \rho X_i + \mu_j + W_i + \epsilon_{ijct}. \end{aligned} \tag{1.2}$$

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 (1.1) 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 1.6.1.

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.

$$y = \alpha_0 \, + \, \gamma' \, F \, . \, P \, + \, \alpha_1 \, P \, + \, \alpha_2 \, F \, + \, \rho \, X_i \, + \, \mu_j \, + \, \epsilon \tag{1.3}$$

$$
\begin{aligned}
y = \beta_0 \; + \; \delta' F \cdot P \cdot A \; + \; \beta_1 F \cdot P \; + \; \beta_2 A \cdot F \; + \; \beta_3 P \cdot A \\
+ \; \beta_4 \, P \; + \; \beta_5 \, F \; + \; \beta_6 \, A \; + \; \rho \, X_i \; + \; \mu_j \; + \; \epsilon.
\end{aligned}
\tag{1.4}
$$

I test whether the parallel trends assumption holds by conducting a placebo check and estimating Equation (1.3). The results are presented in Table 1.3. The DID estimate corresponding for the IITs in Column 2 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 3 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 (1.4) and presented in Column 1, is insignificant indicating 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.

Table 1.3: Placebo Regression - Triple Difference and DID

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

Note: This table provides the coefficients of Equation (1.4) 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.

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

1.7 Results

1.7.1 Main Results

I use a linear probability model to estimate the difference-in-differences (DID) Equation (1.1), and the results are presented in Table 1.4.[25] 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 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

[25] I also estimate corresponding Probit and Logit models. Results are reported in Table A.10

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 1.4: 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 (1.1) 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 1.5 presents the results of the triple difference regression (Equation (1.2)), 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.

Table 1.5: 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 (1.2) 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.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

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 1.4, 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.

1.7.2 Predicted Callback Probability & Policy Impact

I estimate the predicted callback rates of the 8 groups using the Probit model (Table 1.5 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 1.6, along with 95% confidence intervals.

Table 1.6: 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 (1.2)). 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).

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.

1.7.3 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 1.6 and Figure 1.7. As shown in Figure 1.6(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.

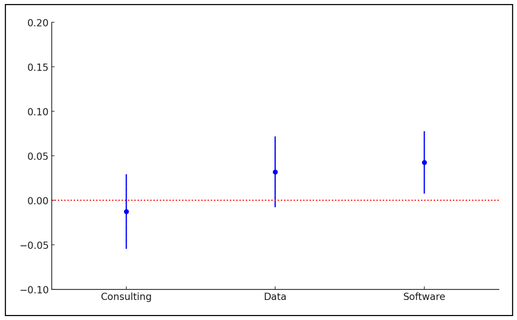
I also split the sample based on whether the listed job provides above or below median compensation, as shown in Figure 1.6(b). Although I do not have actual compensation details for each job, I estimate approximate compensation using data from websites like AmbitionBox and Glassdoor. The median annual 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 1.6(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.

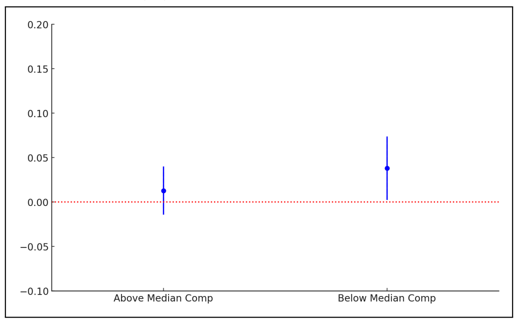
I also perform heterogeneity analysis based on company-specific characteristics. In terms of company size, large firms[26] prefer IIT females over non-IIT females, and the triple difference estimate is statistically significant. However, the results are imprecise for smaller firms. Nevertheless, the two coefficients are not statistically different (Figure 1.7(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 1.7(b)).

I also split the sample based on whether a firm is a multinational corporation (MNC) or not (Figure 1.7(c)). A company is defined as multinational if it has multiple international locations, indicating an international presence. The effect is large and statistically 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

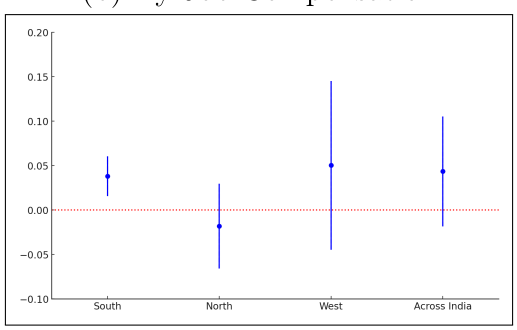
[26] A large firm is defined as one with more than 500 employees. I gather company size and other firm-specific characteristics using information provided on LinkedIn pages of the companies.



(a) By Job Profile



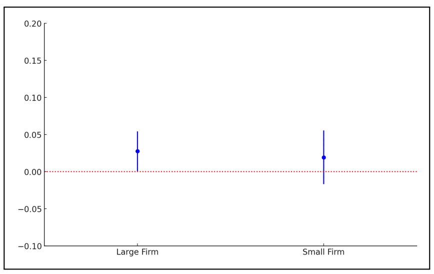
(b) By Job Compensation



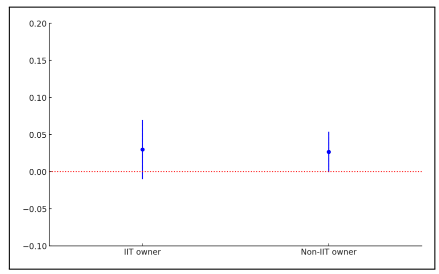
(c) By Job Location

Figure 1.6: Heterogeneity by Job Characteristics

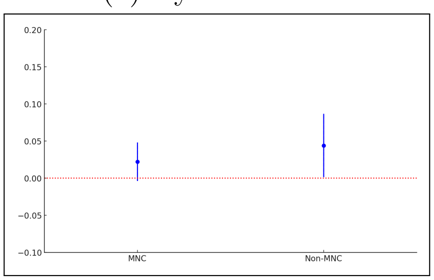
Note: This figure shows the triple difference coefficients (along with 90% confidence intervals) when I split my correspondence study sample by different job characteristics. Standard Errors are clustered at the job level and same controls are used as in the main regression to estimate the coefficient.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



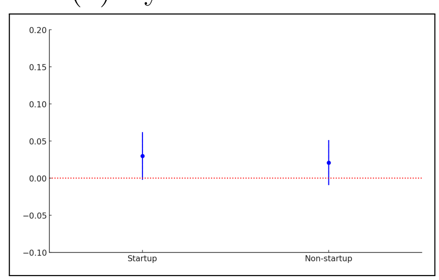
(a) By Firm Size



(b) By Owner of Firm



(c) By Firm being Multi-national



(d) By Firm being Startup

Figure 1.7: 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.

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 1.7(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.

1.8 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*[27]. By utilizing the *Proxycurl* API and the extracted URLs, I scraped data available on each profile page, including the name, education (college, field of study, degree obtained, start and end dates),

[27] 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.

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), I was left with 6,980 profiles for analysis. I then assigned gender to each profile using a publicly available dataset[28] 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 for several reasons. First, active LinkedIn users may represent a self-selected sample, and this selection may vary across different cohorts. Second, 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 collect 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.

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 1.7 provides a breakdown of LinkedIn and correspondence study data by college. Approximately 45% 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 1.8 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

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

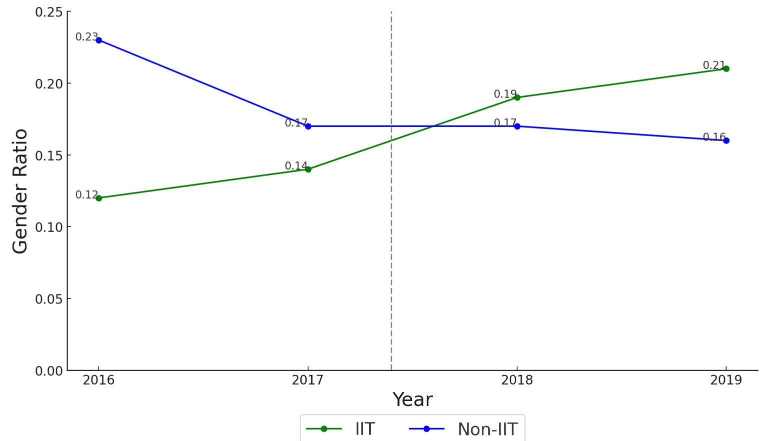


Figure 1.8: Proportion of Females in LinkedIn

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.

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.

1.8.1 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

Table 1.7: 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	0.57
IIT Delhi	0.19	0.21	2	0.38
IIT Kanpur	0.25	0.22	4	0.44
IIT Indore	0.06	0.09	14	0.50
IIIT Hyderabad	0.08	0.04	55	0.30
NSUT Delhi	0.12	0.28	60	0.49
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, 45% of graduates at these colleges who entered between 2016-2019 are present in the data.

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 out-

Table 1.8: 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.

comes. 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 1.8 provides summary statistics for the outcomes described above.

Findings: Employment Outcomes

Table 1.9 provides the estimates from the triple difference regression (Equation (1.2)) 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 (or 26%) 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 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.

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 (1.2) for the wage score measure, and the

Table 1.9: 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 (1.2) 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.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

results are presented in 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.

Findings: Labor Force Participation Outcomes

The effects on time spent working or being employed are presented in Table 1.10. 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 partic-

Table 1.10: 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 (1.2) 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.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

ipation. 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.

1.9 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.

Chapter 2

Fixing the Leaky Pipeline: Affirmative Action in Local Elite Colleges & Subject Choice

2.1 Introduction

The under-representation of women in Science, Technology, Engineering and Mathematics (STEM) fields - an outcome of the progressive loss of women in STEM or the 'leaky pipeline' - is recognized as one of the major causes of the gender wage gap and occupational segregation (Daymont and Andrisani 1984; Beede et al. 2011; Sharpe 1976; Deem 2012; Wolpe 1978; Resmini 2016). Deep-rooted gender norms and the lack of role models hinder the narrowing of the gender gap in STEM - which, if achieved, can lead to an increase of $12-28 trillion in global economy via increased labor market activity and productivity of women, according to a recent research report by McKinsey (Munoz-Boudet and Revenga 2017; Maceira 2017; Woetzel et al. 2020).

One set of policies that aim to narrow this gap involves affirmative action (AA) often developed and employed by educational institutions to break entry barriers

(Bastarrica et al. 2018; Ceci and W. M. Williams 2015). Whether programs like these can influence the career path of women in male-dominated fields is a first order empirical question. On one hand, these are meant to encourage women by increasing their likelihood of entry; but on the other, they can reinforce stereotypes and gender roles (Matheson et al. 1994).

In this paper, I analyze one such program introduced at an elite tier of engineering colleges in India - Indian Institute of Technology (IIT) - that reserved extra seats for women at every new undergraduate STEM course cohort entering an IIT campus in 2018. I investigate the impact of the policy on subject choice pursued by girls after completing Grade 10, by exploiting the exogenous variation in proximity to these institutions in a context where students prefer going to college closer to their homes. The presence of at least one IIT campus in almost every state in India provides large spatial variation in the proximity to the institute. Admission to an IIT is based purely on merit, eliminating any migration or selective sorting patterns that could arise from the knowledge of this policy.

The educational system in India requires students to choose one of three tracks - Science, Commerce or Humanities - after completing Grade 10 in school, which then defines the courses of study in subsequent grades (Grades 11 and 12). In order to choose a STEM major at an Indian university, a prospective student is required to have studied subjects under the Science track in Grades 11 and 12. In particular, getting an admit into an IIT requires qualifying a very selective entrance examination which tests knowledge of science track courses - Physics, Chemistry and Mathematics. As a result, subject choice in high school defines one's career path to a large extent. Any policy, therefore, that can influence choice at this stage can increase the likelihood of advancing into a STEM career. I analyze this subject choice in a context specific but not limited to India[1].

After the implementation of this policy, the proportion of girls at IITs nearly doubled from 8.7% to 16%, resulting in an average yearly increment of over 1300 seats across all IIT campuses. The proportion of women taking the IIT entrance exam increased by 10.5% and those qualifying the exam increased by about 15.3%. Overall, this translates to about 4 more females taking the exam and 1 more female clearing the exam for each extra seat added to the seat pool. Since the policy added new seats and reserved them for women, they didn't displace boys. The male enrolment at IITs only actually increased, although by an insignificant amount.

Students living closer have a comparative advantage in responding to the policy over those living farther as long travel times increase safety concerns. This coupled with strict social norms strongly influences education decisions, especially for girls. I exploit the fact that preference for an educational institute closer to one's home is salient in India. Moreover, conditional on clearing the IIT entrance exam, students indicate their preferred IIT campus and engineering field. However, the location of some IIT campuses in remote areas (Kharagpur, Roorkee, Guwahati etc.) can constrain women's choice set (Borker 2017). Stereotypes associated with certain fields (such as Mechanical or Civil engineering) being "masculine" (Chanana 2007) further limits women's choices, making it difficult for them to enroll in an elite college and instead making them settle for a lower quality college in closer proximity. In light of the aforementioned context, I evaluate the policy for the 'marginal' girl living close to an IIT campus who faces weaker safety and transport barriers.

I build a conceptual framework to illustrate the trade-off faced by a girl when deciding subjects to study in Grade 11. The benefit of studying science are twofold - (1)

[1] Countries like France, Germany etc also impose a first level subject choice at the school level.

higher wage premium associated with science track and (2) possibility of studying STEM at an elite college (EC) and earning the EC wage premium. The cost of studying science is represented by the distaste for the subject, reflecting the gendered stereotype. There is also an additional cost of travel. The framework predicts that for a girl who lives far from an EC, such that the wage premium is not high enough so as to outweigh the extra cost of travel, she will not go to EC and pursue her subject of study from the local college (LC) depending on the distaste for science. For a girl who lives close enough to EC, as long as her distaste for science is low, she will choose to study STEM there if selected. An AA policy such as supernumerary seats can potentially increase the likelihood of entering EC, and thus influence girls closer to ECs and make them switch from a non-science to science subject.

To empirically estimate the impact of the policy, I use nationally representative cross-section data collected in 2017-18 from a special round of the National Sample Survey (NSS) focussing on education and estimate the effect of the announcement of the policy. I compare subjects pursued after Grade 10 for cohorts making their decisions before and after the policy was announced (first difference). I calculate a triple difference estimate which compares the first difference between girls and boys living close to IIT campuses with those that live far. The key identifying assumption in my model is that conditional on district specific characteristics and individual level controls, if the policy would not have been introduced, gender gaps in science between close and far districts from an IIT would follow parallel trends. I test this assumption by testing for differential trends in the older cohorts. I fail to reject the parallel trends assumption for the triple difference estimate.

In order to create the spatial variation, I first find distances of each IIT from all districts. Districts that lie within a 30 kilometer (km) radius of an IIT are considered 'close' whereas districts that lie outside that radius but within 200km are considered 'far'. I use 30km as the threshold as it is a reasonable distance that can be commuted on a daily basis[2]. Moreover, IITs exempt students from living on campus as long as they reside within 30km of an IIT. The fact that I study choices that students make when they are school, i.e. at a time when they reside at home with their parents, alleviates any selective sorting or migration issues as it is unlikely that individuals will change their residence with this policy announcement. One particular concern in considering districts farther from IITs as controls is that these areas can be quite different from the areas closer to these colleges. I address this concern by using synthetic difference-in-difference (SDID) weights for each district and age category. This is done by running a synthetic DID (Clarke et al. 2023) specification on a collapsed district-age panel. Considering the 'close' districts as treated, I find unit-specific weights for 'far' districts and time-specific weights for three age brackets. This allows me to re-weight my original regression to match trends in science in treated and control districts.

The key result of the paper is that the inclusion of supernumerary seats for girls is associated with a 6.7 percentage point increase (about 27% of the baseline average population of women studying science) in the likelihood of choosing the science track after Grade 10 in areas closer to IIT campuses. I find a similar effect when the regression is weighted using SDID. The estimate suggests that the likelihood of choosing science track increased by around 0.02% for every additional seat that was added. This also indicates that the policy has the potential to increase the expected earnings of women by about 6% as the choice of science track is associated with 22% higher earnings on average (Jain et al. 2018), thereby having huge implications in narrowing

[2]Statista survey shows that about 70% urban dwellers across India traveled less than ten kilometers and spent around 27 minutes on average to travel for work and education in 2019.

the gender wage gap.

I also analyze the impact of the policy on other education outcomes. I do not find any effect on educational attainment, private coaching uptake or other expenditure in education. I perform heterogeneity analysis to see whether the increase in science is driven by sibling spillover effects or parents' education level but I do not find an such evidence. Lastly, I perform a variety of sensitivity checks on the key result and the main results are robust.

The paper adds to the broad affirmative action literature and attempts to exploit policy variation to study educational outcomes of women, and STEM in particular. Caste-based reservations have been studied in India to determine its targeting and matching properties (Bertrand, Hanna, and Mullainathan 2010; Aygün and Turhan 2017) as well as schooling and educational outcomes of lower-caste students (Bagde, Epple, and Taylor 2016; Khanna 2020). Other studies in the literature look at racial differences with or without using policy variation focusing on affirmative action ban in California and its impact on minority enrolment and attainment (Arcidiacono, Aucejo, and Hotz 2016; Bleemer 2022; Hinrichs 2012; Backes 2012). Finally, studies on affirmative action for women is limited in corporate board leadership and politics (Beaman et al. 2009; Matsa and Miller 2013). The paper distinguishes itself from other related papers that have looked at post college-entry outcomes of the disadvantaged and minority groups by studying choices *women* make *before* entering college in a setting where the college policy provides a natural experiment.

This paper also contributes to the literature on subject choice, which has implications for labor market earnings and the gender wage gap. Jain et al. 2018 establishes that conditional on ability, choosing the science track in high school generates 22% greater earnings for Indian males. This paper investigates whether this choice at high school can be influenced for girls which can potentially reduce the gender wage gap. Moreover earnings associated with elite public colleges are much higher than other colleges (Sekhri 2020; Zimmerman 2019). A wide variety of factors determine choice of subject such as ability, earnings, tastes and preferences (Wiswall and Zafar 2015), role models (Porter and Serra 2020), siblings spillovers (Altmejd et al. 2020) and peer effects (Fischer 2017). Affirmative action literature has studied enrolment, attainment and graduation outcomes but subject choice has been understudied. This paper analyzes if women's choices can be influenced by such policies.

This paper also contributes to the literature on gender gap in STEM enrolment and the 'leaky pipeline' by analyzing a policy that has the potential to narrow that gap. Previous studies have identified the existence of gender gap in math and participation in STEM fields (Fryer Jr and Levitt 2010; Adams and Kirchmaier 2016) as well as the gender gap in higher secondary subject choice in India (Sahoo and Klasen 2021). Other studies have tried to explain this gap by analyzing gender differences in test-taking behavior in a competitive environment (Niederle and Vesterlund 2010; Buser, Niederle, and Oosterbeek 2014; Buser, Peter, and Wolter 2017) and establishing the role of culture in determining math performance (Nollenberger, Rodríguez-Planas, and Sevilla 2016). While this paper does not establish or explain gender differences in STEM, it attempts to evaluate a policy to answer if it can fix the 'leaky pipeline' by expanding college opportunities for women.

The rest of the paper is organized as follows. Section 2.2 explains the context and the policy. Section 2.3 presents a conceptual framework. Section 2.4 describes the data and identification strategy. Section 2.5 outlines the empirical specifications and discusses the main results. Section 2.6 and 2.7 discusses possible mechanisms and perform robustness tests respectively. Section 2.8 concludes.

2.2 Context & Background

Indian Institutes of Technology (IIT) are public engineering and research institutions in India, and are ranked highest in India. As of 2020, there were 23 IITs located across the country, each of which are autonomous but administered through a common IIT council[3]. The most common, competitive, and sought after degree at IITs is Bachelor of Technology (B.Tech)[4]. To seek admission to one of these B.Tech programs, students are required to pass a competitive entrance examination covering topics from subjects taught in the Science track in Grades 11 and 12. It focuses on application of concepts through novel questions in a stipulated time frame which makes it one of the hardest exams to crack. The highest scorers are admitted into one of the IITs based on their rank and their declared field and location preference. Every year 1.5 million students take the exam and apply to the undergraduate programs for which only about 16,000 seats are available across all IITs. Conditional on having studied Science in Grades 11-12 at school, IITs, therefore, admit students purely on the basis of their performance in the entrance exam (and therefore on merit).

2.2.1 Supernumerary Seats for Women

In terms of the structure and eligibility of admissions to IITs, there are no barriers whatsoever against women in applying. Yet there are large gender differences in application, admission and entry of women generating an acute under-representation of women in undergraduate engineering courses in IITs. N. Gupta 2020 mentions that in 2016 only 19% of the candidates writing the entrance exam were women. Out of

[3] A map of all 23 IIT campuses is provided in Figure B.1

[4] The course offers specialization in various engineering fields such as Computer Science, Electrical, Electronics and Communication, Information Technology etc

the candidates who passed, only 12.5% were women and finally there were only 8% women in the incoming cohort of students across all the IITs. The gender ratio at IITs has been highly skewed since their inception, and this very low proportion of women has led to the introduction of supernumerary seats in 2018. The agenda of the policy is to create new seats for women in every undergraduate program at every IIT until a minimum percentage of female enrolment is achieved.

2.2.2 Trends in Enrolment

I first study the trends in enrolment of women in the undergraduate programs in IITs before and after the policy came into effect in 2018. For this purpose, I utilize the Annual Reports available for 20 IITs on their website to gather yearly data on total new admissions in the 4-year B.Tech degree programs.

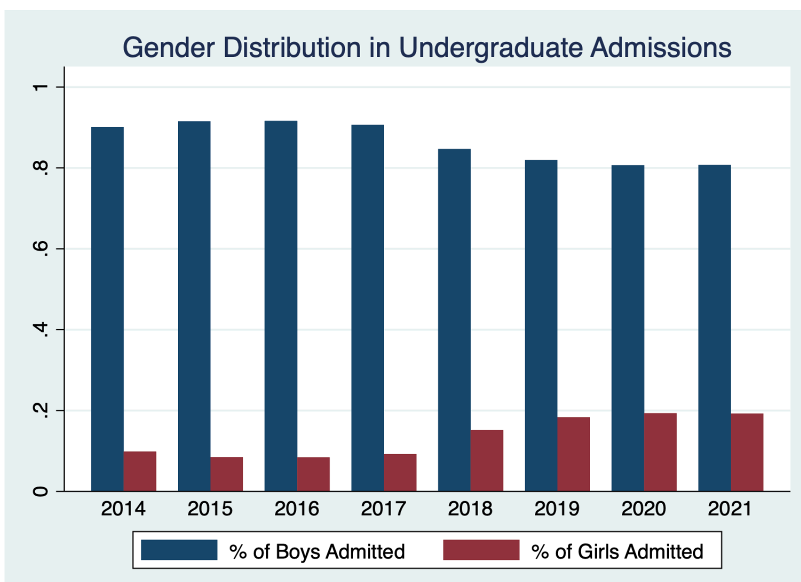


Figure 2.1: Gender Distribution in Admissions

Prior to 2018, each campus on average admitted 350 boys and 33 girls in the new cohort every year. After 2017, these institutes have been admitting 412 boys and 90 girls on average[5]. Figure 2.1 presents the distribution of newly admitted students by gender averaged over IITs using the data for academic years between 2014-15 and 2021-22. There is a clear change in trend after 2017.

I use the IIT-year panel to plot these trends and measure the impact of the policy on the gender ratio and the proportion of women at IITs. I report robust standard errors clustered at each IIT. In particular, I run the following fixed-effects regression:

$$y_{it} = \alpha + \beta Post_t + \mu_i + \epsilon_{it}$$

where y_{it} is the gender-ratio or the proportion of women in IIT i in year t; μ_i are IIT fixed effects that capture any time-invariant IIT-specific characteristics and $Post_t$ is a dummy which takes the value 1 for the years that included supernumerary seats for women (i.e. after 2017). As presented in Table 2.1, we see that on average, the introduction of the policy led to a 11 percentage point increase in the gender ratio and a 8.7 percentage point increase in the proportion of women at IITs. These estimates are statistically significant and suggest that compared to the average baseline, the proportion of girls enrolled in these IITs have nearly doubled. Based on the average enrolment numbers, the absolute number of girls in a cohort increased from 759 to 2070, which is an increase of about 1300 girls. Year-specific coefficients plotted in Figure 2.2 depict the trend of female enrolment at IITs.

2.2.3 Trends in Applications

The increase of women at IITs is an outcome of the policy implementation. In order to investigate if more women are also applying to IITs (or taking the IIT entrance

[5]The increase in girls is statistically significant at 1% but is insignificant for boys.

Table 2.1: Impact on Female Enrolment at IITs

	Gender Ratio	Proportion of Women
Post	0.116***	0.0877***
	(0.00823)	(0.00670)
Constant	0.100***	0.0893***
	(0.00379)	(0.00309)
Observations	128	128
R-squared	0.720	0.725
Number of IITs	20	20

Data Source: Annual Reports of 20 IITs. Gender Ratio is the number of females divided by number of males. Proportion of women is defined as the number of females divided by the total number of students admitted. Independent variable is a dummy taking value 1 for post-policy years.

exam), I collect data on applicants from the IIT entrance exam annual reports. The IIT campuses are divided into seven regional zones. Every year, one of these seven IIT zones conducts the exam and publishes the exam statistics in a report available on their website. I utilize these reports to gather the number of applicants and qualified students. 33,307 girls and 138,506 boys registered (or applied) for the IIT entrance exam in 2017. The corresponding number for those who qualified for a seat at IIT was 7,259 girls and 43,781 boys.

I create an IIT zone-year panel and run the fixed effects regression as in the previous section. As shown in Table 2.2, I observe that there has been an increase of nearly 2 percentage point in the proportion of women who take the IIT entrance exam as well in the proportion of women clearing the exam, suggesting a 10.5% increase in the proportion of women taking the exam and 15.3% increase in the proportion of women qualifying the exam. In absolute terms, this translates to an yearly average of 4,179 more female registrations and 1,080 more females qualifying the exam. For

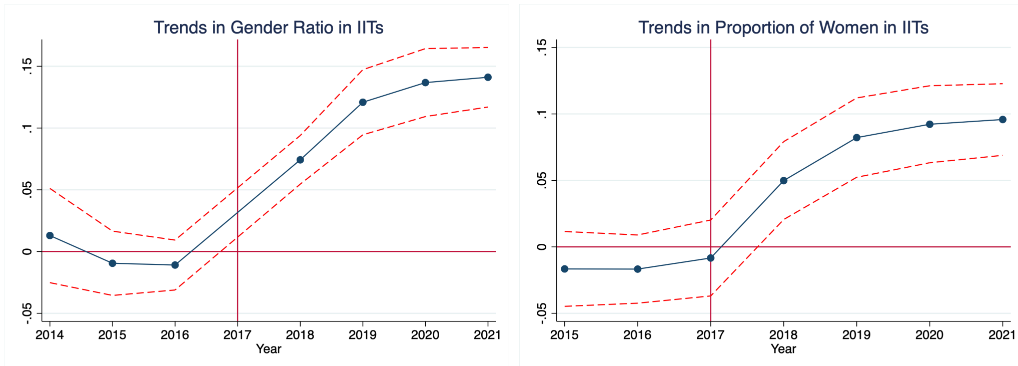


Figure 2.2: Trends in Gender Ratio

Data Source: Annual Reports of 20 IITs between 2014-2021. Gender Ratio is the number of females divided by number of males. Proportion of women is defined as the number of females divided by the total number of students admitted. Independent variable is a dummy taking value 1 for post-policy years.

every additional seat added in IITs for women, 4 more females take the IIT entrance exam and 1 more female qualified the exam[6].

Table 2.2: Impact on Female Applications at IITs

	Prop of Women in Registrations	Prop of Women Qualifying
Post	0.0192**	0.0182***
	(0.00651)	(0.00341)
Observations	49	49
Control Mean	0.18	0.12
R-squared	0.434	0.297
Number of IIT zones	7	7

Data Source: IIT Entrance Exam Reports for years 2013-2020. Dependent variable is the total number of women who register for the IIT entrance exam (qualify the IIT entrance exam) divided by the total number of registrations (students who qualify the exam). Independent variable is a dummy taking value 1 for post-policy years.

[6]The criteria for qualifying the exam is based on cut-off score in the entrance exam which could be directly proportional to the number of seats IIT added to increase the gender ratio.

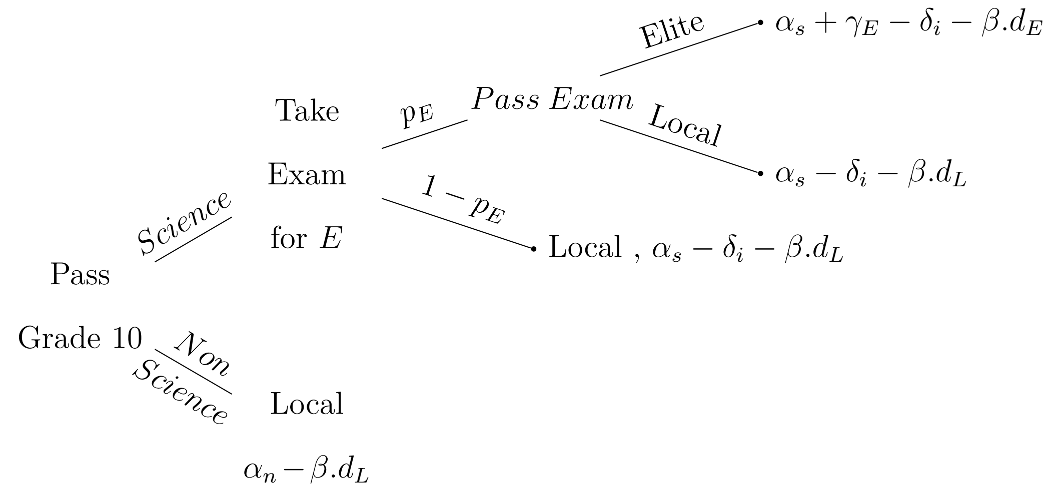
2.3 Conceptual Framework

Consider a simple framework where a girl after finishing Grade 10 decides whether to choose a science track or a non-science track. I denote the labor market return from studying science as α_s which I assume to be strictly greater than the labor market return from non-science, α_n, as science track is associated with higher labor market earnings (Jain et al 2019). However, there is distaste associated with studying science which denotes the notion that science is "bad" for girls. I assume idiosyncratic distaste for studying science, δ_i.

After passing Class 12 in the track she studied in, she proceeds to study in the university. There are two universities - Local (L) and Elite (E). L offers all courses and by definition, is close to the girl's home. E offers only STEM courses and there is wage premium, $\gamma_E > 0$, associated with studying in E. I assume that the girl does not drop out of education before going to college. The choice of studying at University E only becomes available if the girl studies the science track at school and passes the competitive entrance exam to get admission into E. The probability of passing the exam is p_E which I assume is same for everyone. University L, on the other hand, is always open to admission and she can always join it irrespective of whether she gets admission in E or not. I, therefore, assume for simplicity that the probability of attending L is 1[7]. In general, that might not be true. It also offers all courses. There is, however, the social cost of travelling to college which depends on the distance (d) to the college from one's home and represents the social norms, safety concerns and long travel times. The framework is depicted in a decision tree in the picture below. The utility function and the trade offs faced by the girl in making her decisions are

[7] Because of this assumption, the model can not comment on possible spillovers of any policy at the elite college on other colleges.

presented in the next subsections.



2.3.1 Decision at Stage 2

Conditional on having chosen science and gotten admission into E, girl goes to E if the wage premium is greater than the cost associated with travelling the extra distance. Mathematically,

$$U_E > U_L$$

$$\implies \gamma_E > \beta(d_E - d_L) \tag{2.1}$$

Despite choice of science track and getting an admit, girl will not go to E (and go to L) if the above condition is not met.

Definition 1: Girl lives **far** if $\gamma_E < \beta(d_E - d_L)$ and **close** otherwise.

2.3.2 Decision at Stage 1

Case 1: Girl lives far from E

As solved in Stage 2, she will never go to E if she chooses science track as the wage premium associated with E is not enough to cover for her cost of travelling. She will go to L with probability 1 if she chooses science irrespective of her admission outcome in E.

$$U^i = \begin{cases} \alpha_s - \delta_i - \beta.d_L & \text{if S} = 1 \\ \alpha_n - \beta.d_L & \text{if S} = 0 \end{cases}$$

She chooses science if the extra earnings from science track is greater than the distaste associated with studying science.

$$\implies \delta_i < \alpha_s - \alpha_n \tag{2.2}$$

Case 2: Girl lives close to E

As solved above, she will go to E if she chooses science track and gets admission into E (i.e. with probability p_E). She will go to L with probability $1 - p_E$ if she chooses science.

$$U^i = \begin{cases} \alpha_s + p_E.\gamma_E - \delta_i - \beta\{p_E.d_E + (1 - p_E).d_L\} & \text{if S} = 1 \\ \alpha_n - \beta.d_L & \text{if S} = 0 \end{cases}$$

She chooses science if the extra earnings from science track plus the expected increase in the wage premium associated with elite college net of the extra distance cost is greater than the distaste associated with studying science.

$$\implies \delta_i < (\alpha_s - \alpha_n) + p_E(\gamma_E - \beta(d_E - d_L)) \tag{2.3}$$

Proposition 1:

a) If a girl lives close (i.e. 2.1 is satisfied), it is optimal for her to choose science in school as long as her distaste for the subject is not too high (i.e. 2.3 is satisfied). If she gets into the elite college, she studies a STEM course.

b) If a girl lives far (i.e. 2.1 is not satisfied), then the choice of subject only depends on the distaste parameter (i.e. choose science if 2.2 is satisfied). The decision is independent of the probability of getting into the elite college.

Corollary 1:

An affirmative action policy at an elite college will influence those girls who live close. Moreover, if the increase in probability of getting into the elite college is large enough to outweigh their distaste for STEM, they will switch to choosing science.

2.4 Data & Identification

2.4.1 Data

I study the impact of this policy on subject choice by using the 75th round of National Sample Survey (NSS) that focuses on education (NSSO 2017). The survey was conducted between June 2017 to June 2018 and consists of a nationally representative sample of 64,519 rural households from 8,097 villages and 49,238 urban households from 6,188 blocks. The data covers qualitative and quantitative aspects of education such as educational attainment, access to schools and internet, educational expenditure and scholarships, type of education and subject choice of individuals currently attending education. The policy was announced in April 2017 and I utilize this data to study the *announcement* effect of the policy by looking at the subject choice of young boys and girls below the age of 18 years who are being affected by the addition of supernumerary seats at elite engineering colleges across India. My analysis is restricted to a sample of individuals aged 13-24. Descriptive statistics are presented in Table 2.3.

Table 2.3: Descriptive Statistics

	Mean	Std Deviation
All		
Education Level	11.26	1.60
Private Coaching	0.180	0.384
Science	0.29	0.45
Men		
Education Level	11.17	1.52
Private Coaching	0.181	0.385
Science	0.32	0.47
Women		
Education Level	11.38	1.70
Private Coaching	0.178	0.383
Science	0.24	0.43

Notes: The statistics are calculated for the individuals of age greater than 17 years in NSS Education Round 2017-18

2.4.2 Identification

The main outcome of interest is the probability of studying science after Grade 10. The first difference compares this outcome between girls of age less than 18 years ('treated' cohort) who made their subject choice decisions after the policy was announced and older girls ('control' cohort) who would have already chosen their subject.

For the second difference, boys are taken as the control group as they would have also been exposed to all other confounding factors such as a changing educational environment and economic growth in the country but the IITs only increased seats for girls. However, since the proportion of girls studying science is much lower than boys to begin with, it is plausible that the trends in the outcome for girls are different than that of boys. I therefore test for the parallel trends assumption for this double difference[8] in the pre-treatment cohorts. The coefficient on the interaction term in Table 2.6 Panel A is statistically significant and therefore the null hypothesis of parallel trends is rejected.

Table 2.4: Difference-in-differences estimate

Dependent Variable: Probability of Studying Science	(1)
Young X Female	0.113***
	(0.00737)
Young	-0.188***
	(0.00896)
Female	-0.127***
	(0.00645)
Observations	59,664
Control Mean	0.24
R-squared	0.187
District FE	Yes
Controls	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

In order to overcome the non-parallel trends between girls and boys, I conduct a triple difference analysis using proximity to an IIT campus as the exogenous source of variation. To study at an IIT, the decision to study science has to be taken before entering high school, i.e. at a stage when most students are residing with their parents.

[8]The DID estimate corresponding to the double difference is reported in Table 2.4.

Whether or not an IIT is close to a student's home is determined exogenously and the place of residence is not affected by the location of an IIT or the introduction of the policy. This policy is introduced in a context where distance to home is a major determinant of educational choices, gender norms are prevalent and crimes against women are rising[9]. These factors impede female mobility to access schools and colleges and limit their education choices. As presented in Table 2.5, distance to college matters and it matters more for women and therefore, they travel to colleges closer to their homes. Therefore, girls living closer to IITs have a comparative advantage in accessing such institutions over girls living far from IITs.

Table 2.5: Proximity to Educational Institution for Women

Distance	(1)	(2)
Female	-0.243***	-0.163***
	(0.0109)	(0.0173)
Constant	3.003***	4.503***
	(0.0306)	(0.0293)
Observations	151,073	39,260
Sample	All	Above Class 12
R-squared	0.005	0.004

Notes: The data used is the 75th round of National Sample Survey (2017-18) dedicated to education. Dependent variable is a categorical variable for distance (d) of the educational institution from the place of residence for individuals currently attending education. It is coded as: 1 for d < 1km , 2 for 1km < d < 2kms, 3 for 2kms < d < 3kms, 4 for 3kms < d < 5kms and 5 for d > 5kms.

I, therefore, define "close" ("treated") areas as those districts that lie within a 30km radius of an IIT and "far" ("control") areas are the ones that lie outside the 30km radius but within a 200km radius of an IIT[10]. I exclude the districts that are farther

[9] In 2019, cases registered under crime against women rose by 7% relative to 2018. As per the National Crime Records Bureau (NCRB) report 2020, an average of 87 rape cases were registered daily in India in 2019.

[10] Figure B.2 presents a map showing the close ("treated") and far ("control") districts. I choose

than 200km from my analysis to reduce noise and improve precision. Moreover, districts that are too far can be very different from districts closer to IITs. The triple difference estimate is constructed by taking the difference between the double difference in close districts with that of the far districts.

My identifying assumption is that conditional on district specific characteristics and individual level controls, gender gaps in science across closer and farther districts from IIT would be parallel across different age groups in the absence of the policy. If the parallel trends assumption is satisfied, the triple difference will causally estimate the change in probability of choosing science subjects in high school. I test the identifying assumption in Table 2.6 Panel B in the pre-treatment cohort, and I can not reject the null hypothesis of parallel trends.

Synthetic Difference-in-Differences: A potential issue with using distance to IIT is that districts close to IITs can be quite different from districts that are far and therefore can probably not be considered a good control. I control for individual and household specific characteristics in my model and include district fixed effects to capture any time-invariant differences across these districts. Moreover, district specific differences are common for boys and girls and will get canceled out with the triple difference. I further deal with this issue by assigning synthetic difference-in-differences weights (Clarke et al. 2023). This approach is an advanced version of the synthetic control method (Abadie, Diamond, and Hainmueller 2010) which is used in panel datasets to correct for parallel trends by assigning unit-specific and time-specific weights. Since I have a cross-section, I first categorize the data by the age category of the individual to create a time-dimension i.e. individuals below the age

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30km as my threshold as it is not so high that an average individual cannot commute to college daily or parents cannot make visits, as well as not too low that would reduce the power in my analysis. Moreover, IITs allow individuals to choose not to stay at university dorms as long as they are within that radius.

Table 2.6: Testing the Parallel Trends Assumption

Dependent Variable: Probability of Studying Science		
Panel A: Parallel Trends Assumption for DID		
Age X Female	-0.0187***	
	(0.00330)	
Age	-0.0114***	
	(0.00242)	
Female	0.248***	
	(0.0673)	
Observations	29,105	
R-squared	0.182	
Panel B: Parallel Trends Assumption for DDD		
Age X Female X Close	0.00127	0.000674
	(0.0101)	(0.0107)
Age X Female	-0.0186***	-0.0189***
	(0.00319)	(0.00406)
Close X Female	-0.0888	-0.0731
	(0.206)	(0.218)
Close X Age	0.00424	-0.00424
	(0.00723)	(0.00747)
Age	-0.0121***	-0.00432
	(0.00248)	(0.00294)
Female	0.256***	0.262***
	(0.0655)	(0.0838)
Close	0.115	0.533***
	(0.146)	(0.155)
Observations	29,105	28,805
Synthetic DID Weights for districts	No	Yes
R-squared	0.182	0.138

Notes: This analysis uses individuals in the 'control' cohort in NSS Education Round 2017-18. I include district fixed effects, household-specific and individual level controls in the above regressions. Robust standard errors clustered at the district level are reported in parenthesis.

of 18 are young, between 18 to 22 are middle and those with age higher than 22 are categorized old. Then, I collapse the data at the age category and district level to run a synthetic difference-in-difference regression for the main outcome.[11] The method assigns synthetic weights to control districts (those that are farther than 30km) and to the pre-treatment time-periods (the 'middle' and 'old' cohort in this case) in order to obtain balance between close and far districts in each of the pre-treatment period. Using unit-specific weights, I again fail to reject the null of parallel trends for triple difference as shown in Table 2.6 Panel B Column 2[12].

2.5 Estimating Equation & Results

I estimate the triple difference estimate in the following manner:

$$\text{y}_{iaj} = \alpha + \delta\, Female_{ij}\, .\, Young_i\, .\, Close_j + \beta_1\, Female_{ij}\, .\, Young_i + \beta_2\;\, Close_j.\, Female_{ij} + \beta_3\, Young_i\, .\, Close_j\; + \;\beta_4\, Young_i\; + \;\beta_5\, Female_{ij}\; + \;\beta_6\, Close_j\; + \;\rho\, X_i\; + \;\mu_s\; + \;\epsilon_{iaj}$$

where y_{iaj} is an outcome variable of individual i of age a living in district j, $Young_i$ is takes value 1 if individual i's age a is less than 18 (i.e. the treated cohort), $Female_{iaj}$ is a dummy that takes value 1 if i is a female, $Close_j$ is a dummy that takes value 1 if district j lies within a radius of 30 kilometers of an IIT & 0 if district j lies within a radius of 200 kilometers of an IIT but farther than 30 kms, μ_j represent the state (or district) fixed effects and X_i denote individual specific controls such as religion, caste, household consumption expenditure, whether household owns a computer and whether household owns an internet facility. I report robust standard errors clustered

[11]Some districts are dropped in the analysis to make sure that district-age cohort panel is strongly balanced for the SDID to work.

[12]The assumption of parallel trends is not violated even if I use both district and age specific weights but I only show the result with district-specific weights as this regression only includes the pre-treatment data.

at the district level. The parameter of interest, δ, provides the triple difference (DDD) estimate of the change in probability of choosing science amongst girls.

I first estimate the equation for the main outcome of interest - likelihood of studying science after Grade 10. The dependent variable is a dummy that takes value 1 if the individual reports choosing Science or Engineering as their discipline after Grade 10, and 0 otherwise. Table 2.7 Column 1 provides a triple difference estimate when I choose districts farther than 30km as the far districts. I observe a 6.7 percentage point increase in the likelihood of choosing science track amongst girls. In column 2, I use SDID weights and the estimate increases to 7.4. Compared to the baseline mean, these results imply that since the knowledge about implementation of this policy has come into the public domain, girls are 27-30% more likely to choose science as their subject after passing Grade 10, possibly because they anticipate that the choice of this subject is now associated with a higher probability of admission at a reputed engineering college. For every additional seat that IIT increased, the likelihood of switching to science track increased by 2.7%.

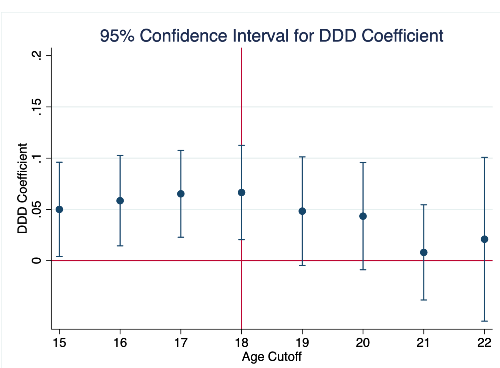
In order to look at the impact on younger girls, I repeat my analysis by changing the age cutoff that I use to determine the treatment cohort. In my main results, younger cohorts are the ones whose age is below 18. I also conduct a triple difference analysis by re-defining the treated cohort as the ones below age a where $a \in \{15, 16, 17, 19, 20, 21, 22\}$. The triple difference coefficients are plotted in Figure 2.3. As I change the treated cohort, the effect diminishes for higher age cutoffs. The effect is still significant when younger ages (below 18) are used as cutoff which shows that the policy affected younger girls. However, the effect is less precise amongst lower ages since the subject choice is made at the higher secondary school level and hence we see the most effect amongst students who are closest to making their decision

Table 2.7: Triple Difference Analysis

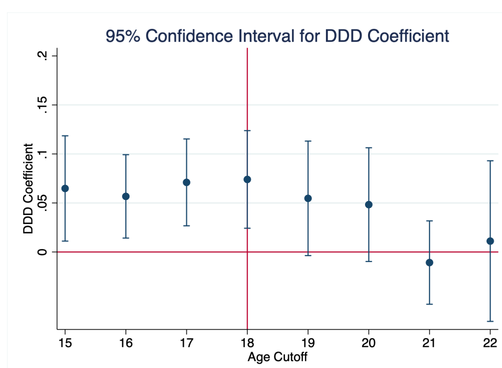
Dependent Variable: Probability of Choosing Science	(1)	(2)
Young X Female X Close	0.0665***	0.0740***
	(0.0235)	(0.0254)
Female X Young	0.103***	0.0888***
	(0.00767)	(0.0111)
Close X Female	-0.0682***	-0.0802***
	(0.0209)	(0.0238)
Young X Close	-0.0337	-0.0527*
	(0.0214)	(0.0311)
Young	-0.183***	-0.170***
	(0.00911)	(0.0242)
Female	-0.116***	-0.0980***
	(0.00682)	(0.0119)
Close	0.0958***	0.281***
	(0.0187)	(0.0260)
Control Mean	0.25	0.23
Synthetic DID weights	No	Yes
Observations	59,664	58,592
R-squared	0.188	0.159
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

when the policy was announced.



(a) Without SDID weights



(b) With SDID weights

Figure 2.3: Impact on younger girls

2.5.1 Other Outcomes

I also estimate the above equation using the highest level of education attained as the dependent variable. Such policies are meant to encourage higher education in general for girls and can have a positive impact. However, since this policy was implemented in elite institutions where students have to face very aggressive competition to enter and therefore specifically targets girls with high ability, the effect on educational attainment can be negligible as compared to the population as a whole. I test this hypothesis and report the triple difference in Table 2.8. I do not find any evidence of a differential impact on the educational attainment of girls living in areas closer to IITs. This suggests the absence of any other educational program or intervention that could be in place to differently impact girls' educational attainment and any impact on subject choice should be coming from the supernumerary policy.

Table 2.8: Educational Attainment

Dependent Variable: Educational Level	(1)	(2)
Young X Female X Close	-0.0414	-0.2643
	(0.0813)	(0.2069)
Synthetic DID weights	No	Yes
Observations	59,664	58,592
R-squared	0.529	0.508
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

I also look at the impact on uptake of private coaching amongst younger girls. The preparation for qualifying the IIT entrance examinations often involves not studying Science subjects but also requires rigorous training for qualifying the competitive examinations. Therefore, students indulge in private coaching or tuition through established coaching centres which aim towards that. The triple difference estimate for this outcome is reported in Table 2.9. I do not find a statistically significant increase in the likelihood of taking private coaching amongst younger girls living close to elite colleges. While it is possible that the policy did not change the private coaching uptake, we should look at this result with caution. In the data that I use, individuals are asked whether they currently take private coaching or not but do not specify if they took private coaching in higher secondary classes. It is possible that students in all age cohorts have joined private coaching at some point and for different reasons which makes it difficult to disentangle whether the private coaching was to prepare for elite engineering colleges or whether it was for something else and specifically, when the private coaching was taken.

Table 2.9: Uptake of Private Coaching

Dependent Variable: Private Coaching Uptake	(1)	(2)
Young X Female X Close	0.0208	0.00599
	(0.0245)	(0.0283)
Synthetic DID weights	No	Yes
Observations	59,664	58,592
R-squared	0.257	0.217
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Finally, I look at some expenditure outcomes where data is collected on the total expenditure made on studying basic course in the current academic year, expenditure on extra tuition and expenditure on preparation for higher studies. The reported expenditure is in Rupees. Again, I do not find a significant effect on any of these outcomes as shown in Table 2.10. Even though the policy seems to have pushed the choices of girls towards studying science, the amount of expenditure incurred for their education does not seem to be changing. However, I would look at these results with caution as well as the data collected asks about expenditure in the current academic year and not at a particular time of the individual's life.

Table 2.10: Other Expenditure Outcomes (in INR)

	Log Total Exp	Log Total Exp	Tuition	Tuition	Higher Studies Prep	Higher Studies Prep
Young X Female X Close	-0.0427	-0.340	237.6	110.5	50.70	50.60
	(0.0527)	(0.278)	(214.5)	(256.5)	(73.60)	(74.06)
SDID weights	No	Yes	No	Yes	No	Yes
Observations	44,939	43,908	59,630	58,558	59,630	58,558
R-squared	0.344	0.324	0.165	0.137	0.022	0.018
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

2.6 Possible Mechanisms

I explore possible mechanisms that can drive the subject choice decisions amongst girls as a consequence of this policy.

2.6.1 Sibling Spillover Effect

It is well documented that subject choice is at times influenced by the decision made by elder siblings. There is an incentive to choose a subject when the elder sibling has studied the same subject so as to benefit from their resources, experience and knowledge. While elder sibling can encourage an individual to take the same subject, it is also possible that elder sibling's (bad) experience can deter an individual from studying the same subject. I explore whether the increase in likelihood of studying science after the introduction of the policy is driven amongst girls whose elder sibling also studied science. I define a variable 'Sibling Science' which takes value 1 if individual i has an elder sibling who studied Science and 0 otherwise. I interact this variable with the triple difference to determine heterogeneity. The fourth difference is insignificant as shown in Table 2.11. Younger students living closer to IITs are more likely to study Science if their elder sibling also studied Science but this effect is not significantly different for girls. The effect of the policy does not seem to be driven differently amongst girls who have an elder sibling who also studied Science.

Table 2.11: Sibling Spillover Effects

Dependent Variable: Probability of Choosing Science	(1)	(2)
Young X Close X Female X Sibling Science	-0.101	-0.114
	(0.0841)	(0.0827)
Young X Close X Female	0.0728***	0.0788***
	(0.0217)	(0.0233)
Young X Close X Sibling Science	0.231***	0.261***
	(0.0586)	(0.0640)
Sibling Science	0.121***	0.136***
	(0.0245)	(0.0300)
SDID weights	No	Yes
Observations	59,664	58,592
R-squared	0.189	0.160
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

2.6.2 Parents' Education

I also explore heterogeneity by parent's education level. The results are presented in Table 2.12. I first identify parents of each individual in the data. I then determine the highest level of education obtained by each parent. I take the maximum of the educational attainment of the two parents. The parent education variable is a continuous variable which determines the educational level attainment of the more educated parent. I interact this variable with the triple difference to determine the heterogeneity. I do not find heterogeneous effects by the parents' education level i.e. the increase in likelihood of studying science amongst younger girls living closer to IITs does not increase as parent's education level rises.

Table 2.12: Heterogeneity by Parent's Education Level

Dependent Variable: Probability of Choosing Science	(1)	(2)
Young X Close X Female X Parent Education	-0.000648	0.00399
	(0.00908)	(0.0115)
SDID weights	No	Yes
Observations	55,863	54,830
R-squared	0.195	0.168
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

2.7 Robustness & Sensitivity of Results

Excluding the old IITs: Out of the 23 IITs, 7 IITs were established between 1951-1963 because of which they continue to be top-ranked owing to their renowned curriculum, faculty, infrastructure and job market placements. As a robustness check, I remove these 7 IITs from my analysis to check if results are driven by these popular IITs. I present the triple difference estimate in Table B.1 and find that there is an increase in the likelihood of choosing the science track even if we only consider the relatively new IITs. The estimate is larger in magnitude indicating that the effect is being driven in areas with newer IITs.

Redefining far districts: The main analysis is restricted to districts which are atmost 200 km away from an IIT. I adjust my sample size by considering districts which are atmost 60km, 90km and 120km away from an IIT. This reduces the sample size at my disposal. I compare the gender gap in the likelihood of choosing science between districts less than 30km away with those that are farther. I still observe robust estimates of the policy impact as shown in Table B.2.

Changing the distance threshold: I test the sensitivity of my results to the threshold level that differentiates a close and a far district in Table B.3. I repeat the analysis when a district is close if within 20km, 40km or 50km of an IIT. I find that the impact of the policy is higher when the treated district is within 20km but fades away as the treated district gets farther from an IIT. The policy, therefore, affects the most who live close to the elite colleges (as concluded in section 2.3).

Dyadic Comparisons: The main analysis compares districts close to any IIT with those of districts far from any IIT. Additionally, I compare gender gap in science across cohorts between close and far districts *within each IIT zone*. I first divide the districts in the data to 23 IIT zones depending on which IIT is closest to that district. For instance, an IIT-Delhi zone consists of all those districts for which the closest IIT is IIT Delhi. For each separate IIT zone, I perform the usual triple difference regression which compares gender gap in the likelihood of choosing science before and after the policy between the districts within 30km radius with those that are outside that radius but within the same zone. I report the average triple difference coefficient from the regressions of 20 IIT zones[13] in Table B.4. The average coefficient of the individual regressions pertaining to each IIT zone is positive, statistically significant

[13]Zones of IIT Bhilai, IIT Ropar and IIT Jammu are omitted due to lack of sufficient data

and similar in magnitude with the triple difference coefficient that I obtained in Table 2.7.

Including IIT-zone and District by Region Fixed Effects: As an additional robustness check, I include IIT zone fixed effects in the main results. The results are robust when I control for any time-invariant IIT-zone specific characteristics (Table B.5). The use of synthetic DID weights increases the average treatment effect. The results are also robust when I include district by rural-urban fixed effects (Table B.6).

Dropping one IIT at a time: The results are robust when I drop one IIT at a time from the regression as shown in Table B.7-B.8. The point estimates vary between 0.053 to 0.076. They vary between 0.058 to 0.089 when SDID weights are used.

2.8 Conclusion

In this paper, I show that reserving seats for girls in elite STEM colleges can impact subject choices in school. While we do see increases in enrolment at these elite STEM colleges, the increase in seats is probably insufficient to meet the increasing demand for STEM courses amongst girls, especially if all the girls who switch to study Science subjects in school actually do pursue engineering courses. That is to say, there is possibly an impact on enrolment in other elite or non-elite colleges as well where this policy was not introduced. There are possible spillover effects of this policy on other institutions. Due to paucity of data and because there are a large number of such institutions, I am unable to estimate the spillover effect in this paper. If such effects are there and if they are non-negative, the policy can have a much larger impact on undergraduate STEM enrolment in the country as a whole.

I use distance to IIT as the identifying channel in order to define my treatment. Another possible channel that is correlated with distance is the information channel. It is important to note that the information about the policy is more relevant in areas closer to IITs than those that are farther. This is especially true since areas closer to IITs often form hubs which provide training and coaching for clearing their qualifying competitive exams. Therefore, any policy-related information that especially pertains to IITs is expected to spread through these hubs which are more likely to be closer to IITs than farther from them.

A possible concern that can be raised given the identification strategy that I use is that students relocate to areas closer to IITs or other places in the country which provide extensive training for the competitive exam and stay away from their parents after passing secondary schooling. However, the sample of my study consists of individuals living with their families and those students are not captured in the data that I use. Therefore, if any girls are moving out of the city in order to attend coaching as they anticipate improved chances of their admission, they would not be captured in my data and I would be underestimating the effect of the policy. However, I do not think the policy would make individuals switch subjects as well as make girls migrate out of hometown at the same time. The girls who believe that the policy has changed their probability of admission into IITs to one would be pursuing science anyway and if they were to make the choice would migrate for better coaching opportunities anyway. In a context where social norms are salient, a joint decision of studying science as well as migrating out of hometown for the same comes at a huge cost, whereas the benefits are only marginal.

Lastly, I would like to mention a possible mechanism which can be driving the effect of the policy - peer effects. Peers play a pivotal role in influencing school, college and subject decisions, especially within the same gender in developing areas with strict gender norms. The information about the policy is more likely to spread in peer groups. As girls discover about the policy, they are more likely to inform their friends about it. They also tend to choose the same subjects as their friends so that they can spend more time together, stay in the same class or join the same tuition. Therefore, one would expect the policy to have a larger effect when their peers also choose Science. Due to insufficient data on the subject choice of peer groups or social networks, I can not explore this mechanism and whether such networks and peer effects are driving the results is an open question for future research.

Chapter 3

Empowering to Conform: Age of Marriage & Violence Against Women

Ritika Gupta, Pooja Khosla & Sheetal Sekhri

3.1 Introduction

Socially determined gender roles, often reinforced by religious practices, are widely accepted by both men and women. Women are conditioned from early childhood to behave in accordance with the socially morphed propriety. In married life, they are socialized to accept domestic violence as an appropriate retribution for deviations from long-established socially accepted behaviors.[1] For example, a recent estimate reveals that 47 percent of the population in South Asian countries accepts domestic violence (Sardinha

[1]Going out of the house without permission, not doing household chores properly, not delivering meals in a timely manner, not looking after the children, and failing to oblige husbands sexually are widespread acceptable reasons for wife-beating.

and Catalán 2018). In 39 among the 47 countries whose data was considered, women were more accepting of violence. Current research has mainly focused on empowerment of women as a lever to challenge or alter these norms. For example, women with higher unearned income are able to bargain better in the household and increase their labor supply (Heath and Tan 2020); women with access to bank accounts where they deposit their earned income, are able to increase their labor supply and change the household's perceptions about female labor force participation (E. M. Field et al. 2019). However, when these norms are ubiquitous, women are not able to necessarily break away from them of their own accord (Dhar, Jain, and Jayachandran 2019, Bursztyn, González, and Yanagizawa-Drott 2020). In this study, we take a different view about empowerment and propose that in settings with widespread acceptance of beating, empowering women enables them to conform to the socially determined gender roles more efficiently, resulting in reduced domestic violence faced by them.

The metric of empowerment we use is the age at marriage. Extant research documents many empowering effects of age at marriage such as increase in autonomy and agency (Jensen and Thornton 2003). Age at marriage also affects educational attainment (E. Field et al. 2004) which can indirectly affect women's agency. But at the same time, possibly because of increased education or physical and emotional maturity, delayed age at marriage can also enable women to strategically conform with the desired social behavior to avoid the resulting sanctions such as beating. For example, delay in age at marriage can increase women's ability to look after children better, organize their time so that meals are delivered in a timely manner which are often cited as reasons for justifying beating in South Asian surveys. In order to shed light on this conformity effect, we develop a model which relates age of marriage to domestic violence. In our model, the husband uses violence in conjunction with transfers as an instrument to incentivise his wife to generate socially desirable behavior.

Specifically, we develop a cooperative household bargaining model in which the threat point is a non-cooperative two-stage Stackelberg equilibrium within marriage that incorporates the threat and incidence of domestic violence.[2] As mentioned above, in our model, the husband desires a threshold level of socially conforming behavior from the wife. If the wife fails to meet his expectations, cooperation breaks down in the household and the spouses operate at the non-cooperative threat point which is characterized by the possibility of spousal battering. In the two-stage strategic game that follows, the husband has two instruments he can use simultaneously to control his

[2]Tauchen, Witte, and Long 1991 proposes a model in which deviations from conformity lead to domestic violence but age at marriage plays no role in the model. Unlike our setting, it is uncertainty in the wife's commitment to conforming behavior that leads to violence.

wife's behavior. He sets a rule determining the amount of reprisal violence as a function of the wife's conforming behavior. He also chooses to make monetary transfers to induce the wife to generate the desired behavior. Given the rule and the level of transfers, the wife then decides how to behave. Both the levers at the husband's disposal have trade-offs. The threat of domestic violence induces the wife to behave in accordance with the husband's preferences but at the same time it lowers the efficiency with which the wife can generate the desired behavior. Similarly, transfers make more resources available to the wife for producing conforming behavior, but they reduce the private consumption of the husband. Age of marriage determines the wife's cost of conforming.[3]

Under this assumption, our model yields the first main prediction that delaying the age of marriage reduces the level and intensity of domestic violence. The underlying mechanism is that the exogenous reduction in conforming costs (due to more maturity with higher age at marriage) leads to the increased production of desired behavior by the wife. This diminishes the *need* to inflict violence by the husband which imposes an efficiency penalty. A second main prediction of our model is that independent access to finan-

[3]Typically, mature brides are less preferred in arranged marriages as they are less amenable to direct control and could experience higher psychological costs of conforming to traditional norms. Our model presumes that even if this effect exists, it is smaller in magnitude than the cost reduction effect. That is, increasing the age of marriage improves the efficacy of generating the conforming behavior.

cial resources by women mutes the effect of delay in age at marriage on domestic violence. Due to the resources, the wife produces more of the desired behavior which results in higher exogenous increase in desired behavior. Therefore, in this case, instead of reducing the level of violence in response to avoid the efficiency penalty, the husband lowers the amount of transfers that he makes (thereby increasing his private consumption) and adjusts violence by a smaller degree. Therefore, delaying the age of marriage amongst these women has a minimal or muted effect on domestic violence.

We provide support for the model's assumptions and causal evidence for the testable implications using two waves of the nationally representative National Family Health Surveys (NFHS 4: 2015-16 and NFHS 5: 2019-21) of India. Our model predicts that a delay in the age at marriage will reduce domestic violence and increase conforming behavior. Using the age of menarche as an instrument for the age of marriage (E. Field and Ambrus 2008; Sekhri and Debnath 2014), we corroborate these predictions. The variation in the timing of first menstruation generates quasi-random variation in the earliest age at which girls get married and helps us identify causal effects. Since malnutrition at birth can affect age of menarche and violate the exclusion restriction, we include adult height and birth year fixed effects as controls in our analysis. Moreover, younger women are more likely to face domestic violence (Angelucci and Heath 2020). Therefore, we also control for women's age. We do not find any correlation between adult height and menarche in our data, and eliminate nutrition as a confounding factor affecting both age of menarche and domestic violence outcomes. We use data from other sources (Indian Human Development Survey; Gender, Marriage & Kinship survey) which exhibit very similar patters with our data and argue that age of menarche affects domestic violence only through age of marriage. We also control for temperature and district fixed effects to provide additional support to the validity of our instrument. We perform various tests to demonstrate that measurement error and systematic misreporting of variables is less of a concern and unlikely to bias our results.

Our first stage estimates indicate that age of menarche is a strong instrument (very high F-stat at 157.7) and a one year delay in age of menarche delays the age of marriage by about 2 months. The instrument predicts age of marriage very strongly and the F-stat remains high, even after controlling for height, temperature, birth year and district fixed effects. We test the main prediction of our model and IV estimates show that a one year delay in age of marriage reduces the probability of facing less severe physical violence by 6.6 p.p. (26.4%), severe physical violence by 2.7 p.p. (38.5%) and emotional violence by 2.4 p.p. (18.4%). Using causal mediation analysis for IV models, we further provide evidence that a large proportion of these effects are driven by norm conforming behaviors such as lower decision making power, more time spent fetching water and less loan taking behavior.

In order to test our second prediction - access to independent financial resources mutes the effect of age of marriage on domestic violence - we make use of historical differences in inheritance norms and marriage practices among Hindus and Muslims. While Hindu women are married with payments to the husbands without enforceable rights on these payments (Anderson and Bidner 2015), Muslim women receive transfers called 'Mehr' (or dower). Muslim women are also entitled to inherit natal property because of Islamic laws, whereas Hindu women were not eligible to inherit property under the Hindu family law until very recently.[4] We use the Rural Economic and Demographic Survey of India (REDS 1999) to show that indeed these differences exist between Hindu and Muslim women although they have similar ages of marriage and similar propensity to face domestic violence. Consistent with our model, a central empirical finding in our analysis is that this relationship between delay in the age of marriage and domestic violence is stronger among Hindu households and gets muted for Muslims. Specifically, delaying the age of marriage amongst Hindu women by one

[4] We show that the differences in how age at marriage effects domestic violence persist even after the changes in inheritance laws plausibly driven by Mehr.

year reduces emotional violence by 3.6 p.p. (28%), less severe physical violence by 7.9 p.p. (27.2%) and severe physical violence by 3.4 p.p. (42.5%). For Muslims, the coefficients corresponding to emotional violence and severe physical violence are positive, small and insignificant. The coefficient corresponding to less severe physical violence is negative at 2.6 p.p. (10%) but is statistically insignificant.

We conduct additional robustness tests to refute alternative mechanisms. Our data doesn't provide information about natal district because of which we are unable to control for natal district or district birth year fixed effects. Instead, we include marital family district effects as an additional robustness and find that it only strengthens our results. We also argue that better spousal quality and marital family with higher age of marriage is unlikely to explain our results. For this purpose, we do two robustness tests. First, we additionally control for various husband's and his family's characteristics such as education levels, differences in the age of spouses, household wealth etc and our results are robust. Second, we restrict our sample to women whose husbands have similar characteristics, matched via a propensity score model, and we find that our results are unchanged even within this sample. We further show that a change in women empowerment due to higher age of marriage also does not explain our results. First we find that delay in age of marriage doesn't affect the beating attitudes and employment outcomes of women. Finally, our results are robust to controlling for these empowerment measures in our analysis.

Our paper complements and extends a growing body of research examining the role of social and cultural norms in shaping economic behavior. Much of the work in this vein has focused on the effects of gender norms and social practices on the educational and labor market outcomes of women (Fernández, Fogli, and Olivetti 2004; Dean and Jayachandran 2019; Ashraf et al. 2020; Jayachandran 2020; Guiso, Sapienza, and Zingales 2006; Jensen and Oster 2009. Other papers have examined the persistence of these norms across generations (Dhar, Jain, and Jayachandran 2019; Alesina, Giuliano, and Nunn 2013; Fernandez and Fogli 2009; Squicciarini 2020) and interventions that can influence these norms and beliefs (Bursztyn, González, and Yanagizawa-Drott 2020; Dhar, Jain, and Jayachandran 2018). An emerging body of work has examined the institution of marriage and the effects of cultural and social norms on empowerment of women within a marriage by way of ability to bargain (Anderson and Bidner 2015; Bhalotra, Chakravarty, and Gulesci 2020). The novel innovation of our work is highlighting how empowering outcomes can facilitate conformity to social norms by women within a marriage instead of challenging them and the effect this has on domestic violence faced by women.

Our paper also contributes to the work distilling the factors that give rise to domestic violence within the household.[5] A common view is that violence is instrumental (Heath 2014; Bloch and V. Rao 2002) and it is a lever used to control the spouse and her resources. Domestic violence is viewed through the lens of higher bargaining power in the household by means of increased education, employment, or income resulting in less spousal violence. The results are ambiguous. An alternate theory is that violence may be expressive, providing direct utility to some men. Tauchen, Witte, and Long 1991 model IPV as both a source of intrinsic utility and a means to control the spouse. Another possibility is that violence may be triggered by stress or scarcity (Card and Dahl 2011, Haushofer and J. Shapiro 2016, Heath, Hidrobo, and Roy 2020, Angelucci 2008). Our work complements this literature by developing an instrumental model of violence where the spouse desires socially conforming behavior and age at marriage helps deliver this behavior efficiently. Our work distinguishes from these previous papers in establishing how empowerment practices (delay in age at marriage) can influence domestic violence through higher conforming behavior and the role that individual wealth plays in shaping this relationship.

Our paper relates to the established literature on household bargaining mod-

[5]See Angelucci and Heath 2020 for a review.

els. Starting with Samuelson 1956's Consensus model and Becker 1974's Altruist model, this literature has advanced significantly over the years. Papers range from cooperative intra-household bargaining models (as in Manser and Brown 1980, McElroy and Horney 1981, Chiappori 1988, Chiappori 1992) to non-cooperative models (like Tauchen, Witte, and Long 1991, Eswaran and Malhotra 2011, Chen and Woolley 2001, Friedberg and Stern 2014) or a combination of both Lundberg and Pollak 1993. These models have looked at the implications of cash subsidies and/or transfers and who receives them on household consumption. Policies that increase the bargaining power of women (like inheritance laws, childcare subsidies) have also received due attention. Our paper develops a cooperative bargaining model with a stackelberg-type non-cooperative threat point. In doing so, our paper extends the 'separate spheres' bargaining model introduced by Lundberg and Pollak 1993 to include the threat and use of domestic violence. We also include the age of marriage as a potential determinant of domestic violence.

Finally, we also speak to the literature documenting the adverse effects of early marriages. Girls who marry young have lower educational attainment, report less sexual and reproductive control, lower social status and decision-making power in the household and experience higher rates of domestic violence (E. Field and Ambrus 2008, Jensen and Thornton 2003), Chari et al.

2017). In the US, delaying age of marriage results in higher later year wages (Loughran, Zissimopoulos, et al. 2004, C. Wang and L. Wang 2017). We contribute to this literature by demonstrating that delay in age at marriage reduces domestic violence but only for women who are not independently wealthy.

Our work is also policy relevant. Global estimates published by the World Health Organization (WHO) in 2017 indicate that approximately one in three women worldwide have experienced physical and/or sexual violence in their lifetime. This can negatively affect women's physical, mental, sexual, and reproductive health. Domestic violence is not only associated with worse outcomes for the woman, but the exposed children and society at large (Carrell and M. L. Hoekstra 2010). Various policy measures have been enacted by governments across the world to counteract this trend. Most of these policies are aimed at economically empowering women and while some have worked, others have led to unintended effects in the form of backlash. Our work shows that social norms and spousal desire for socially acceptable behavior impacts domestic violence. Thus, policies that address such regressive norms might be more effective at reducing violence.

The paper is organized as follows. Section 3.2 provides a brief background of the Indian context and cultural differences across various religious groups.

In section 3.3, we lay down a conceptual framework. This is followed by a discussion of our data and estimation strategy in section 3.4 and 3.5. In section 3.6 we test the predictions of our model and describe our findings. We include robustness checks in section 3.7. Finally, section 3.8 concludes.

3.2 Background

In India, Hinduism and Islam do not grant equal status to women and men. Religious scriptures identify controlled status of women and posit various prescriptions of good behavior for women promoting submissiveness to their families. The religious expectations are operationalized through adherence to social norms. These norms govern the day-to-day life of women as well as significant events such as marriages.

Hinduism and Islam have many similarities. In both religions, women are expected to obey the norms of her natal family while living with her parents before marriage, and that of the husband after she moves into her marital home once married. They also place a very high premium on chastity of women. Among Hindus, chastity is considered 'purity' of woman. Men outside the house are considered as sources of 'pollution' under the caste system. Getting girls married early and limiting interaction with men outside the family by restricting mobility are often used as means to preserve their purity (chastity) (Chen, 1995). In Islam, as well, the practice of *purdah* or female seclusion serves a similar purpose. This ingrained belief results in early age marriages of both Hindu and Muslim girls. Using the two NFHS waves, we plot the age of marriages of women by religion in Figure 3.1. The plot suggests that child marriage (marriage under the age of 18 years) is quite prevalent. Also, the distribution of age at marriage is similar for Hindus and Muslims but displaced to the right for Christians.

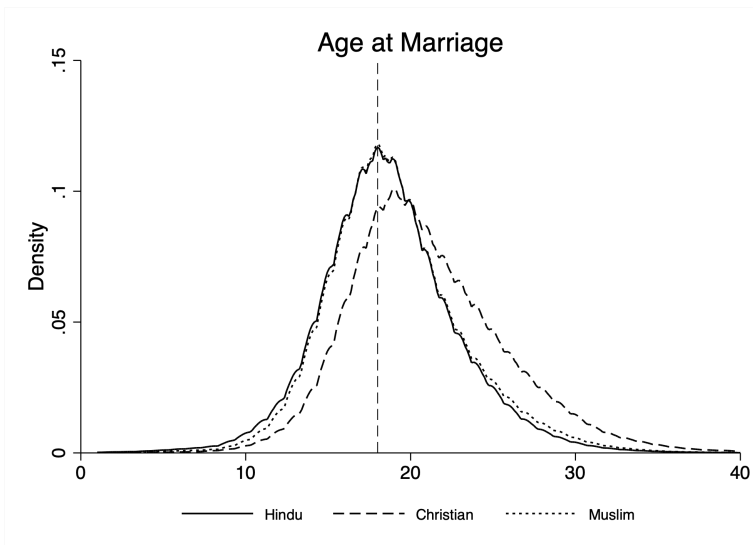


Figure 3.1: Age at Marriage by Religion

Data used is sample of individual women surveyed in the two NFHS waves. The vertical dashed line correspond to the age of 18. Epanechnikov kernel, bandwidth=0.75

Women are expected to be married as soon as they achieve maturity or menarche since waiting too long after menarche can result in corruption of women. According to the Hindu religious text *Manusmriti*, which discusses the rules for family life, a father is considered to have wronged his daughter if he fails to marry her before puberty and if the girl is not married in less than three years after reaching puberty, she can search for the husband herself. Similarly as per Islam:

"*Virgin girls are like fruits on trees. If not plucked in time, the sun will rot them and the wind will disperse them. When girls reach maturity and their sexual instincts arise, like that of women, their only remedy is marriage. If they aren't married, they are prone to moral corruption. It is because they are human beings and human beings are prone to making mistakes.*"

Hence, both Hindu and Muslim households tend to marry the girls at a very young age often soon after they attain menarche. In Figure 3.2, we show that the distribution of age at menarche is remarkably similar across Hindu, Muslim, and Christian households. This social norm of marrying the girls as soon as they attain puberty will form the basis of our identification strategy and we will discuss the relationships in our data later in the paper.

The marital norms within the two religions also exhibit certain different characteristics. While both Hindus and Muslims practice patrilocality, whereby women leave their parents house after marriage and reside with the husband and his family, they have different norms about how to ensure a good respectable position for the girl in her married home. In India, Muslim

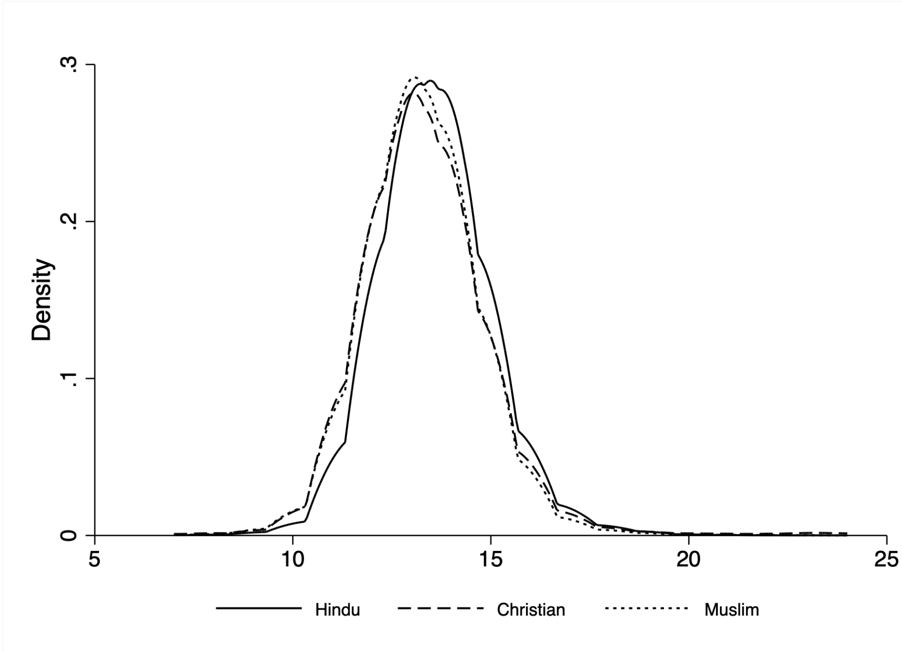
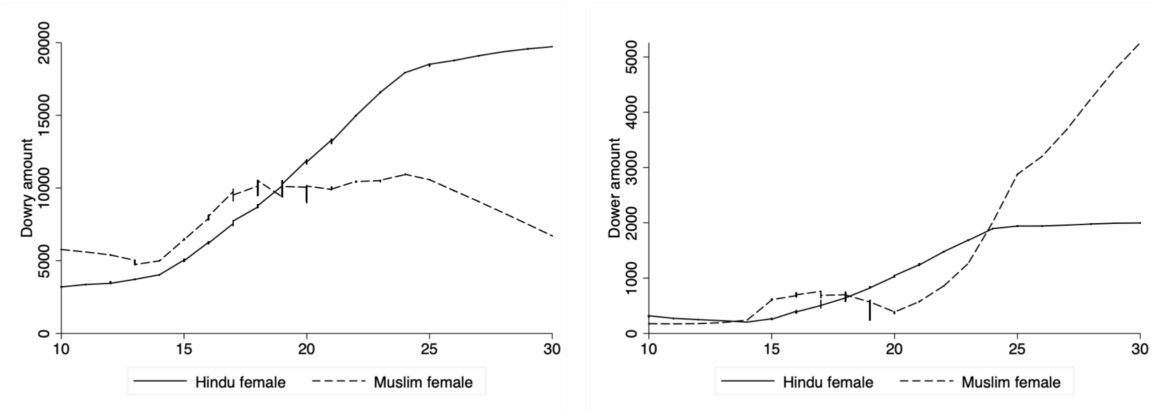


Figure 3.2: Age at Menarche by Religion

Data used is sample of individual women surveyed in the two NFHS waves. Epanechnikov kernel, bandwidth=0.75

husbands typically make a payment called *mehr* to the wife at the time of marriage. Upon divorce, the *mehr*, also known as *Dower* is kept by the woman, thereby serving as a form of divorce insurance (Quale 1988; Ambrus, E. Field, and Torero 2010).

This payment can be in terms of cash or assets of significant value such as land, or a house. Among Hindus, however, the plurality practice dowry. This is a large transfer from the natal family to the husband's family at the time of marriage and may include subsequent stream of smaller payments. Hence, at the time of marriage Muslim women receive wealth, whereas Hindu husbands (instead of the wife) receive transfers.



(a) Dowry Paid (b) Dower Received

Figure 3.3: Age at Marriage and Dowry Paid and Received by Religion

Data Source: 1999 Rural Economic and Demographic Survey (REDS)

Figure 3.3 shows the relationship between the age at marriage and the amount of dowry paid (Panel (a)) and dower received (Panel (b)) for Hindu and Muslim women. As age of marriage increases, the dowry that has to be paid increases steeply for Hindu households. For Muslim women as well, the dowry amount increases till the age of 17 and 18. However, it plateaus thereafter and eventually shows a declining trend after the age of 25. The incidence and amount of dower is lower than that of dowry payments and increases with age at marriage but more so for Muslim women compared to Hindu women.

There are differences in inheritance laws as well. Succession for Hindus in India was traditionally governed by the Mitakshara system. Under this system, joint property was doled out among a group of coparceners, which typically included only male relatives. Daughters or widows were allowed to inherit ancestral property from their fathers or late husbands only in the absence of male heirs. The Hindu Succession Act (HSA) of 1956 clarified women's rights to inherit private property but it continued to exclude women from the inheritance of joint property. In subsequent years, various states enacted amendments that explicitly made daughters coparceners. Between 1976 and 2005, HSA was phased into different states in India. These reforms applied only to women who are Hindu, Buddhist, Sikh, or Jain, and only to women who were not yet married at the time of the reform. In Figure 3.4, we plot the probability of inheriting land against the age of marriage for Hindu and Muslim women using data from the 1999 Rural Economic & Demographic Survey (REDS). As the figure shows, Muslim women are more likely to inherit land than Hindu women.[6]

In order to shed light on the wealth of women by religion, we also examine likelihood of owning large assets such as land and a house in the first two columns of Table 3.5 using data from NFHS 4 and 5. For each additional year increase in the age of marriage, Hindu women are 7.7 p.p. (or 24%) less likely to own land and 8.3 p.p. (or 21.2%) less likely to own a house. All these estimates are statistically significant. We do not find any statistically significant change in the land and house ownership amongst Muslim women.

[6]Unlike information on land inheritance which is collected for all household members separately, data on property ownership is collected for the household as a whole. Hence, we only present results for land inheritance using REDS data.

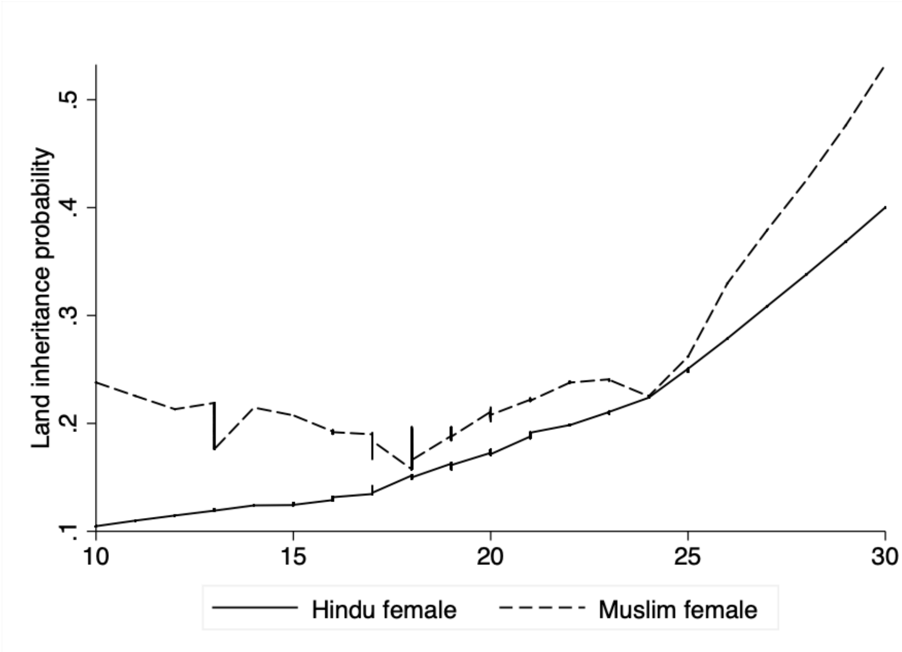


Figure 3.4: Probability of land inheritance by age of Marriage

Data Source: 1999 Rural Economic and Demographic Survey (REDS)

3.2.1 Domestic Violence and Age at First Marriage

A vast social science literature espouses that domestic violence can be instrumental in that the husband wants to control his wife. He expects conformity to socialized norms and expects the wife to behave in a certain way. When these expectations are not met, the husband uses violence as an instrument of retribution. Thus, if women contest gender roles, it can escalate violence.[7]

Given these social norms, from an instrumental perspective, delay in the age at first marriage has ambiguous implications for domestic violence. On

[7]Domestic violence can also be extracting and be a lever for demanding more dowry (Bloch and V. Rao 2002

the one hand, it might increase women's education and wages, making them less compliant and submissive. This could result in increased violence due to non-conformity to prescribed gender roles. However, on the other hand, better education or maturity might make the woman deft in navigating the spousal expectations thereby reducing the cost of compliance and making her comply with socially acceptable behavior, resulting in reduced violence. In addition, the premium on the marriage market for younger brides in South Asia could result in higher resources available to meet the expectations of the spouse at lower marital ages, which can dilute the effect that age of marriage has on domestic violence via improved maturity. With this backdrop, we have two goals. One, we want to assess how age at marriage affects domestic violence. Is there a causal relationship between age at marriage and domestic violence? Two, do social norms and religious practices have a bearing on this relationship and how is it mediated by individual woman's wealth?

3.3 Conceptual Framework

To formalize the relationship between domestic violence and age at marriage, we present a basic model of household bargaining in which the husband uses domestic violence as an instrument to influence the wife's actions and behavior. In this model, the husband has expectations for the conforming behavior he wants and wife's deviation from providing that behavior leads to reprisal violence. Our model also provides insights about how social marital norms dictated by different religions can effect the relationship between age at marriage and domestic violence by influencing the woman's individual wealth.

3.3.1 Model of Intra-household Bargaining

We develop a model resembling the 'separate spheres' bargaining model developed by Lundberg and Pollak 1993 in that the threat point is a non-cooperative equilibrium within the confines of marriage. In Lundberg and Pollak 1993, the threat point is a non-cooperative *Cournot-Nash* equilibrium that reflects socially sanctioned and recognized gender roles and cultural norms. We depart from this model in the way we characterize the threat point. In the bargaining model we develop, the threat point is a non-cooperative *Stackelberg* equilibrium within marriage that includes the threat and incidence of domestic violence.[8] Central to our framework is the age at marriage of the wife that influences the outcomes of the non-cooperative equilibrium.[9]

[8]Other models with divorce as threat point have been developed by Manser and Brown 1980 and McElroy and Horney 1981. However, in India the rate of divorce is very low. According to a recent United Nations (UN) report, only 1.1 per cent of women are divorced in India (Women 2019). Hence we consider the threat point within the marriage.

[9]Tauchen, Witte, and Long 1985 and Eswaran and Malhotra 2011 have also proposed two-stage models of domestic violence within marriage where violence is instrumental in generating desired

Model Setup

Consider the following two-person household bargaining model with a husband, denoted by h, and a wife, denoted by w. Both husband and wife consume a private good x^h and x^w and their incomes are y^h and y^w, respectively. Additionally, we assume that there are certain behaviors of the wife, b, that provide direct utility to the husband. These may include cooking, taking care of the children, and socially conforming gender roles such as not working outside the home, not meeting female friends, not talking to males outside the family, not owning a bank account and so on.[10] In order to keep the model tractable, we assume that these behaviors do not provide utility to the wife. In other words, b is not a public good, even though some activities like child care might yield utility to the wife. The production of these behaviors is costly for her. The partners can make transfers to each other. In equilibrium only the net transfers matter. In our setting, since the income of the husband usually exceeds that of the wife, we model transfers

behavior from the wife. While we take this view, these models are different than ours. In Tauchen, Witte, and Long 1985, the production technology of behavior of the wife has a random component that the husband does not observe and decides the expected punishment (violence) based on deviation from the desired behavior. In the case of Eswaran and Malhotra 2011, men and women have different preferences over household goods while women have the discretionary power over spending. Consequently, husbands use violence as an instrument to induce the wife to curtail her autonomy and give more weight to his preferences when making decisions. Neither of these examine the role that age at marriage has in providing the behavior desired by the husband.

[10]This is similar to the concept of *separate spheres* introduced by Lundberg and Pollak 1993 whereby the responsibility of certain household activities lies with women only. In the cooperative equilibrium, if one assumes that women are more efficient in performing household chores, these activities will be performed by the women. In a non-cooperative equilibrium, traditional gender norms dictate that these activities will fall under the responsibilities of the women.

from the husband to the wife only and not vice-a-versa.

In our model, the husband expects and wants the wife to behave in a way he desires. We denote this desired behavior as B. If the wife provides this expected level of behavior, we assume that the resulting equilibrium will be the cooperative Nash Bargaining solution.[11] However, if the wife digresses from this desired behavior, the non-cooperative equilibrium results. Here, the husband uses violence (or the threat of it) to induce the wife to produce these behaviors if she does not do so willingly. In our model, violence is not expressive but only instrumental. That is, the husband inflicts violence only if the wife digresses from the preferred behavior but not otherwise.[12]

In addition to the threat of violence, the husband also chooses to make a voluntary transfer t to the wife in order to increase the amount of b produced by her. The outside utility for the husband is $\bar{U}^h$ and the wife is $\bar{U}^w$. Both the husband and wife must derive at least this level of utility from the relationship for it to continue and not dissolve. For the purposes of this analysis, we assume that divorce is prohibitively costly so both spouses receive utility greater than or equal to their reservation utilities, even when operating at the non-cooperative equilibrium.[13]

[11] The equilibrium distribution of marital surplus will depend on the bargaining power of the two individuals and the utility at the threat point.

[12] In an expressive utility model, the husband is assumed to derive direct utility from violence (see, for example, Tauchen, Witte, and Long 1985 who consider both expressive and instrumental violence in their model.)

[13] In the NFHS-4 data collected in 2015-16, the proportion of divorced women (including those

Next, we provide a brief overview of the cooperative Nash bargaining solution followed by a more in-depth discussion of the non-cooperative Stackelberg equilibrium. The latter incorporates the possibility of domestic violence and is the primary focus of the this paper.

Cooperative Nash Bargaining Equilibrium

We denote the utility of the husband and wife at the threat point as $T^h(\cdot)$ and $T^w(\cdot)$, respectively. Note that in our model, this is the indirect utility that the agents receive in the non-cooperative equilibrium. Similarly, $W^h(\cdot)$ and $W^w(\cdot)$ denote the indirect utility at the cooperative equilibrium. The standard Nash bargaining solution maximizes the product of the gains to cooperation (relative to the threat point). In order words, it is the point in the feasible set that maximizes the Nash social welfare, $N = (W^h - T^h)(W^w - T^w)$.[14] In a more generalized Nash Bargaining equilibrium, the solution maximizes $N = (W^h - T^h)^{\alpha_h}(W^w - T^w)^{\alpha_w}$, where α_h and α_w represent the bargaining power of both individuals.[15] It is worth noting that the utility of the individuals in the cooperative equilibrium is increasing in their utility at the threat point (see, Lundberg and Pollak 1993

that are separated and no longer living together with their spouses) is less than 1.5 percent.

[14]This approach maximizes the total marital surplus and distributes it equally between the spouses.

[15]The distribution of marital surplus between the spouses will now depend on the bargaining power of the individuals as well.

for more details).

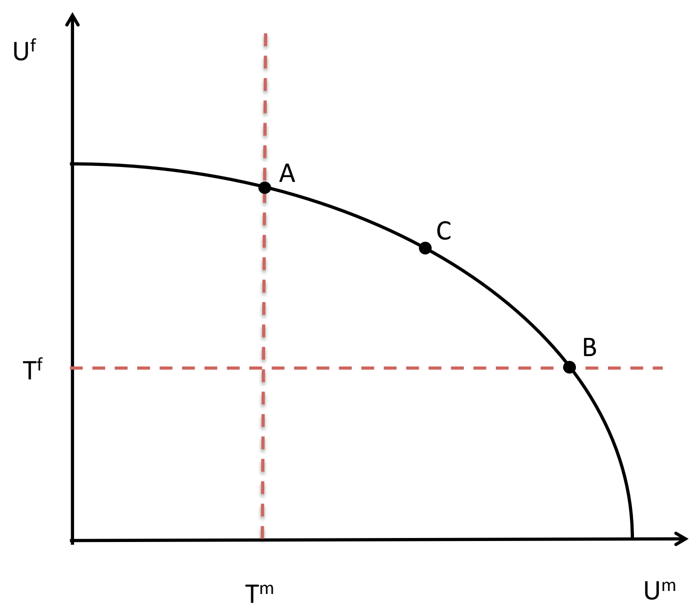


Figure 3.5: Nash Bargaining Solution

Figure 3.5 depicts the utility possibility frontier with the utility of the wife on the y-axis and that of the husband on the x-axis. Points A and B correspond to the threat point utilities of the husband and wife, respectively. The cooperative Nash bargaining equilibrium will be a point on the segment AB, depending on the bargaining power of the two individuals. We denote this equilibrium at point C on the graph. The utilities at point C are given by W^h and W^w.

We are, however, more interested in characterizing the non-cooperative equilibrium and understanding its properties. We do so in the next subsection and derive a few key predictions which we then test empirically.

Non-cooperative Equilibrium (Threat Point)

When the conforming behavior of the wife doesn't meet the husband's expectations, household cooperation breaks down. Consequently, the husband uses violence as an instrument to affect the wife's behavior. As mentioned previously, we model the non-cooperative equilibrium as a two-stage Stackelberg game. In the first stage, the husband sets down the rule by which he decides how much violence he will inflict on his wife for a given level of behavior, and chooses the level of transfers t to induce her to provide the behavior he desires. We assume that the husband commits to a frequency (or intensity) of battering, γ, which inflicts violence on the wife in proportion to the degree of digression from the desired behavior. That is, the violence, V, that she suffers is denoted as $V = \gamma(B - b)$.[16] In the second stage, the wife chooses her behavior b, knowing the level of violence this will result in. The husband's utility is increasing in b, the conforming behavior of the wife. Generating this behavior is costly for the wife. We denote the unit

[16]The choice of modelling the husband as the first mover in this setting is motivated by the fact that patriarchy is an entrenched institution in developing countries. In doing so, we also conform with Eswaran and Malhotra 2011.

cost by p. For the purposes of illuminating how age at marriage factors into the determination of domestic violence, we assume that the age of marriage affects the ease with which the wife can conform to social and cultural norms regarding behavior desired by the spouse. In particular, we assume the following functional form for the per unit cost of producing b.

$$p(\gamma, A) = \phi(A) \cdot \gamma^{1/2} \tag{3.1}$$

That is, p depends on two factors: it is (i) decreasing in the age of marriage (A), and (ii) increasing in the frequency of battering (γ). The rationale for this is the following.

Girls married at older ages are plausibly more mature and are thus able to conform more easily to the expectations of the household they are married into. Delayed marriage might also be associated with increased education and experience which might increase the productivity of household chores. Physical and psychological injuries associated with violence affect the productivity of producing the behavior. We assume that these costs rise at a slower rate than γ.

The utility functions of the husband and wife are denoted by:

$$U^h \equiv U_h(x^h, b) \tag{3.2}$$

$$U^w \equiv U_w(x^w) - C_w(V) \tag{3.3}$$

The functions $U_h(\cdot)$ and $U_w(\cdot)$ are increasing and quasi-concave in their arguments. $C_w(\cdot)$ denotes the direct physical and emotional cost of violence to the wife, and is increasing in V.

3.3.2 Decision Making by the Spouses: Stackelberg Equilibrium

As mentioned previously, the husband first sets down the rule determining the amount of violence, wherein he chooses the frequency of battering γ, and the amount of transfer t to make to the wife. Observing this, the wife makes decisions regarding the amount of private good x^w to consume and behavior b to provide. The model is solved by backward induction.

Taking the husband's decisions from the first stage $(\bar{\gamma}, \bar{t})$ as given, the wife solves the following maximization problem:

$$\begin{aligned} \max_{x^w, b} \quad & U_w(x^w) - C_w(V) \\ \text{s.t.} \quad & x^w + p \cdot b = y_w + \bar{t}, \;\; V = \bar{\gamma} \cdot (B - b), \;\; U^h \geq \bar{U}^h \end{aligned} \tag{3.4}$$

The solution to her optimization problem is denoted by $b^+(\bar{\gamma}, \bar{t})$. Note that the price of private goods is normalized to one and there are no savings in the model. Anticipating the wife's behavior, the husband solves the following optimization problem:

$$\begin{aligned} \max_{x^h, \gamma, t} \quad & U_h(x^h, b^+(\gamma, t)) \\ \text{s.t.} \quad & x^h = y_h - t, \;\; U^w \geq \bar{U}^w \end{aligned} \tag{3.5}$$

The first order conditions from the optimization problems in Equations 3.4 and 3.5 can be solved to characterize the equilibrium: t^*, γ^* and b^*. In order to simplify the algebraic expressions and make meaningful inferences regarding the signs of partial derivatives for the comparative statics, we assume that the utility functions are log linear. The decision making problem by the wife and husband can then be expressed as follows:

Stage 2: Wife's Decision Problem

The wife solves the following:

$$\begin{aligned} &\max_{x^w,b} \quad \alpha^w \cdot logx^w - \delta^w \cdot V \\ &\text{s.t.} \quad x^w + p \cdot b = y_w + \bar{t}, \;\; V = \bar{\gamma} \cdot (B - b), \;\; U^h \geq \bar{U}^h \end{aligned} \tag{3.6}$$

The solution to the above optimization problem is derived in section C.1. Taking the level of battering frequency ($\bar{\gamma}$) and transfers ($\bar{t}$) as given, the optimal choice of behavior b^+ by the wife is given by:

$$b^+(\bar{\gamma}, \bar{t}) = \frac{y^w + \bar{t}}{p(\bar{\gamma}, A)} - \frac{\alpha^w}{\bar{\gamma}\delta^w} \tag{3.7}$$

Stage 1: Husband's Decision Problem

The husband takes this into account and his decision problem is:

$$\begin{aligned} &\max_{x^h,\gamma,t} \quad \alpha^h \cdot logx^h + \beta^h \cdot logb^+(\gamma, t) \\ &\text{s.t.} \quad x^h = y_h - t, \;\; b^+(\gamma, t) = \tfrac{y^w + t}{p(\gamma, A)} - \tfrac{\alpha^w}{\gamma\delta^w}, \;\; U^w \geq \bar{U}^w \end{aligned} \tag{3.8}$$

A detailed solution to the two-stage optimization problem is presented in section C.1.

Now, conditional on the husband's decisions in Stage 1, the wife's behavior is given by Equation 3.7. We characterize the relationship between this behavior produced by the wife and the battering and transfers delivered by the husband in Lemma 1.1 and Lemma 1.2 below.

Lemma 1.1: *Conforming behavior generated by the wife is increasing in the amount of transfers ceteris paribus.*

Proof. This follows directly from the Stage 2 optimization solution. Differentiating Equation 3.7 with respect to the transfers $\bar{t}$, it is straightforward to see that $\frac{\partial b^{+}(\bar{\gamma},\bar{t})}{\partial \bar{t}} > 0$. Under the separate spheres assumption, the behavior b can be produced *only* by the wife. By making more transfers to the wife, *ceteris paribus*, the husband increases the resources available to her and is thus able to increase the amount of desirable behavior produced in equilibrium by her.[17] □

□

Lemma 1.2:*The frequency of battering has an ambiguous effect on the conforming behavior ceteris paribus.*

[17]Since x^{w} is a normal good and V is a bad, the additional income is used to increase private consumption and reduce violence by producing more behavior.

Proof. Again, taking the derivative of Equation 3.7 with respect to ,

$$\frac{\partial b^{+}(\bar{\gamma},\bar{t})}{\partial \bar{\gamma}} = \underbrace{-\frac{y^{w}+\bar{t}}{p(\bar{\gamma},\bar{t})^{2}} \cdot \frac{\partial p(\bar{\gamma},\bar{t})}{\partial \bar{\gamma}}}_{\text{Efficiency Reduction Effect (-)}} + \underbrace{\frac{\alpha^{w}}{\bar{\gamma}^{2}\delta^{w}}}_{\text{Threat/Incentive Effect (+)}}$$

The first term in the above expression is negative since $\frac{\partial p(\bar{\gamma},\bar{t})}{\partial \bar{\gamma}} > 0$; while the second term is positive. The overall sign of the derivative depends on the magnitude of the two terms. The first term captures the *Efficiency Reduction Effect* of battering while the second term captures the *Threat or Incentive Effect.* On the one hand, increasing the frequency or intensity of battering reduces efficiency and raises the cost of conforming but, on the other hand, it increases the threat of violence and provides an incentive to conform in order to reduce the total violence resulting from deviating behavior. The overall direction depends on which effect outweighs the other.

□ □

The Non-cooperative Equilibrium

Solving for the Stackelberg equilibrium, we have the following expressions for transfers made by the husband (t^{*}), the behavior produced by the wife (b^{*}), battering intensity (γ^{*}) and, the level of violence (V^{*}) in equilibrium:

$$t^* = \frac{2\beta^h y^h - \alpha^h y^w}{2\beta^h + \alpha^h} \tag{3.9}$$

$$\gamma^* = \left[\frac{\alpha^w \phi(A)(2\beta^h + \alpha^h)}{\delta^w \beta^h (y^h + y^w)}\right]^2 \tag{3.10}$$

$$b^* = \frac{\delta^w}{\alpha^w}\left(\frac{\beta^h (y^h + y^w)}{\phi(A)(2\beta^h + \alpha^h)}\right)^2 \tag{3.11}$$

$$V^* = B\left[\frac{\alpha^w \phi(A)(2\beta^h + \alpha^h)}{\delta^w \beta^h (y^h + y^w)}\right]^2 - \frac{\alpha^w}{\delta^w} \tag{3.12}$$

3.3.3 Predictions based on the Model: Testable Implications

In the previous section, we characterize the non-cooperative equilibrium, or the threat point, of the bargaining model. In this section, we begin by examining the properties of the equilibrium and derive testable implications that we then take to the data. In particular, we look at the role of the age of marriage.

Proposition 1: *Increasing the age at marriage, ceteris paribus*

(a) reduces the frequency and/or intensity of violence.

(b) increases conforming behavior.

(c) reduces the overall level of violence.

Proof: *The proof is derived in section C.1*

When the age of marriage increases, it reduces the cost of conforming. For any given level of battering and transfers, the husband encounters a more conforming behavior from the wife (follows from Equation 3.7). As a result, the husband does not *need* to threaten as much and/or make transfers of the same magnitude. He can reduce the reliance on violence since the wife is producing more behavior than before.[18] In equilibrium, more conforming behavior is produced, the frequency and intensity of violence is lower. Overall, the wife experiences lower levels of violence when she marries at a later age, all other things unchanged.

Proposition 2: *The effect of delayed marriage on (a) the frequency and/or intensity of violence, and (b) the overall level of violence is muted if the wife has access to more financial resources.*

Proof: *See section C.1 for the proof*

[18]Given the increased efficiency with which the wife is able produce the desired behavior, the husband might want to increase transfers but he faces a trade-off as it would reduce his private consumption. Under the specific assumptions of the model, the two factors cancel each other and the transfers don't change when the age of marriage increases.

When the wife has access to more financial resources, the same increase in age of marriage has a smaller effect on the level and frequency/intensity of violence experienced by her. In order to understand why this is the case, let us first examine the effect of increased wealth alone.

When there is a positive wealth shock, much like transfers, the wife produces more conforming behavior for any given level of battering and transfer chosen by the husband (follows from Equation 3.7).[19] Now, the husband has two instruments that he simultaneously uses to elicit desired behavior from the wife: *transfers (t)* and *violence* (γ). Transfers to the wife reduce his private good consumption and violence adversely affects the efficiency of the production of desired behavior by the wife. When the wife has more wealth, she produces higher levels of conforming behavior. So, the husband reduces the transfers he makes as this increases his private good consumption. At the same time, he is also induced to reduce battering as that makes the wife more efficient at producing the desired behavior. Overall, the wife provides more behavior due to the lump sum wealth gain (net of reduced transfers) and lower frequency and/or intensity of battering and both spouses have a higher private consumption in such a scenario. Now, if the age of marriage is higher for a wealthy wife, the greater maturity will result in more conformity

[19] Wife's private good consumption also increases because it is a normal good.

behavior due to an increase in efficiency of producing the desired behavior as before. However, this will allow the husband to keep the violence at a higher level relative to a pure wealth change case as it generates a threat and induces the wife to keep conforming. Hence, the husband substitutes the age of marriage induced efficiency effect in generating desired conforming behavior for the reduced violence induced efficiency effect for a wealthier spouse.

Together, Propositions 1 and 2 imply that increasing the age of marriage would lower the level of violence experienced by the wife. However, the effects would be muted when the wife has access to more financial resources. In our empirical analysis, we will test these predictions of our model.

3.3.4 Welfare Implications

In this section, we briefly discuss the welfare implications of delaying the age of marriage at the threat point. As Proposition 3 below suggests, increasing the age at marriage is unambiguously welfare improving for the women. In our model, this follows from the assumption that increasing the age at marriage lowers the cost of conforming.[20]

[20] If this were not the case, the results would be ambiguous. Additionally, we don't account for the fact that dowry/dower amounts are also a function of the marriage age. Delaying the age at marriage could also improve welfare directly by increasing the bargaining power of the woman in the cooperative Nash bargaining equilibrium. However, we focus on welfare in the non-cooperative equilibrium that includes the possibility of physical abuse.

Proposition 3: *Increasing the age of marriage is welfare improving for the wife.*

Proof.

Substituting the equilibrium values of x^w into the wife's utility function (see Equation 3.6), the indirect utility at the threat point is given by:

$$T^{w*} = \alpha^w \ln\left(\frac{\beta^h(y^h + y^w)}{2\beta^h + \alpha^h}\right) - \delta^w \cdot V^* \tag{3.13}$$

Differentiating Equation 3.13 with respect to A, we get:

$$\frac{\partial T^{w*}}{\partial A} = -\delta^w \frac{\partial V^*}{\partial A} > 0$$

This follows from the proof of Proposition 1 (c). □ □

Thus, increasing the age at marriage increases the utility of the wife at the non-cooperative threat point, T^w. This is the indirect utility when cooperation breaks down and the wife experiences spousal violence. Since utility in the cooperative bargaining equilibrium, W^w, is increasing in T^w, the wife is also better off when cooperation is maintained in the household.

3.4 Data

The main source of data used is the National Family Health Survey of India. We use the 4^{th} and 5^{th} rounds of the series that collects information about population, nutrition and health. The survey sample is a two-stage stratified sample. The 2011 census served as the sampling frame for the selection of primary survey units (PSUs) which were villages in rural areas and Census Enumeration Blocks (CEBs) in urban areas. The PSU's were selected using probability proportional to size. Then, a complete roster of households was created in every PSU. PSUs with fewer than 40 households were merged with the nearest PSU. If the number of households in the PSU exceeded 300, the PSU was divided into segments of 100-150 households and one segment was chosen for sampling using systematic sampling with probability proportional to the segment size. In the second stage, 22 households were then chosen for the survey. Overall, 28,586 and 30,456 PSUs were selected across the country, and fieldwork was completed in 28,522 and 30,198 clusters in NFHS-4 and NFHS-5 respectively. Comprehensive details about sampling and survey design are publicly available (Iips 2017; Iips 2021).

Within 601,509 and 636,699 interviewed households, 699,686 and 724,115 eligible women age 15-49 were administered the individual women's survey in NFHS-4 and NFHS-5 respectively. The individual surveys administered to the women covered a wide range of topics including background, reproduction and fertility preferences, family planning, female hygiene, marriage and sexual activity, husband's characteristics, work and employment, attitudes and decision making, HIV and other health issues including bio-markers. Only one eligible woman per household was chosen to answer questions about domestic violence.

3.4.1 Our Sample and Summary Statistics

A total of 79,729 women in NFHS 4 and 72,056 women in NFHS-5 completed the module.[21] Restricting the sample to women belonging to Hindu, Muslim or Christian households reduces the total sample of women to 139,618.[22] Further removing negative and/or implausibly large values for the age of marriage leaves us with a final sample consisting of 118,425 married women. Of these 79.4 percent women are from Hindu households. In Table 3.1, we report the summary statistics of the full sample. Average age of marriage among Hindu and Muslim households is 18.83 and 19.29, respectively. However, it is 21.13 for Christians.[23] Minimum age of menarche is 7 which is the same for Hindus, Muslims, and Christians. Average age of achieving

[21]NFHS-4 administered the domestic violence module to women aged 15-49 but NFHS-5 administered the domestic violence module to women aged 18-49.

[22]We also restrict our analysis to birth years between 1968 and 2002 as these birth years are common in both the waves, avoiding collinearity with the wave fixed effects.

[23]The legal age of marriage in India is 18.

menarche is very similar across the three religions - about 13.4.

Table 3.1: Summary Statistics by Religion (Full Sample, DV Module)

	Min	Mean	Std Dev	Median	Observations
Panel A: Hindu					
Age of marriage	1	18.83	4.11	19	93976
Age of menarche	7	13.56	1.27	13	14566
Less severe physical	0	0.29	0.45	0	93795
More severe physical	0	0.08	0.28	0	93795
Emotional	0	0.13	0.34	0	93795
Sexual	0	0.06	0.24	0	93795
Panel B: Muslim					
Age of marriage	1	19.29	4.09	19	15727
Age of menarche	7	13.22	1.23	13	2567
Less severe physical	0	0.24	0.43	0	15700
More severe physical	0	0.07	0.25	0	15700
Emotional	0	0.13	0.33	0	15700
Sexual	0	0.06	0.24	0	15700
Panel C: Christian					
Age of marriage	1	21.13	4.68	21	8722
Age of menarche	7	13.37	1.54	13	969
Less severe physical	0	0.20	0.40	0	8719
More severe physical	0	0.06	0.23	0	8719
Emotional	0	0.10	0.30	0	8719
Sexual	0	0.05	0.22	0	8719

Note: The sample includes all ever-married women from pooled NFHS 4 and 5 selected for domestic violence questions.

Almost 30 percent of the women interviewed for the domestic violence module reported experiencing physical violence (pushing, shaking or thrown something, slap, twisting an arm, pulling hair). The rates of violence by religion are comparable for severe physical violence (punching, hitting with something that could hurt you, kicking, dragging and beating, trying to choke, burning, threatening or attacking with a knife, gun, or any other weapon); emotional violence (humiliation in front of others, threaten to hurt or harm or someone close, insult or demean); and sexual violence (physically forced to have sexual intercourse, physically forced to perform any other sexual acts without consent; forced with threats or in any other way to perform sexual acts). Table 3.2 reports the summary statistics for the subset of sample that is used for the empirical analysis.

Table 3.2: Summary Statistics by Religion (IV Sample)

	Min	Mean	Std Dev	Median	Observations
Panel A: Hindu					
Age of marriage	1	18.29	2.62	18	14396
Age of menarche	7	13.56	1.24	13	14396
Less severe physical	0	0.25	0.43	0	14396
More severe physical	0	0.06	0.24	0	14396
Emotional	0	0.11	0.32	0	14396
Sexual	0	0.06	0.24	0	14396
Panel B: Muslim					
Age of marriage	5	18.18	2.45	18	2548
Age of menarche	7	13.21	1.20	13	2548
Less severe physical	0	0.24	0.43	0	2548
More severe physical	0	0.06	0.24	0	2548
Emotional	0	0.12	0.33	0	2548
Sexual	0	0.06	0.24	0	2548

Note: The sample includes all ever-married women from pooled NFHS 4 and 5 selected for domestic violence questions with non-missing reported values of age of menarche (below 20) and age at marriage (between 0 and 30).

3.4.2 Age of Menarche and Age of Marriage by Religion

In Figure 3.1, we plot the distribution of age of marriage of women by religion. While the distribution for Hindus and Muslims is very similar, that for Christians is displaced to the right. The age of marriage of women is typically higher for Christians but very similar for Muslims and Hindus. While Hindus and Muslims have different marital practices, the age at which women are married is very similar.

In Figure 3.2, we plot the distribution of age at menarche by religion. For all three religions, the age of menarche is very similar. Previous literature that uses the age of menarche as an instrument for age of marriage points that in addition to biology, certain other factors such as climatic conditions at birth, childhood nutrition, and physical labor influences the age of menarche. This figure is illustrative of these factors being no different across the religious groups.

3.5 Estimation Strategy

In order to estimate the causal effect of delayed age of first marriage on the incidence of domestic violence, we use the age of menarche as an instrument for the age of marriage. This instrument has been used previously in the literature to investigate the consequences of early marriages for women and their children (E. Field and Ambrus 2008, Sekhri and Debnath 2014, Chari et al. 2017). As previously documented, the correlation between age of marriage and menarche is culturally determined. In South Asia, cultural norms put a premium on the chastity of women before marriage. Parents prescribe into the view that girls should be married soon after they attain puberty. In India, this norm also emanates from a fear for the safety of girls as the incidence of sexual crimes is high (Sarkar 2024). Sociology literature claims that parents are concerned about pre-marital affairs and hence want to marry their daughters as soon as they attain puberty. Religious beliefs and doctrines reinforce such norms. Hence, age of attaining puberty is highly correlated with age of marriage. This bears out in our data. Over 89% of women in our sample report getting married within first two years of menarche. In Figure 3.6, we plot a kernel density for the two variables. In Figure C.1, we also show the distribution of the age of marriage for the menarche age groups 7-12, 13-14 and 15-20, revealing a significant symmetric shift in the timing of marriage with each menarcheal age group. Reassuringly, these figures lends support to the use of timing of menarche as an instrument for the age of marriage.[24] We estimate the following two-stage instrumental variable model:

[24] The legal age of marriage in India is 18, despite that a large swath of girls get married before this age.

Figure 3.6: Age of Menarche and the Age of Marriage

Note: The sample includes ever-married women from pooled NFHS 4 and 5 with non-missing values for age at marriage between 10 and 25 and age at menarche between 10 and 20. Epanechnikov kernel, bandwidth = 0.75.

3.5.1 Instrumental Variable Empirical Model

The first stage:

$$A_i = \alpha_0 + \alpha_1 \ M_i + \alpha_2 \ X_i + B_\tau + W_t + \epsilon_i \tag{3.14}$$

where A_i is the age at marriage of respondent i and M_i is her age at menarche. B_τ is the full set of birth-year fixed effects. X_i is a vector of controls for household- and individual-level characteristics such as height, rural status and age of the respondent. W_t represents wave fixed effects.

The second stage is:

$$DV_i = \beta_0 + \beta_1 \ A_i + \beta_2 \ X_i + B_\tau + W_t + \epsilon_i \tag{3.15}$$

Here, DV_i represents the incidence of domestic violence for woman i. Other variables are the same as described earlier.

Validity of the Instrument: Relevance Condition

The key requirement for identification using the IV strategy is a strong correlation between the age of marriage and the age of menarche. In addition to the graphical evidence presented above, we present estimates from the first stage regression in Table 3.3 with and without full set of controls. We see that even after controlling for birth year fixed effects, height, district fixed effects, temperature, rural status and the respondent's age, coefficient on the age of menarche remains high and statistically significant. A one year delay in the onset of menarche is associated with around 0.18 years (about 2 months) delay in the age of marriage. The F-statistics remains high (81.89-180.74) suggesting that the instrument is strong. Consistent with the previous literature, we find that age of menarche is a strong predictor for age of marriage in India.

Table 3.3: First Stage Estimates

Age of Marriage	(1)	(2)	(3)	(4)	(5)
Age of Menarche	0.194***	0.195***	0.183***	0.188***	0.142***
	(0.0145)	(0.0144)	(0.0146)	(0.0146)	(0.0156)
Height			0.0026***	0.0025***	0.00148***
			(0.0003)	(0.0003)	(0.0003)
Temperature				0.133***	
				(0.0203)	
Birth Year Fixed Effects	No	Yes	Yes	Yes	Yes
District Fixed Effects	No	No	No	No	Yes
F-stat	180.74	181.88	157.71	166.35	81.89
Prob $\geq F$	0.000	0.000	0.000	0.000	0.000
N	17905	17905	17549	17549	17549

Notes: F-stat refers to the Sanderson-Windmeijer multivariate F test of excluded instruments. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each regression also controls for rural status, respondent's age and NFHS wave.

Validity of the Instrument: Exclusion Restriction

Identification using age of menarche as an instrument for the age of marriage requires that the timing of puberty doesn't directly influence the incidence of domestic violence. In other words, for the exclusion restriction to be satisfied, any relationship between the age of menarche and domestic violence should be mediated through changes in the age of marriage alone.

Medical literature has demonstrated that genetic factors are one of the strongest determinants of physical maturation (Campbell and Udry 1995).

However, other characteristics also influence the age of menarche to some extent such as geographical and climatic conditions, exposure to endocrine-disrupting chemicals, strenuous physical activity and nutrition in utero or early childhood.[25]

Malnutrition and strenuous physical activity in childhood can delay the age of menarche and may also be correlated with the woman's natal family's socio-economic status (SES). To the extent that the SES of the natal family matters for domestic violence (Bloch and V. Rao 2002), the instrument will not meet the exclusion restriction. Laboratory studies indicate that only malnutrition acute enough to result in stunting can delay age of menarche (Stathopolu, Hulse, and Canning 2003). As argued by E. Field and Ambrus 2008, height is widely considered to capture the degree of stunting due to inadequate nutrition and health in childhood, as it is largely driven by pre-pubescent growth. Therefore, if nutrition were to affect the age of menarche, we should observe it to be correlated with height (and stunting). However, we do not find any correlation between the age of menarche and adult height of women in our sample, as plotted in Figure 3.7, alleviating concerns that age of menarche can influence domestic violence through differences in nutrition. Our data, however, does not provide the district or the characteristics of the natal family, limiting us in SES variables that we could control for

[25] See E. Field and Ambrus 2008 for an in-depth discussion.

in our analysis. We address this by controlling for adult height in our main regressions, since it is highly correlated with early age nutrition and childhood investment, thus acting as a proxy for the SES of the natal household. We also control for birth-year fixed effects of the respondents. Any adverse weather, environmental or income shocks experienced by the natal families affecting in-utero or early childhood nutrition or involvement in strenuous physical activity would be absorbed by these fixed effects.[26]

We perform an additional robustness test using the Indian Human Development Survey (IHDS - rounds I (2005)[27] and II (2011-12)[28]) to argue that age of menarche is a strong predictor of age of marriage even after controlling for natal family's SES. First, we observe stark similarities in these variables in our sample with the IHDS data (Figure C.2). While we do not directly observe natal family's characteristics or economic status, we exploit the fact that the women were asked if the economic status of their natal family was the same as their husband's family. We restrict the sample to those women who were married within the same economic status and report the results in Table C.1. We find that age of menarche strongly predicts age of marriage, conditional on height and birth year fixed effects. Even after controlling for

[26]Insufficient data about the natal district of the woman constraints us in using district birth-year fixed effects.

[27]Desai, Vanneman, and National Council of Applied Economic Research 2018a

[28]Desai, Vanneman, and National Council of Applied Economic Research 2018b

an asset index[29] of the husband's family to account for the socio-economic status of the natal family, coefficient of age of menarche on age at marriage is still highly significant.

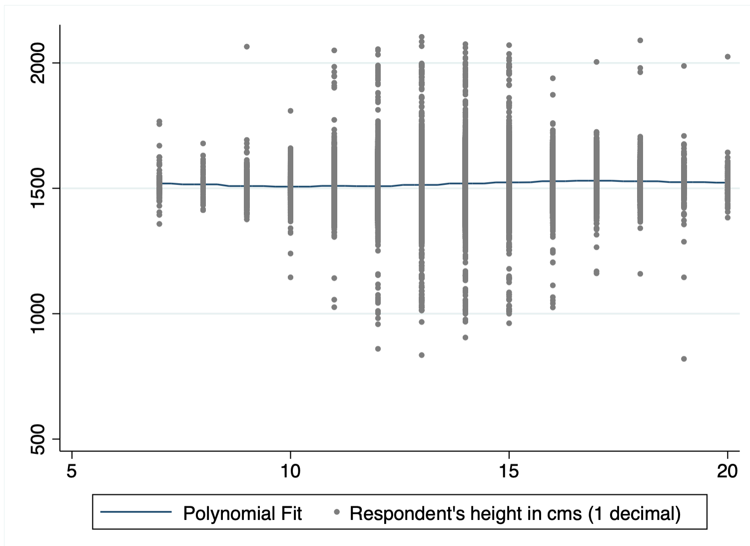


Figure 3.7: Age of Menarche and Adult Height

Data: Ever-married women in NFHS 4 and 5 with non-missing age of marriage between 0 and 30. Correlation = 0.08.

While our data limits us in providing the natal family characteristics of girls, other surveys in India such as Gender, Marriage & Kinship Survey conducted in 1995 also suggest that conditional on height and birth year fixed effects, age at menarche may not be influenced by the socio-economic characteristics of the natal family (father's literacy & ownership of irrigated land) (Sekhri and Debnath 2014). We find stark similarity between the the

[29]The asset index was created using principal component analysis from the household asset (TV, AC/cooler, Clock, Fan, Chair/Table, Cot, Telephone, Cellphone, Fridge, Pressure Cooker, Washing Machine, Computer, Credit Card, Clothes, Footwear, Motor Vehicle, Sewing Machine, Generator, Mixer/Grinder) ownership.

distributions of age of menarche and age at marriage across the two data sets – pooled NFHS 4 & 5 and the Gender, Marriage, and Kinship Survey. This is plotted in Figure C.3.

Other predictors of age of menarche such as exposure to endocrine-disruptive chemicals, temperature, climate and geographical characteristics of the natal district might also be correlated with the SES of natal family. Since we do not know the natal district of a woman in our data, we rely on the approach undertaken by Sekhri and Debnath 2014 and assume that a woman in India is most likely to get married within her natal district. We report the first stage estimates, controlling for average temperature of the district in column 4 of Table 3.3. The coefficient of age of menarche is still highly significant. Our main results are robust to controlling for temperature. We also control for district fixed effects as additional robustness tests.

3.5.2 Measurement Error of Variables

Systematic misreporting and recall bias is a common concern as women may not accurately remember their age of marriage. We perform several tests (similar to Sekhri and Debnath 2014) to demonstrate any measurement error in the reported age of menarche or marriage is not likely to bias the results.

First, we rely on Sekhri and Debnath 2014 that the systematic measurement error in age at menarche is less of a concern. Women are generally able to recall their age at menarche accurately (E. Field and Ambrus 2008). Lack of prior information to girls about menstruation before it begins often traumatizes the event, and women tend to remember the age at which they hit puberty (Nahar et al. 1999). Moreover, onset of menarche brings dramatic changes to a girl's life, particularly in the context where social norms are prevalent. Religious and social sanctions are imposed, such as being forbidden to enter Hindu temples and participate in any religious activity while menstruating, being instructed to pray five times a day amongst Muslims etc. They are expected to dress a certain way, covering most parts of their bodies. Menstruation is considered as a process which transforms a girl to a woman. In fact, there are parts of India where menarche is celebrated with gifts of jewellery and traditional dresses.

Second, we formally check whether women strategically misreport their age of marriage since the legal minimum age at marriage for females in India is 18. Women who were married below 18 might overstate their age at marriage due to the fear that the information might be revealed to the authorities as marrying below age of 18 is a punishable legal offence. We conduct McCrary's RD Density test to check whether there is any discontinuity in the distribution of age of marriage at the legal age of 18. These results are reported in Table C.2. We do not find any significant jump in the reported age at marriage at 18, even after performing the test with several bandwidth levels.

Third, we also check whether menarche and marriage ages might be misreported or not remembered in rural areas. We plot the distribution of age at marriage and age at menarche separately for women living in rural and urban households in Figure C.4, where the top and the bottom panels show the distribution of age at marriage and age at menarche respectively, by rural status. While it is clear that women in urban areas marry later, but there is no such difference in the distribution of age at menarche. This also suggests that the age of menarche is less prone to measurement error and that the age of marriage is unlikely to have been systematic misreported.

As an additional check for systematic measurement error in the reported age of marriage, we test whether the difference in the reported age at first birth of child and age of marriage systematically changes with the respondent's current age. As plotted in Figure C.5, we do not find any such correlation alleviating concerns regarding a systematic recall bias that would increase with women's age.

Finally, we are not concerned that any pre-existing preference for early marriage (which should be uncorrelated with actual puberty) is correlated with the reported age of menarche in our data. As argued earlier, the distribution of age at marriage and age of menarche in our data is very similar to the Gender, Marriage & Kinship Survey 2005 - in which distributions of age at menarche are similar by literacy of the parents and irrigated land holdings of the natal family. We, therefore, do not suspect that any pre-existing preference for early marriage would systematically misreport the variables in our data.

3.6 Results: Testable Predictions

3.6.1 Prediction 1: Delay in the Age at Marriage reduces Domestic Violence and Intensity of Battering

The main prediction from our model is that delaying the age of marriage decreases domestic violence. In Figure 3.8, we show the probability of experiencing violence as a function of age at marriage. All forms of violence (physical, emotional, and sexual) fall with increase in age at marriage. In Table 3.4, we present the results of the IV regression for four different measures of domestic violence: Emotional violence (column 1), Less severe physical violence (column 2), Severe physical violence (column 3), and Sexual violence (column 4). Our estimates indicate that a higher age in marriage is associated with a decrease in domestic violence. An increase in the age of marriage by one year reduces the probability of less severe and severe physical violence by 6.6 and 2.7 percentage points, respectively. This implies that delaying the age at marriage by one year can reduce less severe physical violence by 26.4% and severe physical violence by 38.5%, relative to the sample mean. Emotional violence falls by 2.4 percentage points, which is a decline of 18.4 % relative to the sample mean. Sexual violence falls by 1.2 percentage points, albeit the estimate is imprecise and not statistically significant. Consistent with the predictions of the model, we find that the probability of severe violence falls, implying that the intensity of battering reduces.

Our model shows that the effect on domestic violence is mediated through conforming behavior which would increase by age at marriage. In order to investigate this implication, we need measures of conforming behavior. A conventional social norm is that the wife is not permitted to make important decisions. Husband prefers to make them either independently or in consultation with the spouse or other family members. In the survey, the women were asked who makes important decisions about her health care, visits to natal family, important purchases, and what to do with the husband's in-

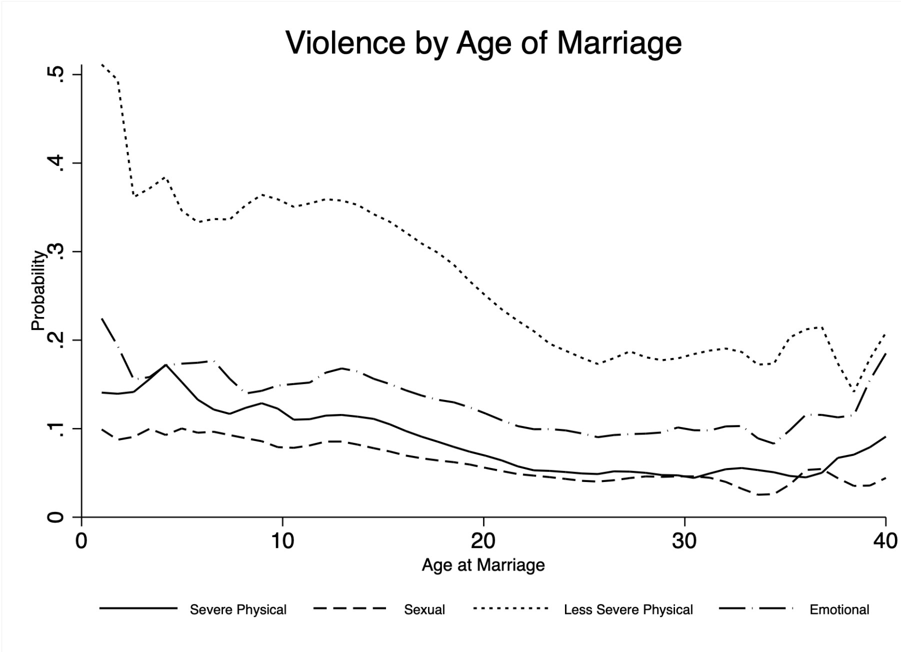


Figure 3.8: Probability of Violence by Age at Marriage

Note: The sample includes ever-married women from pooled NFHS 4 and 5 with non-missing values for age at marriage below 40.

come and earnings. We created an index using these survey questions. For each of these questions, we created an indicator which takes the value of 1 if the wife took the decision. Then we added these indicators and divided by 4 to get an index value between 0 and 1. Lower the value, higher is the conforming behavior in that the wife does not take the decision. A second behavior we look at is taking loans from self help groups. A third expectation in the household is that women will take care of the household chores and provide childcare. The survey asked about time taken to fetch water. We shed light on this behavior by age at marriage. In Figure 3.9, we show that, as expected, the decision making index falls with age at marriage (Panel A);

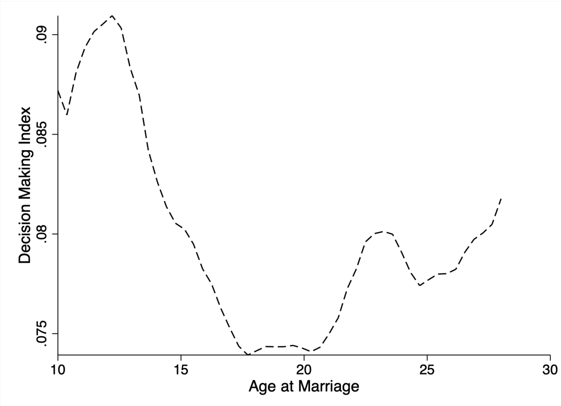
Table 3.4: Instrumental Variable Estimates of Domestic Violence

	Emotional Violence	Less Severe Physical	Severe Physical Violence	Sexual Violence Violence
Age of Marriage	-0.0242**	-0.0657***	-0.0269***	-0.0118
	(0.0103)	(0.0140)	(0.00766)	(0.00788)
F-stat	157.71	157.71	157.71	157.71
N	17549	17549	17549	17549
Panel A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0364***	-0.0785***	-0.0342***	-0.0139
	(0.0131)	(0.0180)	(0.00995)	(0.0101)
F-stat	96.47	96.47	96.47	96.47
N	14124	14124	14124	14124
Panel B: Muslim (Dower Prevalence)				
Age of Marriage	0.00894	-0.0267	0.00494	0.00213
	(0.0187)	(0.0245)	(0.0129)	(0.0135)
F-stat	59.78	59.78	59.78	59.78
N	2478	2478	2478	2478

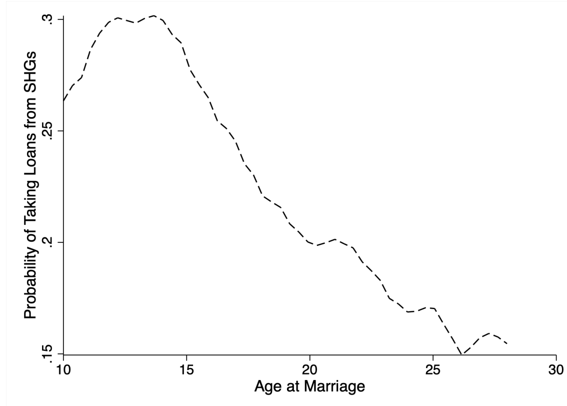
Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each column also controls for age, height, rural status, birth year fixed effects and NFHS wave.

and so does the probability of taking a loan from a self help group (Panel B). In Panel C, we find that time to fetch water is increasing in the age at marriage.

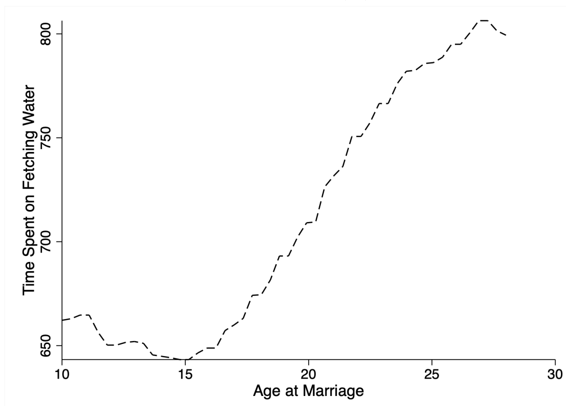
Unpacking mechanisms and causally estimating the impact of age of mar-



(a) Panel A: Decision Making Index



(b) Panel B: Taking Loans from SHGs



(c) Panel C: Time Spent to Fetch Water

Figure 3.9: Conformity Behavior by Age At Marriage

Note: The sample includes ever-married women from pooled NFHS 4 and 5 with non-missing values for age at marriage below 30.

riage on domestic violence mediated through conforming norms is challenging without having separate instruments for age of marriage and norms-conforming behavior. We use Dippel et al. 2019's estimator that performs causal mediation analysis (CMA) in an IV model to estimate the proportion of causal effect of an endogenous treatment mediated through an intermediate variable on outcome using a single instrument.[30] We report the results

[30]This complements existing ways to estimate causal mediation effects that assume randomness

from CMA for the full sample in Table C.3. The total effect provides the causal effect of age of marriage on domestic violence, instrumented by age of menarche. Causal mediation analysis decomposes the total effect into direct effect (effect of age of marriage on domestic violence which is not mediated through the norms) and the indirect effect (effect of age of marriage on domestic violence which is mediated through the norms). We find that norm-conforming behaviors contribute to a substantial proportion of the total effect of age of marriage on domestic violence. Decision Making Index explains 32% of the age of marriage's effect on emotional violence, 53% of the effect on less severe physical violence and 60% of the effect on severe physical violence. Loan taking from SHGs explains 400% of the age of marriage's effect on emotional violence, 79% of the effect on less severe physical violence and 52% of the effect on severe physical violence. However, these estimates are imprecise, which we believe can happen for multiple reasons. Firstly, we may be underpowered to perform this analysis. Secondly, there can be a host number of norms which we can't observe and account for in our analysis. The above discussed behaviors are only a finite number of observable examples of social norms - which often comprises a much larger set of unwritten rules and expectations for women in the society.

in the assignment of treatment (Imai, Keele, and Tingley 2010) or require separate instruments for treatment and mediator (for example, Frolich and Huber [2017]; Jun et al. [2016]).

3.6.2 Prediction 2: The Effect of delaying age of marriage on Domestic Violence is muted for Muslim Women

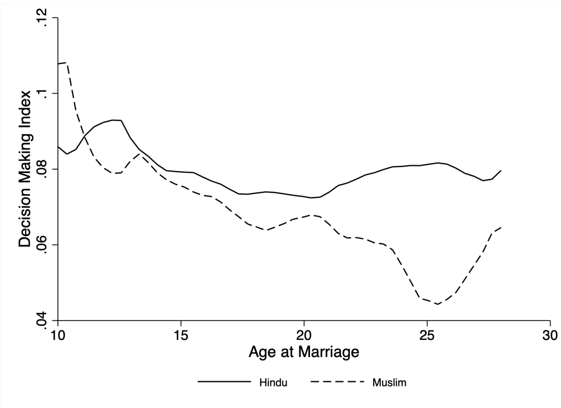
We test the second main prediction of our model - the effect of delaying age of marriage on domestic violence is muted for Muslim women who practice *Mehr* and therefore, have higher independent access to financial resources. We report the IV estimates separately for Hindus and Muslims in Panel A and B of Table 3.4, respectively. These findings show clear differences across the two religious groups. Among Hindu households, we observe a statistically significant decline in violence with age of marriage for emotional, less severe and severe physical violence. Delaying the age of marriage by one year reduces emotional violence by 3.6 p.p., less severe physical violence by 7.9 p.p. and severe physical violence by 3.4 p.p.. Relative to their respective sample means, this is a decline in emotional violence by 28%, less severe physical violence by 27.2% and severe physical violence by 42.5%. The effect on sexual violence is negative albeit statistically insignificant.

However, we find that these effects are muted and imprecise for Muslim women, who typically practice *Mehr*. The corresponding coefficients are positive (opposite to Hindus), small and statistically insignificant. Only the coefficient of less severe physical violence is negative at 2.6 p.p. (about 10% of the sample mean), but is statistically insignificant.

Our model shows that conforming behavior would increase by age at marriage, but Muslim women conform more as they have independent access to higher wealth. In Figure 3.10, we show that the decision making index falls with age at marriage with much lower levels for Muslims (Panel A). A similar patterns is observed for the probability of taking loans from a self help group (Panel B).[31] Time to fetch water (Panel C) is also increasing in the age at marriage and is higher for Muslim women suggesting higher conformity.

We report the results from causal mediation analysis for the sample of Hindu women in Table C.4. We again find that norm-conforming behaviors contribute to a substantial proportion of the total effect of age of marriage on domestic violence. Decision Making Index explains 57.5% of the age of marriage's effect on emotional violence, 60% of the effect on less severe physical violence and 68% of the effect on severe physical violence. Time spent fetching water explains 86% of the age of marriage's effect on emotional violence, 88% of the effect on less severe physical violence and 100% of the effect on severe physical violence. Loan taking from SHGs explains 94% of the effect on less severe physical violence and 95% of the effect on severe physical violence. However, these estimates are also imprecise, for suspected reasons

[31] A concern may be that Islam may preclude women from taking loans. Overall, 10 percent Muslim women do take loans from programs in self help groups in the sample.



(a) Panel A: Decision Making Index

(b) Panel B: Taking Loans from SHGs

(c) Panel C: Time Spent to Fetch Water

Figure 3.10: Conformity Behavior by Age At Marriage

Note: The sample includes ever-married women from pooled NFHS 4 and 5 with non-missing values for age at marriage below 30.

mentioned earlier. While we observe large magnitudes of indirect effects for Muslims as well in Table C.5, we refrain from interpreting them since the total effects are mostly insignificant. Nonetheless, the results show that these effects are mediated through norm-conforming behaviors.

3.6.3 Ancillary Results: Higher Transfers for Hindu Women

As documented previously, Hindu women are less likely to own large assets such as land and a house. Moreover, unlike Muslim women who are the recipient of dowers, Hindu women have little individual wealth of their own. Our model implies that transfers are decreasing in the wealth of the woman. So we would expect the husband to make larger transfers to Hindu women. To shed light on this, we focus on financial resources and behavior within the household. We examine the likelihood of having cash that women alone decide how to spend and own use mobile phone as proxy measures of transfers from the husband to wife.[32] These are assets that women use exclusively.

The third and the fourth column of Table 3.5 show the IV estimates for these outcomes. As expected, with delayed age of marriage, we find an increase in having money the women alone can decide how to spend and own use mobile phone for the Hindus. These estimates indicate a statistically significant increase of 10.2 p.p. and 4.4 p.p. in the likelihood of own use money and own use mobile, respectively. This reflects in a 25% increase in the likelihood of having own use money and 8.8% increase in the likelihood of having a mobile for own use amongst Hindu women. For Muslims in contrast, we find no relationship of age of marriage with ownership of own mobile phone or

[32]Direct measures of transfers from the husband to the wife are not available in our data.

Table 3.5: Asset Ownership & Testing Implications on Own Mobile & Money Usage, by Religion

	Land Ownership	House Ownership	Has Money She Alone can Decide How to Use	Own Use Mobile
Panel A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0772***	-0.0830***	0.102***	0.0443**
	(0.0208)	(0.0219)	(0.0229)	(0.0205)
Panel B: Muslim (Dower Prevalence)				
Age of Marriage	-0.0448	-0.0424	0.0391	-0.0588*
	(0.0277)	(0.0291)	(0.0283)	(0.0311)

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each column also controls for age, height, rural status, birth year fixed effects and NFHS wave.

own use money. In fact, the estimate corresponding to ownership of mobile for own use is negative and statistically significant, suggesting that delay in age of marriage reduces their probability of owning a mobile phone by about 11%, relative to the sample mean.

3.7 Robustness & Alternative Explanations

While we acknowledge that there are a lot of social and anthropological dimensions of why domestic violence occurs, we are able to identify causal effects of age at marriage on domestic violence and explain how that is mediated via departure from socially conforming behavior provided by women. We conduct robustness tests to strengthen our identification strategy and cast doubt on other explanations as driving mechanisms.

3.7.1 Using District Fixed Effects

As mentioned previously, we control for adult height in all our results to proxy for childhood nutrition and the socio-economic status of the natal family. We conduct additional robustness test where we control for district fixed effects (Table 3.6) thereby addressing concerns about the long term features of districts such as temperature and climate affecting both age at menarche and the SES status of the natal families. In the first panel, where we look at the IV estimates of the effect of age of marriage on domestic violence, including district fixed effects strengthen our results with slightly higher magnitudes. In panel 2A, we present the results for Hindus, and our results are again strengthened with slightly larger magnitudes. For Muslims, results are similar as before, except that the effect on less severe physical violence is statistically significant at 10% significance level (compared to when we had negative point estimates but without statistical significance). These results strengthen our theoretical implications that delaying age of marriage reduces domestic violence and the intensity of battering, but the effect is muted amongst Muslim women who have higher independent access to financial resources. Since we are unable to identify natal family district, we are unable to include district FE or district birth year FE in our main specification. However, we suspect that it will only strengthen our results.

Table 3.6: Robustness: IV Estimates of Domestic Violence with District Fixed Effects

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Panel 1: All				
Age of Marriage	-0.0323**	-0.0894***	-0.0412***	-0.0105
	(0.0147)	(0.0199)	(0.0114)	(0.0112)
N	17549	17549	17549	17549
Panel 2A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0431**	-0.0965***	-0.0473***	-0.0127
	(0.0175)	(0.0238)	(0.0139)	(0.0132)
N	14124	14124	14124	14124
Panel 2B: Muslim (Dower Prevalence)				
Age of Marriage	0.0144	-0.0740*	-0.00274	0.00283
	(0.0317)	(0.0401)	(0.0218)	(0.0213)
N	2478	2478	2478	2478

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each column also controls for age, height, rural status, birth year fixed effects, NFHS wave and district fixed effects. Results should be interpreted with caution as the matrix was not full rank.

3.7.2 Do Women's, Spouses, or Spouse's Family Characteristics Explain these Results?

Delaying the age of marriage can affect educational attainment of women which can have different consequences on domestic violence. Moreover, there is a premium for young brides in the marriage markets in India which can result in different SES of marital families, again having consequences for domestic violence outcomes. In order to determine whether these factors drive the results, especially the difference between Hindus and Muslims, we control for various spousal family and women's characteristics such as educational attainment of women, wealth of the household, whether the household has a telephone, and the gender and age of the household head. Moreover, women married at later ages may tend to marry more educated men. Better educated spouses may be less likely to engage in physical and emotional violence, improving the quality of spouse which can result in lower domestic violence. Therefore, we also control for husband's education and the difference in ages of two spouses to rule out spousal quality as the primary channel. The results documented in Table 3.7 remain unchanged, although are less precise. The magnitude of the results for Hindus are exactly similar for all violence types. For Muslims, we yet again find no strong causal relationship between age of marriage and domestic violence.

Table 3.7: IV Estimates by Religion with Additional Control for Spouse & Household Characteristics

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Panel A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0319	-0.0760**	-0.0343*	-0.0120
	(0.0261)	(0.0361)	(0.0198)	(0.0200)
Panel B: Muslim (Dower Prevalence)				
Age of Marriage	0.0216	-0.0135	0.00751	-0.00334
	(0.0251)	(0.0321)	(0.0164)	(0.0174)

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each columns controls for respondent's age, age difference, height, rural status, educational attainment of the respondent and her spouse, birth year fixed effects, NFHS wave, wealth of the household, gender and age of the household head, and whether the household has a telephone.

We conduct an additional robustness test where we repeat our main analysis restricting to women whose husbands have similar characteristics. In order to do this, we first use a propensity score matching (PSM) model to determine the likelihood of marrying with a woman of higher age using husband's age, education and occupation as control variables. This provides propensity weights to each of observations based on the PSM model. This methodology helps us remove observations which don't serve as good 'control' based on husbands' quality measures. By doing this, we are able to identify the causal effect of age of marriage on domestic violence amongst a sample of women where spousal quality is unlikely to play a role. Using PSM weights (and thereby, restricting sample to women with similar husband characteristics), we repeat our main specification and the results are reported in Table C.6. We find that our main results are robust within this sample of women with very similar magnitudes and significance levels. The results do not change even when we repeat our analysis for the sample of Hindus and Muslims separately.

3.7.3 Can Differences in Attitudes or Empowerment Explain the Results?

Later age at marriage can empower women and reduce their acceptance of physical abuse. Simultaneously, it can improve their bargaining capabilities within the marriage. A difference in attitudes and bargaining power of Hindu and Muslim women can drive the differences in results that we find for the two religious groups. In order to shed light on this, we show whether measures of empowerment are impacted by the age at marriage and whether this varies by religion. We use two variables to measure empowerment. The first is a Beating Acceptability Index. The survey asked the women a series of questions about acceptance of beating for various reasons. Based on these, we constructed an index. Our beating acceptability index is the share of reasons out of 5 that women believe it is acceptable for men to beat their wives. These include: goes out without telling husband, argues with husband, does not cook food properly, neglects children, and refuses to have sex with the husband. Second, we use an indicator for whether a woman is currently working. In Table 3.8, we report IV estimates for the effect of age of marriage on these empowerment measures. We do not find any change in attitudes or the probability of being employed with higher age of marriage. The coefficients for both Hindu and Muslim women for the two measures are small and statistically insignificant. Moreover, in Table 3.9, we control for both these measures in addition to marital family and spousal characteristics and the results remain unchanged (if anything, they are stronger).

We do not suspect that an increase in women empowerment with a higher age of marriage is a driving channel here. Our finding that higher age of marriage increases norm-conforming behaviors (such as more time spent fetching water, lower decision making index and lower autonomy to take loans) makes the case for more empowered women to drive the results on domestic violence less compelling.

Table 3.8: IV Estimates for Attitudes towards Beating and Decision Making

	Beating Acceptability Index	Probability Employed
Panel A: Hindu (Dowry Prevalence)		
Age of Marriage	0.0191	-0.00713
	(0.0128)	(0.0156)
Panel B: Muslim (Dower Prevalence)		
Age of Marriage	-0.0131	-0.00845
	(0.0205)	(0.0166)

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each column also controls for age, height, rural status, birth year fixed effects and NFHS wave.

3.8 Conclusion

In this paper, we examine the effect of delaying marriage age on domestic violence. We develop a model in which women who get married later are able to conform to desired social norms at lower cost. This reduces violence faced by them. Consistent with the model, we find increasing the age at marriage leads to a reduction in violence experienced by the women. Our model indicates that the effects would be muted for wealthier women. We find that Muslim women, who are wealthier than the Hindu women at the time of marriage due to traditional customs do not experience a reduction in domestic violence even when married at a later age.

Table 3.9: IV Estimates by Religion with Additional Control for Spouse & Household Characteristics and women's empowerment measures

	Emotional Violence	Less Severe Physical	Severe Physical	Sexual Violence
Panel A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0373	-0.0836**	-0.0383*	-0.0152
	(0.0257)	(0.0357)	(0.0197)	(0.0197)
Panel B: Muslim (Dower Prevalence)				
Age of Marriage	0.0267	-0.00462	0.0118	-0.00238
	(0.0257)	(0.0330)	(0.0171)	(0.0181)

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of individual women selected for the DV module in NFHS-4 and NFHS-5. Robust standard errors are reported in parenthesis. Each columns controls for respondent's age, age difference, height, rural status, educational attainment of the respondent and her spouse, birth year fixed effects, NFHS wave, wealth of the household, gender and age of the household head, whether the household has a telephone and the two empowerment measures – employment probability and acceptability of beating index.

Many policies are targeted towards increasing age at marriage in the developing countries including subsidies and grants given out to parents to marry the girl child at a later age with the view that this will empower the women. While these policies can help achieve lower levels of domestic violence faced by women, they may not necessarily help women increase their agency and challenge the traditional norms if these norms are widely accepted and can especially result in violence if challenged. Therefore, complementary policies that target gender-based norms and beating acceptability attitudes can improve violence outcomes while also empower women and reduce the sole burden of complying to norms on women.

Bibliography

Samuelson, Paul A (1956). “Social indifference curves”. In: *The Quarterly Journal of Economics* 70.1, pp. 1–22.

Phelps, Edmund S (1972). “The statistical theory of racism and sexism”. In: *The american economic review* 62.4, pp. 659–661.

Becker, Gary S (1974). “A theory of marriage: Part II”. In: *Journal of political Economy* 82.2, Part 2, S11–S26.

Sharpe, Sue (1976). *'JUST LIKE A GIRL'.: How Girls Learn to be Women*. Penguin Books.

Wolpe, Ann Marie (1978). “Education and the sexual division of labour”. In: *Feminism and materialism. London: Routledge and Kegan Paul*.

Manser, Marilyn and Murray Brown (1980). “Marriage and household decision-making: A bargaining analysis”. In: *International economic review*, pp. 31–44.

McElroy, Marjorie B and Mary Jean Horney (1981). “Nash-bargained household decisions: Toward a generalization of the theory of demand”. In: *International economic review*, pp. 333–349.

Daymont, Thomas N and Paul J Andrisani (1984). “Job preferences, college major, and the gender gap in earnings”. In: *Journal of Human Resources*, pp. 408–428.

Tauchen, Helen V, Ann Dryden Witte, and Sharon K Long (1985). *Domestic violence: A non-random affair*. Tech. rep. National Bureau of Economic Research.

Chiappori, Pierre-André (1988). “Rational household labor supply”. In: *Econometrica: Journal of the Econometric Society*, pp. 63–90.

Quale, Gladys Robina (1988). *A history of marriage systems*. Greenwood Press.

Tauchen, Helen V, Ann Dryden Witte, and Sharon K Long (1991). "Domestic violence: A nonrandom affair". In: *International Economic Review*, pp. 491–511.

Chiappori, Pierre-André (1992). "Collective labor supply and welfare". In: *Journal of political Economy* 100.3, pp. 437–467.

Lundberg, Shelly and Robert A Pollak (1993). "Separate spheres bargaining and the marriage market". In: *Journal of political Economy* 101.6, pp. 988–1010.

Matheson, Kimberly et al. (1994). "Women's Attitudes Toward Affirmative Action: Putting Actions in Context 1". In: *Journal of Applied Social Psychology* 24.23, pp. 2075–2096.

Campbell, Benjamin C and J Richard Udry (1995). "Stress and age at menarche of mothers and daughters". In: *Journal of Biosocial Science* 27.2, pp. 127–134.

Nahar, Quamrun et al. (1999). "Strategies to meet the health needs of adolescents: a review". In.

Chen, Zhiqi and Frances Woolley (2001). "A Cournot–Nash model of family decision making". In: *The Economic Journal* 111.474, pp. 722–748.

Bloch, Francis and Vijayendra Rao (2002). "Terror as a bargaining instrument: A case study of dowry violence in rural India". In: *American Economic Review* 92.4, pp. 1029–1043.

Riach, Peter A and Judith Rich (2002). "Field experiments of discrimination in the market place". In: *The economic journal* 112.483, F480–F518.

Jensen, Robert and Rebecca Thornton (2003). "Early female marriage in the developing world". In: *Gender & Development* 11.2, pp. 9–19.

Stathopolu, Eleni, J Antony Hulse, and David Canning (2003). "Difficulties with age estimation of internet images of southeast Asians". In: *Child Abuse Rev* 12, pp. 46–57.

Bertrand, Marianne and Sendhil Mullainathan (2004). “Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination”. In: *American economic review* 94.4, pp. 991–1013.

Fernández, Raquel, Alessandra Fogli, and Claudia Olivetti (2004). “Mothers and sons: Preference formation and female labor force dynamics”. In: *The Quarterly Journal of Economics* 119.4, pp. 1249–1299.

Field, Erica et al. (2004). “Consequences of Early Marriage for women in Bangladesh”. In: *draft, October,< efield@ latte. harvard. edu*.

Loughran, David S, Julie Margaretta Zissimopoulos, et al. (2004). *Are there gains to delaying marriage?: The effect of age at first marriage on career development and wages*. Rand Labor and Population.

Van Laar, Colette et al. (2005). “The effect of university roommate contact on ethnic attitudes and behavior”. In: *Journal of Experimental Social Psychology* 41.4, pp. 329–345.

Boisjoly, Johanne et al. (2006). “Empathy or antipathy? The impact of diversity”. In: *American Economic Review* 96.5, pp. 1890–1905.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2006). “Does culture affect economic outcomes?” In: *Journal of Economic perspectives* 20.2, pp. 23–48.

Riach, Peter A and Judith Rich (2006). “An experimental investigation of sexual discrimination in hiring in the English labor market”. In: *The BE Journal of Economic Analysis & Policy* 6.2, p. 0000102202153806371416.

Chanana, Karuna (2007). “Globalisation, higher education and gender: Changing subject choices of Indian women students”. In: *Economic and Political Weekly*, pp. 590–598.

Petit, Pascale (2007). “The effects of age and family constraints on gender hiring discrimination: A field experiment in the French financial sector”. In: *Labour Economics* 14.3, pp. 371–391.

Angelucci, Manuela (2008). “Love on the rocks: Domestic violence and alcohol abuse in rural Mexico”. In: *The BE Journal of Economic Analysis & Policy* 8.1.

Field, Erica and Attila Ambrus (2008). “Early marriage, age of menarche, and female schooling attainment in Bangladesh”. In: *Journal of political Economy* 116.5, pp. 881–930.

Banerjee, Abhijit et al. (2009). “Labor market discrimination in Delhi: Evidence from a field experiment”. In: *Journal of comparative Economics* 37.1, pp. 14–27.

Barnhardt, Sharon (2009). “Near and Dear? Evaluating the Impact of Neighbor Diversity on Inter-Religious Attitudes”. In: *Unpublished working paper*.

Beaman, Lori et al. (2009). “Powerful women: does exposure reduce bias?” In: *The Quarterly journal of economics* 124.4, pp. 1497–1540.

Fernandez, Raquel and Alessandra Fogli (2009). “Culture: An empirical investigation of beliefs, work, and fertility”. In: *American economic journal: Macroeconomics* 1.1, pp. 146–77.

Jensen, Robert and Emily Oster (2009). “The power of TV: Cable television and women’s status in India”. In: *The Quarterly Journal of Economics* 124.3, pp. 1057–1094.

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller (2010). “Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program”. In: *Journal of the American statistical Association* 105.490, pp. 493–505.

Ambrus, Attila, Erica Field, and Maximo Torero (2010). "Muslim family law, prenuptial agreements, and the emergence of dowry in Bangladesh". In: *The Quarterly Journal of Economics* 125.3, pp. 1349–1397.

Bertrand, Marianne, Rema Hanna, and Sendhil Mullainathan (2010). "Affirmative action in education: Evidence from engineering college admissions in India". In: *Journal of Public Economics* 94.1-2, pp. 16–29.

Carrell, Scott E and Mark L Hoekstra (2010). "Externalities in the classroom: How children exposed to domestic violence affect everyone's kids". In: *American Economic Journal: Applied Economics* 2.1, pp. 211–28.

Fryer Jr, Roland G and Steven D Levitt (2010). "An empirical analysis of the gender gap in mathematics". In: *American Economic Journal: Applied Economics* 2.2, pp. 210–40.

Niederle, Muriel and Lise Vesterlund (2010). "Explaining the gender gap in math test scores: The role of competition". In: *Journal of Economic Perspectives* 24.2, pp. 129–44.

Beede, David N et al. (2011). "Women in STEM: A gender gap to innovation". In: *Economics and Statistics Administration Issue Brief* 04-11.

Card, David and Gordon B Dahl (2011). "Family violence and football: The effect of unexpected emotional cues on violent behavior". In: *The quarterly journal of economics* 126.1, pp. 103–143.

Eswaran, Mukesh and Nisha Malhotra (2011). "Domestic violence and women's autonomy in developing countries: theory and evidence". In: *Canadian Journal of Economics/Revue canadienne d'économique* 44.4, pp. 1222–1263.

Backes, Ben (2012). "Do affirmative action bans lower minority college enrollment and attainment?: Evidence from statewide bans". In: *Journal of Human Resources* 47.2, pp. 435–455.

Deem, Rosemary (2012). *Women & schooling*. Routledge.

Hinrichs, Peter (2012). "The effects of affirmative action bans on college enrollment, educational attainment, and the demographic composition of universities". In: *Review of Economics and Statistics* 94.3, pp. 712–722.

Howard, Larry L and Nishith Prakash (2012). "Do employment quotas explain the occupational choices of disadvantaged minorities in India?" In: *International Review of Applied Economics* 26.4, pp. 489–513.

Shapiro, Jenessa R and Amy M Williams (2012). "The role of stereotype threats in undermining girls' and women's performance and interest in STEM fields". In: *Sex roles* 66, pp. 175–183.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn (2013). "On the origins of gender roles: Women and the plough". In: *The Quarterly Journal of Economics* 128.2, pp. 469–530.

Matsa, David A and Amalia R Miller (2013). "A female style in corporate leadership? Evidence from quotas". In: *American Economic Journal: Applied Economics* 5.3, pp. 136–169.

Niederle, Muriel, Carmit Segal, and Lise Vesterlund (2013). "How costly is diversity? Affirmative action in light of gender differences in competitiveness". In: *Management Science* 59.1, pp. 1–16.

Zhou, Xiangyi, Jie Zhang, and Xuetao Song (2013). "Gender discrimination in hiring: Evidence from 19,130 resumes in China". In: *Available at SSRN 2195840*.

Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek (2014). "Gender, competitiveness, and career choices". In: *The Quarterly Journal of Economics* 129.3, pp. 1409–1447.

Deshpande, Ashwini and Thomas E Weisskopf (2014). “Does affirmative action reduce productivity? A case study of the Indian railways”. In: *World Development* 64, pp. 169–180.

Friedberg, Leora and Steven Stern (2014). “Marriage, divorce, and asymmetric information”. In: *International Economic Review* 55.4, pp. 1155–1199.

Heath, Rachel (2014). “Women’s access to labor market opportunities, control of household resources, and domestic violence: Evidence from Bangladesh”. In: *World Development* 57, pp. 32–46.

Reuben, Ernesto, Paola Sapienza, and Luigi Zingales (2014). “How stereotypes impair women’s careers in science”. In: *Proceedings of the National Academy of Sciences* 111.12, pp. 4403–4408.

Rich, Judith (2014). “What do field experiments of discrimination in markets tell us? A meta analysis of studies conducted since 2000”. In.

Sekhri, Sheetal and Sisir Debnath (2014). “Intergenerational consequences of early age marriages of girls: Effect on children’s human capital”. In: *The Journal of Development Studies* 50.12, pp. 1670–1686.

Anderson, Siwan and Chris Bidner (2015). “Property rights over marital transfers”. In: *The Quarterly Journal of Economics* 130.3, pp. 1421–1484.

Ceci, Stephen J and Wendy M Williams (2015). “Women have substantial advantage in STEM faculty hiring, except when competing against more-accomplished men”. In: *Frontiers in psychology* 6, p. 1532.

Wiswall, Matthew and Basit Zafar (2015). “Determinants of college major choice: Identification using an information experiment”. In: *The Review of Economic Studies* 82.2, pp. 791–824.

Adams, Renée B and Tom Kirchmaier (2016). “Women on boards in finance and STEM industries”. In: *American Economic Review* 106.5, pp. 277–81.

Arcidiacono, Peter, Esteban M Aucejo, and V Joseph Hotz (2016). “University differences in the graduation of minorities in STEM fields: Evidence from California”. In: *American Economic Review* 106.3, pp. 525–62.

Bagde, Surendrakumar, Dennis Epple, and Lowell Taylor (2016). “Does affirmative action work? Caste, gender, college quality, and academic success in India”. In: *American Economic Review* 106.6, pp. 1495–1521.

Haushofer, Johannes and Jeremy Shapiro (2016). “The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya”. In: *The Quarterly Journal of Economics* 131.4, pp. 1973–2042.

Nollenberger, Natalia, Núria Rodríguez-Planas, and Almudena Sevilla (2016). “The math gender gap: The role of culture”. In: *American Economic Review* 106.5, pp. 257–61.

Resmini, Marina (2016). *The ‘leaky pipeline* .

Aygün, Orhan and Bertan Turhan (2017). “Large-scale affirmative action in school choice: Admissions to IITs in India”. In: *American Economic Review* 107.5, pp. 210–13.

Bertrand, Marianne and Esther Duflo (2017). “Field experiments on discrimination”. In: *Handbook of economic field experiments* 1, pp. 309–393.

Borker, Girija (2017). “Safety first: Perceived risk of street harassment and educational choices of women”. In: *Job Market Paper, Department of Economics, Brown University*, pp. 12–45.

Buser, Thomas, Noemi Peter, and Stefan C Wolter (2017). “Gender, competitiveness, and study choices in high school: Evidence from Switzerland”. In: *American economic review* 107.5, pp. 125–30.

Chari, AV et al. (2017). "The causal effect of maternal age at marriage on child well-being: Evidence from India". In: *Journal of Development Economics* 127, pp. 42–55.

Fischer, Stefanie (2017). "The downside of good peers: How classroom composition differentially affects men's and women's STEM persistence". In: *Labour Economics* 46, pp. 211–226.

Glover, Dylan, Amanda Pallais, and William Pariente (2017). "Discrimination as a self-fulfilling prophecy: Evidence from French grocery stores". In: *The Quarterly Journal of Economics* 132.3, pp. 1219–1260.

Iips, ICF (2017). "National Family Health Survey (NFHS-4), 2015–16". In: *International Institute for Population Sciences (IIPS), Mumbai, India.*

Maceira, Helena Morais (2017). "Economic benefits of gender equality in the EU". In: *Intereconomics* 52.3, pp. 178–183.

Munoz-Boudet, AM and A Revenga (2017). "Breaking the STEM ceiling for Girls". In: *Brookings. Retrieved on January* 14, p. 2018.

NSSO (2017). *Education, NSS 75th Round Schedule-25.2: July 2017–June 2018.* Data collected 2017-2018. National Data Archive.

Wang, Chunbei and Le Wang (2017). "Knot yet: minimum marriage age law, marriage delay, and earnings". In: *Journal of Population Economics* 30.3, pp. 771–804.

Agan, Amanda and Sonja Starr (2018). "Ban the box, criminal records, and racial discrimination: A field experiment". In: *The Quarterly Journal of Economics* 133.1, pp. 191–235.

Bastarrica, María Cecilia et al. (2018). "Affirmative action for attracting women to STEM in Chile". In: *Proceedings of the 1st International Workshop on Gender Equality in Software Engineering*, pp. 45–48.

Desai, Sonalde, Reeve Vanneman, and New Delhi National Council of Applied Economic Research (Aug. 2018a). *India Human Development Survey (IHDS), 2005*. Version v12. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]. DOI: 10.3886/ICPSR22626.v12. URL: https://doi.org/10.3886/ICPSR22626.v12.

— (Aug. 2018b). *India Human Development Survey-II (IHDS-II), 2011–12*. Version v6. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]. DOI: 10.3886/ICPSR36151.v6. URL: https://doi.org/10.3886/ICPSR36151.v6.

Dhar, Diva, Tarun Jain, and Seema Jayachandran (2018). *Reshaping adolescents' gender attitudes: Evidence from a school-based experiment in India*. Tech. rep. National Bureau of Economic Research.

Funk, Cary and Kim Parker (2018). "Women and men in STEM often at odds over workplace equity". In.

Jain, Tarun et al. (2018). "Labor Market Effects of High School Science Majors in a High STEM Economy". In.

Kahn, Shulamit and Donna Ginther (2018). "Women and Science, Technology, Engineering, and Mathematics (STEM)". In: *The oxford handbook of women and the economy*.

Sardinha, LynnMarie and Héctor E Nájera Catalán (2018). "Attitudes towards domestic violence in 49 low-and middle-income countries: A gendered analysis of prevalence and country-level correlates". In: *PloS one* 13.10, e0206101.

Carrell, Scott E, Mark Hoekstra, and James E West (2019). "The impact of college diversity on behavior toward minorities". In: *American Economic Journal: Economic Policy* 11.4, pp. 159–182.

Dean, Joshua T and Seema Jayachandran (2019). “Changing Family Attitudes to Promote Female Employment”. In: *AEA Papers and Proceedings*. Vol. 109, pp. 138–42.

Dhar, Diva, Tarun Jain, and Seema Jayachandran (2019). “Intergenerational transmission of gender attitudes: Evidence from India”. In: *The Journal of Development Studies* 55.12, pp. 2572–2592.

Dippel, Christian et al. (2019). “Mediation analysis in IV settings with a single instrument”. In: *Unpublished manuscript*.

Field, Erica M et al. (2019). *On Her Own Account: How Strengthening Women's Financial Control Affects Labor Supply and Gender Norms*. Tech. rep. National Bureau of Economic Research.

Miller, Amalia R and Carmit Segal (2019). “Do female officers improve law enforcement quality? Effects on crime reporting and domestic violence”. In: *The Review of Economic Studies* 86.5, pp. 2220–2247.

Rao, Gautam (2019). “Familiarity does not breed contempt: Generosity, discrimination, and diversity in Delhi schools”. In: *American Economic Review* 109.3, pp. 774–809.

Women, UN (2019). “Progress of the World's Women 2019–2020: Families in a Changing World”. In: *New York: United Nations*.

Zimmerman, Seth D (2019). “Elite colleges and upward mobility to top jobs and top incomes”. In: *American Economic Review* 109.1, pp. 1–47.

Altmejd, Adam et al. (2020). “O brother, where start thou? Sibling spillovers on college and major choice in four countries”. In.

Angelucci, Manuela and Rachel Heath (2020). “Women Empowerment Programs and Intimate Partner Violence”. In: *AEA Papers and Proceedings*. Vol. 110, pp. 610–14.

Ashraf, Nava et al. (2020). “Bride price and female education”. In: *Journal of Political Economy* 128.2, pp. 591–641.

Bhalotra, Sonia, Abhishek Chakravarty, and Selim Gulesci (2020). “The price of gold: Dowry and death in India”. In: *Journal of Development Economics* 143, p. 102413.

Bursztyn, Leonardo, Alessandra L González, and David Yanagizawa-Drott (2020). “Misperceived social norms: Women working outside the home in saudi arabia”. In: *American Economic Review*.

Gupta, Namrata (2020). “Patriarchy reinforced or challenged? A study of engineering students in an elite Indian institute”. In: *Gender, Technology and Development* 24.2, pp. 250–270.

Heath, Rachel, Melissa Hidrobo, and Shalini Roy (2020). “Cash transfers, polygamy, and intimate partner violence: Experimental evidence from Mali”. In: *Journal of Development Economics* 143, p. 102410.

Heath, Rachel and Xu Tan (2020). “Intrahousehold bargaining, female autonomy, and labor supply: Theory and evidence from India”. In: *Journal of the European Economic Association* 18.4, pp. 1928–1968.

Jayachandran, Seema (2020). *Social norms as a barrier to women’s employment in developing countries*. Tech. rep. National Bureau of Economic Research.

Khanna, Gaurav (2020). “Does affirmative action incentivize schooling? evidence from India”. In: *Review of Economics and Statistics* 102.2, pp. 219–233.

Mousa, Salma (2020). “Building social cohesion between Christians and Muslims through soccer in post-ISIS Iraq”. In: *Science* 369.6505, pp. 866–870.

Porter, Catherine and Danila Serra (2020). “Gender differences in the choice of major: The importance of female role models”. In: *American Economic Journal: Applied Economics* 12.3, pp. 226–54.

Prakash, Nishith (2020). “The impact of employment quotas on the economic lives of disadvantaged minorities in India”. In: *Journal of Economic Behavior & Organization* 180, pp. 494–509.

Sekhri, Sheetal (2020). “Prestige matters: Wage premium and value addition in elite colleges”. In: *American Economic Journal: Applied Economics* 12.3, pp. 207–25.

Squicciarini, Mara P (2020). “Devotion and Development: Religiosity, Education, and Economic Progress in Nineteenth-Century France”. In: *American Economic Review* 110.11, pp. 3454–91.

Woetzel, J et al. (2020). *How advancing women’s equality can add $12 trillion to global growth. McKinsey & Company.*

Iips, ICF (2021). “National Family Health Survey (NFHS-5), 2019–21”. In: *International Institute for Population Sciences (IIPS), Mumbai, India.*

Lowe, Matt (2021). “Types of contact: A field experiment on collaborative and adversarial caste integration”. In: *American Economic Review* 111.6, pp. 1807–1844.

Rogers, Adam A et al. (2021). “School connectedness and STEM orientation in adolescent girls: The role of perceived gender discrimination and implicit gender-science stereotypes”. In: *Sex Roles* 85, pp. 405–421.

Sahoo, Soham and Stephan Klasen (2021). “Gender segregation in education: Evidence from higher secondary stream choice in india”. In: *Demography* 58.3, pp. 987–1010.

Birkelund, Gunn Elisabeth et al. (2022). “Gender discrimination in hiring: evidence from a cross-national harmonized field experiment”. In: *European Sociological Review* 38.3, pp. 337–354.

Bleemer, Zachary (2022). “Affirmative action, mismatch, and economic mobility after California’s Proposition 209”. In: *The Quarterly Journal of Economics* 137.1, pp. 115–160.

Corno, Lucia, Eliana La Ferrara, and Justine Burns (2022). “Interaction, stereotypes, and performance: Evidence from South Africa”. In: *American Economic Review* 112.12, pp. 3848–3875.

Exley, Christine L and Judd B Kessler (2022). “The gender gap in self-promotion”. In: *The Quarterly Journal of Economics* 137.3, pp. 1345–1381.

Kline, Patrick, Evan K Rose, and Christopher R Walters (2022). “Systemic discrimination among large US employers”. In: *The Quarterly Journal of Economics* 137.4, pp. 1963–2036.

Sukhtankar, Sandip, Gabrielle Kruks-Wisner, and Akshay Mangla (2022). “Policing in patriarchy: An experimental evaluation of reforms to improve police responsiveness to women in India”. In: *Science* 377.6602, pp. 191–198.

Adamovic, Mladen and Andreas Leibbrandt (2023). “A large-scale field experiment on occupational gender segregation and hiring discrimination”. In: *Industrial Relations: A Journal of Economy and Society* 62.1, pp. 34–59.

Brandon, Alec et al. (2023). *Minimum wages and racial discrimination in hiring: Evidence from a field experiment.* Tech. rep. Upjohn Institute Working Paper.

Choudhury, Prithwiraj, Ina Ganguli, and Patrick Gaulé (2023). “Top talent, elite colleges, and migration: Evidence from the Indian Institutes of Technology”. In: *Journal of Development Economics* 164, p. 103120.

Clarke, Damian et al. (2023). “Synthetic difference in differences estimation”. In: *arXiv preprint arXiv:2301.11859*.

Fernando, A Nilesh, Niharika Singh, and Gabriel Tourek (2023). “Hiring frictions and the promise of online job portals: Evidence from India”. In: *American Economic Review: Insights* 5.4, pp. 546–562.

Gupta, Ritika (2023). "Fixing the Leaky Pipeline: Affirmative Action in Local Elite Colleges and Subject Choice". In: Available at SSRN: https://ssrn.com/abstract=4763745 or http://dx.doi.org/10.2139/ssrn.4763745.

Sarkar, Sudipa (2024). "Local crime and early marriage: Evidence from india". In: *The Journal of Development Studies* 60.5, pp. 763–787.

Appendices

Appendix A

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

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:

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

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.2 Additional 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: Number of jobs for each number of successful application

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 (1.1) 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.

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

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

Figure A.1: Other CV characteristics

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.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 (1.2) 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: List of 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: 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.

SOMYA MEHRA

E-mail: somyamehra00@gmail.com ✻ *Telephone number:* +91 7320965083

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.2: Sample CV

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

Appendix B

Fixing the Leaky Pipeline: Affirmative Action in Local Elite Colleges & Subject Choice

B.1 Additional Tables & Figures

Table B.1: Triple Difference Analysis for 16 new IITs

Dependent Variable: Probability of choosing Science	(1)	(2)
Young X Female X Close	0.0971***	0.103***
	(0.0319)	(0.0380)
Observations	35,464	34,494
Control Mean	0.22	0.24
Synthetic DID weights	No	Yes
R-squared	0.183	0.156
District FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.2: Restricting the Sample

Dependent Variable: Probability of choosing Science	(1)	(2)	(3)
Young X Female X Close	0.0726**	0.0653**	0.0634**
	(0.0299)	(0.0268)	(0.0259)
Observations	14,839	24,029	36,244
R-squared	0.192	0.181	0.179
Band	30km	30km	30km
Far Control	60km	90km	120km
District FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.3: Distance Threshold

Dependent Variable: Probability of choosing Science	(1)	(2)	(3)
Young X Female X Close	0.0795***	0.0489**	0.0379*
	(0.0251)	(0.0213)	(0.0205)
Observations	59,664	59,664	59,664
R-squared	0.188	0.188	0.187
Band	20 km	40 km	50 km
District FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.4: Dyadic Comparison: Average DDD Coefficient

Probability of Choosing Science	(1)	(2)
Young X Female X Close	0.0672***	0.0606***
	(0.0156)	(0.01504)
Synthetic DID weights	No	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.5: IIT zone Fixed Effect

Dependent Variable: Probability of choosing Science	(1)	(2)
Young X Close X Female	0.0665***	0.0906***
	(0.0241)	(0.0311)
Observations	59,664	58,592
Control Mean	0.25	0.23
Synthetic DID weights	No	Yes
R-squared	0.117	0.140
Band	30km	30 km
IIT Zone FE	Yes	Yes
Controls	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.6: Including District by Rural/Urban FE

Dependent Variable: Probability of choosing Science	(1)	(2)
Young X Female X Close	0.0635***	0.0727***
	(0.0235)	(0.0254)
Observations	59,664	58,592
Control Mean	0.25	0.23
Synthetic DID weights	No	Yes
R-squared	0.197	0.162
District-Rural/Urban FE	Yes	Yes

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.7: Sensitivity Check: Dropped one IIT campus a time

IIT Dropped	DDD Estimate	DDD Estimate using SDID weights
(BHU) Varanasi	0.0574**	0.0708***
	(0.0230)	(0.0260)
(ISM) Dhanbad	0.0637**	0.0766***
	(0.0245)	(0.0270)
Bhilai	0.0615**	0.0755***
	(0.0243)	(0.0268)
Bhubaneshwar	0.0535**	0.0685**
	(0.0267)	(0.0280)
Mumbai	0.0619**	0.0794***
	(0.0249)	(0.0268)
Delhi	0.0584**	0.0589**
	(0.0259)	(0.0255)
Dharwad	0.0628**	0.0760***
	(0.0244)	(0.0280)
Gandhinagar	0.0605**	0.0756***
	(0.0245)	(0.0265)
Goa	0.0596**	0.0750***
	(0.0241)	(0.0268)
Guwahati	0.0615**	0.0768***
	(0.0246)	(0.0268)
Hyderabad	0.0691***	0.0829***
	(0.0253)	(0.0275)
Indore	0.0747***	0.0875***
	(0.0243)	(0.0276)
Jammu	0.0621**	0.0764***
	(0.0243)	(0.0269)
Jodhpur	0.0562**	0.0723**
	(0.0250)	(0.0276)

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Table B.8: Sensitivity Check: Dropped one IIT campus a time (Previous table continued..)

IIT Dropped	DDD Estimate	DDD Estimate using SDID weights
Kanpur	0.0667***	0.0793***
	(0.0240)	(0.0269)
Kharagpur	0.0673***	0.0821***
	(0.0251)	(0.0275)
Madras	0.0552**	0.0693**
	(0.0266)	(0.0288)
Mandi	0.0628**	0.0763***
	(0.0249)	(0.0271)
Palakkad	0.0756***	0.0898***
	(0.0254)	(0.0265)
Patna	0.0616**	0.0760***
	(0.0242)	(0.0266)
Roorkee	0.0653***	0.0762***
	(0.0239)	(0.0273)
Ropar	0.0622**	0.0769***
	(0.0245)	(0.0267)
Tirupati	0.0568**	0.0734***
	(0.0246)	(0.0272)

Notes: Robust Standard Errors clustered at the district level are reported in parenthesis.

Figure B.1: 23 IIT Campuses

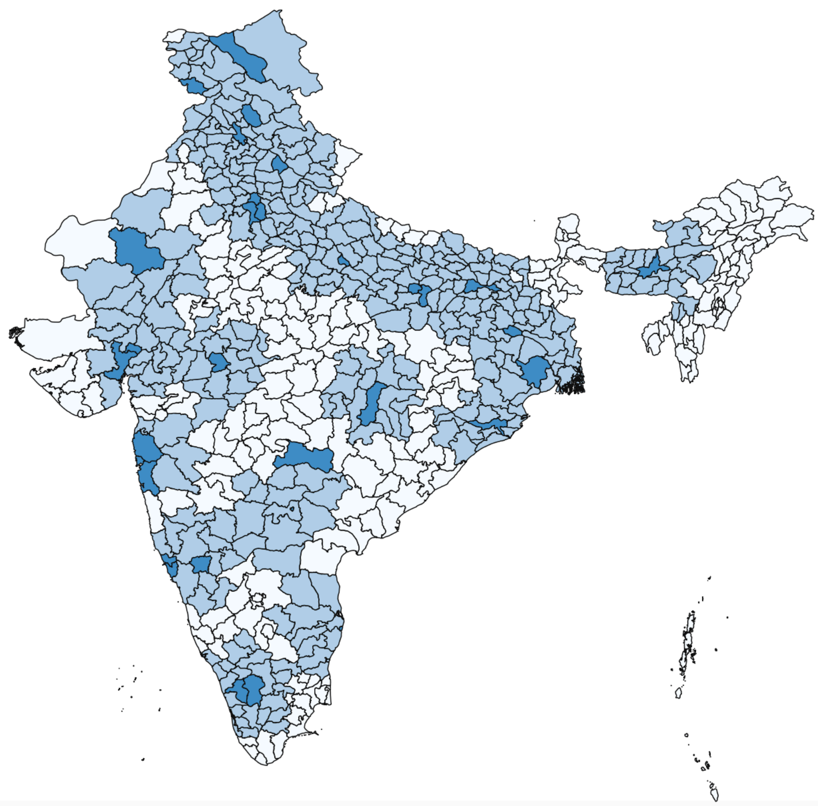


Figure B.2: Close & Far Districts

Close: Districts that come under 30km radius of an IIT Campus

Far: Districts that come under 200km radius (but more than 30km) of an IIT Campus

Appendix C

Empowering to Conform: Age at Marriage, Social Norms and Violence Against Women

C.1 Non-Cooperative Equilibrium Solution

This section solves for the equilibrium values of b^*, γ^* and t^* using backward induction along with the equilibrium level of violence V^*.

C.1.1 Stage 2: Wife's Decision Problem

Starting with the wife's optimization problem (as in Equation 3.6):

$$\begin{aligned} \max_{x^w,b} \quad & \alpha^w \cdot log x^w - \delta^w \cdot V \\ \text{s.t.} \quad & x^w + p \cdot b = y_w + \bar{t}, \;\; V = \bar{\gamma} \cdot (B - b), \;\; U^h \geq \bar{U}^h \end{aligned}$$

The Lagrangean for this optimization problem can be written as

$$= \alpha^w \cdot log(y_w + \bar{t} - p \cdot b) - \delta^w \cdot \bar{\gamma} \cdot (B - b) + \lambda^w (U^h - \bar{U}^h) \qquad \text{(C.1)}$$

This yields the following first order condition for b (when the reservation utility constraint is not binding)[1]:

$$\frac{\partial L}{\partial b} = \frac{\alpha^w}{x^w} \cdot (-p) - \delta^w \cdot \gamma(-1) = 0$$

$$x^{+w} = \frac{p\alpha^w}{\bar{\gamma}\delta^w} \qquad \text{(C.2)}$$

Using the budget constraint, we have

$$b^+ = \frac{y^w + \bar{t}}{p} - \frac{\alpha^w}{\bar{\gamma}\delta^w} \qquad \text{(C.3)}$$

Note that the dependence of p on A and γ has been suppressed until now. This is purely for notational convenience. We make this dependence explicit when solving the husband's maximization problem in the next section.

[1] We assume that divorce is prohibitively costly in our setting. If this condition were to be violated, however, the marriage will end in a divorce instead of the non-cooperative equilibrium presented in the paper.

C.1.2 Stage 1: Husband's Decision Problem

Starting with the husband's optimization problem (as in Equation 3.8):

$$\begin{aligned}\max_{\gamma,t} \quad & \alpha^h \cdot log x^h + \beta^h \cdot log b^+ \\ \text{s.t.} \quad & x^h = y_h - t, \;\; b^+ = \tfrac{y^w+t}{p(\gamma,A)} - \tfrac{\alpha^w}{\gamma\delta^w}, \;\; U^w \geq \bar{U}^w\end{aligned}$$

The Lagrangean for this optimization problem can be written as

$$\begin{aligned}= \alpha^h \cdot log(y_h - t) + \beta^h \cdot log[\gamma\delta^w(y^w+t) - \alpha^w p(\gamma,A)] \\ -\beta^h \cdot log[\gamma\delta^w p(\gamma,A)] + \lambda^h(U^w - \bar{U}^w)\end{aligned} \tag{C.4}$$

This yields the following first order conditions for t and γ (when the reservation utility constraint is not binding)

$$\frac{\partial L}{\partial t} = \frac{-\alpha^h}{y_h - t} + \frac{\gamma\delta^w\beta^h}{\gamma\delta^w(y^w+t) - \alpha^w p(\gamma,A)} = 0$$

$$\frac{\partial L}{\partial \gamma} = \frac{\beta^h[\delta^w(y^w+t) - \alpha^w p_\gamma(\gamma,A)]}{\gamma\delta^w(y^w+t) - \alpha^w p(\gamma,A)} - \frac{\beta^h[p(\gamma,A) + \gamma p_\gamma(\gamma,A)]}{\gamma p(\gamma,A)} = 0$$

Equivalently,

$$t = \frac{\alpha^h \alpha^w p(\gamma, A)}{\gamma \delta^w} + \beta^h y^h - \alpha^h y^w \tag{C.5}$$

and

$$\alpha^w p^2(\gamma, A) = \gamma^2 \delta^w p_\gamma(\gamma, A)(y^w + t) \tag{C.6}$$

Equations C.5 and C.6 can be solved for the equilibrium values γ^* and t^*.

C.1.3 Solving for the Equilibrium

Using equation 3.1, Equations C.5 and C.6 can now be written as:

$$t = \frac{\alpha^h \alpha^w \phi(A)}{\delta^w \sqrt{\gamma}} + \beta^h y^h - \alpha^h y^w \tag{C.7}$$

and

$$2\alpha^w \phi(A) = \delta^w \sqrt{\gamma}(y^w + t) \tag{C.8}$$

Solving Equation C.7 and C.8, the equilibrium decisions of the husband are given by

$$t^* = \frac{2\beta^h y^h - \alpha^h y^w}{2\beta^h + \alpha^h} \tag{C.9}$$

and

$$\gamma^* = \left[\frac{\alpha^w \phi(A)(2\beta^h + \alpha^h)}{\delta^w \beta^h (y^h + y^w)}\right]^2 \tag{C.10}$$

It is easy to see that increasing the age at marriage A, keeping everything else constant, decreases γ. However, if the income (or wealth) of the wife increases, the same increase in age of marriage is associated with a smaller change in the magnitude of γ. These results are formalized as Proposition 1 and Proposition 2 in the paper.

Substituting the equilibrium values of t^* and γ^* into Equations C.2 and C.3, we have

$$x^{w*} = \frac{\alpha^w}{\delta^w \sqrt{\gamma^*}} = \frac{\beta^h (y^h + y^w)}{2\beta^h + \alpha^h} \tag{C.11}$$

and

$$b^* = \frac{\alpha^w}{\delta^w \gamma^*} = \frac{\delta^w}{\alpha^w}\left(\frac{\beta^h (y^h + y^w)}{\phi(A)(2\beta^h + \alpha^h)}\right)^2 \tag{C.12}$$

In our model, the rule governing violence is such that $V = \gamma(B - b)$. Using the equilibrium value of γ and b from Equations C.10 and C.12, respectively, we can solve for the equilibrium quantity of violence that the wife experiences:

$$V^* = \gamma^* \left(B - \frac{\alpha^w}{\delta^w \gamma^*} \right) = B \left[\frac{\alpha^w \phi(A)(2\beta^h + \alpha^h)}{\delta^w \beta^h (y^h + y^w)} \right]^2 - \frac{\alpha^w}{\delta^w} \tag{C.13}$$

C.1.4 Model Predictions and Proofs

This section presents the proofs for Propositions 1 and 2.

Proposition 1 (a): *Increasing the age at marriage, ceteris paribus, reduces the frequency and/or intensity of violence.*

Proof. Differentiating Equation C.10 with respect to A

$$\frac{\partial \gamma^*}{\partial A} = \frac{\partial \gamma^*}{\partial \phi(A)} \frac{\partial \phi(A)}{\partial A}$$

or

$$\frac{\partial \gamma^*}{\partial A} = \left[\frac{\alpha^w (2\beta^h + \alpha^h)}{\delta^w \beta^h (y^h + y^w)} \right]^2 2\phi(A) \frac{\partial \phi(A)}{\partial A} < 0$$

As discussed in the paper, we assume that $\frac{\partial \phi(A)}{\partial A} \leq 0$. It follows directly then from the last equation that increasing age at marriage A, keeping everything else constant, will lower the equilibrium intensity of battering γ. □

□

Proposition 1 (b): *Increasing the age at marriage, ceteris paribus, increases conforming behavior.*

Proof. Differentiating Equation C.12 with respect to A

$$\frac{\partial b^*}{\partial A} = -2 \cdot \frac{\delta^w}{\alpha^w} \left(\frac{\beta^h (y^h + y^w)}{2\beta^h + \alpha^h} \right)^2 \frac{1}{\phi(A)^3} \frac{\partial \phi(A)}{\partial A} > 0$$

Thus, increasing age at marriage A, keeping everything else constant, will increase the equilibrium level of conforming behavior. □

□

Proposition 1 (c): *Increasing the age at marriage, ceteris paribus, reduces the overall level of violence.*

Proof. Differentiating Equation C.13 with respect to A

$$\frac{\partial V^*}{\partial A} = B \frac{\partial \gamma^*}{\partial A} < 0$$

Violence decreases faster than the intensity of battering because of a simultaneous increase in conforming behavior of the female when age of marriage increases. □

□

Proposition 2 (a): *The effect of delayed marriage on the frequency and/or intensity of violence is muted if the wife has access to more financial resources*

Proof. To examine the role of wife's wealth in determining how the frequency of battering responds to delayed marriage age, we take the cross-partial of $\frac{\partial \gamma^*}{\partial A}$ with respect to y^w:

$$\frac{\partial^2 \gamma^*}{\partial y^w \cdot \partial A} = -4 \cdot \left[\frac{\alpha^w(2\beta^h + \alpha^h)}{\delta^w \beta^h}\right]^2 \frac{\phi(A)}{(y^h + y^w)^3} \frac{\partial \phi(A)}{\partial A} > 0$$

As resources available to the wife increase, $\frac{\partial \gamma^*}{\partial A}$ increases, i.e. become less in magnitude. Equivalently, the magnitude of response of γ^* when A increases is smaller. □

□

Proposition 2 (b): *The effect of delayed marriage on the overall level of violence is muted if the wife has access to more financial resources*

Proof. As before, we take the cross-partial of $\frac{\partial V^*}{\partial A}$ with respect to y^w:

$$\frac{\partial^2 V^*}{\partial y^w \cdot \partial A} = B \frac{\partial^2 \gamma^*}{\partial y^w \cdot \partial A} > 0$$

Here again, delaying marriage age has a smaller effect on violence when the wife has more financial resources. □

□

C.2 Additional Tables & Figures

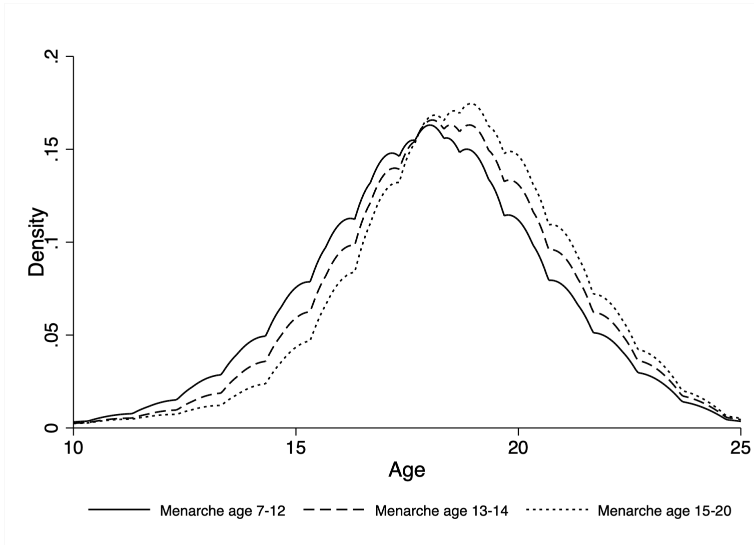


Figure C.1: Age of Marriage by the Age of Menarche Group

Data: Ever-married women in NFHS 4 and 5. Epanechnikov kernel, bandwidth=0.75

Table C.1: IV Robustness: Women married in households with same economic status as natal family in IHDS data

	Age of Marriage	Age of Marriage
Age of Menarche	0.219***	0.139***
	(0.0172)	(0.0167)
Height	0.0497***	0.0172***
	(0.00309)	(0.00304)
Asset Index		1.216***
		(0.0219)
Birth-Year FE	Yes	Yes
F-Stat	14.40	70.92
N	23501	22079

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married women in IHDS-1 and IHDS-2. Robust standard errors are reported in parenthesis

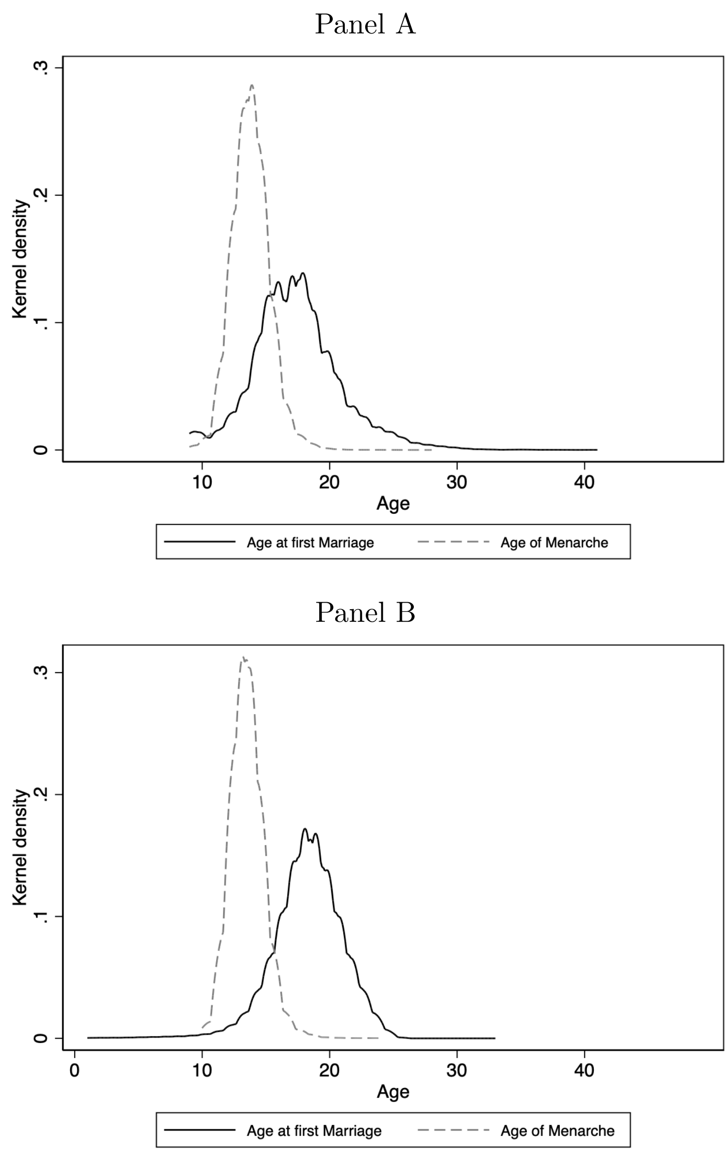


Figure C.2: Density, age at first marriage & age at menarche: Panel A: IHDS-I and IHDS-II; Panel B: National Family Health Survey, 2015-16 & 2019-21.

Notes: Epanechnikov kernel, bandwidth=0.6. Data from NFHS, 2014-15 & 2019-21 and IHDS, 2015-16 & 2011-12. Sample includes all ever married women aged between 15 and 49.

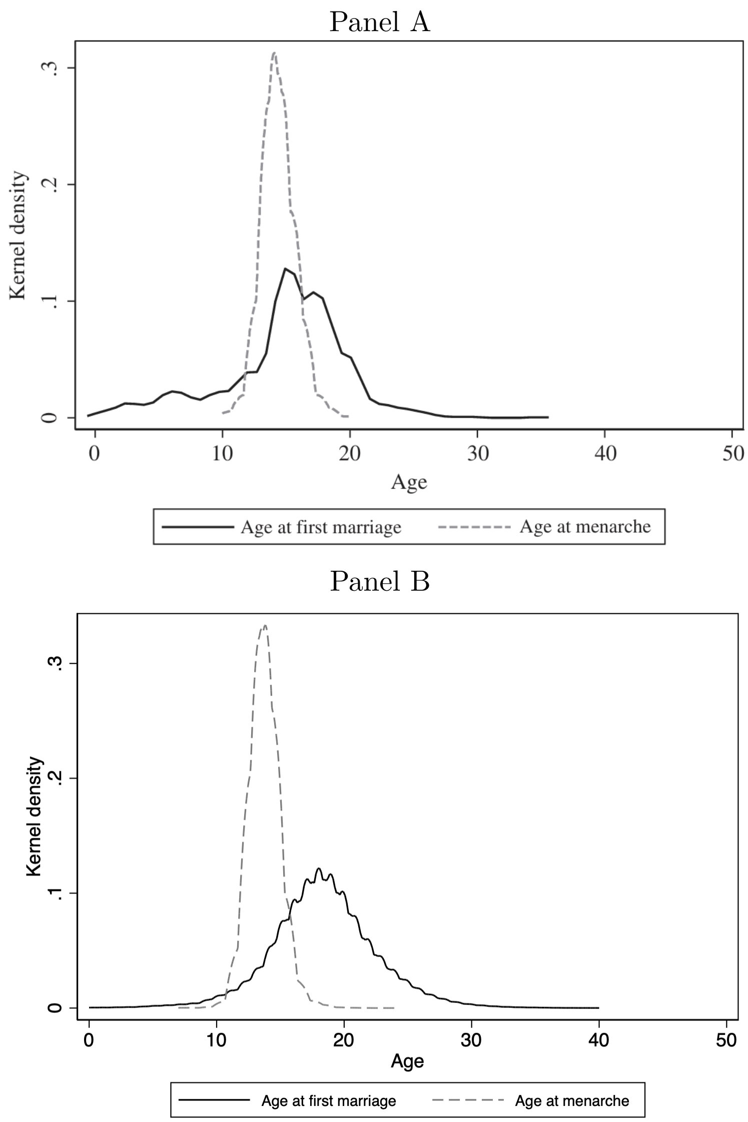


Figure C.3: Density, age at first marriage & age at menarche: Panel A: Gender Marriage, Kinship Survey, 1995; Panel B: National Family Health Survey, 2015-16 & 2019-21.

Notes: Epanechnikov kernel, bandwidth=0.6. Data from NFHS, 2015-16 & 2019-21 and Gender Marriage, Kinship Survey, 1995 in the states of Uttar Pradesh and Karnataka. Sample includes all ever married women aged between 15 and 49.

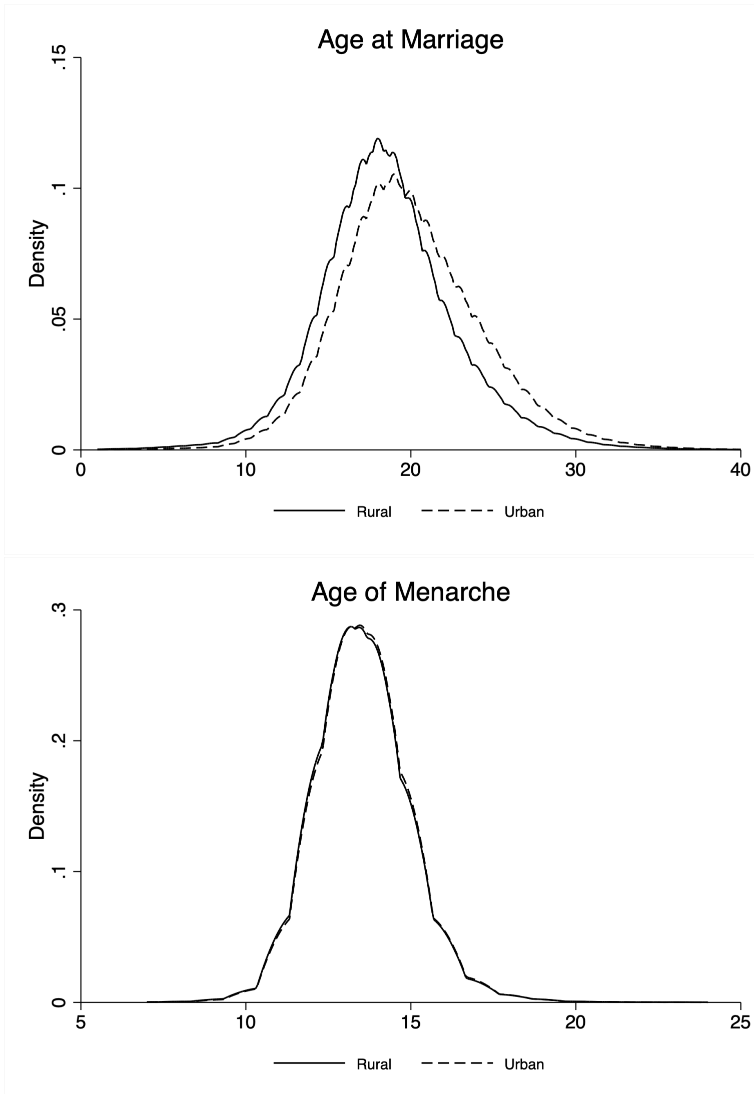


Figure C.4: Age of Marriage & Age of Menarche by Region

Data: Ever-married women in NFHS 4 and 5 with age of marriage below 40.
Epanechnikov kernel, bandwidth=0.75

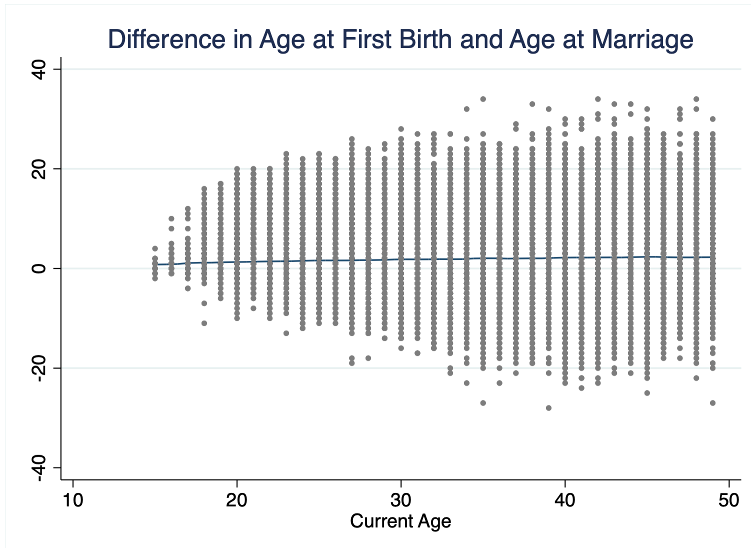


Figure C.5: Measurement Error Test

Data: Ever-married women in NFHS 4 and 5 with age of marriage below 40.
Epanechnikov kernel, bandwidth=0.75

Table C.2: McCrary's RD density test for Age of Marriage at cutoff 18

Bandwidth	T-stat (P-Value)
16	-1.2540
	(0.2098)
17 (Default)	-0.8999
	(0.3682)
18	-0.2303
	(0.8178)
19	0.1385
	(0.8898)
N	18081

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married women in NFHS-4 and NFHS-5 exposed to the DV module. McCrary's RD Density test was performed on the age of marriage using Epanechnikov kernel and cutoff of age 18. Multiple bandwidths were used. T-stat are reported for the test along with p-values in parenthesis.

Table C.3: Causal Mediation Analysis for Linear IV Model: Effect of Age of Marriage on Domestic Violence, instrumented using Age of Menarche

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Mediator: Decision Making Index				
Total effect	-0.0192*	-0.0613***	-0.0239***	-0.0114
	(0.0105)	(0.0144)	(0.00775)	(0.00798)
Direct effect	-0.0133***	-0.0294***	-0.00979***	-0.00697***
	(0.00135)	(0.00350)	(0.00165)	(0.00101)
Indirect effect	-0.00654	-0.0324	-0.0145	-0.00467
	(0.0137)	(0.0467)	(0.0212)	(0.0100)
N	16660	16660	16660	16660
Mediator: Time Spent Fetching Water				
Total effect	-0.0242**	-0.0657***	-0.0269***	-0.0118
	(0.0103)	(0.0140)	(0.00766)	(0.00788)
Direct effect	-0.0399	-0.121	-0.0527	-0.0189
	(0.122)	(0.419)	(0.197)	(0.0572)
Indirect effect	0.0157	0.0549	0.0258	0.00707
	(0.0870)	(0.300)	(0.141)	(0.0403)
N	17549	17549	17549	17549
Mediator: Taking Loans from SHGs				
Total effect	0.00469	-0.0369*	-0.0134	-0.0200*
	(0.0151)	(0.0197)	(0.0108)	(0.0114)
Direct effect	-0.0183***	-0.0235***	-0.0100***	-0.00563*
	(0.00399)	(0.00509)	(0.00288)	(0.00297)
Indirect effect	0.0189	-0.0292	-0.00700	-0.0150
	(0.0191)	(0.0249)	(0.0133)	(0.0145)
N	7042	7042	7042	7042

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married women in NFHS-4 and NFHS-5. Causal mediation analysis is conducted to look at the effect of age of marriage on DV outcomes mediated through different norms, using age of menarche as an instrument. Robust standard errors are reported in parenthesis.

Table C.4: Causal Mediation Analysis for Linear IV Model Amongst **Hindus**

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Mediator: Decision Making Index				
Total effect	-0.0320**	-0.0747***	-0.0306***	-0.0148
	(0.0138)	(0.0192)	(0.0104)	(0.0103)
Direct effect	-0.0139***	-0.0299***	-0.00990***	-0.00691***
	(0.00152)	(0.00282)	(0.00138)	(0.000981)
Indirect effect	-0.0184	-0.0451	-0.0208	-0.00800
	(0.0200)	(0.0410)	(0.0196)	(0.0118)
N	13401	13401	13401	13401
Mediator: Time Spent Fetching Water				
Total effect	-0.0364***	-0.0785***	-0.0342***	-0.0139
	(0.0135)	(0.0185)	(0.0102)	(0.00994)
Direct effect	-0.00501	-0.00913	0.000349	-0.00406
	(0.00856)	(0.0164)	(0.00839)	(0.00437)
Indirect effect	-0.0313	-0.0694	-0.0345	-0.00986
	(0.0356)	(0.0712)	(0.0361)	(0.0166)
N	14124	14124	14124	14124
Mediator: Taking Loans from SHGs				
Total effect	-0.00117	-0.0339	-0.0198	-0.0254*
	(0.0192)	(0.0255)	(0.0144)	(0.0139)
Direct effect	-0.0169***	-0.0250***	-0.00819***	-0.00504*
	(0.00391)	(0.00530)	(0.00300)	(0.00288)
Indirect effect	0.00771	-0.0319	-0.0188	-0.0196
	(0.0218)	(0.0302)	(0.0172)	(0.0165)
N	5854	5854	5854	5854

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married Hindu women in NFHS-4 and NFHS-5. Causal mediation analysis is conducted to look at the effect of age of marriage on DV outcomes mediated through different norms, using age of menarche as an instrument. Robust standard errors are reported in parenthesis.

Table C.5: Causal Mediation Analysis for Linear IV Model Amongst **Muslims**

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Mediator: Decision Making Index				
Total effect	0.0108	-0.0256	0.00188	0.000365
	(0.0188)	(0.0242)	(0.0138)	(0.0137)
Direct effect	-0.0145***	-0.0289***	-0.00931***	-0.00737***
	(0.00391)	(0.00404)	(0.00254)	(0.00241)
Indirect effect	0.0243	0.00217	0.0105	0.00727
	(0.0289)	(0.0258)	(0.0174)	(0.0160)
N	2380	2380	2380	2380
Mediator: Time Spent Fetching Water				
Total effect	0.00894	-0.0267	0.00494	0.00213
	(0.0192)	(0.0243)	(0.0143)	(0.0140)
Direct effect	-1.580	-0.143	-1.010	-0.709
	(351.3)	(25.71)	(224.4)	(157.3)
Indirect effect	1.589	0.116	1.015	0.711
	(356.1)	(26.06)	(227.5)	(159.4)
N	2478	2478	2478	2478
Mediator: Taking Loans from SHGs				
Total effect	0.00158	-0.0452	0.0188	-0.00659
	(0.0263)	(0.0360)	(0.0210)	(0.0207)
Direct effect	-0.0167	-0.0236	-0.0270	-0.0115
	(0.0149)	(0.0191)	(0.0187)	(0.0111)
Indirect effect	0.0175	-0.0163	0.0460	0.00626
	(0.0439)	(0.0552)	(0.0607)	(0.0318)
N	935	935	935	935

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married Muslim women in NFHS-4 and NFHS-5. Causal mediation analysis is conducted to look at the effect of age of marriage on DV outcomes mediated through different norms, using age of menarche as an instrument. Robust standard errors are reported in parenthesis.

Table C.6: IV Results Robustness for Women married to husbands with similar characteristics

	Emotional Violence	Less Severe Physical Violence	Severe Physical Violence	Sexual Violence
Panel 1: All				
Age of Marriage	-0.0194*	-0.0632***	-0.0251***	-0.0110
	(0.0110)	(0.0150)	(0.00796)	(0.00837)
N	17225	17225	17225	17225
Panel 2A: Hindu (Dowry Prevalence)				
Age of Marriage	-0.0314**	-0.0782***	-0.0324***	-0.0143
	(0.0139)	(0.0192)	(0.0103)	(0.0108)
N	13907	13907	13907	13907
Panel 2B: Muslim (Dower Prevalence)				
Age of Marriage	0.00804	-0.0216	0.00319	-0.000711
	(0.0196)	(0.0256)	(0.0128)	(0.0136)
N	2425	2425	2425	2425

Notes: ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively. Data Source used is a pooled sample of ever-married women in NFHS-4 and NFHS-5. The sample is restricted to women with husbands matched based on similar characteristics (age, education and occupation) using propensity score matching and weighting is used based on propensity scores. Robust standard errors are reported in parenthesis.