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Restart: Women, career breaks and employer response

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Abstract

Gender gap in access to gainful employment opportunities is a striking feature across countries. An under studied aspect of this gap includes the labor market constraints faced by women who return after a career break due to care responsibilities. In India, the number of women who have taken a career break and are seeking work are estimated to be around 7 million. This paper uses a correspondence study experiment to determine the extent of discrimination faced by women returning back to work after a break in the Indian private sector. On average, women who take a break receive 49% lower call backs than other women with similar characteristics but who have not taken a break. This penalty is larger in skill intensive sectors like finance that in sectors like HR which require more generic skills. However, simply indicating upskilling certifications does not lead to a statistically significant difference in callbacks for women who take a break. Further, this penalty is larger in smaller firms and in those located in north India. These findings are consistent with taste-based theories of discrimination since large firms often make commitments to have gender inclusive policies and northern Indian states have more regressive gender attitudes.

JEL Codes: J71, J16, O15, C93

Keywords: career breaks, upskilling, labor, gender, discrimination

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1 Introduction

Global evidence points at persistent employment and wage gaps by gender. Recent studies show that both gaps widen with age (García Román & Gracia, 2022; Goldin *et al.*, 2017; Barth *et al.*, 2021). For instance, Goldin *et al.* (2017) finds that college educated men have on average 50 percent higher earnings growth than comparable qualified women during their prime working years. Factors such as marriage and motherhood have been largely identified with the widening gaps. However, one of the factors that has been relatively under studied is the role played by career breaks in contributing to the observed differences in employment and pay gaps across gender. Taking a break from the labor market results in time away from work and employers may view such job applications less favorably. Given the higher propensity of women to take such breaks for care responsibilities, this can be a potential barrier to women's employment when they wish to restart.

India has one of the largest gender gaps in employment, having one of the lowest female labor force participation (LFP) among countries with similar per capita incomes Afridi *et al.* (2019). On average, among women and men aged 25-60, while almost 93% men participate in the labor market, only 27% women are engaged in the work force. Even among educated women i.e., those having at least college education, the proportion of employed women stands at 37% in urban India (2021-22), much lower than other countries. Figure 1 plots the LFP rate for urban women by age using data from the nationally representative Periodic Labor Force Survey (PLFS) of India for 2021-22. Panel (a) shows that among women having at least college education, their labor market attachment rate peaks at 46% in mid 20's and then sharply falls to 30% up to the age of 35.[1] It rises thereafter but remains around 36% till women reach the age of mid 50's and thereafter declines for both women and men as they become older and closer to the age of retirement at 60. The fall in educated women's labor force attachment after the mid 20's could be due to withdrawal of women from the

[1] Fletcher *et al.* (2017) also find that female labor force participation (FLFP) in urban India starts to decline around mid-late 20s and women who get married have lower FLFP in comparison to unmarried women in the country.

labor market as they get married and have children. However, it does not fully return to the peak observed at 46%. This could partly reflect discrimination in the labor market against female candidates taking career breaks, contributing to the observed difference in labor force participation rates by gender for educated individuals as they age. Typically, women take a break to provide care for young children, and later wish to join the workforce when care responsibilities reduce. On the other hand, for women who have only completed schooling or even less, only 20% are working by their mid 20's. They witness a steady increase in their employment rate upto the age of 35, with a peak of 25-35%. This could be reflective of early childbearing by these women which allows them to enter the workforce only later.[2] However, on average their LFP rate remains lower than for college educated women.

These patterns suggest that around 10% of educated urban women quit the labor force around marriageable or childbearing ages. According to a recent report by Avtar, the number of women who have taken a career break and are seeking work in India stand at around 7 million.[3] With increasing education levels, understanding the role played by various factors, including employer discrimination, that impede the re-entry of women into the workforce is an important question. There are two primary reasons why employers may be hesitant to employ women returning after a career break. One, they may fear lack of commitment towards work and the possibility that they may withdraw again. Second, obsolete skills during the time of the career break may also dissuade employers from employing women returning from a break (Kaushiva & Joshi, 2020). Upskilling can indicate upgradation and acquisition of new skills by the female applicant if obsolete skills are a consideration. However, if the former channel dominates then skill upgradation may not lead to a decrease in employer penalty.

To understand these aspects in the Indian job market, we conduct a correspondence study wherein we send fictitious job applications, that are similar on all accounts except

[2] National Family Health Survey-5 shows that median age at marriage for urban women who have completed schooling or less is 20 years while for those who are graduate and above this stands at 25. Similarly, median age at first birth for urban women who have completed schooling or less is 22 while for those who are graduate and above it is 28.

[3] This comes close to the number of women who were ever employed but currently not working in urban India using the PLFS (2021-22).

that presence of career breaks and undertaking upskilling are randomized across resumes. Based on the average length of the career break for women in India (Avtar report), we create 4 fictitious female profiles with 4 years career break right before the job application and another 4 profiles without any breaks in their career. Since it is often married women with children who tend to take such career breaks, all profiles in our study are married with children. Further, 2 out of the 4 profiles with a career break have recent skills certifications. Additionally, we vary by the number of children – employers may believe that women with 2 children are less likely to go on a break again since they have attained their desired fertility while those with one child may opt for another child and hence are more likely to withdraw from the labor force again. At the same time, since childcare responsibilities are likely to be more with 2 children, employers may have a lower preference for returnee women with more kids.[4] To examine the role of completed fertility and childcare burden on the career break penalty (which go in opposite directions), half of the 8 profiles have one child whereas the other half have two children. We randomly select 4 profiles from the above set of female profiles and send them to active job openings.

We find that women with a career break face a 49% lower callback rate than women with no career break but having similar skills, education and experience. The magnitude of the career break penalty is lower in HR (36%) than Finance (55%). Upskilling certifications do not significantly alter the career break penalty. Additionally, the career break penalty is greater for women with 2 children than 1, albeit the difference is not statistically significant. On average, women with career breaks who haven't completed upskilling programs and have 2 children receive the highest career break penalty from employers. Overall, juxtaposed with the fact that women are, in general, more likely to take career breaks than men, these findings show that career break penalty is more likely to decrease labor market prospects for women.[5] Lastly, jobs offering wages below industry median, those posted by smaller firms

[4]The total fertility rate (TFR) in India is about 1.6 children per women in urban areas, as per NFHS-5 report.

[5]For instance, a survey by LinkedIn shows that working women are 1.6 times more likely to take a career break to look after their children compared to men. Another UK-based national study of 3,001 adults

and located in the north impose the largest penalty on women returning after a career break. This shows that gender attitudes of employers, reflecting taste based discrimination, play a role in explaining the penalty.

The existing literature largely documents length of career breaks, rates of returns across countries and the associated gender wage gaps using survey data. Aisenbrey *et al.* (2009) using nationally representative data from Germany, Sweden and the US find that 80% of mothers are back at work within one year in the US given the restrictive maternity leave policies, whereas in Germany 60% return after 3 years given the generous maternity leave policy. They also find that in the US women return to a comparably similar job but in Germany 10% women move to a lower prestige job. In both countries, the probability of returning to a similar job decreases with increasing length of the break. Arun *et al.* (2004) using data from Australia find that around 40% working women reported taking a career break and of these 60% had returned to the labor market after the break. Of those returning, 72% reported no change in occupation after re-entry. It also finds women returning to the same occupation suffered a 5 percent wage penalty from a short non-child related career break but a 10 percent penalty from taking a short-childcare related career break. A longer break resulted in a 17 percent wage penalty upon re-entry. Staff & Mortimer (2012) using data for 486 women in Minnesota find that half of the 6% wage gap between mothers and non-mothers can be explained by career interruptions.

However, none of the above studies use a causal framework to understand what drives these penalties since women who take a career break can be different on various unobservable characteristics from women who do not take a break. While there has been extensive research around causal motherhood and marriage penalty for women in the labor market (see Baert (2018) for a review), there is little evidence on whether time taken off the labor market hinders future job prospects. There exists experimental evidence showing reduced job application success when candidates report contemporary unemployment spells of minimum nine months

conducted by AIG Life Insurance and another study of 2000 respondents by the Applied group finds that women are three times more likely than men to take career breaks owing to caregiving duties.

(Eriksson & Rooth, 2014). Relatedly, Weisshaar (2018) finds that both mothers and fathers in the US who temporarily opted out of work for family care needs face a 66 percent lower call-back rate, relative to applicants who were continuously employed. However, to the best of our knowledge there is no existing evidence that points whether and to what extent there is a penalty for taking career breaks for women in India (or any other developing country). None of the studies have so far examined whether upskilling can help reduce such a penalty and whether taste based employer discrimination plays a role. We further augment the literature by examining any differential variation by number of children (childcare vs fertility concerns) and firm characteristics.

Lastly, several correspondence studies have implemented a similar experimental setup of sending out fictitious job applications in order to examine different aspects of labor market discrimination like race, religion, gender, age, caste, disability in various countries (Becker *et al.*, 2019; Ameri *et al.*, 2018; Arceo-Gomez & Campos-Vazquez, 2014; Siddique, 2011; Albert *et al.*, 2011; Banerjee *et al.*, 2009a; Bertrand & Mullainathan, 2004). In the Indian context there are only two audit studies on gender based discrimination by Bedi *et al.* (2018) and Bedi *et al.* (2022) which measure the penalty of having children for women in the Indian labor market and the role played by social norms. Thus, we directly extend this literature by studying the penalty arising from career breaks for women.[6]

Apart from audit based studies, recent literature has also used incentivized rating based experiments in the labor market to elicit employer preferences by non-deception (Kessler *et al.*, 2019). While such designs avoid deception and allow researchers to examine varied aspects of a candidate's characteristics, the exact biases which may lead employers to deviate from their usual behaviour in a laboratory setting remain unknown. Also, in our context, the presence of a career break may alert employers about the possible objective of the study

[6] A few qualitative studies reveal that outdated skills, societal expectations, and psychological challenges like diminished confidence are significant barriers faced by women rejoining the workforce after a break (Panteli, 2006; Shaw *et al.*, 1999; Herman, 2011). The difficulty in finding flexible work arrangements (Gwal, 2016), along with limited access to upskilling programs and mentorship (Das *et al.*, 2024), further inhibits their search for suitable roles. We add to this literature by examining the role played by employer discrimination.

since usually women returning from a break are a small fraction of total applicants. Using data from a job platform which specializes in hiring of female returnees, we find that around 30% candidates had a career break. Employers hiring through such platforms are more likely to be open to hiring women returnees. Hence, we prefer the audit study based method in our case to analyze the discriminatory behavior across a range of employer types. The rest of the paper is organized as follows. Section 2 details the experimental setup. Sections 3 and 4 discuss the results and mechanisms, respectively. Section 5 concludes.

2 Experiment Design

There is little survey based evidence on hiring or shortlisting decisions by employers since such data are usually difficult to obtain. Hence, measurement of discrimination in hiring has usually been analyzed by researchers based on field experiments like audit or correspondence studies. We describe the experimental details of our audit study design below to measure discrimination against women who are returning back from a career break and the role of upskilling and completed fertility therein. We created fictitious female candidate profiles on the biggest job portal in India with 70% market share, which had 1.2 million posted job ads in 2023 from 0.3 million employers. Online job portals are a well established mode for recruitment into white collar jobs in the country. Employers post job openings on the portal and candidates apply to the postings of interest.

We chose two sectors for our experiment – HR and Finance – for two reasons. One, these sectors have the most number of job openings listed on the online job portal where we source our job ads from. Second, the eligibility criteria and job requirements are standard across different roles in these sectors, which makes our fictitious resumes suitable to a large number of job openings. These sectors also differ in the skill intensity. While HR has fewer skills that would become obsolete over time, the field of finance requires one to be up to date with taxation rules and finance based software.

2.1 Creating Fictitious Profiles

To create our profiles we sourced resumes from subscription based online resume databases so that candidate profiles and resumes were similar to that of actual job seekers. We created 8 different resume formats based on this sample of actual resumes, wherein the broad sub-headings remained the same but the order of sections, font, colour, text alignment and other formatting aspects were randomized across profiles. We ensured that these 8 formats were aesthetically of similar standards, but did not look identical at a glance. Text within each sub-heading was different but generated to convey the same information.

We created 8 fictitious profiles within each sector (Table A.1): 4 profiles with a career break and 4 profiles without a career break. To decide the career break duration we used the existing evidence which shows the average length of the career break for women in India to be 4 years and 4 months (2019 report). Subsequently the female candidate profiles having a career break had 4 year a gap in work experience just preceding the application. In addition, to examine the role of upskilling which may help women transition into workforce after career breaks, 2 out of the 4 profiles with a career break had recent skills certifications completed during the career break. Certification courses chosen were on average 1-2 months long, and we added 2-3 different certifications so that it signalled that our candidates spent around 3 months completing these courses. These were completed in the months preceding the job applications. The two profiles with upskilling courses had identical certifications listed in their resumes. Courses were chosen such that the content of the certification was relevant to the sector - tailored to HR and finance separately – imparting relevant technical skills.[7] As the core objective of the study is to measure the career break penalty for women and in India it is often married women with childcare responsibilities who tend to take such career breaks, all profiles in our study are married women having children.[8] To examine the role of expected

[7]For HR profiles, we added courses in MS Excel, analytics and digital strategies/tools, such as automation, focusing specifically on how these tools could be used in generic HR functions. For finance profiles, we added courses in advanced excel, financial Modelling and Data Analytics tailored for professionals working in Accounting, Auditing and Finance related roles.

[8]Time of India Article reports that 80% working women in India report undertaking a career break, with

fertility vs. childcare responsibilities on the career break penalty, half of the 8 profiles had one child and the rest had 2 children. The total fertility rate (TFR) in India is about 1.6 children per woman in urban areas (NFHS-5 report). Hence, employers can perceive that women with 2 children have achieved "family completion", while women with 1 child may take another maternity break in the near future. All profiles had 4 years of total experience.[9]

The other candidate details on the resumes such as educational qualifications, title and description of previously held jobs, key areas of competencies and technical skills were similar in content with only language and presentation modifications, with educational institutions and companies similar in quality chosen for each profile within a sector. To create the content for these, we filtered job openings within the relevant experience requirement on the online job portal. Using the job ads posted in the previous month, we obtained the distribution of job roles and job titles within each sector. We used the most frequently occurring job titles to obtain the preferred educational qualifications and detailed list of tasks that an ideal applicant would require to be familiar with for these positions. Based on this information on the filtered job ads, we decided the job titles for prior experiences held by the candidates. We indicated the educational qualification of the HR profiles as BA and MBA (Human Resource Management), and that of the finance profiles as B.Com. and Chartered Accountants. Additionally, we obtained the modal job title among jobs requiring 0-2 years and 1-3 years of experience in each sector to detail the previous job experience of the candidates. Finally, based on these descriptions, we added areas of key competencies and technical skills to each resume.[10]

One concern in our experiment design was that our profiles with career breaks would have

more than half of them taking it due to childcare responsibilities.

[9]Employers may perceive that women with two children and without career break would have taken maternity leaves, and consequently may discount their years of experience for the same. In order to keep the perceived net years of work experience same across profiles, we give 4.5 years of work experience for women with 2 children and without career breaks. Further, we added 3 years of Articleship experience, which is requirement for completing CA, to our finance profiles.

[10]These profiles were also reviewed by an HR recruiter who rated the CV's along various parameters – on the basis of educational qualifications, work experience, skills and general CV construction found them to be of the same quality.

to be 4 years older than the profiles without career break. Studies have shown that older applicants tend to receive fewer callbacks than younger applicants (Riach & Rich, 2007, 2010). Since academic calendar of schools in India runs from April to March, children born in first half of a calendar year usually start schooling an academic year earlier to the children born in the second half of the same calendar year. We set the month of birth of candidates such that women without a career break finished schooling at age 18 years while women with a career break at age 17. To further reduce the age gap between profiles with and without a career break, we let the women without career breaks to take one year break between undergraduate and postgraduate degrees, which is quite common in the country since many students take a gap year before postgraduate admission. Similarly, a gap year between schooling and first year college is quite common when students prepare for college entrance examinations. These adjustments allow us bring the difference in age of our fictitious candidates with and without career breaks down to 1 year. In addition, since the one year gap between undergraduate and postgraduate degree will be visible on the resumes, we added another fictitious female candidate without career break and one year break after undergraduate degree which made them 2 years younger to the women with career breaks. This enables us isolate the effect of an additional year of age on the likelihood of getting a callback and check whether this drives the career break penalty. With these adjustments, the age of women with a career break in HR was 31 years, and that of women without a career breaks was 29 and 30 years. Finance sector profiles had completed CA which included 3 years of full-time Articleship (in place of a 2-year postgraduate degree in HR profiles). This led to the age of finance profiles to be an year older for each type as compared to the HR profiles.

We procured unique phone numbers and created personal emails for each candidate, and mentioned the same on the resumes. First names and surnames of these women were chosen in such a way that it did not signal any differences in their socio-economic backgrounds – all were from upper caste Hindu families. We added other details to the resumes such as language proficiency in Hindi and English, Delhi/NCR as current location, and a short profile summary. We mentioned the years of experience and area of expertise in the profile summary. For profiles with a career break we added the reason for the break and expressed motivation to re-join work in the profile summary. We also mentioned completing multiple upskilling certifications during the break in the profile summary of women with career break and upskilling. We created profiles for our fictitious candidates on the job portal using the resume details. Some additional fields were mandatory on the portal which are not generally included in the CV, like location preference. Here, we chose New Delhi/NCR, Mumbai, Bangalore and Hyderabad as the desirable locations since we applied to jobs in these locations.

2.2 Applying to Jobs

We filtered active job openings listed on the portal during our study period based on job role, location of job, years of experience and skills required. We used the functional area listed on a job ad to filter job opening within the HR and finance sectors. We restricted ourselves to job ads that were at least listed in one for the preferred locations of our profiles. The job ads usually mentioned minimum and maximum years of experience expected from applicants. As our profiles had 4 years of experience each, we only applied to job ads that had 4 years included within the range of expected years of experience. Further, we dropped job ads if none of the technical skills mentioned on the job ad matched with skills on our profiles. Lastly, if the same company posted for the same job title multiple times, we restricted our application to the first two openings. We created a roaster of relevant and active job openings within each sector, and sent out applications between 15^{th} December 2023 and 9^{th} May 2024.

For each job opening, we randomly selected 4 profiles within the corresponding sector based on certain rules. Appendix Table A.2 shows the 14 combinations of the 4 profiles that were chosen. In type I combination, we ensured that a job ad received applications from women having a career break with and without upskilling. Type II combinations included women with and without a career break with variation in the number of children. After randomly choosing the set of 4 profiles that were to be sent to a particular job ad, based on the above combinations, we further randomized the order in which those 4 selected profiles were sent. These applications were sent on 4 different days based on count of additional applications received for that job. The portal shows the total count of applications received for a job ad till date. In order to reduce the chances of suspicion due to similarities between our fictitious profiles, we sent the applications on consecutive days either if the total count of applicants was more than 50 or if the count of applications had increased by more than 3 from our previous application.[11]

2.3 Recording Responses to Applications

We recorded response for each job application through multiple modes such as phone calls, text messages, e-mails and notifications from the job portal. Using the title and the company name mentioned, we identified to which application the call, text, e-mail or notification corresponded to. For some jobs the employers updated the current status of job-application on the portal itself. We recorded these status updates such as 'Resume Viewed', 'Contact Viewed', 'Shortlisted' and 'Not Shortlisted' as response to our application but only considered 'Shortlisted' as a positive response. Response to job application could not be through physical mail/post since we did not provide detailed address of the candidates in the CV or job portal profile. A job application is considered to have received a callback if we received a positive response from the employer through one of the sources listed above.[12] We recorded responses from 15^{th} December 2023 to 22^{nd} May 2024.

Caveats: The usual weaknesses of audit studies apply in our case as well. First, we observe initial shortlisting and not final hiring. To the extent that lower probability of receiving

[11]We automated the entire process of filtering relevant jobs ads, selecting 4 profiles to be sent, randomizing the order of application and submitting applications through a python algorithm which was run on all days except Fridays and Saturdays. This was to avoid the applications sent on Fridays and Saturdays from being at the bottom of the pile of job applications the employer would look through on Monday. This ensured that all applications got similar visibility.

[12]In situation where candidates were called for interviews or were asked about feasible dates for interviews, we politely declined by stating that we have already accepted another job offer recently.

an interview call is correlated with final job offers, this helps us measure the differential likelihood of final job offers. Second, the differential effect of upskilling measured in our study captures whether employers value such certifications. However, it is possible that women with a career break who have undergone upskilling perform better in interviews vs. women who have not and are able to get better final offers – whether in quantum or wages. Therefore, our results do not speak to the overall effectiveness of the upskilling programs for women who return after a career break. Third, online job portals represent only one mode of job search. Referrals/social networks or newspaper ads or placement agencies may be other mediums of search. Newspaper ad spend (the breakup for only employment ads is not available but newspapers primarily advertize government vacancies in India which constitute less than 5% formal employment in the country) has shown constant growth at 2% per annum whereas online job matching platform market in India has grown by almost 13.5% per annum over the last decade, showing the increasing importance of using portals for placement in private sector jobs.[13] Therefore, we are more likely to capture the private sector demand for female employees.

3 Results

3.1 Callback and Response Rates

We applied to 1932 and 2036 job openings in the HR and finance sectors, respectively. We sent 15872 applications in total – 3411 applications were sent from profiles with a career break and upskilling, 4525 from profiles with a career break and no upskilling and 7936 from profiles not having a career break.[14] As discussed earlier, our experiment design ensured that the total number of applications from profiles having a career break were equal to the number

[13]See: LinkedIn, Statista.

[14]The number of applications is not balanced across the three profile types because we have younger and older profile variety within the without career break profiles.

of applications from profiles without a break. The overall callback rate was 2.5%.[15]

The low callback rate is a feature of the current labor market in India. Another recent correspondence study in India by Tauheed (2023) with male and female profiles regarding marriage penalty within the HR sector found an average callback rate of 4.3%. We find that the callback rate in our experiment is higher within finance than in HR, similar to the results in Bedi *et al.* (2022) for India. In another study, Bedi *et al.* (2018) examine the motherhood penalty in the Indian job market and report that mothers within finance and BPO sectors faced an average callback rate of 10%. Notably, these profiles consisted of either freshers or those having at most 2 years of experience. Usually employers prefer to hire freshers due to low cost of hiring. Since all profiles in our study consist of women, mothers, having experience and about half of them have a career break, the average callback rates in our study are expected to be lower than the other correspondence studies conducted in India. Lastly, except for the study by Tauheed (2023), rest of the resume correspondence studies in India were conducted before the COVID-19 pandemic when the labor market was relatively tight.[16] For instance, Vuolo *et al.* (2017) shows that when labor markets are slack there is a fall in callback rates.

Table 1 summarizes the average callback rates received by profiles type – with a career-break and upskilling (column 1), with a career break (column 2) and without a career break (column 3). The callback rate for profiles with a career break, irrespective of completing upskilling courses, is 2% in comparison to 3% callback rate for profiles without a career break. This translates to a 1 percentage point (or 33%) smaller likelihood of receiving a positive callback for women with a career break vs. those without a career break. The last two columns show that this penalty is statistically significant at 1% level. The difference

[15] Appendix Table A.3 shows the characteristics of jobs with at least one callback vs. those with no callbacks, across different job characteristics. It shows that job openings with wages below the industry median wage or those at smaller firms tend to be more responsive to applications. Further, we observe that jobs listed in Delhi-NCR or Mumbai (i.e. North Indian cities) are more likely to respond to applications than those listed in Hyderabad or Bangalore (i.e. South Indian cities) which suggests that geographical distance between the candidate and the job affects the response rate by employers for women.

[16] Details about other resume correspondence studies in India are summarized in Appendix Table A.4.

in callback rates is smaller in the HR sector, and larger and statistically significant in the finance sector.

Further, we find that women with one child and a career break face 0.4 and 0.7 percentage points lower callback with and without upskilling respectively vs. female profiles having one child and no career break, where only the latter difference is significant at 10% level. Mothers of two children having a career break face a larger and statistically significant penalty of 1.6 and 1.4 percentage points with and without upskilling, respectively. As the current location on our profiles was Delhi-NCR, the average callback rates were highest for jobs based in Delhi-NCR across all profile types. Additionally, we see that the career break penalty was the largest and statistically significant at 1% level for jobs listed in Delhi-NCR. The career break penalty is comparatively lower in magnitude and statistically insignificant for Mumbai and Bangalore, and completely disappears for jobs listed in Hyderabad. Notably, Delhi is a northern state and Hyderabad and Bangalore are classified as southern states. Extant literature shows that gender attitudes are more regressive in the north as compared to the southern parts of India (Dyson & Moore, 1983) and the larger penalty in Delhi-NCR for women with career breaks may reflect this. We further examine these differences in the callback rates below.

3.2 Career Break Penalty

We verify the above findings after controlling for the number of children and the unobserved differences across jobs driving the callback rates. We first estimate the overall career break penalty faced by women using the below specification:

$$C_{i,j} = \beta \, CB_i + \delta X_i + \gamma_j + \epsilon_{i,j} \tag{1}$$

where, $C_{i,j}$ is an indicator variable that takes a value of 1 if the job application from profile i to job j receives a positive callback, and 0 otherwise; CB_i is an indicator variable that takes a value of 1 if profile i has a career break, and 0 otherwise; X_i is a vector of controls for characteristics like the number of children which vary across profiles; γ_j denotes job ad level fixed effects. We cluster the standard errors at job-ad level. As we include job ad level fixed effects in all our estimating equations, the estimates show within-job level difference in callback rates in presence of a career break. β shows the difference in percentage points between the callback rates received by female profiles having a career break vs. not having a career break.

Table 2 reports the estimates for equation 1 for all jobs (column 1), HR jobs (column 2) and finance jobs (column 3). The career break penalty estimates are statistically significant at 1% level across the three columns. Female profiles with a career break receive on average 1.1 percentage points lower callback rates vs. female profiles with no career break. This translates to a 49% lower callback rate over the mean (=0.011/0.0225) for women who take a break. This penalty is larger in the finance sector (55% lower call back rate) in comparison to the HR sector (36% lower call back rate). This contrast in the career break penalties across sectors can be attributed to how skills in these sectors evolve over time. In finance, accounting and auditing jobs, one is required to be up-to-date with all the recent changes in tax and accounting laws. Employers may perceive the knowledge and work experience of candidates with a career break to be obsolete, despite having the same years of work experience. Skills in the HR sector are relatively generic and slow evolving, and hence, the career break penalty maybe be smaller. We show robustness of these findings to using a logit model with job ad level random effects in Appendix Table A.5 and continue to find similar results. Given the profiles with a career break are an year older to the profiles without a break, we also test for the impact of age among profiles which do not have a career break. We do not find any difference in callback rates by one year of age difference (Appendix Table A.6). Hence, the observed career break penalty is not driven by an year of age penalty in the callback rates.

Further, we examine whether signalling that a profile took upskilling courses after the break before entry into the labor market mediates the penalty, using the below specification:

$$C_{i,j} = \beta_1 \text{ CB (no upskilling)}_i + \beta_2 \text{ CB (upskilling)}_i + \delta X_i + \gamma_j + \epsilon_{i,j} \tag{2}$$

where, $C_{i,j}$ is an indicator variable that takes a value of 1 if the job application from profile i to job j receives a positive callback, and 0 otherwise; CB (no upskilling)_i is an indicator variable that takes a value of 1 if profile i has a career break and no upskilling certifications, and 0 otherwise; CB (upskilling)_i is an indicator variable that takes a value of 1 if profile i has a career break and upskilling certifications, and 0 otherwise; X_i controls for the number of children across profiles and γ_j denotes job ad level fixed effects. We cluster the standard errors at job-ad level. β_1 (β_2) shows the difference in percentage points between the callback rates received by profiles having a career break with no upskilling (career break and upskilling) vs. those not having a career break.

Table 3 reports the results for equation 2 for all jobs (column 1), HR jobs (column 2) and finance jobs (column 3). The career break penalties, with and without upskilling, are both 1.1 percentage points for all sectors. Within the HR sector, the career break penalty falls from 0.5 percentage points to 0.4 percentage points when the candidate completes upskilling courses during the break, which accounts for a 20% drop in career break penalty. However, this is not statistically significant. Similarly, the career break penalty for profiles with and without upskilling in the finance sector not significantly different from each other. The almost null effect of upskilling programs in the finance sector suggests that employers do not perceive these skilling programs as a substitute for skills/expertise gained on the job. Additionally, we show the robustness of these results to using a logit model with job ad level random effects in Appendix Table A.7. Our conclusions do not change.[17]

[17]We also estimate a job ad fixed effects model, but given the incidental parameters problem that afflicts non-linear models with fixed effects we do not report the results. Our conclusions do not change with this alternative specification.

3.3 Perceived Childcare and Career Break Penalty

We next test if the number of children affects the career break penalty by estimating the below specification:

$$C_{i,j} = \beta_1\, CB_i + \beta_2\, CB_i \times Child_i + \phi\, Child_i + \gamma_j + \epsilon_{i,j} \tag{3}$$

where, $C_{i,j}$ is an indicator variable that takes a value of 1 if the job application from profile i to job j receives a positive callback, and 0 otherwise; CB_i is an indicator variable that takes a value of 1 if profile i has a career break and 0 otherwise; $Child_i$ is an indicator variable that takes a value of 1 if profile i has two children, and 0 if one child; γ_j denotes job ad level fixed effects. We cluster the standard errors at job-ad level.

Table 4 reports the estimates for equation 3 for all jobs (column 1), HR jobs (column 2) and finance jobs (column 3). The results show that the career break penalty in callbacks is higher for mothers with 2 children than women with 1 child across industries, but these differences are not statistically significant (albeit large in magnitude). In fact, in HR jobs the career break penalty is only significant for women who have two children. Employers recruiting for HR roles put higher weight on perceived childcare burden, in comparison to the finance sector, while evaluating candidates with a career break. Employers recruiting for finance roles seem to be more concerned about the lack of work experience in recent past and assign a career break penalty of 1.6-1.8 percentage points, which translates to a 57% fall in mean callback rate, for all profiles irrespective of the number of children.

4 Taste based discrimination

In this section, we examine if the career break penalty differs across different job characteristics which can potentially reflect employer's taste based preferences. We interact the career break indicator variable in equation 1 with dummy variables for various job characteristics like firm size, posted salary and job location, and report the estimates in Appendix A. Almost 99% of the jobs on the portal post an annual salary on the job platform. It is generally provided as a range between a minimum and a maximum value. We take the mid-value of the range as the salary associated with a job. Appendix Table A.8 shows that the career break penalty is lower in jobs offering above median salary for the industry. Female profiles having a career break are 26% less likely to receive a callback from jobs offering above median salary but almost 75% less likely to receive a callback from jobs offering below median salary. Employers offering above median salary maybe more labor constrained and hence willing to consider women returning after a break. These could also be bigger and more productive organisations which may have more inclusive hiring processes.

Next, in Appendix Table A.9 we examine whether the career break penalty varies by firm size. We collected firm size information from Ambition Box based on the firm names posting for a given position. We were able to get this information for 1374 jobs out of the 3968 jobs we applied to (approximately 35% of the jobs). We find that mid-sized firms having 51-200 employees impose a slightly lower career break penalty vs. those having less than 51 employees - but only in the finance sector. Strikingly, the penalty almost disappears in organisations with more than 200 employees and stands at 57% for firms having less than 51 employees. This pattern is consistent across sectors. Notably, employers in bigger organisations are less likely to receive a call back on average. The call back rate is 1% for jobs posted by firms having more than 200 employees but it is 3.7% by firms having 1-50 employees, showing that the number and the quality of applications are likely to be higher for bigger firms. Despite this, the lower career break penalty imposed by them reflects inclusive workplace policies. This is also consistent with findings in Siddique (2011) that low caste groups are less likely to face discrimination in Indian firms having multiple domestic or foreign offices (likely to be larger in size).[18]

[18]In general, correspondence studies for other countries that have examined different types of discrimination in the labor market show inconsistent results on whether larger firms display lower or higher degree of gender bias in the callback rates. Baert *et al.* (2018) show that smaller firms display a greater degree of differential treatment by gender in Belgium, but this is not statistically significant. However, Zhang *et al.* (2021) find

Finally, Appendix Table A.10 shows whether there exists any differential career break penalty across the northern and the southern cities of India based on the job location. Hyderabad and Bangalore job locations are classified as southern cities while Delhi and Mumbai are classified as northern cities. Jobs having locations in both north and south (since a given job posting can have multiple possible locations if the firms has the same opening across multiple offices) are dropped from this analysis. Extant literature shows spatial heterogeneity on gender attitudes in India, with states in the north being more gender unequal relative to the south of the country due to historical cultural differences (Dyson & Moore, 1983; Rahman & Rao, 2004; Afridi *et al.*, 2023).[19] If gender attitudes of employers play a role behind the lower call back rates for women returning after a career break, then employers located in the south will be less likely to engage in this discriminatory behavior. Indeed, we find that the career break penalty is smaller by employers located in the south (0.4 percentage points in the south vs. 1.3 percentage points in the north). This translates into a 40% lower callback rate for profiles having a career break in the south (over the mean callback rate of 1 percentage point in the south) and a 54% lower callback rate for profiles having a career break in the north (over the mean callback rate of 2.4 percentage point in the south). Notably since all our profiles belong to the north and have typical northern names this is not driven by the possible perception of employers about gender norms across profiles but rather by differences arising solely from employers' gender attitudes.

5 Conclusion

The problem of low female labor force participation in South Asian countries remains a sticky one to solve. Usually, the burden of care falls heavily in these countries on women than men. For instance, time use statistics show that women in South Asia spend 7-8 times more time in

that gender discrimination is only present in organisations with more than 100 employees and the same vanishes in firms with less than 100 employees in China.

[19] Dyson & Moore (1983) shows that the northern states have more patriarchal attitudes and consequential worse economic outcomes for women. They find that southern states have later age at marriage, lower marital fertility, higher labor market participation and a higher status of women across multiple other indicators.

domestic work than men (UN Report). The large gender gap in domestic work persists even at higher levels of education. The burden of care work often leads to women withdrawing from the labor force to take care of children or elders with a desire to return after a hiatus. In this paper, we examine the extent of penalty faced by women who return to work after a break in India and find that they are 49% less likely to get a callback than women who do not take any break but have otherwise similar characteristics. This penalty is larger in the skill intensive finance sector in comparison to the HR sector. However, signalling undertaking upskilling courses on the CV does not reduce the penalty. Exploiting the characteristics of jobs like firm size and location, we are further able to throw light on the presence of taste based discrimination in explaining some part of the penalty, as smaller firms and those located in the north India impose larger penalties on women who have taken a break. Given that estimates show that 7 million women in India are likely to be returnees, this has consequences for their labor force attachment rates. Employer discrimination can demotivate returnee women and also lead to inadequate utilization of skilled labor in the country.

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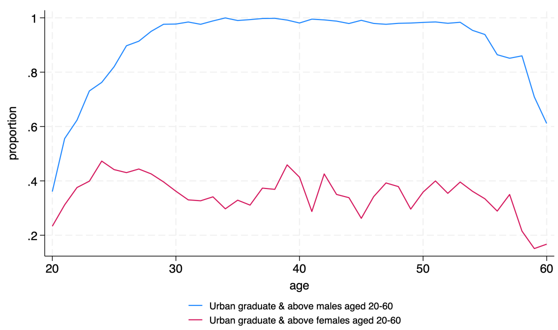
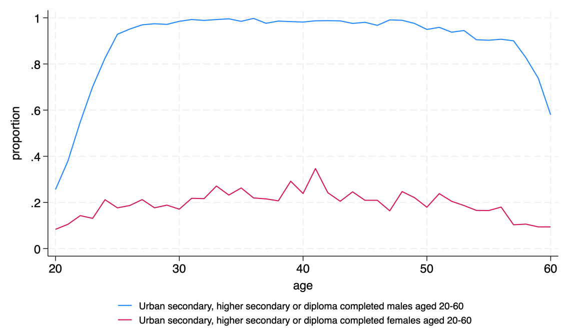
Figure 1: Labor Force Participation Rate in Urban India by Age: Men vs Women

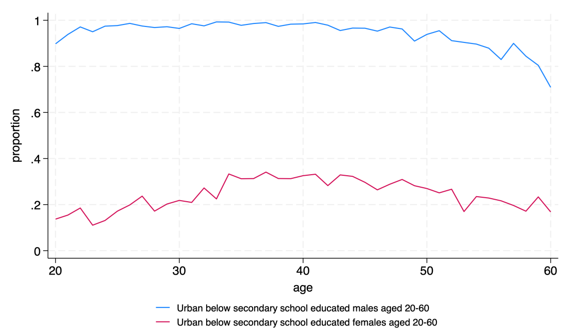
(a) Graduate or above



(b) Secondary-Schooled



(c) Below secondary education



Notes: Panel (a), (b) and (c) show labor force participation rates for graduate and above, completed schooling or secondary education and those have below secondary education men and women in urban India, respectively, by age.
Source: Periodic Labor Force Survey (2021-22).

Table 1: Mean Callback Rates by Female Profiles

	(1)	(2)	(3)	(1)-(3)	(2)-(3)
	With CB & Upskilling	With CB	Without CB	Pairwise T-test	
All Jobs	0.020 (0.002) [3411]	0.020 (0.002) [4525]	0.030 (0.002) [7936]	-0.010***	-0.010***
Industry:					
HR	0.017 (0.003) [1671]	0.014 (0.003) [2193]	0.019 (0.002) [3864]	-0.002	-0.005
Finance	0.024 (0.004) [1740]	0.025 (0.003) [2332]	0.041 (0.003) [4072]	-0.017***	-0.016***
Motherhood Status:					
One Child	0.023 (0.004) [1711]	0.020 (0.003) [2278]	0.027 (0.003) [3967]	-0.003	-0.007*
Two Children	0.017 (0.003) [1700]	0.020 (0.003) [2247]	0.034 (0.003) [3969]	-0.016***	-0.014***
Job Location:					
Delhi NCR	0.031 (0.004) [1573]	0.028 (0.004) [2103]	0.044 (0.003) [3676]	-0.013**	-0.016***
Mumbai	0.010 (0.003) [864]	0.012 (0.003) [1124]	0.022 (0.003) [1988]	-0.012**	-0.010*
Hyderabad	0.014 (0.005) [485]	0.012 (0.004) [683]	0.016 (0.004) [1168]	-0.002	-0.005
Bangalore	0.009 (0.003) [772]	0.011 (0.003) [994]	0.019 (0.003) [1766]	-0.010*	-0.008

Notes: The table reports mean callback rates for all jobs (first row) and for different sub-samples of jobs across 3 profile types - without career break (column 1), with career break but without upskilling (column 2), and with career break and upskilling (column 3). Corresponding standard errors of the mean callback rate and number of observations are shown within parentheses and square brackets, respectively. The last two columns present the t-statistics from pairwise t-tests conducted to compare the mean callback rates between profiles without a career break and those with a career break and upskilling (Column (1)-(3)), and profiles without a career break and those with a career break (Column (2)-(3)). ***, **, * show significance of the t-statistics at 1%, 5% and 10%, respectively.

Table 2: Career Break Penalty for Women

	(1)	(2)	(3)
	Overall	HR	Finance
CB	-0.011***	-0.005**	-0.017***
	(0.002)	(0.002)	(0.003)
Outcome Mean	.0225	.0138	.0307
R-Squared	.614	.595	.621
Observations	15872	7728	8144
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The table shows the estimates for equation 1. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. *CB* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 3: Career Break Penalty for Women: By Upskilling

	(1)	(2)	(3)
	Overall	HR	Finance
CB (No Upskilling)	-0.011***	-0.005**	-0.016***
	(0.002)	(0.002)	(0.003)
CB (Upskilling)	-0.011***	-0.004*	-0.017***
	(0.002)	(0.002)	(0.004)
Outcome Mean	.0225	.0138	.0307
R-Squared	.614	.595	.621
Observations	15872	7728	8144
CB (No Upskilling) - CB (Upskilling)	-0.000	-0.001	0.001
	(0.002)	(0.003)	(0.003)
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The table shows the estimates for equation 2. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. *CB (No Upskilling)* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break but without upskilling, or 0 otherwise. *CB (Upskilling)* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break and upskilling, or 0 otherwise. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table 4: Career Break Penalty for Women: By Number of Children

	(1)	(2)	(3)
	Overall	HR	Finance
CB	-0.009***	-0.003	-0.016***
	(0.003)	(0.003)	(0.004)
CB $\times$ Children=2	-0.003	-0.005	-0.002
	(0.004)	(0.005)	(0.006)
Outcome Mean	.0225	.0138	.0307
R-Squared	.614	.595	.621
Observations	15872	7728	8144
(CB=1) + (CB=1 $\times$ Children=2)	-0.013***	-0.007**	-0.017***
	(0.003)	(0.003)	(0.004)
Job FE	Yes	Yes	Yes
Children FE	Yes	Yes	Yes

Notes: The table shows the estimates for equation 3. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. CB denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. The candidates can either have 1 or 2 children, Children FE in this case denotes an indicator variable for candidates with 2 children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

A Appendix: Additional Figures and Tables

Table A.1: Fictitious Candidate Profiles for a Sector

Gender	Motherhood	Career Break	Upskilling	Age
Female	With 1 Child	Without Career Break	-	29 years
Female	With 1 Child	Without Career Break	-	30 years
Female	With 1 Child	With Career Break	Without Upskilling	31 years
Female	With 1 Child	With Career Break	With Upskilling	31 years
Female	With 2 Children	Without Career Break	-	29 years
Female	With 2 Children	Without Career Break	-	30 years
Female	With 2 Children	With Career Break	Without Upskilling	31 years
Female	With 2 Children	With Career Break	With Upskilling	31 years

Note: Age mentioned in this table are that of HR profiles. The age for finance profiles will be one year more than the age in the corresponding HR profiles (i.e., 30, 31 and 32 years). Overall, we uploaded 16 female profiles across all sectors, with 8 profiles uploaded for each sector.

Table A.2: Selection of 4 Profiles for each Job Ad

	Description	Combinations
Type 1: Focus on Career Break and Upskilling		
Profile 1:	29 year old without career break [*Choose between 1 child and 2 children*]	8 combinations*
Profile 2:	30 year old without career break [*Choose between 1 child and 2 children*]	
Profile 3:	31 year old with career break but without upskilling [*Choose between 1 child and 2 children*]	
Profile 4:	31 year old with career break and upskilling [*Choose between 1 child and 2 children*]	
Type 2: Focus on Career Break and Expected Fertility		
Profile 1:	Mother of 1 child without career break [*Choose between 29 and 30 year olds*]	6 combinations**
Profile 2:	Mother of 1 child with career break [*Choose between with and without upskilling*]	
Profile 3:	Mother of 2 children without career break [*Choose between 29 and 30 year olds*]	
Profile 4:	Mother of 2 children with career break [*Choose between with and without upskilling*]	

* *Criteria:* Either all four profiles have the same number of children (resulting in 2 possible combinations), or there are two pairs of profiles - one pair with one child each and another pair with two children each (resulting in 6 possible combinations).
This leads to total 8 combinations, which are (*1:* 1 child, *2:* 1 child, *3:* 1 child, *4:* 1 child), (*1:* 2 children, *2:* 2 children, *3:* 2 children, *4:* 2 children), (*1:* 1 child, *2:* 1 child, *3:* 2 children, *4:* 2 children), (*1:* 1 child, *2:* 2 children, *3:* 1 child, *4:* 2 children), (*1:* 1 child, *2:* 2 children, *3:* 2 children, *4:* 1 child), (*1:* 2 children, *2:* 1 child, *3:* 1 child, *4:* 2 children), (*1:* 2 children, *2:* 1 child, *3:* 2 children, *4:* 1 child) and (*1:* 2 children, *2:* 2 children, *3:* 1 child, *4:* 1 child).
** *Criteria:* Both without career break profiles will have same age, so they could either be the younger profiles i.e., 29 year old in HR (resulting in 4 possible combinations) or the older profiles i.e., 30 year old in HR (resulting in 4 possible combinations). Both profiles with career breaks cannot be those with upskilling as the certifications are identical for these profiles (resulting in 2 combinations being dropped).
This leads to total 6 combinations, which are (*1:* 29-year old, *2:* without upskilling, *3:* 29-year old, *4:* without upskilling), (*1:* 29-year old, *2:* with upskilling, *3:* 29-year old, *4:* without upskilling), (*1:* 29-year old, *2:* without upskilling, *3:* 29-year old, *4:* with upskilling), (*1:* 30-year old, *2:* without upskilling, *3:* 30-year old, *4:* without upskilling), (*1:* 30-year old, *2:* with upskilling, *3:* 30-year old, *4:* without upskilling) and (*1:* 30-year old, *2:* without upskilling, *3:* 30-year old, *4:* with upskilling).

Table A.3: Response Rates at Job-level by Job Characteristics

	(1)	(2)	(3)
	No Callback	Atleast 1 Callback	Total
All Jobs	94.68% [3757]	5.32% [211]	100% [3968]
Industry:			
HR	96.22% [1859]	3.78% [73]	100% [1932]
Finance	93.22% [1898]	6.78% [138]	100% [2036]
Wages:			
Below Industry Median	93.60% [1829]	6.40% [125]	100% [1954]
Above Industry Median	95.76% [1922]	4.24% [85]	100% [2007]
Firm Size:			
1-50 employees	92.81% [155]	7.19% [12]	100% [167]
51-200 employees	95.35% [369]	4.65% [18]	100% [387]
More than 200 employees	97.44% [799]	2.56% [21]	100% [820]
Job Location:			
South	97.41% [1204]	2.59% [32]	100% [1236]
North	93.39% [2415]	6.61% [171]	100% [2586]

Notes: The table displays the distribution of jobs across two response categories: no callbacks (Column 1) and at least one callback (Column 2) for the four applications sent per job. The sample is job-level, with total callbacks received per job and other job-level characteristics. Values in square brackets indicate the number of observations within each response category, for entire sample (first row) and sub-samples broken down by industry, wages, firm size, and job location.

Table A.4: Callback Rates in Resume Correspondence Studies in India

Studies	Description	Callback Rate
Banerjee *et al.* (2009b)	Study Year: 2004 Industry: Software and BPO Gender: Female and Male Experience Requirement: ∼ 4 years Categories: UC, OBC, SC, ST, Neutral, Muslim Mode: Newspaper and Job Portals	5.23% in Software and 16.7% in BPO [Total of 3160 applications to 371 jobs]
Siddique (2011)	Study Year: 2006 Industry: Customer Service, Office Administration Gender: Female and Male Experience: 0 years (Fresher) Categories: High/low caste indicated by name Mode: Newspaper and Job Portals	15% [155 callbacks out of 1046 applications to 523 jobs]
Bedi *et al.* (2018)	Study Year: 2018 Industry: Finance and BPO Gender (Age): Male and Female (25-28 years old) Experience: 0 or 2 years Motherhood: Married women with/without 1 child Categories: Bengali, Khasi and Naga applicants Mode: Job Portal	10% for Mothers and 38% for Non-mothers [Total of 957 applications to 258 jobs]
Bedi *et al.* (2022)	Study Year: 2019 Industry: Finance and BPO Gender (Age): Female (26-27 years old) Experience: 2 years Categories: Married women with/without 1 child Mode: Job Portal	22% in BPO and 24% in Finance [Total of 450 applications to 150 jobs]
Tauheed (2023)	Study Year: September-November, 2022 Industry: HR Gender: Female and Male Marital Status: Single and Married Experience: 5 years Mode: Job Portal	4.3% [166 callbacks out of 3832 applications to 1916 jobs]

Notes: The table summarises the overall/sub-sample mean callback rates along with the experimental design, resume types and other useful information about the fictitious profiles in used in resume correspondence studies in India.

Table A.5: Career Break Penalty for Women (Logit)

	(1)	(2)	(3)
	Overall	HR	Finance
Marginal Effects:			
CB=1	-0.038***	-0.005**	-0.049***
	(0.012)	(0.002)	(0.015)
Observations	15872	7728	8144
Outcome Mean	.0225	.0138	.0307
Job RE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The table presents results from a logit model with job-level random effects, estimating the career break penalty in overall sample and sub-samples by sector. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. CB denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.6: Age Effect on Callback Rates

	(1)	(2)	(3)
	Overall	HR	Finance
Age	-0.002	0.000	-0.001
	(0.003)	(0.004)	(0.004)
Outcome Mean	.028	.0163	.00704
R-Squared	.773	.734	.776
Observations	7936	3864	2558
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The table shows the results from estimating the effect of age on callback rate. Sample is restricted to applications made from profiles without career break. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. Age represents the numeric variable measuring the age on the fictitious profiles (in years). Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.7: Career Break Penalty for Women: By Upskilling (Logit)

	(1)	(2)	(3)
	Overall	HR	Finance
Marginal Effects:			
CB (No Upskilling)=1	-0.033***	-0.005**	-0.041***
	(0.011)	(0.002)	(0.013)
CB (Upskilling)=1	-0.031***	-0.004*	-0.041***
	(0.010)	(0.002)	(0.012)
CB (No Upskilling) - CB (Upskilling)	-0.002	-0.001	0.000
	(0.005)	(0.003)	(0.007)
Observations	15872	7728	8144
Outcome Mean	.0225	.0138	.0307
Job RE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The table presents results from a logit model with job-level random effects, estimating the career break penalty for profiles with and without upskilling in overall sample and sub-samples by sector. The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. *CB (No Upskilling)* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break but without upskilling, or 0 otherwise. *CB (Upskilling)* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break and upskilling, or 0 otherwise. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.8: Career Break Penalty in Jobs offering Wages below the Median Wage in respective Industries

	(1)	(2)	(3)
	Overall	HR	Finance
CB	-0.006**	-0.001	-0.010**
	(0.002)	(0.002)	(0.004)
CB × Below Median=1	-0.011***	-0.009**	-0.013**
	(0.004)	(0.004)	(0.006)
Outcome Mean	.0225	.0138	.0307
R-Squared	.615	.599	.621
Observations	15844	7700	8144
(CB=1) + (CB=1 × Below Median=1)	-0.017***	-0.010***	-0.023***
	(0.003)	(0.003)	(0.005)
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. *CB* denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. *Below Median* denotes an indicator variable that takes a value of 1 if the application was sent to a job that was offering wages below the industry median wage, or 0 otherwise. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.9: Firm Size and Career Break Penalty

	(1)	(2)	(3)
	Overall	HR	Finance
CB	-0.021**	-0.007	-0.030*
	(0.010)	(0.007)	(0.016)
CB $\times$ $51 - 200$ Employees	0.007	-0.009	0.018
	(0.012)	(0.012)	(0.018)
CB $\times$ >200 Employees	0.021**	0.007	0.030*
	(0.010)	(0.008)	(0.016)
Outcome Mean	.0156	.012	.0198
R-Squared	.624	.589	.647
Observations	5496	2916	2580
(CB=1) + (CB=1 $\times$ $51 - 200$ Employees)	-0.014**	-0.016*	-0.013
	(0.007)	(0.009)	(0.010)
(CB=1) + (CB=1 $\times$ >200 Employees)	-0.000	0.000	-0.000
	(0.003)	(0.003)	(0.005)
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. CB denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. The firm size categories are $1 - 50$, $51 - 200$ and > 200 employees. Indicator variables for each firm size category was interacted with CB. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Table A.10: Career Break Penalty: By Job Location

	(1)	(2)	(3)
	Overall	HR	Finance
CB	-0.013***	-0.008**	-0.017***
	(0.003)	(0.003)	(0.004)
CB $\times$ South=1	0.009***	0.008**	0.007
	(0.003)	(0.004)	(0.006)
Outcome Mean	.0226	.0142	.0307
R-Squared	.622	.595	.632
Observations	15288	7512	7776
(CB=1) + (CB=1 $\times$ South=1)	-0.004**	-0.000	-0.010**
	(0.002)	(0.002)	(0.004)
Job FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The dependent variable is a callback indicator that takes a value of 1 if the job application received a positive callback, or 0 otherwise. CB denotes an indicator variable that takes a value of 1 if the application was sent from a profile with a career break, or 0 otherwise. South is an indicator variable that takes a value of 1 if the application was sent to a job ad listing Hyderabad or Bangalore as job location, or 0 if the application was sent to a job ad listing Delhi or Mumbai as job location. Job ads with atleast one North-Indian city and atleast one South-Indian city are dropped from these specifications. Control variable is number of children. Standard errors in parentheses are clustered at job ad level. ***, **, * show significance at 1%, 5% and 10%, respectively.