Barriers to entry: Decomposing the gender gap in job search in urban Pakistan[†]

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Abstract

Gender gaps in labor market outcomes persist in South Asia. An open question is whether supply or demand side constraints play a larger role. We investigate this using matched data from three sources in Lahore, Pakistan: representative samples of jobseekers and employers; administrative data from a job matching platform; and an incentivized binary choice experiment. Employers' gender restrictions are a larger constraint on women's job opportunities than supply-side decisions. This demand-side gap in quantity of job opportunities closes as education levels increase and jobs become more "white-collar".

Keywords: gender, discrimination, job search, jobs platform, vacancies, applications.

JEL Codes: J16, J22, J23, R23.

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1 Introduction

Vast gender gaps in employment, stemming from low levels of women's employment, persist in many low- and middle- income economies, particularly in South Asia, the Middle East, and North Africa (Addati *et al.*, 2016). A growing literature documents that supply side factors such as self-selection into occupations that conform to gender identity, differing preferences for job attributes, gendered social norms about time use, and household members' preferences that women stay at home constrain women's labor supply in these contexts. However, demand-side rather than supply-side factors might form the binding constraint to women's labor for a larger fraction of the population in contexts with low female labor force participation (FLFP). Indeed, a smaller body of work demonstrates that demand-side factors can contribute to gender gaps in employment (Kuhn and Shen, 2013; Goldin and Rouse, 2000; Hangartner *et al.*, 2021; Ozen *et al.*, 2019).

Despite the wealth of research on low female employment, we have limited evidence quantifying the relative size of demand and supply factors that give rise to this phenomenon. In addition, much of the existing evidence focuses on specific populations (e.g. educated women) or sectors (e.g. government work). Knowing whether supply or demand constraints are binding in the broader labor market is important to target policy to either supply-side interventions, such as provision of financial services to women, exposure to female role models, or interventions with women's families (Field *et al.*, 2021; Ahmed *et al.*, forthcoming; Dean and Jayachandran, 2019), or to demand-side interventions such as eliminating gender criteria in job ads, hiring quotas, wage subsidies, physical infrastructure such as women's toilets, or employer-based childcare (Card *et al.*, 2021; Miller *et al.*, 2022; Kuhn and Shen, 2023).

We address this gap in the literature by combining data from a job search platform and incentivized binary choice experiment from Lahore, Pakistan, to quantify the relative importance of demand-side and supply-side sources of the gender gap. We define demand-side constraints as those that stem from decisions made by the hiring firm, and define supply-side constraints as those that stem from decisions made by an individual - including how she responds to preferences of other members of her household. We document that at low education levels demand-side constraints are much larger than supply-side factors, but this demand-side gap in quantity of job opportunities closes as education levels increase and jobs become more "white-collar".

Our empirical approach uses a novel combination of matched data from representative surveys, administrative data on job search, and experimental data to overcome four key challenges to quantifying the size of demand and supply side factors contributing to the the gender gap in the labor market. The first empirical challenge is that survey data from representative samples of households or firms can be used to quantify the realized gender gap in equilibrium, but do not allow the analyst to decompose how much of this gap comes from men's and women's willingness to supply labor versus firms' demand for male and female labor. Second, alternative data sources such as job platform data allow researchers to observe the details of search activity by jobseekers and firms; however, such data often have limitations (Nomura *et al.*, 2017). They typically do not allow the researcher to observe jobseeker preferences directly, only to infer them from application choices, which are also influenced by other factors such as the vacancies available on the platform. Similarly, they typically do not allow the researcher to observe a well-defined choice set of vacancies considered by the jobseeker, making it difficult to disentangle whether the decision to apply to a given vacancy is a function of the characteristics of that vacancy or of search effort in browsing the platform (e.g. Belot *et al.* (2018); Wheeler *et al.* (2021); Jones and Sen (2022); Banfi *et al.* (2019); Matsuda *et al.* (2019)). Third, selection of both firms and workers into search and the use of job search platforms limits the extent to which results can be extrapolated to the population as a whole (Kureková *et al.*, 2015).

Addressing these first three challenges, our research partners at the Centre for Economic Research in Pakistan developed a new job matching platform, Job Talash, and offered it as a free service to representative listings of thousands of households and thousands of firms in a single urban labor market. We emphasize the importance of studying the former group, economically inactive "latent workers," who might be interested in working but are economically inactive due to lack of opportunities, who represent the population with the largest potential benefit from reductions in labor market barriers. This group is particularly important for understanding gender differences in settings such as Pakistan, where survey data suggest that a high fraction of the female population are latent workers. Female labor force participation in Pakistan was 21% in 2020 compared to a male labor force participation rate of 78% (International Labour Organization, 2019a,b); however, a quarter of women are not working but report they would like to work if they could find a suitable job (Field and Vyborny, 2016). The research design involved development, piloting, and refinement of a high-frequency job matching service that lists jobs and delivers information to respondents about them through text message and a call center. Job Talash allows us to precisely observe each step of job search activity on the supply and demand side (Field and Vyborny, 2022; Subramanian, 2024; Field *et al.*, 2023). The platform works by matching each jobseeker to open vacancies based on whether they satisfy minimal criteria set by the firm for the vacancy, and occupational preferences set by the jobseeker. The platform sends information to the jobseeker about all the vacancies that meet all criteria (we refer to such a pairing that satisfies all criteria as a "platform match"), and the jobseeker can decide whether to apply to each one. Thus, the platform generates high-frequency, detailed data on both the supply and demand sides of the labor market for millions of potential job platform matches between firm and jobseeker. The platform does not have a search function, which means that we observe the full set of vacancies that the jobseeker sees, and the full set of candidates sent to the firm. Because we provide information to both sides, we observe exactly the same information as both sides of the market up to the point of an interview. The representative recruitment of both jobseekers and firms (rare in the literature (Kureková *et al.*, 2015)) and the rich administrative data observed on the platform provide us unique leverage to help pinpoint the supply-side versus demand-side constraints to women's versus men's job search.

The fourth challenge in quantifying supply versus demand side constraints is that even if the initial sample of jobseekers and firms is representative, when observing downstream outcomes in the job search process such as interviews and hires, selection problems arise again, because male and female candidates who choose to apply for a given vacancy may differ systematically from each other and from non-applicants. To address this challenge, we combine the administrative data with an incentivized binary choice experiment which we conducted with firms in the Job Talash sample, adapted from the design of incentived resume rating experiments by Kessler *et al.* (2019). We show employers on the platform a series of pairs of CVs and in each pair ask the respondent to select the one that they would be most likely to hire, with the incentive that this could help inform the applicant pool sent to them through the Job Talash platform. CVs for this exercise were constructed using the actual job applicant data from the Job Talash pool, making them a realistic representation of the candidates the firm might see on the platform; we randomly varied the gender of the applicant on the CV to identify firm preferences over gender, holding constant potential confounders such as differences in levels of education and experience between men and women in the pool, and differential selection into application.

Our first key finding is that when considering women and men overall, firm gender criteria, an entirely demand-side constraint, are more often binding for women than men, and are also a larger constraint than supply-side decisions. Women in our setting are 53% less likely than men to satisfy the explicit gender requirements for any given vacancy. These patterns persist even when we restrict to vacancies where the individual met the education and experience criteria, and expressed interest in the occupation: demand-side criteria are the binding constraint on opportunities available to women. In fact, in the set of vacancies where individuals satisfied all basic criteria and were eligible to apply, women apply at a higher rate than men, overall. Household preferences have been shown to be influential in women's job search decisions in Pakistan and other settings in the literature (Subramanian, 2024; Dean and Jayachandran, 2019). In our setting, we cannot separate out fully how much of a jobseeker's search decisions are driven by her own preferences versus the preferences of others in her household; we consider these as a bundle of factors affecting supply-side decisions as a whole. However, we show that firm decisions of whether to open a vacancy to female applicants limit women's job opportunities more than any supply-side decisions. If firms' gender criteria were lifted, women would be matched by the platform to more than double the number of vacancies that they match to currently; in contrast, for men, removing gender criteria would only increase the number of vacancies available to them by 14%.

Our second key finding is that the demand side gender gap in quantity of job opportunities substantially closes as education levels rise. The gender gap in satisfying the gender criteria for a position shrinks by 70% for the minority of women with secondary education and effectively disappears for the third of women with a tertiary education. We document this through both the administrative data and the binary choice experiment. We find that firms' gender criteria and the educational requirements of the job are mirrored; vacancies with "blue collar" characteristics such as manual labor and longer and late work hours are more likely to exclude women and more common among jobs with low education requirements, even conditional on industry and occupation fixed effects.

We next study potential mechanisms behind these main results. First, we find that our main results persist even if we consider jobseeker selection into search and applications, which may differ by gender. We replicate our main findings on the full representative listing of households, showing that even if every man and woman from a representative sample of households signed up for the platform, the gaps in job opportunities on the platform favor men, and that this is due to women overwhelmingly not meeting firm-side gender criteria. We further document that for vacancies which are open to both men and women, women are neither more nor less likely to apply than men.

Second, we show that these firm-side gender criteria vary substantially across firms within occupation and industry. Firms that have restrooms or a separate prayer space for women are both more likely to be willing to hire women and more likely to be hiring at a high education level. This connects to a broader literature pointing to the role of non-wage characteristics of firms and vacancies in gender gaps in the labor market (Mas and Pallais, 2017; Flory *et al.*, 2015; Field and Vyborny, 2022; Goldin and Katz, 2016; Chiplunkar and Goldberg, 2021; Miller *et al.*, 2022). Firm gender criteria excluding women are also correlated with firms' stated perceptions that jobs in their industry are physically demanding or that clients/coworkers either do not want women or misbehave with female employees. Using the administrative data, we cannot explicitly separate whether firms impose such gender criteria due to anticipation that women would not want to work at their vacancy, or due to a preference not to hire women. However, using the incentivized binary choice experiment we show that firm gender criteria are unlikely to be due to anticipated self-selection of weaker female candidates into application. Firms that have never posted an ad open to women are significantly less likely to select the female CV in a pair of CVs - even though the CVs are of equal quality by design. In contrast, firms that have ever posted an ad open to women do not impose this penalty on female-named CVs.

Third, we show that women face lower quality vacancies than men at all education levels. But particularly at the tertiary education level, women are more likely than men to qualify by gender for the lowest-salary vacancies. This pattern could explain why women at the tertiary education level are more selective in their search.

We advance the literature in two key ways. First, our novel combination of matched data allow us to separately quantify the role of demand and supply side decisions in the gender gap in job opportunities. Second, we are able to document these results in a more representative sample than most studies.

A growing literature uses data from job search and matching platforms and does find differences in job search by gender, but does not directly observe firm gender criteria. Women in Chile, Nigeria, and Denmark, respectively, have been shown to be more selective than men in their job applications, to be more qualified for the jobs they do apply to conditional on applying, and to apply to lower-wage jobs (Banfi *et al.*, 2019; Archibong *et al.*, 2022; Fluchtmann *et al.*, 2021). Like other existing platform-based studies, these papers include a sample of jobseekers who take the initiative to sign up to the platform. In contrast, we start with a representative listing and approach all adults to sign up for the platform. This allows us to characterize selection into the platform sample and quantify its importance; and our signup process enrolls many women with "latent" labor supply who are not searching at baseline, who would not appear in standard platform samples.

This links to a literature that has documented explicit firm gender criteria in labor markets such as China and India. Gender criteria are common on job ads on internet job boards in China, and also in part determine the gender mix of applicants (Kuhn and Shen, 2013; Kuhn *et al.*, 2020). Such gender criteria explain some of the gender wage gap on a job portal in India (Chaturvedi *et al.*, 2022). Going further, Kuhn and Shen (2023) and Card *et al.* (2021) document that when policy changes led to gender criteria being removed in China and Austria, the gender composition of applications increased, without sacrificing match quality. Relative to these papers, we are able in a single setting to observe the exact vacancies that each jobseeker is matched to via the platform, observe whether the jobseeker satisfies the minimum requirements for each vacancy, and additionally observe interviews as an outcome through the administrative data and hypothetical interviews through the incentivized binary choice experiment. This allows us to compare the relative magnitude of gender criteria (demand-side) versus jobseeker (supply-side) decisions. Furthermore, we advance the literature by starting with a sample representative of a broader urban labor market, not restricted by employment or search status.

Furthermore, the literature establishes a theoretical basis for a U-shaped relationship between education levels and women's labor supply (Gaddis and Klasen, 2014; Goldin, 1995). Empirical work shows that the pattern of the relationship between educational attainment and labor force participation varies greatly for women across low- and middle- income countries around the world (Aromolaran, 2004; Cameron *et al.*, 2001; Klasen, 2019). Within India, a context similar to ours with low female labor force participation, women's own education is positively correlated with labor force participation in urban settings but the opposite in rural settings (Afridi *et al.*, 2017; Klasen and Pieters, 2015). We are able to decompose gender gaps in fine-grained job search steps across education levels, and document that gender gaps stemming from firm-side criteria close as education levels rise.

An ancillary contribution of our study is methodological. We combine large-scale, representative and administrative data from real choices in the field (the signup and platform data) with a controlled, lab-in-field style experiment (the incentivized binary choice experiment). This builds on approaches combining the advantages of large-scale, naturalistic field data with small, controlled lab style experiments (Garlick *et al.*, 2023; Cortes *et al.*, 2022).

We describe the context of our study, including data collection and the binary choice experiment design in Section 2. We report results showing that gender gaps in job opportunities stem from firm-side gender criteria in Section 3.1, and that these gender gaps close as education levels rise in Section 3.2. We explore mechanisms for these results in Section 4. Section 5 concludes.

2 Context and Data

Our study is set in Pakistan, the world's fifth most populous country (United Nations Population Division, 2023). Male labor force participation across Pakistan is 78%, while female labor force participation is much lower at 21% (International Labour Organization, 2019b,a). These figures are similar to countries in the Middle East, North Africa, and South Asia (International Labour Organization, 2019b,a). This project takes place in Lahore, the second largest city in Pakistan, with a population of about 11 million. The male employment rate is 83% while the female employment rate is just under 10% (author calculations from the Pakistan Labor Force Survey, Appendix Table A.1). In contrast with the gender gap in employment, women and men in this setting have similar levels of educational attainment. About 71% have at most primary education, 12% have at most secondary education, and 15% have tertiary education.

2.1 Job Talash platform

We use administrative data from Job Talash, a free job search and matching platform developed by our research partners at the Center for Economic Research in Pakistan, to serve the district of Lahore.[1] The team began with a representative household listing across Lahore, fielded between October 2016 and September 2017, which yielded a starting sample nearly identical to the population of Lahore, in terms of age, gender, education, and employment rates. This is shown in the comparison of columns 1 and 2 in Appendix Table A.1.

The area covered in the listing for both employers and households is a single metropolitan commuting area; the mean distance between jobseekers and firms in our sample is 11 kilometers. The representative household listing comprised approximately 180,000 individuals. From here, we are able to decompose gender gaps at every stage of the search process, allowing us to isolate supply-side versus demand-side constraints to women's versus men's employment.

In the representative household listing, the service first offered every adult in the household free sign-up onto the Job Talash platform. Job Talash followed up by telephone and gathered the information about their work history and education to help them construct a CV used for job applications through the platform. At the stage of signing up for the service and constructing the CV, individuals specified the occupations in which they wanted to search for jobs. Nearly 10,000 individuals registered for the platform and constructed a CV to facilitate job applications through the platform.

Job Talash also conducted a representative listing of firms across Lahore. The team listed a representative sample of approximately 10,000 firms across the metropolitan area, using a cluster-randomized selection of Enumeration Blocks followed by listing of all firms in each selected block. A team of enumerators presented the Job Talash service to firms that were open and were willing to speak with the enumerators (approximately 6000), offering them the opportunity to enroll to list vacancies immediately or later.

Appendix Table A.2 examines selection into platform use on the employer side. 3.2% of firms approached in the listing signed up and posted at least one ad over the course of the study. Firms that did so are larger in terms of number of employees, frequency of recruitment, and physical size. They are also more likely to have any women employees at baseline: Only 8% of firms that did not post an ad had any female employees

[1] Other platforms such as as Rozee and LinkedIn also operate in this labor market, and thus the concept of job search platforms is not novel in this setting. However, other platforms require access to the internet and literacy skills, and cater more to firms and vacancies hiring at a high education level (Matsuda *et al.*, 2019). To address potential novelty effects, we replicate our main results dropping the first two months of data when novelty effects would have been strongest; the results are nearly identical (Appendix Table A.4).

at baseline, compared to 21% among those who did post. Among those who reported details of physical infrastructure, firms that use the platform are also more likely to have a separate toilet and separate prayer space for women. These patterns suggest that our results on demand-side barriers are a lower bound.[2][3]

This process generated 675 ads on the platform, placed between August 2017 and September 2022. Each ad posted through the platform specifies the education and experience required for the position. Given the nature of the labor market in Lahore, firms also could specify if the vacancy is open only to men (59.7% of ads), women (15.1% of ads), or open to any gender (25.2% of ads). Explicit gender criteria are a phenomenon observed in labor markets in many countries (Kuhn and Shen, 2013; Card *et al.*, 2021; Chaturvedi *et al.*, 2022).

The platform matches individuals to open vacancies, based on four criteria. If all four criteria were satisfied, then the platform sends the "platform match" to the individual, for the individual to decide whether to apply. The first criterion is whether the vacancy is within the set of occupations that the individual wanted to be matched with via the platform.[4] The second and third criteria are whether the individual satisfies the minimum education and experience qualifications for the vacancy, as set by the firm. The fourth criterion is whether the individual satisfies the gender criteria for the position, if the firm imposed such a restriction. Individuals receive text messages for each of these job ads that satisfy all four criteria ("platform matches"); messages are sent in batches, approximately once a month. See Appendix Figure A.1 for a sample text message. The text messages contain the job title, firm name, firm location, and salary of each platform match, along with the deadline to apply. Jobseekers only learn about vacancies to which they matched via the platform, as the platform does not have a search function. Participants can ask to pause or stop receiving job ads at any time. For each job ad, the individual decides whether to apply. The platform is completely free and calls back prospective applicants, so the monetary cost of application is minimal (a maximum of 5 Pakistani rupees or 0.03 USD PPP, less than 1% of a day's earnings at minimum wage), so financial cost is unlikely to affect gender and education patterns in search on platform. If the jobseeker chooses to apply, Job Talash sends their CV to the firm; the firm decides whether to invite the applicant for an interview. The platform calls each firm a few weeks after the CVs are delivered and follows up as needed

[2]Unlike most of the literature on platforms, our firms are drawn from a representative listing (see discussion in Field *et al.* (2023)). Thus, the firms are much smaller compared to other platforms, and correspondingly, do not post vacancies at a very high frequency. Firms on our platform are small (median firm size is 4 employees), and posted a median of only 1 vacancy in the last year as measured at baseline. The median firm posts 1 vacancy on our platform in a year.

[3]The most common search method that firms in our study state (nearly 80% of firms) is hiring via referrals. Women may have weaker social networks for job search since women's employment rates are less than 10% in Lahore, and thus we expect that off-platform hiring by firms, which takes place largely through referrals, would have even stronger gender gaps.

[4]The occupation categories were devised by the platform team to reflect broad categories of jobs common in Lahore with similar skill sets and working conditions, to facilitate the platform's matching algorithm, which filters job ads to send those of interest to a particular jobseeker. The full list of categories in the data and example job descriptions is available in Appendix Table A.3. Appendix Figure A.3 provides frequencies of these occupations.

to confirm which applicants were interviewed.

Crucially, we observe choices by both the individual and the firm separately. This distinguishes our data from typical labor force data in which the researcher only observes an equilibrium outcome, such as the occupation in which a woman is employed. The latter could be an outcome of the woman's preferences for a certain occupation, employers' criteria to hire women into that occupation, or both. In contrast, we observe the constraints placed by both sides on their search: occupations that individuals select to receive as platform matches; qualifications that the individual has and the firm requires; and the firm's explicit gender criteria. We construct a dataset of every possible jobseeker-job ad dyad within the potential list of occupations offered to the jobseeker's broad education level, regardless of whether the dyad actually satisfied all of the criteria placed by both the jobseeker and firm. We construct dyads only within occupations that jobseekers could select. Our main results are robust to instead including all the infeasible dyads; results available on request. Since we observe the firm's and the jobseeker's criteria separately, we are able to observe whether each dyad satisfied all jobseeker and firm criteria and was shown to the jobseeker (referred to as a "platform match") for them to decide whether to apply. For dyads that do not meet all criteria, and thus the jobseeker did not see the vacancy to decide whether to apply, we observe whether this was due to the individual not meeting the firm's constraints, vice versa, or both. We can then observe for each platform match sent whether the jobseeker applies, and ultimately is invited for an interview. We also observe all information that the firm and jobseeker have about each other up until the point of an interview.

This dataset contains over 3.5 million jobseeker-job ad dyads, of which 18.6% result in a platform match sent to the jobseeker. We use this to further pinpoint patterns in men's and women's job search behavior and success.

2.2 Incentivized binary choice experiment

The administrative data has the advantage of starting out from a representative sample, and showing us gender gaps at fine-grained decision-points through the job search process. However, at the stage of the interview decision, the relationship between applicant gender and the outcome is affected by selection into the applicant pool. Therefore, the estimate of gender differences in interview outcomes from the administrative data (discussed in Section 3.1.1), represents employer responses to the pool of male versus female applicants. This aggregates together the effects of employers' initial gender restrictions (if an employer does not allow female applicants, no women will appear in the sample); jobseekers' decisions to apply; and firms' preferences over the gender and other characteristics of candidates. To address this, we combine this data with an incentivized binary choice experiment (IBCE) with employers, adapting the Incentivized Resume Rating method developed by Kessler *et al.* (2019). This allows us to isolate employer criteria for gender versus other CV characteristics and thus shed light on what patterns might drive gender gaps on the demand side.

We implemented this experiment with employers signing up for the Job Talash service over a part of the sign-up period (January 2019 to December 2020). An enumerator presented the respondent with a series of three pairs of CVs, and advised the respondent that while the choices are hypothetical, their answers could help inform the applicant pool for future ads they place on the platform.[5] Jobseekers matching an employer's revealed preferences over gender, education and experience will be encouraged to apply for the jobs posted by that employer. Particularly in reference to the gender criteria, we refer to the employer's "revealed preferences" due to the nature of the data collection, but are not ruling out (as explored in further analysis in the paper), that the gender criteria could be a taste-based preference, or due to internalizing gender norms about the types of work that women would or would not pursue.

CVs for this exercise were constructed using anonymized versions of the real CVs of jobseekers from the Job Talash pool. We selected a random sample of 176 unique CVs to span educational levels ranging from no formal education to a Master's degree; and with no more than five years of work experience, to avoid including CVs that were too specialized in a particular field to be relevant for the broad based pool of employers in our sample. We stratified the sample by each combination of the level of education (less than secondary, secondary, or tertiary) and years of experience (0 years or 1-5 years) regardless of gender. We then randomly selected pairs such that within each pair, neither CV has tertiary education or both CVs have tertiary education, and neither CV has work experience or both CVs have some experience with at most a 2 year gap in experience.

Personal information such as applicant name and address was removed. CVs were assigned fictitious names out of a list of common names based on the gender of the applicant. We randomly selected characteristics including gender, educational institution, grades, and secondary school standardized exam scores to be swapped between the two CVs in a pair to ensure exogenous variation in these characteristics. We used a series of independent randomizations for each trait to determine whether they would be swapped between the two CVs in the pair; thus a pair may have had all traits swapped, some traits swapped, or no traits swapped.

More details about the protocol for the binary choice experiment are presented in Appendix B. Appendix Figure B.1 is an illustration of the swapping exercise for a CV pair, and Appendix Table B.1 summarizes the design. Because the applicant gender is randomized across CVs, traits are balanced across male- and

[5] Appendix Table B.3 shows that firms that participated are more likely to have some female employees, and separate facilities for women.

female- named CVs, as shown in Appendix Table B.2.

We anonymize real candidate CVs from the Job Talash pool; thus the final CVs shown have the same content and level of detail on the (anonymized) candidates' education levels, institution, grades, job title, job dates and job description as the real CVs employers will receive from applicants on the platform. This is a key advantage of our setting, making the incentivized binary choice more realistic.

During the period this experiment was active, 392 firms from the representative listing signed up; due to partial survey non-response by firms, 189 of these firms responded to the CV choice module. We have a total of 447 binary choices in the full sample. For this analysis, we drop 232 binary choices in which both candidates are the same gender; thus the resulting estimation sample consists of 430 CVs (215 binary choices) shown to 136 firms.

3 Main Results

3.1 Gender Gaps Arise from Firm-Side Gender Criteria

Quantitatively, demand-side barriers, namely explicit firm-imposed gender criteria, are the largest barrier to women's job opportunities. In this section, we provide evidence for this using both the administrative data and the incentivized binary choice experiment.

3.1.1 Administrative Data

To decompose gender gaps in job search, we construct all possible jobseeker (i) and vacancy (j) dyads; including all individuals who completed the Job Talash sign-up process. We begin by examining whether the individual's qualifications, the individual's choices, and the firm's requirements resulted in the individual and vacancy being platform matched, such that the individual sees the vacancy ad and can make a decision of whether to apply. This allows us to decompose gender gaps on supply-side and demand-side margins.[6] We estimate gender gaps in whether each dyad satisfied each of the criteria such that the vacancy became available for the individual to decide to apply: whether the individual selected the occupation of the vacancy, whether the individual met the education, experience criteria, and conditional on being matched to the position via the platform, whether the individual chose to apply. We also estimate gender gaps in whether the individual met the vacancy's explicit gender criteria, and whether the individual was selected to interview, conditional on applying to the position. The unit of observation is the jobseeker-job ad dyad. For all

[6] Individuals with less than a secondary education and those with at least a secondary education were shown different sets of approximately 20 occupations to choose from as shown in Appendix Table A.3. In our main analysis we construct dyads only from occupations that were in the potential option set of occupation list shown to the jobseeker (e.g. we do not construct a dyad for a college graduate and a janitor job, as this occupation was not in the option list offered to this jobseeker); our central results are quantitatively and qualitatively similar if we include such dyads in the analysis.

jobseeker-job ad dyad regressions we cluster standard errors on the jobseeker and job ad.

Overall, 18.6% $(657,312)$ of dyads satisfy all four criteria and thus convert to a "platform match," a job ad sent to the jobseeker, that the jobseeker can see and decide whether to apply. 31.4% $(1,112,609)$ of dyads are not shown to the jobseeker only because they are in occupations that the jobseeker did not select, and 17.5% $(619,454)$ of dyads are not shown to the jobseeker only because the jobseeker did not meet the firm's education, experience, or gender criteria. 32.5% $(1,152,557)$ are not shown because neither condition was met.

When we consider all vacancy-jobseeker dyads, we find that women meet gender criteria for only 40.58% of dyads, while men meet gender criteria for 86.40% of dyads. Furthermore, women are interested in the occupation, satisfy education and experience criteria, but do not meet gender criteria for 11.09% of dyads. Women are interested in the occupation, satisfy education and experience criteria (and thus meet all four criteria for the dyad to convert to a platform-match) for only 9.09% of dyads. This means that if gender criteria were lifted, women would automatically platform-match to more than double the number of vacancies that they match to currently. For men, removing gender criteria would only convert an additional 14% of dyads to platform matches (3.09% from a base platform-match rate of 22.17%), a relatively small increase.[7].

In Table 1 we examine gender gaps in each component of the platform-matching process.

Table 1: Supply and Demand Side Gender Gaps

	Platform Matching Algorithm Components						
	(1) Selected occup.	(2) Qualify educ	(3) Qualify exper.	(4) Qualify gender	(5) Platform Matched	(6) Apply | platform matched	(7) Interview | apply
β_1: Female$_i$	-0.006	-0.001	-0.175***	-0.458***	-0.132***	0.002**	0.022
	[0.009]	[0.005]	[0.008]	[0.028]	[0.010]	[0.001]	[0.023]
β_0: Constant	0.361***	0.799***	0.866***	0.864***	0.225***	0.006***	0.071***
	[0.007]	[0.010]	[0.006]	[0.013]	[0.007]	[0.000]	[0.012]
β_1/β_0	-0.02	-0.00	-0.20	-0.53	-0.59	0.34	0.31
N	3,541,932	3,541,932	3,541,932	3,541,932	3,541,932	606,579	3,548

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable in column 4 is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The dependent variable in column 5, "matched," is an indicator for whether the algorithm identified job j as a potential platform-match for jobseeker i and sent the vacancy ad to the jobseeker; this occurs if and only if the jobseeker selected the relevant occupation category (column 1), meets the minimum education and experience qualifications (columns 2-3) and meets the firm's gender restrictions (column 4). The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

The main takeaway is that demand-side barriers, namely explicit firm-imposed gender criteria, are quanti-

[7]We complement this analysis with Oaxaca-Blinder-Kitagawa decompositions presented in Appendix C

tatively the largest barrier preventing a jobseeker-vacancy dyad from meeting all of the criteria and converting to a platform match shown to the jobseeker, who can then decide whether to apply, and this barrier impacts women more than it impacts men. We see this in columns 1-4 of Panel A in Table 1. Women and men have statistically indistinguishable probabilities of choosing the occupation of a given vacancy (col 1), which is a purely supply-side decision.[8] There is no statistically significant difference in the likelihood of meeting educational requirements for a given vacancy between women and men (col 2). However, women are 20% less likely (17.5 pp; col 3) to have met the experience requirements for the vacancy. The latter is unsurprising since low employment rates for women overall in the context are consistent with women having less work experience compared to men. In column 4, the last column that explores criteria under which a dyad would or would not be shown to a jobseeker, women are 53% (45.8 pp) less likely than men to meet the gender criteria for a vacancy.

All together, women are 59% less likely (13.2 pp; Table 1 col 5) to be platform-matched to a vacancy, meaning that they satisfy all four criteria and are shown the vacancy/able to choose whether to apply. The results in Columns (1)-(5) denote the basic matching algorithm that the platform uses; across all of these columns, the jobseeker does not observe anything about a specific vacancy, and the firm does not observe anything about a specific jobseeker. These results demonstrate that women access far fewer opportunities on the platform primarily because firms simply decide to restrict ads by gender - not because of jobseekers' own search preferences or qualifications.

Conditional on satisfying all four criteria and being shown the vacancy, women are 34% (0.2pp) *more* likely to apply to a vacancy than men (Table 1, column 6). In column 7 of Table 1, we see that overall there are no statistically significant gender gaps in being invited for an interview, among vacancies to which the jobseeker submitted an application.

In the next set of results, we delve further into the firm-side hiring constraints. We saw in Table 1 that women are 53% less likely than men to satisfy a firm's explicit gender criteria, with much smaller gaps coming from women's occupational choices and qualifications. But it is possible that to some extent firms' ex ante gender restrictions screen out women from jobs they would not have qualified for or selected in any case. To what extent do firms' explicit gender restrictions form the *binding* constraint on the number of opportunities available for women to apply to? We explore this in Table 2. Column 1 of Table 2 replicates column 4 of Table 1: the dependent variable is an indicator for whether the jobseeker meets the gender requirements of the vacancy. In column 2, we restrict the sample to dyads where the individual met the vacancy's

[8] While women and men choose different occupations, this does not change the average number of vacancies to which they platform-match from the firms from the representative listing who choose to post vacancies on the platform.

education requirements; and in column 3, dyads in which the individual met both education and experience requirements. Finally, in column 4, we restrict to dyads where the individual met the vacancy's education and experience requirements, and additionally, the individual selected the occupation of the vacancy for platform-matching. In column 2, we see that women are 55% (48.4 pp) less likely than men to meet the firm's gender criteria, among dyads where the qualify based on education; in column 3, we see that women are 52% (45.5pp) less likely than men to meet the firm's gender criteria, among dyads where they qualify based on education and experience. In column 4, we see that women are 49% (42.7 pp) overall less likely than men to meet the firm's gender criteria, for dyads for which they qualify based on education and experience, and additionally selected into the occupation of the vacancy. In all of these cases, the firm's gender criteria are the binding constraint on potential platform-matches that female jobseekers would otherwise have received. Across the board, it is the firm side criteria rather than education, experience or occupation preferences that restrict women's access to these potential job opportunities. This suggests again that demand-side gender criteria are a key constraint.[9]

[9] In Appendix Table A.5 we complete a similar exercise to Table 2, but restricting in columns 2 through 4 to matches where the jobseeker satisfies the gender criteria for the vacancy. We see that conditional on satisfying the gender criteria, women are only 4% less likely than men to satisfy the education criteria, 17% less likely than men to satisfy both education and experience, and 13% less likely than men to satisfy education and experience criteria and have selected the occupation of the match. These magnitudes are all smaller than the magnitudes of the gender gap in Table 2 of satisfying gender criteria conditional on satisfying the remaining criteria for a platform match.

Table 2: Role of firm-side gender restrictions in gender gap

	Qualify based on gender			
	(1)	(2)	(3)	(4)
β_1: Female_i	-0.458***	-0.484***	-0.455***	-0.427***
	[0.028]	[0.028]	[0.031]	[0.035]
β_0: Constant	0.864***	0.881***	0.878***	0.878***
	[0.013]	[0.012]	[0.013]	[0.014]
β_1/β_0	-0.53	-0.55	-0.52	-0.49
Sample	Full Sample	Qualify educ	Qualify educ+exp	Qualify educ+exp +select occp
N	3,541,932	2,827,515	2,317,189	841,114

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The sample in Column 1 includes all dyads, as in Table 1; in Column 2 includes only those in which the jobseeker qualified for the vacancy in terms of education; in Column 3 includes only those in which the jobseeker qualified for the vacancy in terms of both education and experience; and in Column 4 includes only those who qualified and also selected the occupation (i.e. met all other criteria for being "platform-matched" to the vacancy other than the gender restriction). The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

3.1.2 Binary Choice Experiment

The administrative data results suggest the importance of *ex ante* demand-side gender constraints—limitations on whether the employer will even consider female applicants—in limiting women's opportunities on the job market. However, the anticipation of selection can also affect employer decisions upstream even at the job posting stage: employers might not open a vacancy to women simply because they anticipate that there are few qualified women and wish to minimize screening costs. If this is the case, an employer who closes applications to women might still consider an application from a qualified female applicant if presented (Kuhn and Shen, 2023; Card *et al.*, 2021)). Conversely, the decision to close the ad to women could reflect a strong preference by the firm, such that applications from women would be ignored even if the firm were forced to allow them. Thus the fact that employers close positions to women does not clearly establish how an employer would respond to an application from a female with similar or higher qualifications to those of male applicants. Moreover, the estimates of gender gaps at the interview stage in Table 1 are difficult to interpret to address this question because they are complicated by self-selection of jobseekers into application, which may differ by gender (we examine this empirically in Section 4.2).

Therefore, we conduct an incentivized binary choice experiment with employers in which we hold constant the characteristics of the applicant pool. This allows us to examine what a firm would do in the case they were *not* able to impose the gender restriction at the ad posting stage, and were presented with similarly qualified female and male applicants. Because it presents a single pair of CVs for the firm to judge, it also holds at least initial screening costs constant, partially shutting down the mechanism of firms closing ads to women in anticipation that they would have to screen out many applications from unqualified female applicants. As described in Section 2.2, employers selected between pairs of anonymized CVs from subscribers to the platform, replacing their names with generic male and female names and swapping characteristics between members of the pair at random. Employers were incentivized with the information that their selection could inform the process used to send them job applicants for future vacancies.

The unit of observation is a CV k shown to a firm for vacancy j; this includes both CVs in a binary choice as separate observations. We first estimate a linear probability model, regressing an indicator for whether the CV was chosen on an indicator for whether the CV was randomly assigned a female name and other attributes of the CV. We cluster standard errors by the binary choice pairs of CVs, and include fixed effects for the binary choice pairs of CVs.[10][11] This allows us to quantify the revealed preference of an employer for a male versus a female CV.

Table 3 shows the revealed preferences of employers for various attributes of the CVs in the binary choice experiment. The result is striking: female candidates are substantially less likely to be selected, with a 12 percentage point gap. This point estimate remains nearly unchanged with the inclusion of an increasing number of covariates about other characteristics of the CV; this is expected given that we randomized gender and other characteristics on the CV. [12]

[10] Results are similar when we omit fixed effects, as seen in Appendix Tables B.4, B.5 and Appendix Figure B.2 in Appendix B.

[11] We include all CV pairs including those that do not have differences by gender (and therefore do not contribute to the identification of the coefficient of interest) in Appendix Table B.6. The results are similar in magnitude to those in Table 3, although less precisely estimated.

[12] Employers are also more likely to choose CVs with higher tertiary grades. The effects of other characteristics that vary between CVs in the pair are estimated very imprecisely. Because the pairs are selected to have similar experience levels (see Appendix B), we do not include the level of experience in these pair fixed effects estimates.

Table 3: Employer revealed preferences for CV attributes in Incentivized Binary Choice Experiment

	(1) CV chosen	(2) CV chosen	(3) CV chosen
CV assigned female name	-0.126*	-0.122*	-0.120*
	(0.069)	(0.069)	(0.069)
Above Median Tertiary grades	0.554**	0.844***	0.823***
	(0.254)	(0.276)	(0.287)
CV reports tertiary grade	0.626	0.172	0.195
	(0.462)	(0.396)	(0.417)
Tertiary institute ranking=Medium		0.659*	0.639
		(0.379)	(0.398)
Tertiary institute ranking=High		-0.240	-0.237
		(0.178)	(0.180)
Above Median Secondary Standardized Exam score			0.087
			(0.203)
CV reports Secondary Standardized Exam Score			-0.049
			(0.287)
Constant	-0.126	-0.314	-0.367
	(0.264)	(0.254)	(0.344)
Observations	430	430	430

Note: This table displays results from a fixed effects regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on different CV attributes. The unit of observation is a CV. CV reports secondary standardized exam scores/ tertiary grade is a binary indicator for secondary/ tertiary grade reported on the CV. Above median secondary standardized exam score/ tertiary grade is a binary indicator for secondary/ tertiary grade higher than the median for the respective grade in our sample. Tertiary institute ranking is based on the ranking scores of universities by the Higher Education Commission. 'High' ranking is assigned to all the universities that have a ranking score higher than the median score in our sample. 'Medium' indicates universities at below-median ranking. 'Low' is the omitted category for all those universities that have not been assigned any score due to non-recognition by the Higher Education Commission. All specifications include a control for the CV randomly assigned to be first in the pair. CV pair fixed effects are used. Robust standard errors in parentheses clustered by CV pairs. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

We next explore heterogeneity by firm gender composition and restrictions (Appendix Table B.7). Hiring managers in all-male firms (the majority of firms) are 22 percentage points less likely to select a CV with a randomly assigned female name than a male name (Column 1, row 1). At firms with any female employees, this pattern reverses; hiring managers are 25 percentage points *more* likely to select a CV with a female name (Column 1, 'Total Effect on HTE Group'). In firms with all female employees, this rate increases further; hiring managers are 93 percentage points more likely to select a CV with a female name than a male name (Column 2, 'Total Effect on HTE Group'). This pattern is consistent with findings from India on female-headed firms (Chiplunkar and Goldberg, 2021). The results also reinforce the pattern of firm-level gender segregation seen in the *ex ante* gender restrictions in Appendix Table A.6. The pattern in Column 1 also shows, however, that even firms without any women currently employed are choosing a female-named CV some of the time ('CV assigned female name'< -0.5). This is consistent with recent literature showing that removing gender criteria from job ads in China and Austria has been shown to increase gender diversity of hires (Kuhn and Shen, 2023; Card *et al.*, 2021).

We next estimate regressions analogous to the estimates in the incentivized binary choice experiment, using the administrative data. In Appendix Table A.7, we replicate the analysis in Table 1, Column 7, which estimates the gender gap in interviewing for a vacancy, but unlike in Table 1, we do not restrict to dyads where the jobseeker matched to and applied for the vacancy. When we examine the full set of dyadic observations, considering all job opportunities including those never opened to women, female candidates are 27% less likely to be invited to interview for a given job opportunity, although this is imprecisely estimated ($p = 0.26$, Column 1). Column 2 includes controls for jobseeker characteristics including flexible controls for age, education and experience; employment at baseline; and an index of household socioeconomic status. Even controlling for these observable differences, the point estimate suggests an almost identical gap. The Column 2 estimate is the most similar conceptually to the estimates produced in the incentivized binary choice experiment, which examine how employers select candidates when they were unable to pre-screen out either gender and when candidates are similar in characteristics; reassuringly, the results broadly align with the incentivized binary choice experiment results in direction and magnitude, although they are imprecisely estimated. Here we cannot control for all characteristics of the jobseeker CV; nor can we account for differences in the composition of the applicant pool; this, in addition to improved precision, is the advantage of the incentivized experiment.

3.2 Gender Gaps close as Education Levels Rise

The second major takeaway is that women with less than a secondary education are more likely to apply to a vacancy they have been shown than men, but that this reverses at higher education levels. In the next set of results, we study how gender gaps change across education levels.

3.2.1 Administrative Data

To study gender gaps by education, we again turn to the dataset of jobseeker (i) - job ad (j) dyads used in Section 3.1.1. We now estimate the following equation to examine how patterns in gender gaps shift with education.

$$Y_i = \beta_0 + \beta_1 F_i + \beta_2 F_i \times S_i + \beta_3 F_i \times T_i + \beta_4 S_i + \beta_5 T_i + \varepsilon_i \quad (1)$$

In Table 4, columns 1-4, we see that women at higher levels of education are more selective in choosing occupations. Among jobseekers with tertiary education, the gender gap in qualifying by education favors women, and the gender gaps in qualifying by experience and gender narrow. Putting this together, the gender gap in platform-matching is largest among those with primary education, and narrows substantially among those with secondary and tertiary education, as seen in column 5. In column 6 we see that among those with less than a secondary education, women are more likely than men to apply to any given vacancy, but that this pattern reverses at higher levels of education.

Table 4: Supply and Demand Side Gender Gaps - by Education

	Platform Matching Algorithm Components						
	(1) Selected occup.	(2) Qualify educ	(3) Qualify exper.	(4) Qualify gender	(5) Platform Matched	(6) Apply | platform matched	(7) Interview | apply
β_1: Female$_i$	0.002	-0.028***	-0.211***	-0.623***	-0.179***	0.007***	0.021
	[0.011]	[0.006]	[0.011]	[0.030]	[0.010]	[0.002]	[0.035]
β_2: Female$_i$ × Secondary Ed$_i$	-0.015	0.013	0.123***	0.439***	0.119***	-0.009***	0.030
	[0.019]	[0.013]	[0.017]	[0.041]	[0.016]	[0.002]	[0.044]
β_3: Female$_i$ × Tertiary Ed$_i$	-0.038**	0.049***	0.121***	0.558***	0.151***	-0.012***	0.000
	[0.018]	[0.009]	[0.016]	[0.051]	[0.021]	[0.002]	[0.044]
β_4: Secondary Ed$_i$	0.033***	0.013	-0.099***	-0.084***	-0.032***	0.004***	-0.041**
	[0.012]	[0.017]	[0.013]	[0.021]	[0.011]	[0.001]	[0.018]
β_5: Tertiary Ed$_i$	0.013	0.134***	-0.043***	-0.112***	-0.012	0.004***	-0.036*
	[0.015]	[0.014]	[0.012]	[0.027]	[0.014]	[0.001]	[0.021]
β_0: Constant	0.356***	0.782***	0.882***	0.886***	0.230***	0.005***	0.084***
	[0.008]	[0.012]	[0.006]	[0.014]	[0.008]	[0.000]	[0.017]
P-value:β_1+β_2=0	0.43	0.24	0.00	0.00	0.00	0.24	0.09
P-value:β_1+β_3=0	0.01	0.00	0.00	0.14	0.14	0.00	0.44
N	3,541,932	3,541,932	3,541,932	3,541,932	3,541,932	606,579	3,548

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable in column 4 is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The dependent variable in column 5, "matched," is an indicator for whether the algorithm identified job j as a potential platform-match for jobseeker i and sent the vacancy ad to the jobseeker; this occurs if and only if the jobseeker selected the relevant occupation category (column 1), meets the minimum education and experience qualifications (columns 2-3) and meets the firm's gender restrictions (column 4). Education variables are mutually exclusive and exhaustive indicators. Primary Education is the omitted category. Primary Education includes no education, completed primary or secondary (0-10 years). Secondary education refers to completed higher secondary (12 years). Tertiary education refers to completed tertiary education (16 years or more). The constant is the mean for males with a primary education. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Gender gaps in interview selection do not vary detectably by education, but these results are imprecise (column 7). In addition, the sample of applicants may also differ systematically in other characteristics between men and women. This motivates the use of the binary choice experiment.

In Appendix Table A.8, we replicate the analysis in Table 2 on the role of firm-side gender restrictions in the gender gap, but break down these patterns by education level. Within the set of dyads where they qualify for the vacancy based on education and experience (col 3), women with less than secondary education are 65.4pp less likely to qualify based on firm gender criteria compared to men with less than secondary education. At the tertiary level, the gender gap is nearly eliminated (col 3). When the sample is restricted to dyads in which the individual also selected the occupation of the vacancy, the gender gap is completely closed (column 4).

3.2.2 Binary Choice Experiment

Finally, we examine whether the pattern of the gender gap closing with education observed in the administrative data is evident in the binary choice experiment (Appendix Figure A.4). The pattern of gender segregation seen in Table 3 is large and statistically significant for CVs at low levels of education. Firms with no female employees are less likely to select CVs with female names, while firms with at least some female employees are more likely to do so. As the education level of the hypothetical candidate rises, the gender gap closes. While we cannot reject statistically that the coefficients are equal across subgroups, the point estimate for candidates with a tertiary education is almost zero, suggesting that women's CVs are equally likely to be selected regardless of whether women already work at the firm.

4 Mechanisms

4.1 Jobseeker Selection into Search

Individuals select into job search, and thus gender gaps in job search can be influenced by gender differences in this selection into search. We study selection into search using a few methods. The patterns from all approaches suggest latent female labor supply.

In Appendix Table A.1, we show how those who signed up for the Job Talash platform (column 3) compare to the population of Lahore overall (column 1). Individuals who signed up are more likely to be male, slightly younger, and have higher education. Women who sign up are more likely to be employed than women in Lahore overall (18% versus 10%). As seen in Table 5, 7.4% of men sign up. However, men who sign up are less likely to be employed than men in Lahore overall (41% versus 83%).

We next estimate gender gaps in employment and willingness to search at the individual level. Our data are well-suited to studying this margin of selection, since we begin with a representative listing and observe whether each individual from this representative listing selects into using the platform and thus enters our administrative data. We regress the outcome on an indicator for whether the individual is female, and report heteroskedasticity-robust standard errors. Table 5 reports the results of the estimation and the gender gap in percentage terms: the ratio of the coefficient on the indicator for female against the constant term. Women are 89% (63 p.p.) less likely to be working (Panel A, col 1).

In Panel A, column 2, we show the gender gap in indicating interest in Job Talash at the time of household listing. A key respondent was interviewed for the household, with 83.3% of respondents female. For adult household members who were not present at the time of the interview, the respondent was asked to indicate whether she thought the individual would be likely to be interested. The gender gap in whether the respondent thinks the individual would be interested is 32% (9.5 p.p.). This is a far smaller gap than the gap in employment. Since this outcome in column (2) is not necessarily directly from the individual, in column (3) we consider whether individuals complete the sign-up process. There is still a large gender gap, but again smaller than the gender gap in employment. Women are 53% (3.9p.p.) less likely than men to complete the sign-up process (column 3).

Baseline survey data from individuals who do sign up reveal that 59.1% of women who sign up are neither working nor searching at baseline as compared to 18.7% of men, again reinforcing the idea of latent female labor supply.[13] As education levels rise, as shown in Panel B of Table 5, gender gaps in selection into search close. The gender gap in work closes by 20% (13.4 pp) for women with a tertiary education compared to women with less than a secondary education. The gender gap in interest closes completely with tertiary education, and and sign-up to the job search platform closes by 66% (2.9 pp). These patterns reinforce the idea of latent female labor supply across education levels: women who are interested in search but are not working.

[13]The absolute magnitude of sign-up is 7.4% for men, and 3.5% for women. While sign-up does not have a monetary cost, there is a time cost to providing information to construct a CV.

Table 5: Gender gaps in work and interest in search

Panel A: Overall			
	(1) Working at baseline	(2) Interested in Job Talash	(3) Completed signup
β_1: Female$_\mathrm{i}$	-0.632***	-0.095***	-0.039***
	[0.002]	[0.002]	[0.001]
β_0: Constant	0.713***	0.302***	0.074***
	[0.001]	[0.002]	[0.001]
β_1/β_0	-0.89	-0.32	-0.53
N	182,491	182,491	182,491

Panel B: By Education levels			
	(1) Working at baseline	(2) Interested in Job Talash	(3) Completed signup
β_1: Female$_\mathrm{i}$	-0.669***	-0.121***	-0.044***
	[0.002]	[0.002]	[0.001]
β_2: Female$_\mathrm{i}$ $\times$ Secondary Ed$_\mathrm{i}$	0.131***	0.039***	-0.005
	[0.006]	[0.006]	[0.004]
β_3: Female$_\mathrm{i}$ $\times$ Tertiary Ed$_\mathrm{i}$	0.134***	0.126***	0.029***
	[0.005]	[0.006]	[0.003]
β_4: Secondary Ed$_\mathrm{i}$	-0.111***	0.026***	0.027***
	[0.005]	[0.005]	[0.003]
β_5: Tertiary Ed$_\mathrm{i}$	0.016***	-0.011**	0.012***
	[0.004]	[0.004]	[0.003]
β_0: Constant	0.724***	0.301***	0.069***
	[0.002]	[0.002]	[0.001]
P-value:$\beta_1+\beta_2=0$	0.00	0.00	0.00
P-value:$\beta_1+\beta_3=0$	0.00	0.28	0.00
N	182,491	182,491	182,491

Notes: The unit of observation is the individual in the household listing. Education variables are mutually exclusive and exhaustive indicators. Primary Education is the omitted category. Primary Education includes no education, completed primary or secondary (0-10 years). Secondary education refers to completed higher secondary (12 years). Tertiary education refers to completed tertiary education (16 years or more). The constant is the mean for males (panel A) or for males with a primary education (panel B). Robust SEs in brackets. * $p < .1$, $^{**}p < .05$, *** $p < .01$.
Source: Authors' estimates.

We next return to the dyad analysis from Section 3.1.1, and address selection into search, and how that can influence job opportunities on the platform. Individuals must complete a phone call to sign up for the platform. Even though the pecuniary cost is zero, not all individuals from the representative household listing complete this process. We construct individual (i)-job ad (j) dyads for every individual in the full representative sample, whether or not that individual completed the sign-up process for Job Talash. For this sample we observe education and gender. We re-estimate Columns (2) (qualifying for the job ad by education) and (4) (qualifying for the job ad by meeting gender criteria) of Table 1 for the full representative sample, including individuals who did not even sign up for the job search platform. Results are reported in Table 6. In the representative sample, the gender gap in qualifying by education is small and favoring men at 2% (1.3 percentage points). Unlike in the analysis sample, this gap is statistically significant, though as in the analysis sample, the magnitude is small. The gender gap in qualifying by gender in the representative sample is 53%. These results are nearly identical in magnitude to the main results among jobseekers who signed up for the platform.

In Table 6, column (3), we construct the gender gap in qualifying based on gender, for the subset of platform-matches where the individual would have qualified based on education, analogous to column (2) in Table 2, as a robustness check using the full representative sample, for whom we have education and gender information. Here, we see that among dyads that would have qualified for the posting based on education, women are 69% less likely to qualify based on gender than men. This is an even starker gender gap than that in Table 2. This confirms that jobseeker selection mitigates the observed magnitude of the gender gap in meeting gender criteria: women correctly anticipate that there are limited opportunities for them and decide not to search. However, a very large gender gap remains even with the selection.

As we show in Appendix Table A.1, women at primary education levels are less represented on the platform than their proportion in Lahore overall. Again, this suggests they correctly anticipate that there would be few job opportunities for them. We explore this further in Section 4.3.

Table 6: Supply and Demand Side Gender Gaps: Assuming Full Sign-up

	(1) Qualify educ	(2) Qualify gender	(3) Qualify gender
β_1: Female_i	-0.013***	-0.446***	-0.618***
	[0.001]	[0.029]	[0.028]
β_0: Constant	0.614***	0.849***	0.892***
	[0.013]	[0.014]	[0.013]
β_1/β_0	-0.02	-0.53	-0.69
Sample	Full Sample	Full Sample	Qualify educ
N	123181425	123181425	74824633

Notes: The unit of observation is a jobseeker-job dyad, assuming every individual surveyed signs up for the platform. We collect gender and education information for all individuals surveyed, and we use this to understand if these individuals would qualify for a given job along these two dimensions, had they signed up. The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

4.2 Jobseeker Selection into Application

Jobseekers can further select into applications based on vacancy characteristics. In this section, we show evidence that differential selection into application by gender is unlikely to explain gender gaps in employment or firm-imposed gender criteria.

One concern might be that women and men select differentially into application, which might increase the incentive for firms to impose gender criteria as a form of statistical discrimination. We address this first by studying attributes of women and men who choose to apply to vacancies in Appendix Table A.9. We find that overall, women who apply have almost one year more work experience than women who don't apply, but that men who apply have about 5.5 years more work experience than women who apply. This translates to men who apply having more experience than women who apply for the platform-match based on both the vacancy's minimum and preferred work experience. However, we see that women who apply exceed both the vacancy's minimum and preferred education by a larger margin than men who apply. In addition, for a subset of individuals who ever platform-matched to a call-center job through the platform, an independent hiring manager scored CVs. We see that women who apply are more likely to have a CV receiving the highest scores, compared to men.

The pattern that male applicants have higher levels of experience but lower levels of education than do female applicants mirrors the pattern upstream at the platform-matching stage; Table 1 showed that women on the platform are more likely to qualify to be platform-matched based on education, but less likely to qualify based on experience. Appendix Table A.9 shows that this pattern repeats after qualification and in selection into application.

Of course, lack of experience itself stems in part from a lack of opportunities open to women in the labor market. Thus, it is of interest to examine the gaps which emerge at the entry level. We first repeat the analysis in Table 2 for the subset of entry-level job opportunities (those requiring less than 1 year of experience); the results are shown in Appendix Table A.10. The gap arising from firm gender restrictions is nearly identical. When we compare the break down by education (Appendix Table A.11), the results are also nearly identical to the full sample (Appendix Table A.8). Second, we repeat the analysis in Appendix Table A.9 for entry level jobseekers who have less than one year of experience. Here in Appendix Table A.12, we see that there are no discernable differences between women and men who apply, but again women who apply have slightly higher qualifications than women who do not apply. This demonstrates that gender restrictions imposed by firms do not simply reflect statistical discrimination by firms in search of more experienced candidates.

We finally consider the possibility that women are simply less likely to apply to a given vacancy, holding the vacancy characteristics constant. Conditional on being matched by the platform and seeing the opportunity, the jobseeker's decision to apply (Column 6 of Table 1) could be influenced by additional information the jobseeker gains from the job title or firm title (see Appendix Figure A.1). To explore this possibility, we incorporate occupation, industry, and vacancy specific fixed effects to the dyadic analysis of applications in Table 1 and report results in Appendix Table A.13.[14] Column 1 of Appendix Table A.13 replicates Column 6 of Table 1, showing that unconditional on occupation and industry, women are *more* likely to apply to a given vacancy than men (column 1). In contrast, conditional on occupation and industry fixed effects (column 2), and even on fixed effects for the specific vacancy (column 3), women are *equally* likely to apply as men. The change in results between the specifications could be due to a variety of reasons; for example, men may be more likely to search broadly, selecting a broader range of occupations, and women target a narrow range of occupations perceived as socially acceptable, and have a higher likelihood of applying to any vacancy within those categories. However, the key takeaway is that neither result is consistent with supply side selection into applications driving the gender gap in employment which favors men.

Overall, we do not find evidence consistent with the idea that anticipated jobseeker selection in terms of observable quality measures can explain firm side gender restrictions. We further examine other potential mechanisms for firm side gender restrictions in the next section.

[14]Note that mechanically occupation and industry cannot change the coefficient on female in columns 1-4 of Table 1 (selected occupation; qualify on each criterion) because these estimates use the full set of dyads, and each jobseeker appears once against every job - therefore "female jobseeker" cannot be correlated with any occupational category or industry in this data structure.

The limitation of this analysis is that we can only examine selection into application in the subsample of potential dyads that were "platform-matched," i.e. the candidate met basic requirements including the gender requirement, and thus received the job ad. With the administrative data, analysis of jobseeker selection into application must always use a sample of platform-matches already selected based on jobseeker qualification by gender. Thus we cannot directly examine whether there would be positive or negative selection into applications by gender in the type of jobs that employers never open to women. In contrast, the incentivized binary choice experiment directly addresses this issue, as it presents male and female CVs to all sample employers. The binary choice experiment demonstrates employer side gender constraints, not driven by differences in candidate quality.

4.3 Vacancy and Firm Selection into Gender Criteria

In this section, we examine firm-imposed gender criteria. We show large within-occupation/industry variation in whether firms impose gender criteria, and show that firms that impose such criteria are more likely to cite firm/vacancy-side factors as the challenge to hiring women than household/individual-side factors.

First, we find that the gender criteria reflect existing gender composition of the firm. As shown in Appendix Table A.2, our listing of employers has substantial gender segregation at the firm level. As a result, 70% of vacancies in the sample are at firms that have no female employees at baseline, while only 10% are at firms with majority or all women employees. In Appendix Table A.6 we explore how this firm-level gender segregation mediates the ex ante gender restrictions and their impact on the number of opportunities available to women. The outcome variable is again an indicator for whether the individual qualified for the firm's explicit gender criteria; the unit of observation is again the individual-vacancy dyad. At all-male firms, women are 74% (69pp) less likely to qualify based purely on gender (column 1). This gap only narrows very slightly when restricting the sample to vacancies where the individual met the education and experience qualifications (column 2), and additionally the individual's selected occupations (column 3). The gap closes dramatically for firms that have any women, and reverses at firms that are at least half female at baseline. Gender segregation is thus a symmetric phenomenon; but because male-dominated firms represent the vast majority of the market (Appendix Figure A.5), this results in many opportunities being closed to women.

One possible explanation for firm level gender segregation is that firms incur fixed costs to integrate female employees (Miller *et al.*, 2022). These costs could be social or related to physical infrastructure, and could matter via firm-side decisions even though jobseekers cannot directly observe these attributes through the platform. In fact, only 44.2% of firms responding to survey questions at baseline reported having a women's toilet, and 52.3% reported having a place for women to pray, both key accommodations for female workers in the Pakistani context. Appendix Table A.14 shows that firms which have more of these features are more likely to open opportunities to women *and* select women applicants for interviews. However, firms' investment in such accommodations is endogenous to their preference for hiring women. It is noteworthy, however, that a quarter of firms without any female employees did post an ad open to women - so baseline composition does not fully determine demand side gender restrictions at the posting stage (Appendix Figure A.5).

To understand to what extent the firm's decision to close ads to women upfront fully reflects the firm's preferences and decision-making downstream, we extend the heterogeneous treatment effects analysis of the incentivized binary choice experiment from Appendix Table B.7. Column 3 shows that in firms that have never posted an ad open to women, a female-named CV leads to a 33 percentage point decrease in the probability of being chosen, while in firms that have ever posted an ad open to women, there is no statistically significant impact of a female-named CV on the probability of being chosen, though the direction of the effect actually favors women ('Total Effect on HTE Group' in Column 3).

Because the experimental CVs are by design similar in qualifications, these results suggest that firms' ad listing choices reflect firm-level preferences over candidates' gender rather than anticipated self-selection of weaker female candidates into application. This might suggest that, unlike in the case of Kuhn and Shen (2023), explicitly enforcing a requirement on firms to open ads to female applications might not change their outcomes at the interview and hiring stage in this setting.

A natural question is from where these gender criteria arise. We document that firms that impose such criteria are more likely to cite firm/vacancy-side factors as the challenge to hiring women than household/individual-side factors. During firm enrollment onto the platform, we asked firms about challenges they face in hiring women in their industry. Panel A of Appendix Figure A.6 reports the percentage of firms who specify each reason. Over half of respondents state that womens' families are opposed to work and/or that marriage/children are the barrier. Other common responses are challenges related to transport to work, long hours, and that the firm is concerned that clients or coworkers would misbehave with female employees. The latter two are more closely related to firm-level or vacancy-level constraints. In Panel B, we report correlations between each response and whether the vacancy is open to women. We find that firms that state that jobs in their industry are too physically demanding for women, or that clients/coworkers don't want women or misbehave with female employees, are less likely to open their own firm's vacancy to women. These are all broadly demand-side constraints. However, firms that report that they anticipate that marriage/children or transport to work are challenges, are more likely to open their own firm's vacancy to women. Firms' stated perceptions are not a perfect measure of what underlies stated gender criteria, but this pattern is striking. The pattern suggests that firms considering demand-side constraints related to the work environment are the ones who are not opening their vacancy to women, but firms considering supply-side constraints are the ones who do open their vacancy to women. In Panel C of the same figure (Appendix Figure A.6), we see that this pattern roughly parallels the correlation between each perceived challenge and whether the vacancy posted by a firm has a high education requirement. Firms recruiting in the white collar labor market are more likely to report jobseeker-side constraints, whereas those recruiting in the blue collar market report firm-side constraints. This echoes the patterns in the administrative data (Table 4). Fully disentangling the origin of gender criteria is beyond the scope of this paper. However, these descriptive patterns suggest that firm gender criteria arise from job and firm constraints for the labor market hiring at low education levels, i.e. the blue collar labor market, which comprises most of the population of Lahore, as shown in Appendix Table A.1.

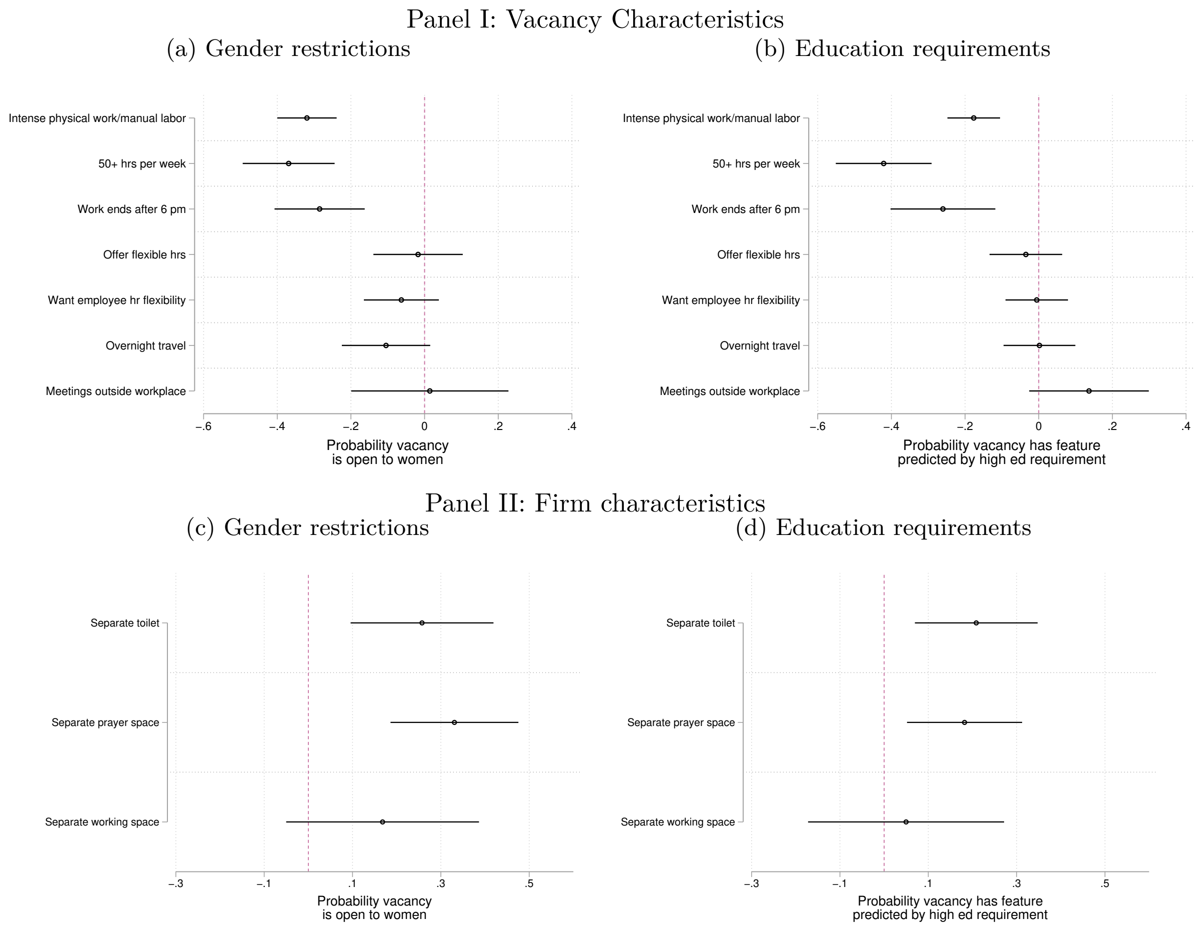
Next, we show in Appendix Figure A.7 that among vacancies hiring at the primary education level, the vast majority are open to only men, but this fraction reduces as the education requirement for the vacancy increases. For vacancies open to jobseekers with tertiary education, over 50% are open across gender. One possible mechanism through which education may help to close the gender gap is that "white collar" jobs are less likely to have requirements that lead employers to consider them unsuitable for women. For example, social norms permit women to engage in certain types of activities (such as office work) and not others (such as physical labor), and higher education requirements are correlated with these more appropriate "white collar" job requirements (Cortes and Pan, 2017). Other possible explanations include differences in social norms across education levels, or that at higher education levels, firms might see male and female labor as substitutable. [15]

We further find that certain vacancy and firm characteristics are correlated with both gender criteria and high education requirements. Vacancies that require intense manual labor and more working hours (50+ hours/week) are significantly less likely to be open to women (Figure 1, Panel a). In Panel b of Figure 1, we see the analog of Panel a, but comparing characteristics of vacancies seeking candidates with greater or less than secondary education. The pattern mirrors Panel a. Panels c and d show a similar pattern for firm-level characteristics; vacancies at firms with a separate toilet or prayer space for women are also more likely to have a high education requirement. We cannot rule out that employers who wish to hire women set shorter or earlier hours in order to attract female applicants; however, there is no similar pattern on offering flexible

[15] A broader literature finds in a variety of settings, male and female labor are imperfect substitutes, and that this varies across education levels (Acemoglu *et al.*, 2004; Giorgi *et al.*, 2013; Udry, 1996; Weinberg, 2000; Ghosh, 2018).

hours to employees.

Figure 1: Vacancy and firm characteristics, gender restrictions and education



Notes: Unit of observation is the vacancy. Panel I: Data from 319 firms who post a total of 675 job advertisements. Panel II: Data on separate toilet and prayer space for women and men at the firm come from 397 ads from 172 firms who agreed to participate in this module of the survey. Data on separate work space comes from 339 ads from 144 firms (some observations are missing due to enumerator error). In Panels a and c, an indicator for 'is the vacancy open to women?' is regressed on each characteristic in separate regressions, and the coefficient from each regression is shown. In Panels b and d, an indicator for 'does the vacancy have a high education requirement?' is regressed on each characteristic in separate regressions, and the coefficient from each regression is shown. High education requirement refers to completed tertiary education (16 years or more). Standard errors clustered at the firm level; 95% confidence intervals shown. Appendix Figures A.8 and A.9 replicate the results in Panels A and C including occupation and industry fixed effects.

This raises the question of whether industry or occupation might drive the patterns that firms that already have women are more likely to hire women. First, we show that the patterns in Figure 1 persist with occupation and industry fixed effects (Appendix Figures A.8 and A.9), suggesting that firm-level variation is important. For example, even conditional on both industry *and* occupation fixed effects, intense physical work requirements and long working hours are both associated with a 10 percentage point decrease in the probability that a firm opens a vacancy to women.

Appendix Figures A.2 - A.3 show the composition of gender requirements of job ads by industry and occupation. While these categories predict whether ads are open to women to some degree, there is a substantial degree of variation within industry and occupation in the gender restrictions employers place on ads. In our data, we find that even the combination of industry fixed effects, occupation fixed effects and observable firm characteristics including number of employees, number of vacancies in the last year, and the size of the premises occupied by the firm explain only 40% of the variation in whether a vacancy will accept applications from women (Appendix Table A.15). A large part of this decision remains unexplained by all these characteristics, suggesting firm-specific factors play an important role in the decision to open a vacancy to women. [16]

4.4 Why Tertiary Educated Women Might Be Applying Less

In Section 3.2.1, we show that tertiary-educated women are more selective in their job search than women with lower levels of education. In Section 4.2, we show that with occupation and industry fixed effects, or with vacancy fixed effects, the overall pattern that women apply to jobs at a higher rate than men, attenuates (Panel A of Appendix Table A.13). However, in Panel B of Appendix Table A.13, we see that even with occupation/industry fixed effects, or vacancy fixed effects, women with tertiary education are more selective in their applications. In this section, we further study the mechanisms for this effect.

We find that at all education levels, women are searching and working at lower rates than men (Appendix Figures A.10 and A.11), but tertiary educated women are working at baseline at higher rates than less-educated women. This could explain the education-gender gradient we observe for the occupation selection and application decisions (columns 1 and 6 of Table 4), as tertiary-educated women might be more selective in their job search as they are comparing job opportunities via the platform to their current job. To investigate this potential mechanism, we control for work at baseline in Appendix Table A.13, and find that variation in baseline work status does not explain the pattern of heterogeneity by gender and education levels.

The specific attributes of platform-matches could drive tertiary-educated women to apply at lower rates. We investigate this in two ways. First, Column 3 of Appendix Table A.13 shows that the education-gender gradient in applications observed in Column 6 of Table 4 persists even with vacancy fixed effects. However, these coefficients are identified off of only vacancies that are open to both men and women.

When she receives an SMS from the platform about a platform-match, the jobseeker does not observe

[16]This is very similar to data from the Labor Force Survey 2018 for Pakistan; here, industry and occupation explain at most 37% of the variation in whether a worker is female. Similar calculations range from as low as 1.7% in China to as high as 73% in Saudi Arabia (Kuhn and Shen, 2013; Miller *et al.*, 2022).

whether the vacancy allows remote work, specific hours, or other details that would usually be revealed through the interview process and might be particularly relevant for vacancies hiring at tertiary education levels. However, she does observe the salary of the position. We regress the application decision on the salary of the platform-match for all platform-matches, separately by education/gender, but including vacancies that impose gender criteria, finding that particularly at secondary and tertiary education levels, women are more likely to apply to a vacancy with a higher listed salary (Appendix Figure A.12).

If highly-educated women are more likely to apply to higher-salary matches, then their lower application rates could be driven by whether they platform-match to sufficient numbers of high-salary vacancies. Thus, we next explore the quality margin of potential platform-matches, and how that might explain the pattern that tertiary-educated women are more selective in their job search. At every education level, women platform-match to lower-salary vacancies than men: The mean salary for platform matches sent to men and women respectively at primary education levels is 12211 and 10319 PKR, at secondary education levels is 15640 and 15258 PKR, at tertiary education levels is 18649 and 15587 PKR. This relates to a broader literature that firm-side gender criteria may give rise to a gender wage gap (Chaturvedi *et al.*, 2022; Nomura *et al.*, 2017; Matsuda *et al.*, 2019).

We extend this analysis in Figure 2, where we repeat the dyadic analysis in Section 3.2.1, splitting the sample by jobseeker education level and quintiles of salary distribution within each education level. The dependent variable is an indicator for whether the jobseeker meets the vacancy's gender requirements. The results are striking. At the primary education level (Panel A), the gap by gender is large, mirroring the results in Table 1; as the salary level of the vacancy rises, the gap widens. This pattern changes dramatically as the jobseeker's education level rises (Panels B - C). Overall, the gap in gender restrictions shrinks, again mirroring the results in Table 4. At the tertiary education level, for vacancies with lower posted salaries, women actually meet the gender criteria for *more* jobs than men do; this difference is statistically significant at the 5% level. The result reverts to the previous pattern at higher salary levels, with men qualifying for significantly more vacancies based on gender alone. While the gender gap in the *quantity* of opportunities due to firm-side gender constraints closes with higher education, there is still a gender gap in quality which does not disappear. In contrast, the gender gap in satisfying education and experience criteria are smaller and stable across salary levels (Appendix Figure A.13).

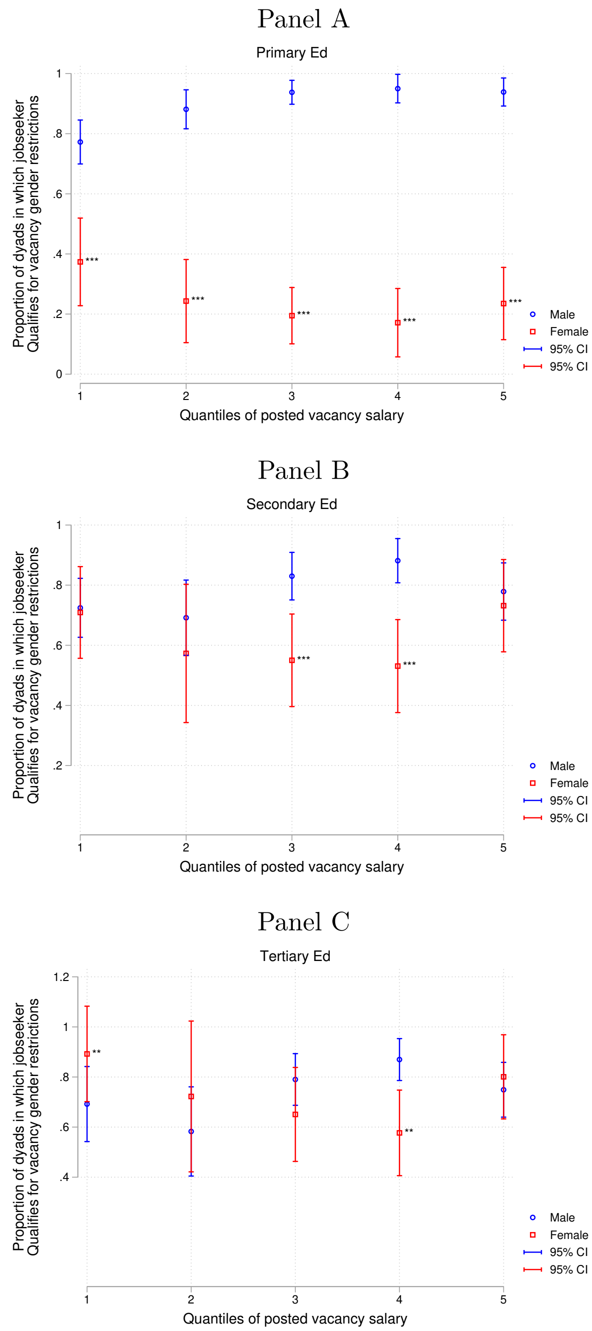


Figure 2: Qualify Gender Across Salary Quintiles; by Education

Notes: This figure shows the results of repeating the dyad level analysis in Table 1, with separate estimations on samples for each education level and within level, each quintile of the posted vacancy salary. The unit of observation is jobseeker-vacancy dyad. The outcome variable is an indicator for whether the jobseeker meets gender criteria for the vacancy. Robust SEs two-way clustered by jobseeker and vacancy; 95% confidence intervals shown. Stars shown alongside coefficients denote P-values testing equality between female and male jobseekers. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

5 Conclusion

We assemble a unique dataset from a job matching platform in Lahore, Pakistan, with several advantages. First, rare in literature that studies labor markets through job search and matching platforms, we begin with a representative listing of households and firms across a large metropolitan city. Second, the nature of the platform allows us to observe fine-grained search decisions by both employers and individuals. Third, due to the matching process on this platform, we observe which vacancies are seen by individuals and which individuals are considered by firms, and consequently observe the fine-grained decisions that result in some individual-vacancy dyads converting to platform-matches, and some not.

We use this administrative dataset to decompose supply- versus demand- side constraints that give rise to gender gaps in employment. To help isolate firm-side decisions after the ad posting stage, we combine this analysis with an incentivized binary choice experiment to shed light on how firms decide between female- and male- named CVs, holding other observables constant. Through this combination of data and methods, we have two main findings. First, explicit firm gender criteria are more binding for women than for men, and are a larger constraint to women's job opportunities than any supply-side decision in our context. Second, the demand side gap in the quantity of job opportunities substantially closes as education levels rise, while on the supply side, women become more selective as education levels rise.

We find that these results persist even when accounting for selection into job search and applications. We also find that firm-side gender criteria vary substantially across firms, within occupation and industry, and are correlated with specific vacancy and firm characteristics. In stated perceptions, firms that indicate that the barriers to hiring women are that jobs are physically demanding or safety/security concerns are less likely to open their vacancies to women. Finally, we find particularly at the highest education levels, women are more likely than men to meet gender criteria for the lowest-salary vacancies, suggesting that the quality margin might drive women to be more selective at higher education levels.

These results help contextualize a growing literature documenting specific barriers to women's employment on both the supply and demand side. Much of the recent literature that studies low female employment focuses on alleviating supply-side constraints via interventions such as overcoming information asymmetries, training in socio-emotional skills, addressing norms by engaging partners and family members, safe transport, and social protection programs that target women. Relatively less emphasis has been placed on demand-side interventions, including incentives such as tax breaks or grants, for firms to offer workplace facilities that would be inclusive to women which might in turn increase firms' willingness to hire women. Furthermore, much of the existing literature focuses on across-sector occupational gender segregation, rather than within-sector across-firm variation.

The majority of women and men in the population we study, and indeed in many settings with low levels of women's employment, have less than a secondary education. We demonstrate that in one such population, firm gender criteria are overwhelmingly the binding constraint to women's job opportunities, compared to any decisions that individuals make in their own job search. Across-sector variation does not fully explain whether firms are willing to hire women; rather within-sector differences in firm infrastructure and vacancy characteristics are correlated both with the education level at which firms are hiring and whether they are open to hiring women. Thus, our results suggest that while supply-side decisions are important, alleviating demand-side constraints to female employment might have larger impact. An area for future work would be to incorporate explicit gender criteria into models of firm production to examine the role of such criteria in productivity and substitutability of male and female labor.

We propose two avenues for future work. First, our data comes from a nearly representative listing of firms, and the number of vacancies open to highly educated women is comparatively low. Due to the nature of our data, we do not observe if highly educated women are finding work off-platform. An area for future work would be to understand how to reach highly educated women who are interested in job search, especially as we have shown that at tertiary education levels, vacancies are more likely to be open across gender. Second, we show that explicit gender criteria are quantitatively the largest constraint for the majority of women in our setting, who have less than a primary education. An area for future work would be to incorporate explicit gender criteria into models of firm production to examine the role of such criteria in productivity and substitutability of male and female labor.

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A Additional Tables and Figures

Table A.1: Jobseeker selection into use of Job Talash platform

	Full Sample		
Sample	LFS Lahore	HH Listing	JT Signup
	(1)	(2)	(3)
Female	0.493	0.496	0.316
	(0.500)	(0.500)	(0.465)
Age	34.0	33.2	30.5
Highest education level			
Primary Ed	0.692	0.708	0.595
Secondary Ed	0.141	0.121	0.146
Tertiary Ed	0.167	0.154	0.260
Employed	0.471	0.397	0.335
N	6464	184048	9919
	Women		
Sample	LFS Lahore	HH Listing	JT Signup
	(1)	(2)	(3)
Age	33.8	32.9	30.7
	(11.6)	(11.3)	(9.5)
Highest education level			
Primary Ed	0.678	0.702	0.494
Secondary Ed	0.149	0.126	0.144
Tertiary Ed	0.173	0.158	0.362
Employed	0.098	0.081	0.177
N	3189	91351	3132
	Men		
Sample	LFS Lahore	HH Listing	JT Signup
	(1)	(2)	(3)
Age	34.2	33.5	30.4
	(11.8)	(11.6)	(9.9)
Highest education level			
Primary Ed	0.705	0.715	0.641
Secondary Ed	0.135	0.117	0.146
Tertiary Ed	0.160	0.151	0.212
Employed	0.834	0.708	0.408
N	3275	92697	6787

Notes: Table compares the sample of individuals surveyed in the household listing exercise of this study (column 2) to an external benchmark: the area of Lahore where the study takes place (column 1). Lahore statistics are calculated from the Lahore subsample of the Pakistan Labour Force Survey (LFS) 2018. Standard deviations are shown in parentheses for continuous variables.

Table A.2: Firm selection into use of Job Talash platform

Employees and Gender composition					
	Did not post ad		Posted ad		
	n	mean	n	mean	Diff
Number of employees	1561	3.01	297	21.07	18.066**
Number vacancies posted last year	1647	0.74	310	6.72	5.984*
Firm has 0% female employees	1549	0.92	299	0.79	-0.132***
Firm has 1-50% female employees	1549	0.02	299	0.12	0.106***
Firm has 51-99% female employees	1549	0.03	299	0.05	0.021
Firm has 100% female employees	1549	0.04	299	0.04	0.005
Missing gender composition	5789	0.73	318	0.06	-0.673***

Firm infrastructure and space					
	Did not post ad		Posted ad		
	n	mean	n	mean	Diff
Separate toilet for women	1003	0.20	172	0.44	0.238***
Separate prayer space for women	1003	0.23	172	0.52	0.295***
Separate working space for women	860	0.03	144	0.10	0.076***
One room/shop	5776	0.75	317	0.65	-0.103***
Several rooms/shops	5776	0.16	317	0.22	0.063***
One or more buildings	5776	0.09	317	0.13	0.040**

Industry Classification					
	Did not post ad		Posted ad		
	n	mean	n	mean	Diff
Manufacturing	5718	0.06	318	0.07	0.014
Electricity, gas	5718	0.00	318	0.01	0.003
Water, sewerage, waste management	5718	0.00	318	0.00	0.001
Construction	5718	0.00	318	0.01	0.005
Wholesale, retail trade	5718	0.53	318	0.36	-0.170***
Transportation, storage	5718	0.01	318	0.02	0.009
Accommodation, food services	5718	0.07	318	0.07	-0.006
Information, communication	5718	0.01	318	0.02	0.013*
Finance, insurance	5718	0.01	318	0.02	0.005
Real estate	5718	0.03	318	0.03	0.005
Scientific, technical	5718	0.02	318	0.05	0.035***
Admin, support service	5718	0.00	318	0.00	0.001
Education	5718	0.03	318	0.05	0.020
Human health, social work	5718	0.02	318	0.03	0.010
Arts & entertainment	5718	0.01	318	0.00	-0.004
Other service	5718	0.20	318	0.25	0.059**

Notes: 6107 total firms listed. Firms who participate in the survey respond to questions about their employees, vacancies, gender composition and infrastructure; missingness varies across variables due to drop-off during the survey. Information on firm space and industry classification was collected for almost all listed firms through enumerator observation. $^{*}\ p < .1$, $^{**}p < .05$, $^{***}\ p < .01$.

Table A.3: Occupation Lists Provided to Jobseekers on Job Talash Platform

Primary Education	Secondary and Tertiary Education
Office Assistant *Handling tasks including tea making, office cleaning, and kitchen maintenance.*	Sales/Marketing *Will handle marketing, bringing in clients, and selling products.*
Courier *Delivering food to designated areas.*	Manager/Assistant Manager *Will handle the hiring process for new staff, conduct training sessions, and maintain records.*
Childcare worker *Providing childcare, ensuring cleanliness, and cooking meals.*	Customer Service Officer / Enumerator *Handle client interactions, arrange meetings with foreign clients, and maintain records*
Cook *Expertise in cooking food*	Telemarketing Officer/Call Center Agent *To initiate calls to clients, collect and maintain data.*
Factory Worker *Operating and handling machinery.*	Data Entry Operator *Data Entry of daily sale and expenses and all computer related work.*
Waiter *Managing tables, taking orders, serving customers, and processing bills.*	Teacher *Teaching primary classes across various subjects.*
Storekeeper/Inventory Manager *Customer dealing and managing store activities*	Research and Writing Jobs *The candidate must have expertise in writing articles in english and translate the document in urdu to English*
Security Guard *Ensuring shop security and managing incoming and outgoing traffic.*	Accountant/Cashier *Responsible for managing accounts and handling all computer-related tasks.*
Housekeeping/Domestic Help *Cleaning the rooms , bathrooms, dusting and buying the grocery*	Administration/Operations Officer/Clerk *Driving business growth through policy implementation and product sales.*
Sweeper/Janitorial Staff *Performing cleaning duties in a plaza.*	Computer Operator *Data Entry of daily sale and expenses and all computer related work.*
Parlor employee *Dealing with clients and performing haircuts*	Receptionist/Front Desk Officer/Telephone Operator *Welcoming customers warmly and providing guidance as needed.*
Driver *Operating a school van.*	Supervisor/Controller *Monitoring site activities.*
Electrician/Technician *Expertise in auto mechanics and vehicle repair.*	Lab Assistant *Conducting laboratory technical work proficiently.*
Plumber/Carpenter *Conducting plumbing work at customers' locations and in shops.*	Software Developer/Graphic Designer/IT *Undertake website development and resolve office-related IT issues.*
Other Skilled Labor (e.g. Brick Mason) *Stitching men's pants and coats, including cutting.*	Doctors/Nurses *Treatment of Gynae patients and Ladies specialist*
	Designer *Do interior design tasks, including space planning, material selection, and concept development* *Overseeing service operations, managing wiring, and machinery functions.*
	Lawyer *Will assist in legal documentation tasks assigned by supervisor*
	Journalist/Media Officer *Will conduct field interviews, host events, and speak in front of the camera.*
	Armed Forces - Police, Army, Firemen, etc, *Ensuring implementation of security protocols, provide security guidelines,Ensuring that security meet company regulation*

Notes: The first column includes occupation categories for jobseekers with less than a secondary education. The second column includes occupation categories for jobseekers with at least a secondary education. In italics after each category is an example job description for a vacancy in that category.

Table A.4: Supply and Demand Side Gender Gaps - Drop first 2 months

	Panel A: Overall						
	Platform Matching Algorithm Components						
	(1) Selected occup.	(2) Qualify educ	(3) Qualify exper.	(4) Qualify gender	(5) Platform Matched	(6) Apply | platform matched	(7) Interview | apply
β_1: Female$_\mathrm{i}$	-0.007	0.001	-0.172***	-0.458***	-0.132***	0.001*	0.027
	[0.009]	[0.005]	[0.008]	[0.029]	[0.010]	[0.001]	[0.026]
β_0: Constant	0.363***	0.797***	0.865***	0.861***	0.224***	0.005***	0.079***
	[0.007]	[0.011]	[0.006]	[0.014]	[0.007]	[0.000]	[0.014]
β_1/β_0	-0.02	0.00	-0.20	-0.53	-0.59	0.28	0.34
N	3,360,437	3,360,437	3,360,437	3,360,437	3,360,437	576,031	3,179
	Panel B: By Education						
	Platform Matching Algorithm Components						
	(1) Selected occup.	(2) Qualify educ	(3) Qualify exper.	(4) Qualify gender	(5) Platform Matched	(6) Apply | platform matched	(7) Interview | apply
β_1: Female$_\mathrm{i}$	0.001	-0.027***	-0.208***	-0.625***	-0.179***	0.006***	0.031
	[0.011]	[0.006]	[0.011]	[0.031]	[0.011]	[0.001]	[0.042]
β_2: Female$_\mathrm{i}$ $\times$ Secondary Ed$_\mathrm{i}$	-0.016	0.013	0.122***	0.439***	0.119***	-0.008***	0.023
	[0.019]	[0.013]	[0.017]	[0.042]	[0.016]	[0.002]	[0.050]
β_3: Female$_\mathrm{i}$ $\times$ Tertiary Ed$_\mathrm{i}$	-0.038**	0.049***	0.119***	0.555***	0.150***	-0.010***	-0.007
	[0.018]	[0.009]	[0.016]	[0.052]	[0.021]	[0.002]	[0.051]
β_4: Secondary Ed$_\mathrm{i}$	0.034***	0.012	-0.099***	-0.085***	-0.033***	0.004***	-0.052**
	[0.013]	[0.017]	[0.013]	[0.021]	[0.011]	[0.001]	[0.020]
β_5: Tertiary Ed$_\mathrm{i}$	0.012	0.135***	-0.043***	-0.113***	-0.013	0.004***	-0.047**
	[0.015]	[0.015]	[0.013]	[0.028]	[0.014]	[0.001]	[0.023]
β_0: Constant	0.357***	0.780***	0.881***	0.884***	0.230***	0.004***	0.096***
	[0.008]	[0.013]	[0.006]	[0.014]	[0.008]	[0.000]	[0.019]
P-value:$\beta_1+\beta_2=0$	0.38	0.27	0.00	0.00	0.00	0.23	0.08
P-value:$\beta_1+\beta_3=0$	0.01	0.00	0.00	0.13	0.13	0.00	0.42
N	3,360,437	3,360,437	3,360,437	3,360,437	3,360,437	576,031	3,179

Notes: This version of the table drops observations from the first two months of platform data. The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable in column 4 is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The dependent variable in column 5, "matched," is an indicator for whether the algorithm identified job j as a potential platform-match for jobseeker i and sent the vacancy ad to the jobseeker; this occurs if and only if the jobseeker selected the relevant occupation category (column 1), meets the minimum education and experience qualifications (columns 2-3) and meets the firm's gender restrictions (column 4). The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p<.1$, $^{**}p<.05$, *** $p<.01$.

Table A.5: Role of firm-side education restrictions in gender gap, conditional on satisfying gender criteria

	(1)	(2)	(3)	(4)
	Qualify educ	Qualify educ	Qualify educ & exper.	Qualify educ exper. & selected occup.
β_1: Female$_\mathrm{i}$	-0.001	-0.034**	-0.122***	-0.033***
	[0.005]	[0.016]	[0.018]	[0.012]
β_0: Constant	0.799***	0.814***	0.705***	0.257***
	[0.010]	[0.010]	[0.011]	[0.007]
β_1/β_0	-0.00	-0.04	-0.17	-0.13
Sample	Full Sample	Qualify gender	Qualify gender	Qualify gender
N	3,541,932	2,577,825	2,577,825	2,577,825

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The sample in Column 1 includes all dyads, as in Table 1; in Columns 2-4 include only those in which the jobseeker qualified for the vacancy in terms of gender. The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.6: Firm-level gender segregation and opportunities open to women

	Qualify based on gender		
	(1)	(2)	(3)
β_1: Female_i	-0.691***	-0.683***	-0.681***
	[0.028]	[0.031]	[0.036]
β_2: Female_i $\times$ Firm has $<$ 50% female employees	0.564***	0.618***	0.619***
	[0.064]	[0.070]	[0.080]
β_3: Female_i $\times$ Firm has 51-99% female employees	1.029***	1.035***	1.125***
	[0.143]	[0.161]	[0.136]
β_4: Female_i $\times$ Firm has 100% female employees	1.612***	1.603***	1.625***
	[0.061]	[0.064]	[0.055]
β_5: Firm has $<$ 50% female employees	-0.088**	-0.106***	-0.099**
	[0.034]	[0.040]	[0.043]
β_6: Firm has 51-99% female employees	-0.478***	-0.495***	-0.492***
	[0.090]	[0.096]	[0.094]
β_7: Firm has 100% female employees	-0.856***	-0.857***	-0.874***
	[0.055]	[0.057]	[0.043]
β_0: Constant	0.935***	0.937***	0.930***
	[0.011]	[0.012]	[0.014]
P-value:β_1+β_2=0	0.03	0.30	0.38
P-value:β_1+β_3=0	0.02	0.03	0.00
P-value:β_1+β_4=0	0.00	0.00	0.00
Sample	Full Sample	Qualify educ+exp	Qualify educ+exp +select occp
N	3,330,146	2,185,452	791,681

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform, excluding the 41 vacancies for which the firm did not report gender composition. Zero female firm is the omitted category. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.7: Interview Outcomes (with controls)

	Interview	
	(1)	(2)
β_1: Female_i	-0.00002	-0.00002
	[0.00002]	[0.00002]
β_0: Constant	0.00008***	0.00008**
	[0.00001]	[0.00003]
Mean for Men	0.00008	0.00008
β_1/Mean for Men	-0.27	-0.20
P-value:β_1=0	0.26	0.40
Jobseeker Characteristics Controls		X
N	3,541,932	3,540,816

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. Column 2 controls for jobseeker characteristics including flexible controls for age, education and experience; employment at baseline; and an index of household socioeconomic status. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.8: Role of firm-side gender restrictions in gender gap - by Education

	Qualify based on gender			
	(1)	(2)	(3)	(4)
β_1: Female_i	-0.623***	-0.680***	-0.654***	-0.643***
	[0.030]	[0.029]	[0.032]	[0.037]
β_2: Female_i × Secondary Ed_i	0.439***	0.454***	0.440***	0.500***
	[0.041]	[0.042]	[0.046]	[0.053]
β_3: Female_i × Tertiary Ed_i	0.558***	0.615***	0.605***	0.668***
	[0.051]	[0.051]	[0.055]	[0.062]
β_4: Secondary Ed_i	-0.084***	-0.101***	-0.106***	-0.131***
	[0.021]	[0.020]	[0.022]	[0.026]
β_5: Tertiary Ed_i	-0.112***	-0.138***	-0.144***	-0.170***
	[0.027]	[0.028]	[0.029]	[0.033]
β_0: Constant	0.886***	0.909***	0.906***	0.914***
	[0.014]	[0.013]	[0.014]	[0.013]
P-value:β_1+β_2=0	0.00	0.00	0.00	0.00
P-value:β_1+β_3=0	0.14	0.16	0.31	0.65
Sample	Full Sample	Qualify educ	Qualify educ+exp	Qualify educ+exp +select occp
N	3,541,932	2,827,515	2,317,189	841,114

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The sample in Column 1 includes all dyads, as in Table 1; in Column 2 includes only those in which the jobseeker qualified for the vacancy in terms of education; in Column 3 includes only those in which the jobseeker qualified for the vacancy in terms of both education and experience; and in Column 4 includes only those who qualified and also selected the occupation (i.e. met all other criteria for being "platform-matched" to the vacancy other than the gender restriction). Education variables are mutually exclusive and exhaustive indicators. Primary Education is the omitted category; it includes no education, completed primary or secondary (0-10 years). Secondary education refers to completed higher secondary (12 years). Tertiary education refers to completed tertiary education (16 years or more). The constant is the mean for males with a primary education. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.9: Jobseeker Selection into Application

Variable	(1) Female - Not applied	(2) Female - Applied	(3) Male - Not Applied	(4) Male - Applied	(5) 1 vs 2	(6) 2 vs 4
Years of work experience	4.493	5.336	11.753	10.830	-0.844***	-5.494***
	(5.274)	(6.392)	(9.090)	(9.467)	(0.204)	(0.384)
Yrs of experience beyond min. requirement	3.797	4.536	10.604	9.680	-0.739***	-5.143***
	(5.095)	(6.199)	(9.051)	(9.440)	(0.198)	(0.382)
Yrs of experience beyond preferred requirement	3.233	3.818	9.938	8.969	-0.585***	-5.150***
	(5.303)	(6.360)	(9.216)	(9.661)	(0.211)	(0.401)
Yrs of education beyond min. requirement	4.911	6.263	6.446	5.146	-1.352***	1.117**
	(8.937)	(11.749)	(10.122)	(9.795)	(0.352)	(0.442)
Yrs of education beyond preferred requirement	2.774	4.463	4.840	3.347	-1.689***	1.116**
	(8.994)	(11.794)	(10.460)	(10.126)	(0.349)	(0.448)
CV: excellent score	0.216	0.225	0.102	0.124	-0.009	0.101***
	(0.411)	(0.419)	(0.303)	(0.330)	(0.029)	(0.028)
CV: good score	0.376	0.421	0.275	0.255	-0.045	0.166***
	(0.484)	(0.495)	(0.447)	(0.436)	(0.034)	(0.036)
CV: average or lower score	0.409	0.354	0.622	0.621	0.055	-0.267***
	(0.492)	(0.479)	(0.485)	(0.486)	(0.034)	(0.039)

Notes: Includes data on individual who have been matched to jobs by the platform algorithm. N = 559,672 for men and N = 97,640 for women. CVs were scored for all men or women who were matched by the platform algorithm to a call-center job; N = 67,659 for men and N = 30,180 for women. SD reported in brackets for cols 1-4, SE reported for differences in means in cols 5-6. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A.10: Role of firm-side gender restrictions in gender gap (entry level vacancies)

	Qualify based on gender			
	(1)	(2)	(3)	(4)
β_1: Female$_\mathrm{i}$	-0.403***	-0.410***	-0.410***	-0.416***
	[0.046]	[0.047]	[0.047]	[0.051]
β_0: Constant	0.829***	0.838***	0.838***	0.844***
	[0.022]	[0.022]	[0.022]	[0.023]
β_1/β_0	-0.49	-0.49	-0.49	-0.49
Sample	Full Sample	Qualify educ	Qualify educ+exp	Qualify educ+exp +select occp
N	1,514,678	1,247,289	1,247,289	493,299

Notes: This version of the table restricts observations to dyads with entry level vacancies (requiring no past years of experience). The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The sample in Column 1 includes all dyads, as in Table 1; in Column 2 includes only those in which the jobseeker qualified for the vacancy in terms of education; in Column 3 includes only those in which the jobseeker qualified for the vacancy in terms of both education and experience; and in Column 4 includes only those who qualified and also selected the occupation (i.e. met all other criteria for being "platform-matched" to the vacancy other than the gender restriction). The constant is the mean for males. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.11: Role of firm-side gender restrictions in gender gap - by Education (entry level vacancies)

	Qualify based on gender			
	(1)	(2)	(3)	(4)
β_1: Female_i	-0.564***	-0.593***	-0.593***	-0.605***
	[0.049]	[0.049]	[0.049]	[0.051]
β_2: $\text{Female}_\text{i} \times$ Secondary Ed_i	0.443***	0.438***	0.438***	0.492***
	[0.065]	[0.066]	[0.066]	[0.075]
β_3: $\text{Female}_\text{i} \times$ Tertiary Ed_i	0.569***	0.597***	0.597***	0.680***
	[0.083]	[0.084]	[0.084]	[0.095]
β_4: Secondary Ed_i	-0.113***	-0.117***	-0.117***	-0.150***
	[0.034]	[0.034]	[0.034]	[0.039]
β_5: Tertiary Ed_i	-0.152***	-0.165***	-0.165***	-0.210***
	[0.046]	[0.047]	[0.047]	[0.052]
β_0: Constant	0.858***	0.872***	0.872***	0.886***
	[0.023]	[0.023]	[0.023]	[0.022]
P-value:$\beta_1+\beta_2$=0	0.05	0.01	0.01	0.12
P-value:$\beta_1+\beta_3$=0	0.95	0.96	0.96	0.38
Sample	Full Sample	Qualify educ	Qualify educ+exp	Qualify educ+exp +select occp
N	1,514,678	1,247,289	1,247,289	493,299

Notes: This version of the table restricts observations to dyads with entry level vacancies (requiring no past years of experience). The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. The dependent variable is an indicator for whether the jobseeker meets any gender requirements for the vacancy; it equals 1 for all jobseekers for vacancies that are open to both men and women. The sample in Column 1 includes all dyads, as in Table 1; in Column 2 includes only those in which the jobseeker qualified for the vacancy in terms of education; in Column 3 includes only those in which the jobseeker qualified for the vacancy in terms of both education and experience; and in Column 4 includes only those who qualified and also selected the occupation (i.e. met all other criteria for being "platform-matched" to the vacancy other than the gender restriction). Education variables are mutually exclusive and exhaustive indicators. Primary Education is the omitted category; it includes no education, completed primary or secondary (0-10 years). Secondary education refers to completed higher secondary (12 years). Tertiary education refers to completed tertiary education (16 years or more). The constant is the mean for males with a primary education. Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.12: Jobseeker Selection into Application - Jobseekers with less than One Year of Experience

Variable	(1) Female - Not applied	(2) Female - Applied	(3) Male - Not Applied	(4) Male - Applied	(5) 1 vs 2	(6) 2 vs 4
Years of work experience	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Yrs of experience beyond min. requirement	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Yrs of experience beyond preferred requirement	-0.533	-0.692	-0.587	-0.729	0.159**	0.037
	(0.871)	(1.106)	(1.213)	(1.406)	(0.080)	(0.164)
Yrs of education beyond min. requirement	5.641	6.531	6.578	4.748	-0.890	1.783
	(9.989)	(11.717)	(10.095)	(8.569)	(0.888)	(1.273)
Yrs of education beyond preferred requirement	3.327	4.403	4.656	2.379	-1.076	2.024
	(10.106)	(11.723)	(10.555)	(9.036)	(0.878)	(1.285)
CV: excellent score	0.047	0.031	0.041	0.037	0.016	-0.006
	(0.211)	(0.177)	(0.197)	(0.190)	(0.037)	(0.039)
CV: good score	0.366	0.125	0.312	0.222	0.241***	-0.097
	(0.482)	(0.336)	(0.463)	(0.418)	(0.085)	(0.083)
CV: average or lower score	0.587	0.844	0.647	0.741	-0.257***	0.103
	(0.492)	(0.369)	(0.478)	(0.441)	(0.087)	(0.088)

Notes: Includes data on individual who have less than one year of experience reported at baseline, and have been matched to jobs by the platform algorithm. N = 20,229 for men and N = 18,138 for women. CVs were scored for all men or women who were matched by the platform algorithm to a call-center job; N = 7,552 for men and N = 4,710 for women. SD reported in brackets for cols 1-4, SE reported for differences in means in cols 5-6. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A.13: Apply|Platform Matched - all FEs

Panel A: Overall				
	Apply | Platform Matched			
	(1)	(2)	(3)	(4)
β_1: Female_i	0.002**	0.001	-0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
β_0: Constant	0.006***	0.006***	0.006***	0.006***
	[0.000]	[0.000]	[0.000]	[0.000]
Mean for Men	0.00557	0.00557	0.00557	0.00557
β_1/Mean for Men	0.34	0.11	-0.16	0.16
Controls	Orig No FE	Occp + Ind FE	Vacancy ID FE	Work at baseline
N	606,579	606,579	606,579	606,579

Panel B: By Education levels				
	Apply | Platform Matched			
	(1)	(2)	(3)	(4)
β_1: Female_i	0.007***	0.006***	0.005***	0.006***
	[0.002]	[0.002]	[0.002]	[0.002]
β_2: $\text{Female}_\text{i} \times \text{Secondary Ed}_\text{i}$	-0.009***	-0.010***	-0.009***	-0.009***
	[0.002]	[0.002]	[0.002]	[0.002]
β_3: $\text{Female}_\text{i} \times \text{Tertiary Ed}_\text{i}$	-0.012***	-0.011***	-0.009***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.002]
β_4: $\text{Secondary Ed}_\text{i}$	0.004***	0.001	0.000	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]
β_5: $\text{Tertiary Ed}_\text{i}$	0.004***	-0.001	-0.002	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]
β_0: Constant	0.005***	0.006***	0.006***	0.005***
	[0.000]	[0.000]	[0.000]	[0.000]
P-value:β_1+β_2=0	0.24	0.05	0.06	0.15
P-value:β_1+β_3=0	0.00	0.00	0.00	0.00
Controls	Orig No FE	Occp + Ind FE	Vacancy ID FE	Work at baseline
N	606,579	606,579	606,579	606,579

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. Education variables are mutually exclusive and exhaustive indicators. Primary Education is the omitted category. Primary Education includes no education, completed primary or secondary (0-10 years). Secondary education refers to completed higher secondary (12 years). Tertiary education refers to completed tertiary education (16 years or more). The constant is the mean for males (panel A) or for males with a primary education (panel B). Robust SEs in brackets, two-way clustered by jobseeker and vacancy. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table A.14: Mechanisms - Index of Female Friendly Physical Workspace

	(1) Qualify gender	(2) Interview | apply	(3) Qualify gender	(4) Interview | apply
β_1: Female_i	-0.377***	-0.007	-0.393***	0.022
	(0.037)	(0.029)	(0.037)	(0.028)
β_2: $\text{Female}_\text{i} \times$ Index	0.301***	0.094**	0.289***	0.101**
	(0.051)	(0.039)	(0.051)	(0.042)
β_3: Index	-0.116***	-0.024	-0.141***	-0.017
	(0.025)	(0.022)	(0.027)	(0.025)
β_0: Constant	0.831***	0.098***	0.835***	0.090***
	(0.019)	(0.021)	(0.017)	(0.019)
FE	No FE	No FE	Occp+Ind FE	Occp+Ind FE
N	2,076,849	2,148	2,076,849	2,148

Notes: The unit of observation is a jobseeker-job dyad, for all jobseekers who sign up and all jobs posted on the platform. Index refers to female friendly workspace index. Index includes indicators for if the firm has separate toilets and prayer spaces for women, and an indicator for if women work in a separate space (separate room/hall). This index is only computed for firms who answer questions about their infrastructure (53.9% of the sample). Robust SEs in brackets, two-way clustered by jobseeker and vacancy.* $p < .1$, $^{**}p < .05$, *** $p < .01$.

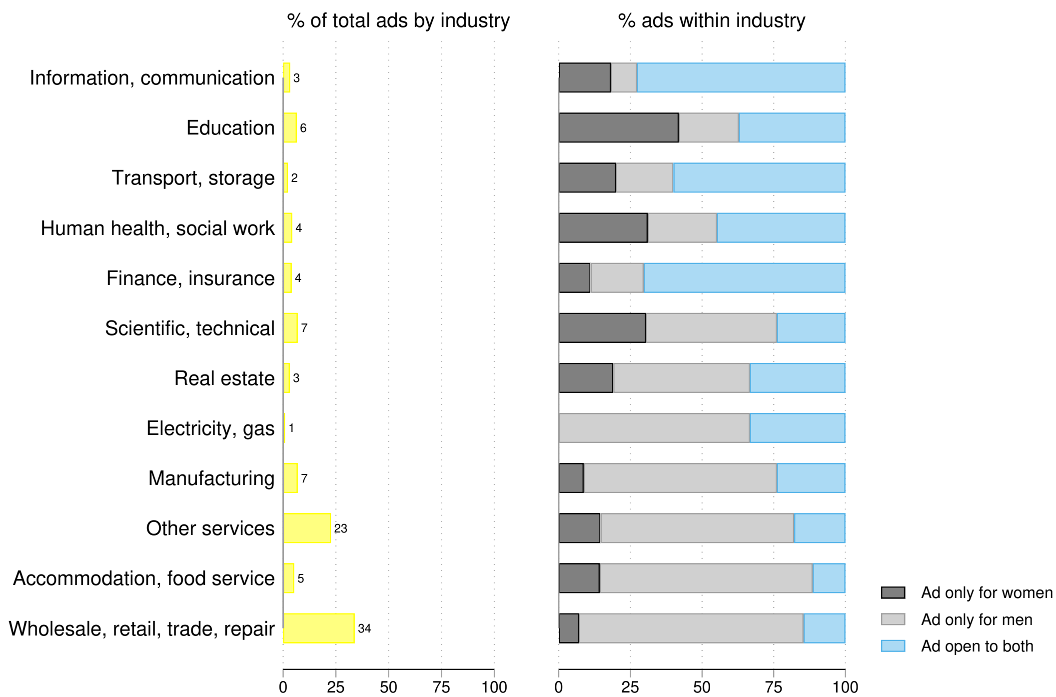
Table A.15: Explanatory power of firm characteristics, industry and occupation in predicting gender restrictions

Panel A: Restricted to cells with at least 2 job ads							
	Ad open to women						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N	672	674	619	631	629	630	580
R2	0.34	0.21	0.40	0.06	0.33	0.22	0.40
OccpFE	X		X		X		X
IndFE		X	X			X	X
FirmChars				X	X	X	X
Panel B: Restricted to cells with at least 5 job ads							
	Ad open to women						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N	653	667	481	631	611	623	447
R2	0.33	0.21	0.40	0.06	0.32	0.22	0.40
OccpFE	X		X		X		X
IndFE		X	X			X	X
FirmChars				X	X	X	X

Notes: This table reports the explanatory power (R-squared) of industry and occupation in gender restrictions. We regress an indicator for whether an ad is open to women on indicators for occupation (column 1), industry (column 2) or both (column 3). Column 4 controls for firm characteristics, which include number of employees, number of vacancies in the last year, and the size of the premises occupied by the firm. Columns 5-7 repeat the pattern from 1-3, but adding firm characteristics controls. In panel A, each analysis drops singletons, i.e, occupations with only 1 ad (columns 1 and 5), industries with only one ad (columns 2 and 6), industry-occupation combinations with only 1 ad (columns 3 and 7); hence the sample size varies between columns. Panel B shows robustness to dropping industries, occupations and industry-occupation combinations with fewer than 5 ads. Standard errors are clustered by firm. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

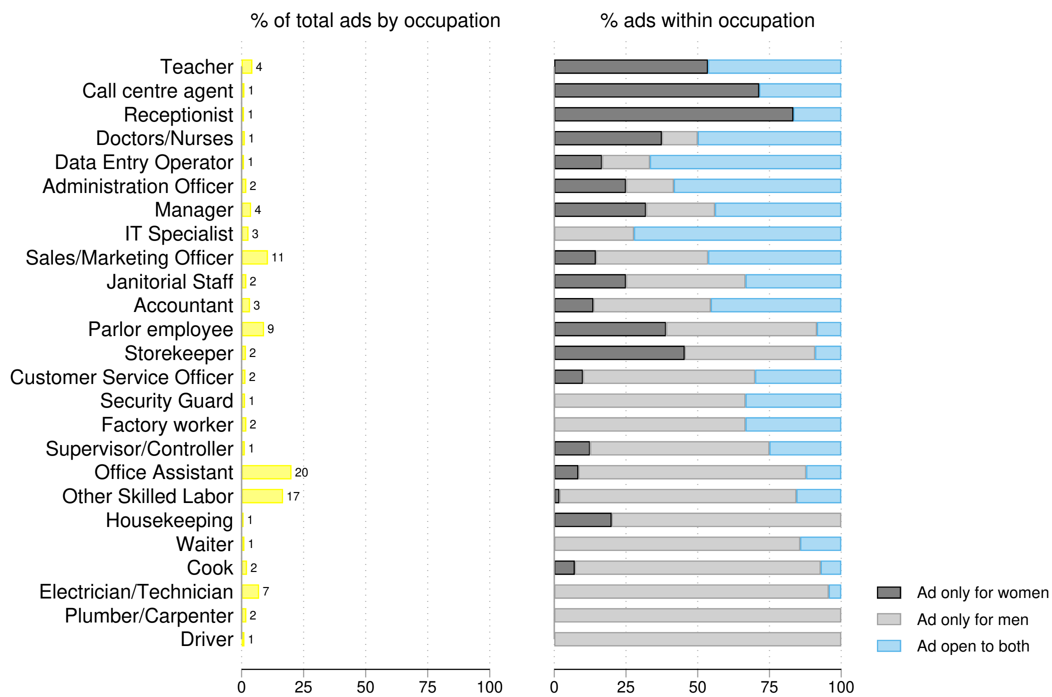
Figure A.1: Text Message Screenshot (translation of Urdu text)

Figure A.2: Composition and gender restrictions of ads on platform by industry



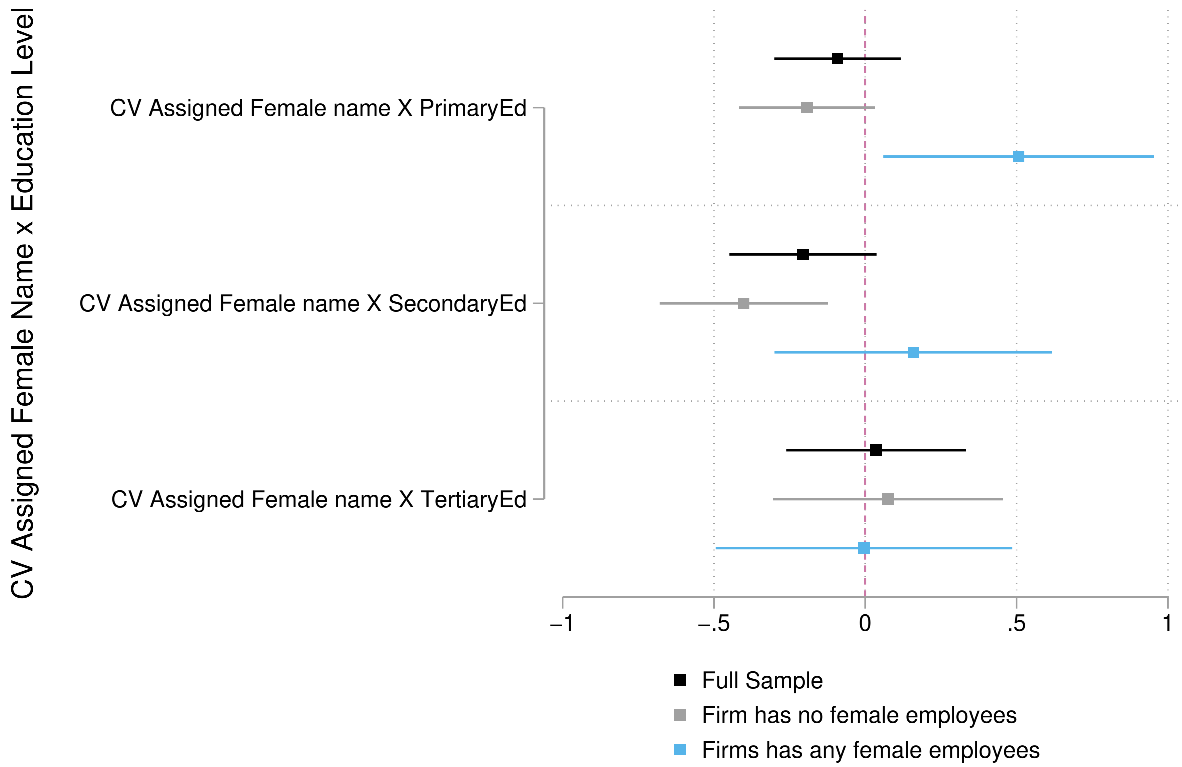
Note: Restricted to occupations with 5 or more ads

Figure A.3: Composition and gender restrictions of ads on platform by occupation



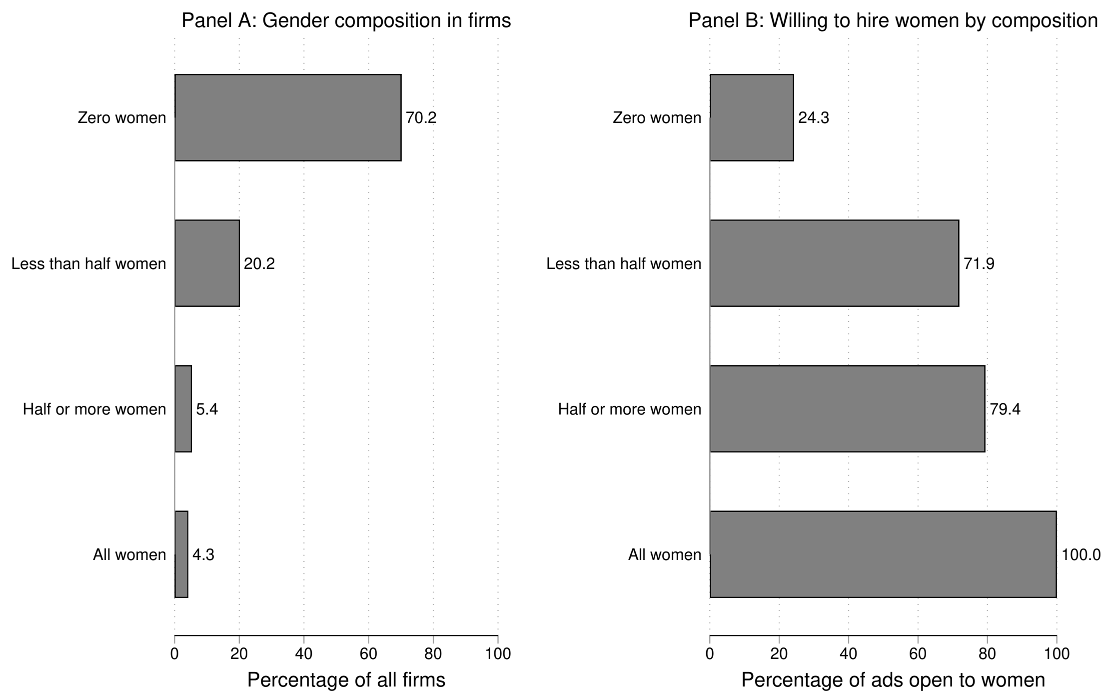
Note: Restricted to occupations with 5 or more ads

Figure A.4: Incentivized Binary Choice: Heterogeneity by CV Education Level with fixed effects



Note: This figure displays coefficients from a fixed effects regression run separately for full sample, for firms with no women (75% of the sample), and firms that already have at least one female employee (25% of the sample). The dependent variable 'CV Chosen' is a binary indicator equal to 1 if CV k was chosen by the respondent in the incentivized binary choice experiment. The coefficients shown are for the interaction of 'Female CV' and education levels (Primary, Secondary, and Tertiary). Each observation in these regressions is one CV shown to the firm. CV pair fixed effects are used. Standard errors clustered by CV pair IDs; 95% confidence intervals shown. The p-value of F-stat for a null of equality is 0.456, 0.133 and 0.283 for the full sample, firms with no female employees and firms having female employees respectively.

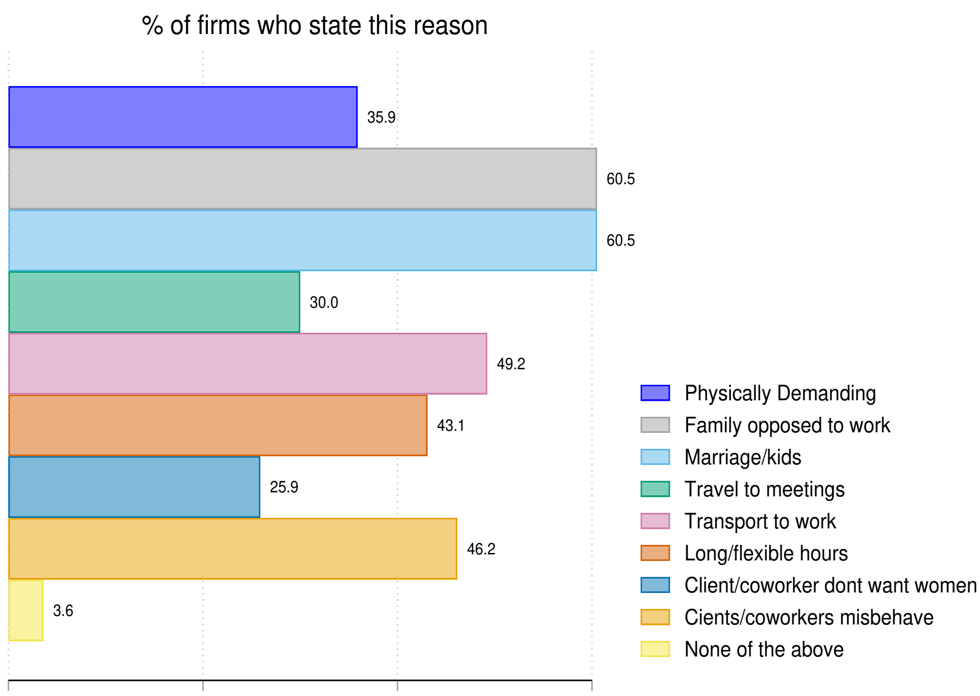
Figure A.5: Firm Gender Composition and Willingness to Hire Women



Notes: In panel A, unit of observation is the firm (N = 319).
In panel B, unit of observation is the job ad (N = 675)

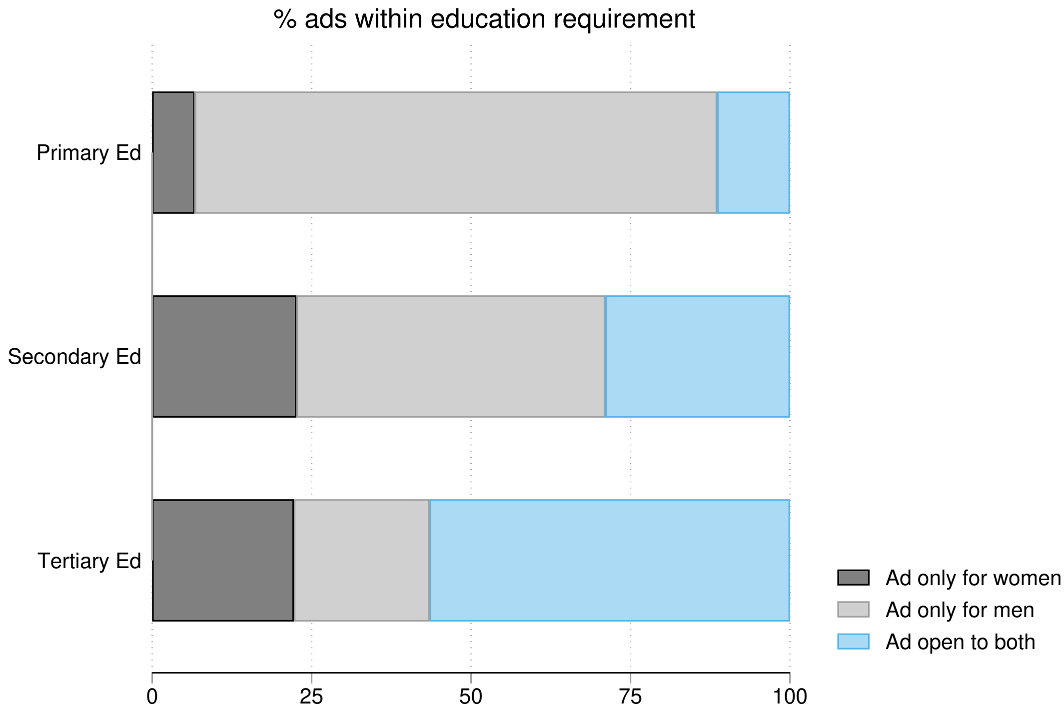
Figure A.6: Firm-reported challenges to hiring women

Panel I:



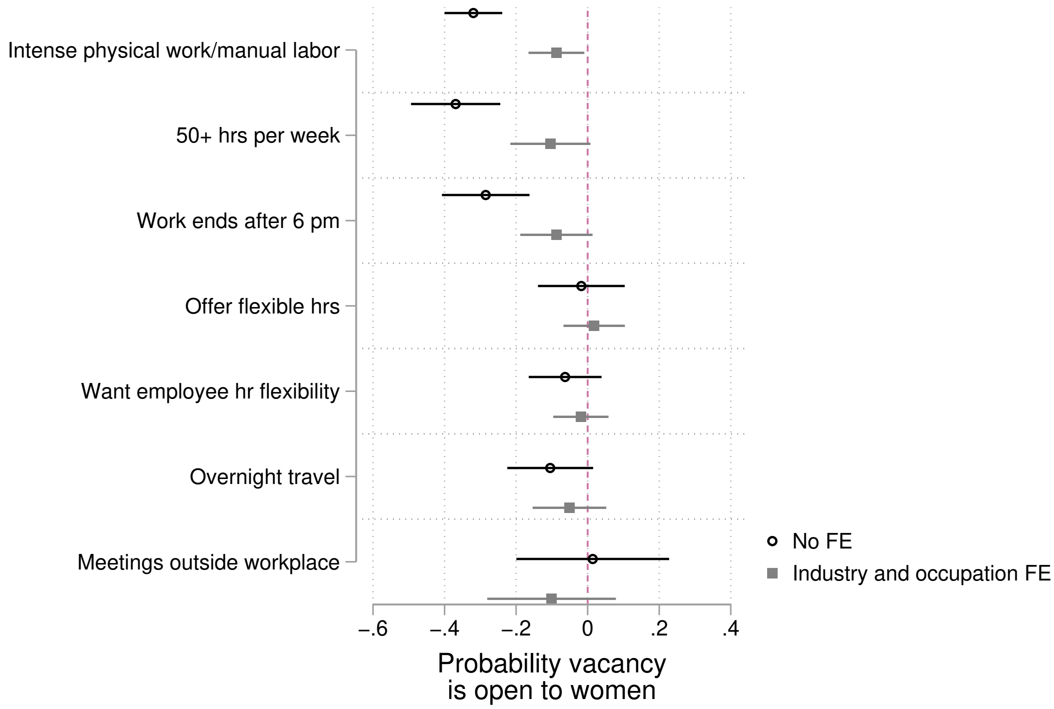
Panel II:

Figure A.7: Gendered ads and education requirements



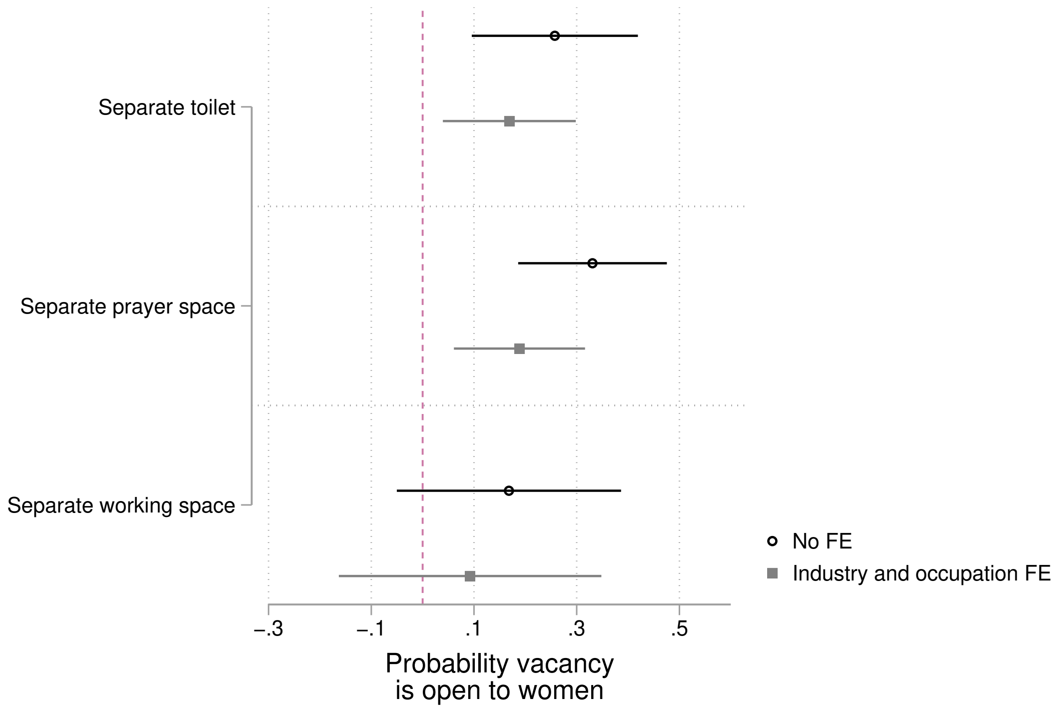
Notes: Data come from 675 vacancy postings; 46.7% vacancies list a primary education requirement, 37.3% vacancies list secondary, and 16.0% vacancies list a tertiary requirement. Of the primary education vacancies, 6.7% are open to only women, 81.9% open to only men and 11.4% open to both men and women. Among Secondary education vacancies, 22.6% are open to only women, 48.4% open to only men and 29.0% open to both men and women. Among tertiary education vacancies, 22.2% are open to only women, 21.3% open to only men and 56.5% open to both men and women.

Figure A.8: Vacancy characteristics and gender restrictions - with and without fixed effects



Notes: Unit of observation is the vacancy. Data comes from 319 firms who post a total of 675 job advertisements. Standard errors clustered at the firm level; 95% confidence intervals shown.

Figure A.9: Firm characteristics and gender restrictions - with and without fixed effects



Notes: Unit of observation is the vacancy. Data on separate toilet and prayer space for women and men at the firm come from 397 ads from 172 firms who agreed to participate in this module of the survey. Data on separate work space comes from 339 ads from 144 firms (some observations are missing due to enumerator error). Separate implies separate spaces for women and men at the firm. Standard errors clustered at the firm level; 95% confidence intervals shown.

Figure A.10: Baseline search for individuals

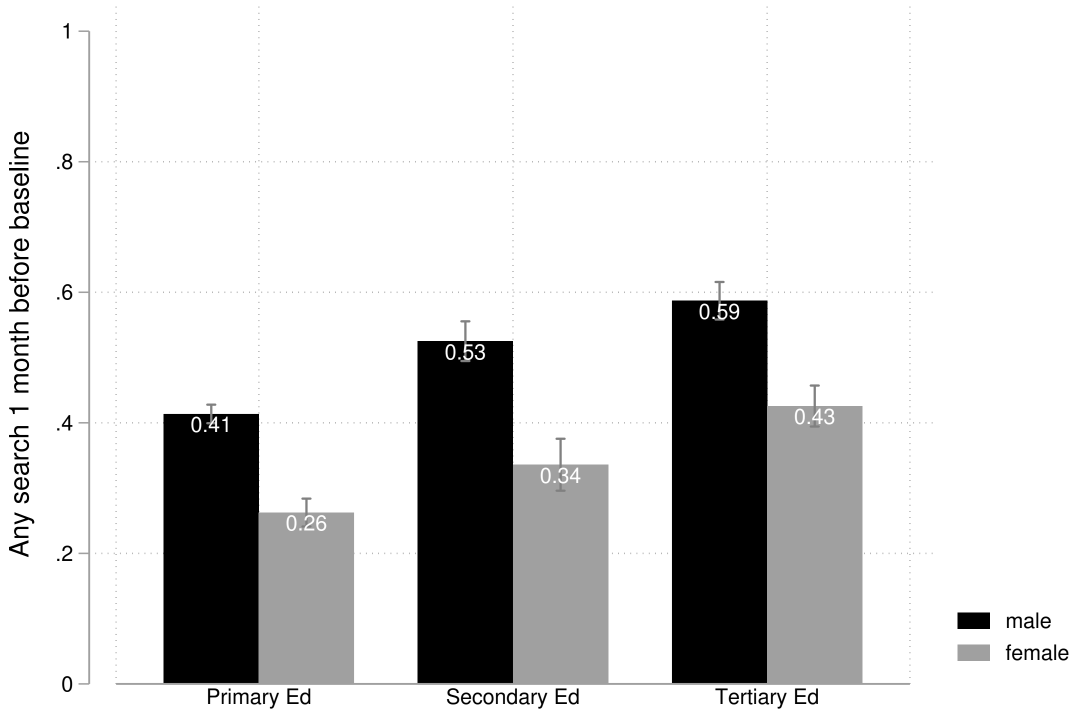


Figure A.11: Baseline work for individuals

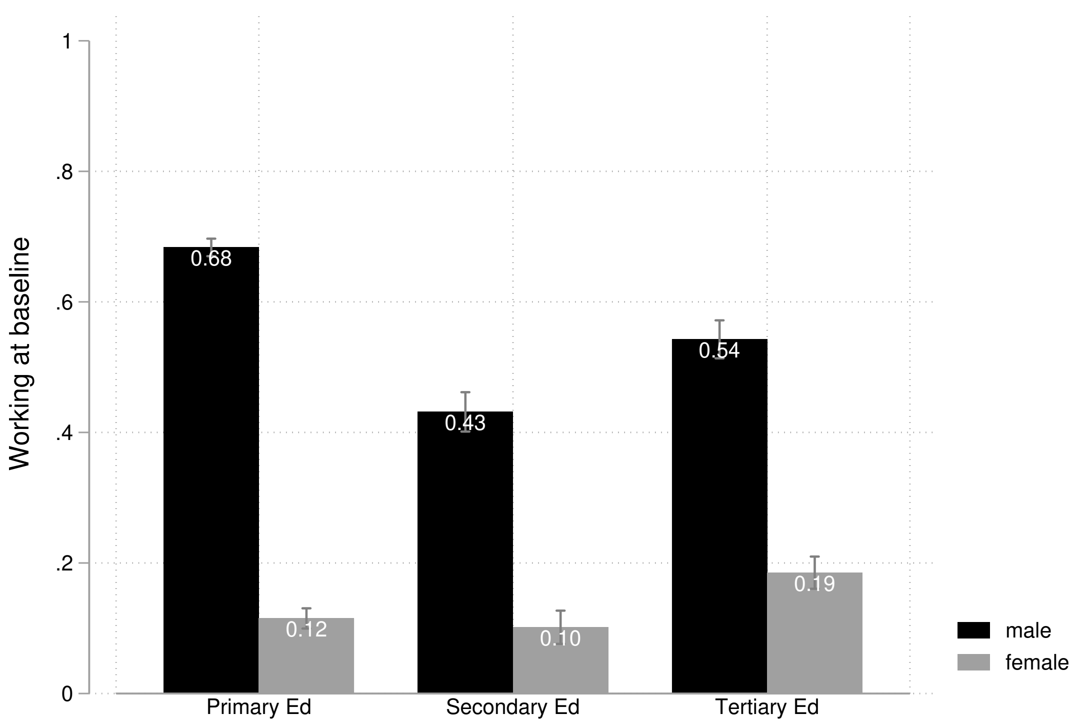
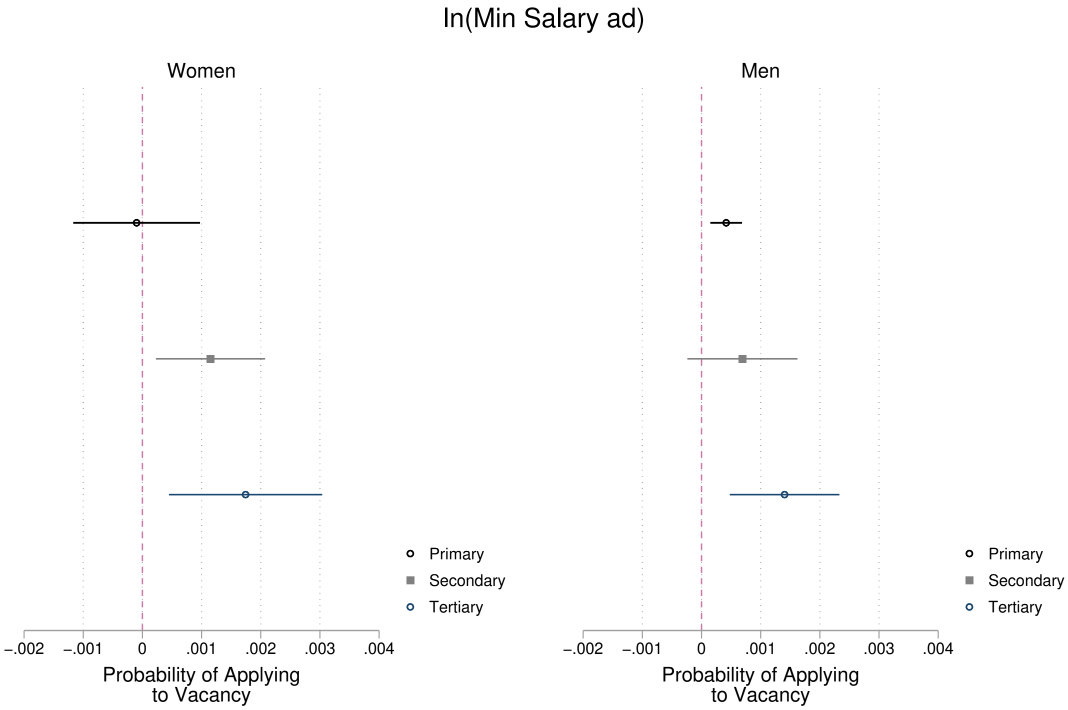


Figure A.12: Applying to jobs and Vacancy characteristics



Notes: Data restricted to vacancies where women match. Outcome variable is apply, regressed on logged minimum salary. Robust SEs two-way clustered by jobseeker and vacancy.

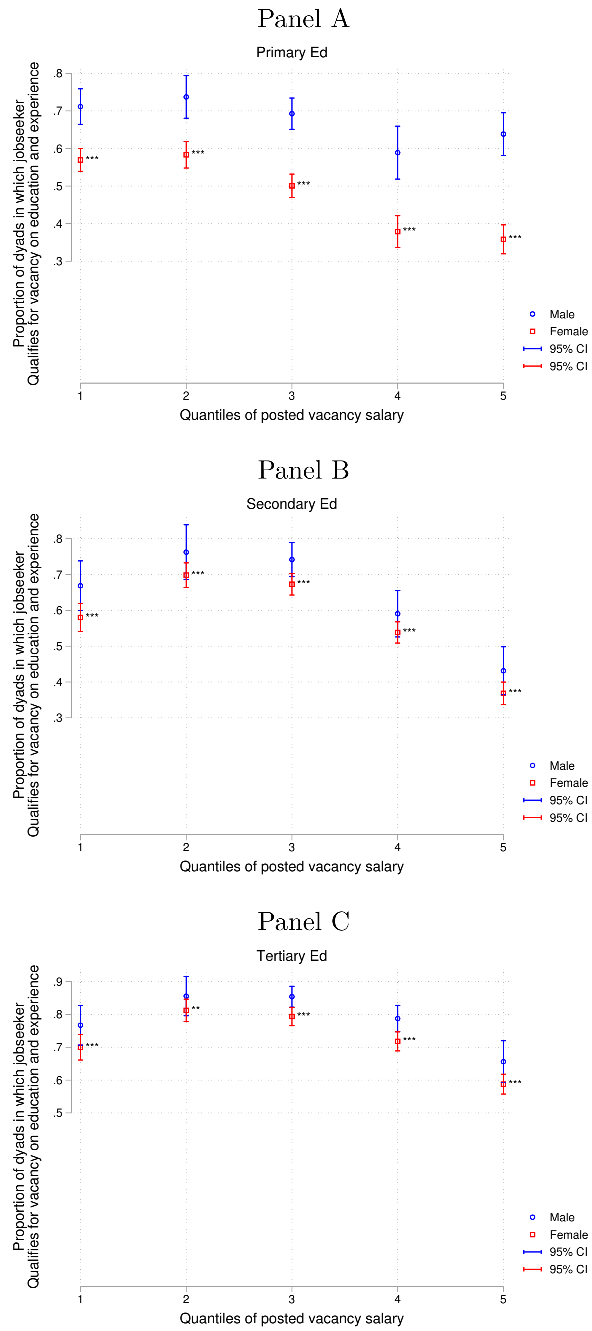


Figure A.13: Qualify Education/Experience Across Salary Quintiles; by Education

Notes: This figure shows the results of repeating the dyad level analysis in Table 1, with separate estimations on samples for each education level and within level, each quintile of the posted vacancy salary. The unit of observation is jobseeker-vacancy dyad. The outcome variable is an indicator for whether the jobseeker meets education and experience criteria for the vacancy. Robust SEs two-way clustered by jobseeker and vacancy; 95% confidence intervals shown. Stars shown alongside coefficients denote P-values from testing equality between female and male jobseekers. $^{*}\ p<.1$, $^{**}p<.05$, $^{***}\ p<.01$.

B Additional Details on Incentivized Binary Choice Experiment

In designing the binary choice experiment, we face a tradeoff between making the exercise more realistic (using real CVs from jobseekers on the platform that are simply anonymized) versus more stylized and precise (for example, using pairs of CVs that are identical and only vary on one dimension of interest). We chose a design that would maximize the realism of the experiment for employers. Using CVs from real Job Talash subscribers and anonymizing them allows us to make the experiment more incentive compatible and align better with the real characteristics of jobseekers in the administrative data. It also ensures we avoid mechanically exaggerating the effect of gender on employer choices in the experiment; for example, if the two CVs in a binary choice are identical except for gender, the employer can only choose on that basis, thus even a mild preference would dominate. Thus, we use anonymized real CVs, and also randomize the exchange of several key features of the CV which are expected to be relevant to employer decisions, including work experience and education (Figure B.1).

CVs for this exercise were constructed using anonymized versions of the real CVs of jobseekers from the Job Talash pool. We selected a random sample of 176 unique CVs to span educational levels ranging from no formal education to a Master's degree; and with no more than five years of work experience, to avoid including CVs that were too specialized in a particular field to be relevant for the broad based pool of employers in our sample. We stratified the sample by each combination of the level of education (primary, secondary, or tertiary) and years of experience (0 years or 1-5 years) regardless of gender. We then randomly selected pairs such that within each pair, the two CVs are no more than one education level apart, and no more than two years of experience apart.

Personal information such as applicant name and address was removed. CVs were assigned fictitious names out of a list of common names based on the gender of the applicant. Extremely common Pakistani names such as Muhammad Ali or Ayesha Ahmed (the local equivalents of John Smith and Jane Doe) were used, to avoid any risk that the fictitious CV in some way is associated with a real individual. We randomly selected characteristics including gender, educational institution and standardized exam scores to be swapped between the two CVs in a pair to ensure exogenous variation in these characteristics. We used a series of independent randomizations for each trait to determine whether they would be swapped between the two CVs in the pair; thus a pair may have had all three traits swapped, some of them, or none of them.

Figure B.1 is an illustration of the swapping exercise for a CV pair, and Table B.1 summarizes the design. Because the applicant gender is randomized across CVs, traits are balanced across male- and female- named CVs, as shown in Appendix Table B.2.

At the point when an employer signed up for the Job Talash service in person, an enumerator presented the respondent with a series of three pairs of CVs, and advised the respondent that while the choices are hypothetical, their answers could help inform the applicant pool for future ads they place on the platform. The script used to present this exercise is as follows: "We will now show you two sample CVs. Take your time to browse through them. Out of the two, choose a CV which you will hire if these were the candidates presented to you. This choice will help us determine which CVs to send you for your opening."

Jobseekers matching an employer's revealed preferences over gender, education and experience will be encouraged to apply for the jobs posted by that employer. Fifty-two percent of the firms responding to the binary choice experiment posted at least one ad during the time period we study. CV gender is generally balanced in this sample (Appendix Table B.8), barring slight imbalance with a p-value of 0.096 for an indicator variable for whether the CV has a public institute for tertiary education. Firms that did post ads look similar to those that did not but are slightly more likely to have any female employees (Appendix Table B.9). The main results are similar though underpowered on this subsample, for whom the incentive compatibility should presumably be stronger (Appendix Table B.10, and Appendix Figure B.3).[17]

To avoid complicating the administrative data analysis by changing the pool of matches sent to jobseekers or applications sent to these firms, the implementation of their preferences is delayed to after the completion of the study. However, firms are not aware of the timing at the point of answering the binary choice experiment; thus the potential for some influence over future pools of candidates makes the exercise incentive compatible. Moreover, given the small size of firms in this representative sample of firms in Lahore (the median firm has 4 employees), 80.4% of firms responding to the binary choice experiment posted two or fewer vacancies on the platform over the time period we studied; thus there is limited scope for firms to adapt their behavior in response to a perceived discrepancy between their preferences as indicated in the binary choice experiment and the pool of applicants they later receive.

Some firms dropped out of the survey before reaching this module; Appendix Table B.3 compares characteristics of firms that participated versus those that did not participate in the binary choice experiment. Participation in the experiment reflects interest in the platform. During the period this experiment was active, 392 firms from the representative listing signed up; due to partial survey non-response by firms, 189 of these firms responded to the CV choice module. We have a total of 447 binary choices in the full sample. For this analysis, we drop 232 binary choices in which both candidates are the same gender; thus the resulting estimation sample consists of 430 CVs (215 binary choices) shown to 136 firms.

[17] The binary variable for whether the CV has a public institute for tertiary education is included as a covariate in all analysis of the incentivized binary choice experiment that restricts to this subsample of firms that participated in the experiment and posted an ad.

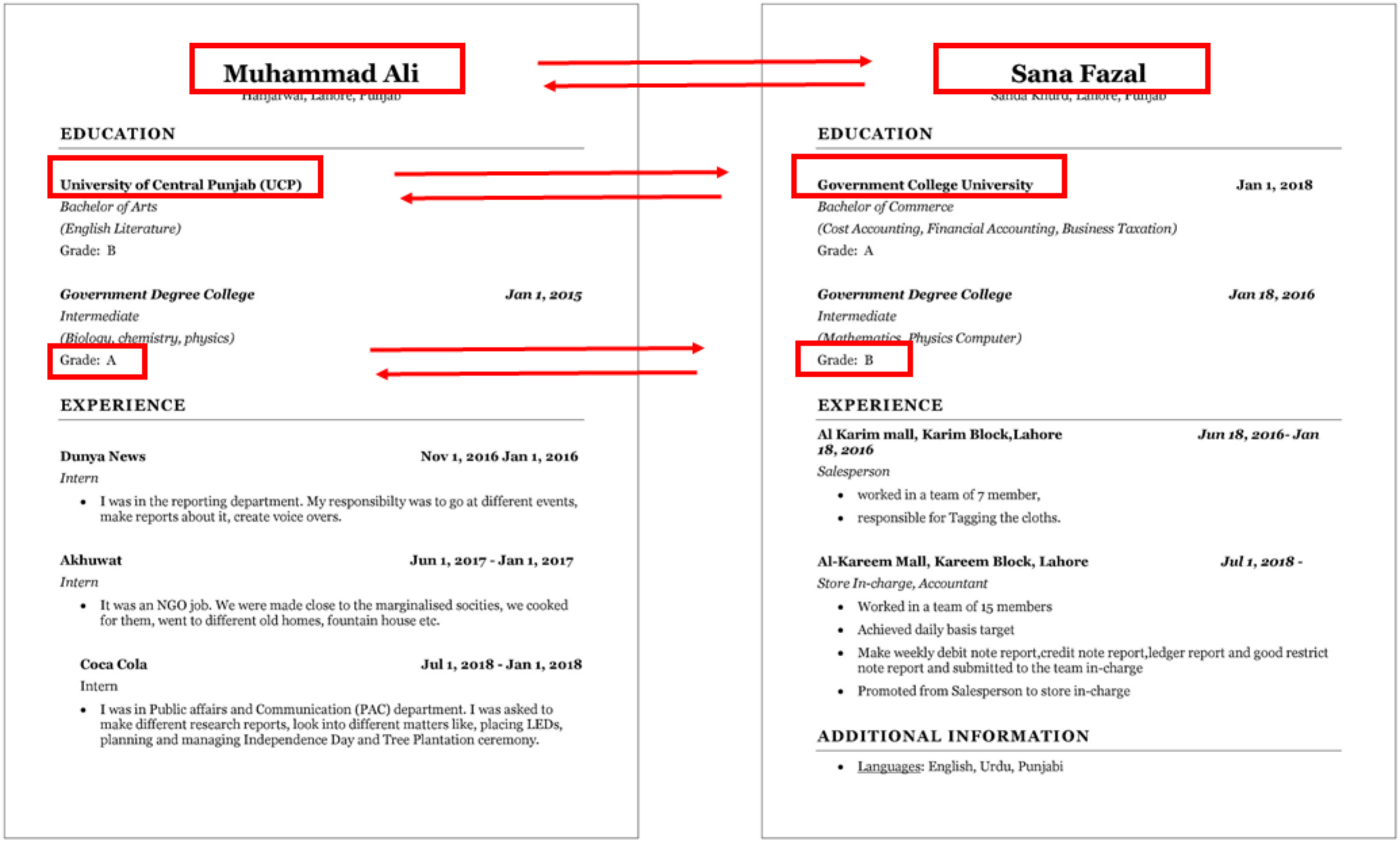


Figure B.1: Design of incentivized binary choice experiment: randomized swapping of traits on CV

Notes: This exhibit shows the swapping exercise for a CV pair. Three traits that were swapped in CV pairs were gender,Secondary standardized exam score and university names. The traits to be swapped in any CV pair were determined randomly. Each of the traits was swapped with a probability of 50%.

Table B.1: CV Selection Criteria and Randomization Components

Education	Experience	Other
Panel A: Held Constant within a Pair		
Both or Neither have Tertiary Education	<1 Year or 1-5 Years Experience	
Panel B: Not Held Constant within a Pair		
Secondary vs Primary Education (if Secondary Education or less) Tertiary Grades: A, B, C, or Not Reported (if Tertiary Education)	1-5 Years of Experience (if $\nless$ 1 Year Experience)	
Panel C: Randomly Swapped Between Members of the Pair		
Secondary School Standardized Exam Scores or Not Reported (if Secondary Education or higher) Tertiary Institute Ranking: High, Medium, or Low (if Tertiary Education)		Gender: Male, Female

Notes: If neither CV in a pair has any (1-5) years of experience, then both have 0 years of experience. Tertiary institute ranking is based on the ranking scores of universities by the Higher Education Commission (HEC). 'High' ranking is an indicator for universities that have a ranking score higher than the median score of 48.9 in our sample. 'Medium' is an indicator for institutes lying between 0 and 48.9. 'Low' indicates institutes that are not recognized by the Higher Education Commission.

Table B.2: Incentivized Binary Choice Experiment: Balance of CV Traits by Gender

Variable	(1) CV randomly assigned male name	(2) CV randomly assigned female name	(3) P-values
Tertiary Ed	0.209	0.209	1.000
Secondary Ed	0.326	0.349	0.611
Primary Ed	0.465	0.442	0.629
Tertiary grade	0.553	0.619	0.588
Secondary Standardized Exam Score	1.116	0.967	0.381
Public Tertiary Institute	0.079	0.060	0.450
Any Experience	0.502	0.502	1.000
Observations	215	215	430

Note: Column 1 and 2 report average value of a CV trait for men and women. Column 3 reports p-values of the difference of means in column 1 and 2. 'Tertiary grades' range from 2-5 where 5 is A and 2 is D. 'Secondary standardized exam score' are coded the same as tertiary grades and apply to only those people who have higher than ten years of education. Any experience is a binary indicator for years of experience between one to five years and zero for less than one years of experience. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.3: Firm selection into incentivized binary choice experiment

Employees and Gender composition					
	Did not participate in IBCE		Participated in IBCE		
	n	mean	n	mean	Diff
Firm has 0% female employees	1761	0.90	87	0.77	-0.133***
Firm has < 50% female employees	1761	0.03	87	0.11	0.084**
Firm has 51-99% female employees	1761	0.03	87	0.08	0.054*
Firm has 100% female employees	1761	0.04	87	0.03	-0.005
Missing gender composition	6020	0.71	87	0.00	-0.707***

Firm infrastructure and space					
	Did not participate in IBCE		Participated in IBCE		
	n	mean	n	mean	Diff
Separate toilet for women	1156	0.23	19	0.79	0.560***
Separate prayer space for women	1156	0.26	19	0.79	0.526***
Separate working space for women	986	0.03	18	0.28	0.243**

Industry Classification					
	Did not participate in IBCE		Participated in IBCE		
	n	mean	n	mean	Diff
Agriculture	5952	0.00	87	0.00	-0.000
Manufacturing	5952	0.06	87	0.07	0.013
Electricity, gas	5952	0.00	87	0.00	-0.003***
Water, sewerage, waste management	5952	0.00	87	0.00	-0.003***
Construction	5952	0.00	87	0.00	-0.002***
Wholesale, retail trade	5952	0.52	87	0.43	-0.099*
Transportation, storage	5952	0.01	87	0.02	0.010
Accommodation, food services	5952	0.07	87	0.07	-0.003
Information, communication	5952	0.01	87	0.00	-0.007***
Finance, insurance	5952	0.01	87	0.00	-0.011***
Real estate	5952	0.03	87	0.06	0.028
Scientific, technical	5952	0.02	87	0.06	0.041
Admin, support service	5952	0.00	87	0.01	0.009
Education	5952	0.03	87	0.08	0.047
Human health, social work	5952	0.02	87	0.00	-0.023***
Arts & entertainment	5952	0.01	87	0.02	0.016

Notes: 6,107 total firms surveyed. Firms who participate in the longer survey respond to questions about their employees, vacancies, gender composition and infrastructure along with the incentivized binary choice experiment. A total of 87 firms agreed to participate in the binary choice experiment. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.4: Employer revealed preferences for CV attributes in incentivized binary choice experiment without fixed effects

	(1) CV chosen	(2) CV chosen	(3) CV chosen
CV assigned female name	-0.110	-0.115*	-0.116*
	(0.069)	(0.069)	(0.069)
Above Median Tertiary grades	0.274**	0.395***	0.397***
	(0.128)	(0.124)	(0.135)
CV reports tertiary grade	0.072**	0.194	0.199
	(0.033)	(0.133)	(0.139)
Tertiary institute ranking=Medium		0.369	0.366
		(0.225)	(0.228)
Tertiary institute ranking=High		-0.099	-0.101
		(0.141)	(0.143)
Above Median Secondary Standardized Exam score			-0.006
			(0.092)
CV reports Secondary Standardized Exam Score			-0.016
			(0.068)
Constant	0.242*	0.125	0.130
	(0.136)	(0.134)	(0.137)
Observations	430	430	430

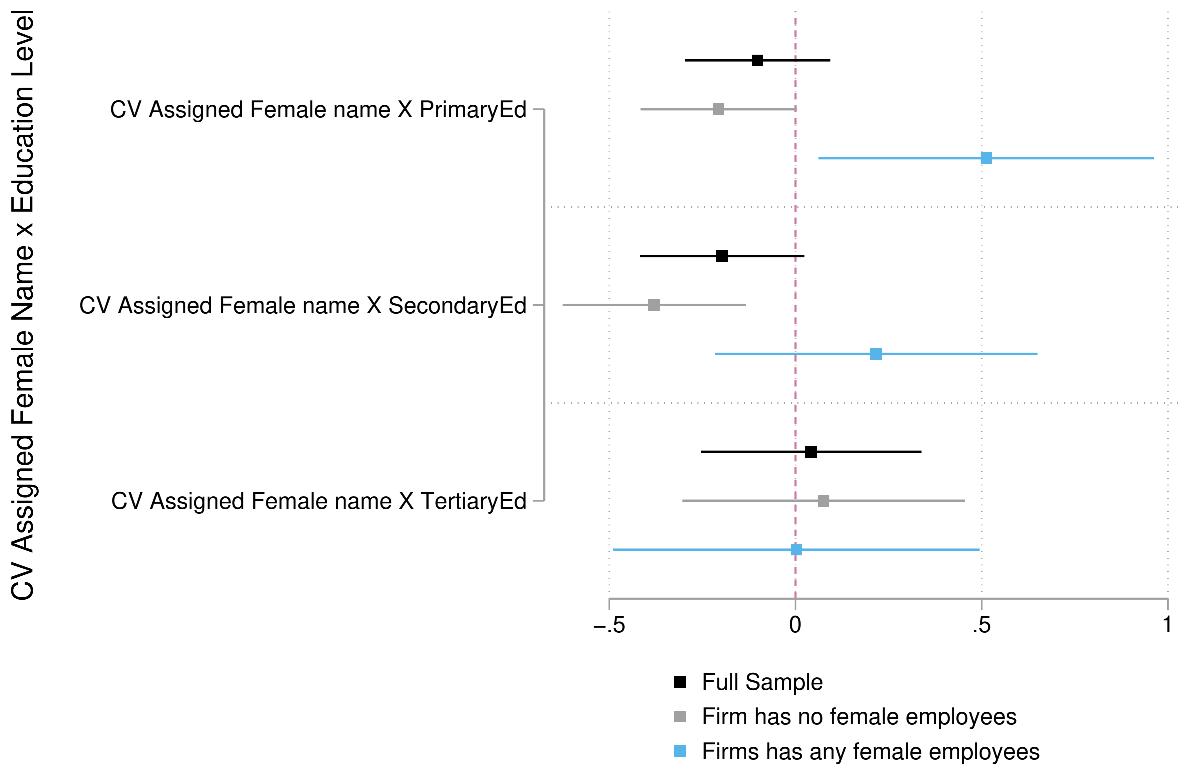
Note: This table displays results from an OLS regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on different CV attributes. The unit of observation is a CV. Tertiary institute ranking is based on the ranking scores of universities by the Higher Education Commission. 'High' ranking is assigned to all the universities that have a ranking score higher than the median score in our sample. 'Medium' indicates universities at below-median ranking. 'Low' is the omitted category for all those universities that have not been assigned any score due to non-recognition by the Higher Education Commission. CV reports secondary standardized exam scores/ tertiary grade is a binary indicator for secondary/ tertiary grade reported on the CV. Above median secondary standardized exam score / tertiary grade is a binary indicator for secondary/ tertiary grade higher than the median for the respective grade in our sample. All specifications include a control for the CV randomly assigned to be first in the pair. Standard errors in parentheses clustered by CV pairs. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.5: Heterogeneity Analysis in Incentivized Binary Choice Experiment without fixed effects

	(1) Firm has any female employees	(2) Firm has all female employees	(3) Firm posts ad open to women
CV assigned female name	-0.221*	-0.125	-0.323*
	(-2.29)	(-1.41)	(-2.41)
CV assigned female name X Group	0.473*	1.053***	0.427*
	(2.61)	(8.70)	(2.46)
Observations	256	256	256
Total Effect on HTE Group	0.252	0.928	0.104
P-value	0.107	0.000	0.341

Note: This table displays results from an OLS regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on a binary indicator for CV assigned a female name, firm's gender composition (Group) and their interaction. The unit of observation is a CV. Standard errors are clustered by firm ID. t-values reported in the parentheses. Column 1 interacts 'CV Assigned Female name' with a binary indicator for 'Firm having any female employees', Column 2 with a binary indicator for 'Firm having all female employees' and Column 3 with a binary indicator for 'Firm having posted ads open to women'. All specifications include a control for the CV randomly assigned to be first in the pair and a fixed effect for Public Tertiary Institute (refer to section B for discussion). * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Figure B.2: Incentivized Binary Choice: Heterogeneity by CV Education Level without fixed effects



Note: This figure displays coefficients from an OLS regression run separately for full sample, for firms with no women (75% of the sample), and firms that already have at least one female employee (25% of the sample). The dependent variable 'CV Chosen' is a binary indicator equal to 1 if CV k was chosen by the respondent in the incentivized binary choice experiment. The coefficients shown are for the interaction of 'Female CV' and education levels (Primary, Secondary, and Tertiary). All regressions Each observation in these regressions is one CV shown to the firm. Standard errors clustered by CV pair IDs; 95% confidence intervals shown. The p-value of F-stat for a null of equality is 0.434, 0.130 and 0.298 for the full sample, firms with no female employees and firms having female employees respectively.

Table B.6: Employer revealed preferences for CV attributes in incentivized binary choice experiment with fixed effects- Sample including single gender pairs

	(1) CV chosen	(2) CV chosen	(3) CV chosen
CV assigned female name	-0.109	-0.108	-0.103
	(0.068)	(0.068)	(0.069)
Above Median Tertiary grades	0.296	0.341*	0.342*
	(0.180)	(0.204)	(0.202)
CV reports tertiary grade	0.309	0.215	0.160
	(0.465)	(0.481)	(0.494)
Tertiary institute ranking=Medium		0.121	0.134
		(0.272)	(0.286)
Tertiary institute ranking=High		-0.052	-0.047
		(0.150)	(0.149)
Above Median Secondary Standardized Exam score			0.060
			(0.137)
CV reports Secondary Standardized Exam Score			0.113
			(0.180)
Constant	0.144	0.119	0.042
	(0.198)	(0.204)	(0.239)
Observations	894	894	894

Note: This table displays results from fixed effects regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on different CV attributes. The unit of observation is a CV. Tertiary institute ranking is based on the ranking scores of universities by the Higher Education Commission. 'High' ranking is assigned to all the universities that have a ranking score higher than the median score in our sample. 'Medium' indicates universities at below-median ranking. 'Low' is the omitted category for all those universities that have not been assigned any score due to non-recognition by the Higher Education Commission. CV reports secondary standardized exam score / tertiary grade is a binary indicator for secondary/ tertiary grade reported on the CV. Above median secondary standardized exam score/ tertiary grade is a binary indicator for secondary/ tertiary grade higher than the median for the respective grade in our sample. All specifications include a control for the CV randomly assigned to be first in the pair. CV pair ID fixed effects are used. Robust standard errors in parentheses clustered by CV pairs. $^{*}\ p < .1$, $^{**}p < .05$, $^{***}\ p < .01$.

Table B.7: Heterogeneity Analysis in Incentivized Binary Choice Experiment: Subsample of Firms that Posted Ads on the platform with fixed effects

	(1) Firm has any female employees	(2) Firm has all female employees	(3) Firm posts ad open to women
CV assigned female name	-0.220*	-0.125	-0.325*
	(-2.28)	(-1.40)	(-2.42)
CV assigned female name X Group	0.474*	1.053***	0.435*
	(2.61)	(8.68)	(2.46)
Observations	256	256	256
Total Effect on HTE Group	0.254	0.928	0.110
P-value	0.106	0.000	0.326

Note: This table displays results from a fixed effects regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on a binary indicator for CV assigned a female name, firm's gender composition (Group) and their interaction. Pair ID fixed effects are used. The unit of observation is a CV. Standard errors are clustered by firm ID. t-values reported in the parentheses. Column 1 interacts 'CV Assigned Female name' with a binary indicator for 'Firm having any female employees', Column 2 with a binary indicator for 'Firm having all female employees' and Column 3 with a binary indicator for 'Firm having posted ads open to women'. All specifications include a control for the CV randomly assigned to be first in the pair and a fixed effect for Public Tertiary Institute (refer to section B for discussion).* $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.8: Incentivized Binary Choice Experiment: Balance of CV Traits by Gender- Subsample of firms that posted ads on the platform

Variable	(1) CV randomly assigned male name	(2) CV randomly assigned female name	(3) P-values
Tertiary Ed	0.234	0.234	1.000
Secondary Ed	0.352	0.398	0.441
Primary Ed	0.414	0.367	0.444
Tertiary grade	0.617	0.695	0.629
Secondary Standardized Exam Score	1.211	1.031	0.427
Public Tertiary Institute	0.102	0.047	0.096
Any Experience	0.508	0.508	1.000
Observations	128	128	256

Note: Column 1 and 2 report average value of a CV trait for men and women. Column 3 reports p-values of the difference of means in column 1 and 2. 'Tertiary grades' range from 2-5 where 5 is A and 2 is D. 'secondary standardized exam scores' are coded the same as tertiary grades and apply to only those people who have higher than ten years of education. Any experience is a binary indicator for years of experience between one to five years and zero for less than one years of experience. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.9: Firm selection into incentivized binary choice experiment-Subsample of firms who posted ads on the platform

Employees and Gender composition					
	Did not post an ad		Posted an ad		
	n	mean	n	mean	Diff
Firm has 0% female employees	40	0.85	47	0.70	-0.148*
Firm has < 50% female employees	40	0.03	47	0.19	0.166**
Firm has 51-99% female employees	40	0.10	47	0.06	-0.036
Firm has 100% female employees	40	0.03	47	0.04	0.018

Firm infrastructure and space					
	Did not post an ad		Posted an ad		
	n	mean	n	mean	Diff
Separate toilet for women	6	0.83	13	0.77	-0.064
Separate prayer space for women	6	0.83	13	0.77	-0.064
Separate working space for women	6	0.33	12	0.25	-0.083

Industry Classification					
	Did not post an ad		Posted an ad		
	n	mean	n	mean	Diff
Manufacturing	40	0.05	47	0.09	0.035
Wholesale, retail trade	40	0.42	47	0.43	0.001
Transportation, storage	40	0.00	47	0.04	0.043
Accommodation, food services	40	0.13	47	0.02	-0.104*
Real estate	40	0.07	47	0.04	-0.032
Scientific, technical	40	0.00	47	0.11	0.106
Admin, support service	40	0.00	47	0.02	0.021
Education	40	0.10	47	0.06	-0.036
Arts & entertainment	40	0.03	47	0.02	-0.004

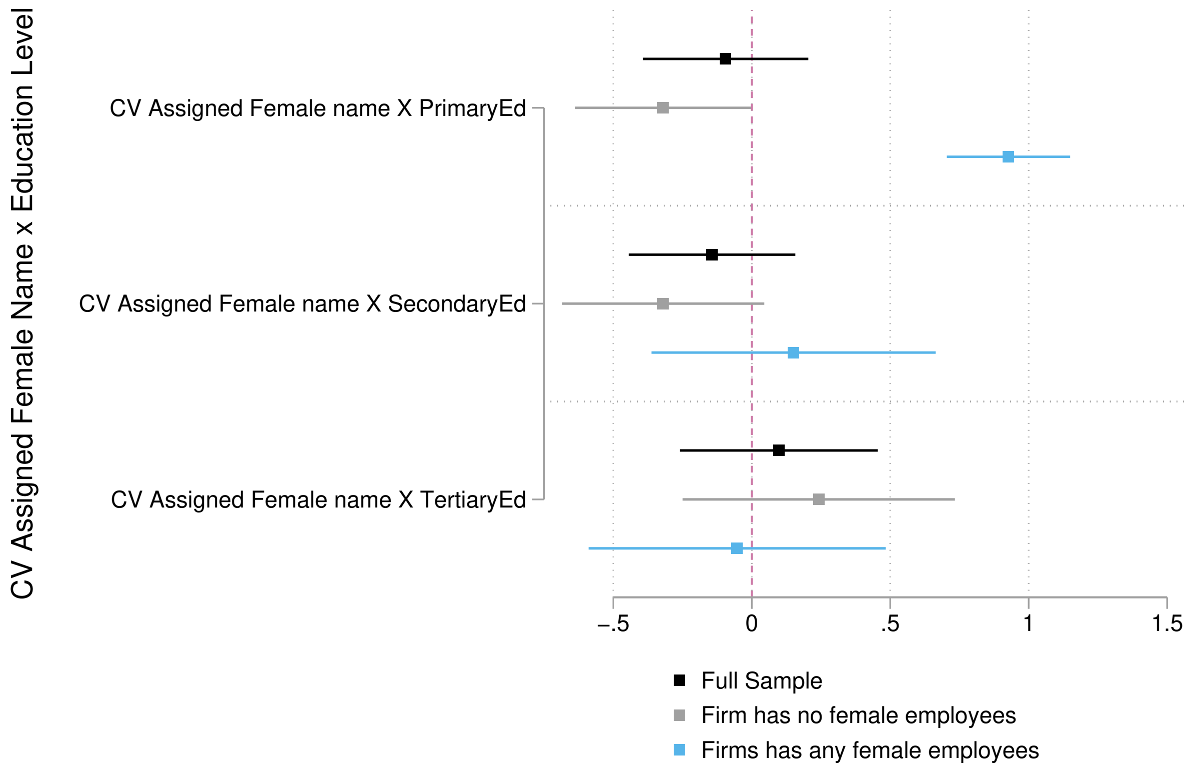
Notes:Firms who participate in the longer survey respond to questions about their employees, vacancies, gender composition and infrastructure along with the incentivized binary choice experiment. A total of 87 firms agreed to participate in the binary choice experiment. This table shows differences between firms that * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Table B.10: Employer revealed preferences for CV attributes in incentivized binary choice experiment- Subsample of Firms that ever posted an ad, with fixed effects

	(1) CV chosen	(2) CV chosen	(3) CV chosen
CV assigned female name	-0.111	-0.102	-0.103
	(0.091)	(0.092)	(0.094)
Above Median Tertiary grades	0.482	0.914**	0.923**
	(0.416)	(0.365)	(0.370)
CV reports tertiary grade	1.162***	0.372	0.367
	(0.123)	(0.483)	(0.516)
Tertiary institute ranking=Medium		1.122***	1.133***
		(0.370)	(0.392)
Tertiary institute ranking=High		-0.040	-0.033
		(0.422)	(0.426)
Above Median Secondary Standardized Exam score			-0.035
			(0.244)
CV reports Secondary Standardized Exam Score			0.014
			(0.424)
Observations	256	256	256

Note: This table displays results from a fixed effects regression of 'CV Chosen' (a binary indicator equal to 1 if CV was chosen) on different CV attributes. The unit of observation is a CV. Tertiary institute ranking is based on the ranking scores of universities by the Higher Education Commission. 'High' ranking is assigned to all the universities that have a ranking score higher than the median score in our sample. 'Medium' indicates universities at below-median ranking. 'Low' is the omitted category for all those universities that have not been assigned any score due to non-recognition by the Higher Education Commission. CV reports secondary standardized exam score/ tertiary grade is a binary indicator for secondary/ tertiary grade reported on the CV. Above median secondary standardized exam score/ tertiary grade is a binary indicator for secondary/ tertiary grade higher than the median for the respective grade in our sample. All specifications include a control for the CV randomly assigned to be first in the pair and a fixed effect for Public Tertiary Institute (refer to B for discussion). CV pair fixed effects are used. Robust standard errors in parentheses clustered by CV pairs. * $p < .1$, $^{**}p < .05$, *** $p < .01$.

Figure B.3: Incentivized Binary Choice: Heterogeneity by CV Education Level -Subsample of Firms that ever posted an ad, with fixed effects



Note: This figure displays coefficients from a fixed effects regression run for firms that ever posted ads on the platform. The regressions are run separately for full sample, for subset of firms with no women (75% of the sample), and firms that already have at least one female employee (25% of the sample). The dependent variable 'CV Chosen' is a binary indicator equal to 1 if CV k was chosen by the respondent in the incentivized binary choice experiment. The coefficients shown are for the interaction of 'Female CV' and education levels (Primary, Secondary, and Tertiary). Each observation in these regressions is one CV shown to the firm. All specifications include a control for the CV randomly assigned to be first in the pair. CV pair fixed effects are used. Standard errors clustered by CV pair IDs; 95% confidence intervals shown. The p-value of F-stat for a null of equality is 0.563, 0.125 and 0.001 for the full sample, firms with no female employees and firms having female employees respectively.

C Oaxaca-Blinder-Kitagawa Decompositions

We conduct a series of Oaxaca-Blinder-Kitagawa decompositions to study the role of gender restrictions on the gender gap in opportunities on the platform. There are two complications with such a decomposition in our setting compared to most. First, due to the large gender employment gap in Pakistan, the gender wage gap is a less informative outcome than in other settings where the gender employment gap is smaller.

Thus, we focus on decompositions of the following three outcome variables: whether the jobseeker-vacancy dyad converts to a platform-match, whether the jobseeker-vacancy dyad receives an application from the jobseeker, and whether the jobseeker-vacancy dyad results in an interview for the jobseeker. Second, due to explicit firm gender criteria in job postings, gender is in and of itself an "endowment" in the Oaxaca-Blinder-Kitagawa framework, unlike in most settings where an Oaxaca-Blinder-Kitagawa decomposition is utilized. Thus, as shown in the discussion below, the 'explained' or 'endowment' portion seems to comprise much of the gender gap in each outcome, when mechanically gender is part of the 'explained' component. In the canonical gender wage gap literature in high-income settings, Oaxaca-Blinder-Kitagawadecompositions are used to quantify the component of the gender wage gap that remains unexplained after accounting for observable differences in men's and women's observable attributes and qualifications. Gender discrimination is never observed explicitly, and is thus expected to contribute to this *unexplained* gap (Blau and Kahn, 2017). However, in our setting, firms' gender specifications are in fact observed directly and captured in the "qualifies on gender" variable. Thus, these form a part of the *explained* gap, unlike in the standard applications of the decomposition.

Table C.1 conducts a decomposition with the outcome of whether the jobseeker-vacancy dyad converts to a platform-match. The four explanatory variables are whether the jobseeker was interested in the occupation of the vacancy, whether the jobseeker satisfied the education criteria for the vacancy, whether the jobseeker satisfied the experience criteria for the vacancy, and finally, whether the jobseeker satisfied the gender criteria for the vacancy. Since a jobseeker's own gender must match with a vacancy's explicit gender criteria for the jobseeker-vacancy dyad to convert to a platform-match, in our setting, gender becomes an endowment of the jobseeker unlike in most settings. As seen in Column 1 of Table C.1, the endowment/explained portion explains most of the gap between men's and women's rates of matching. However, as seen in Column (2), whether the jobseeker meets the gender criteria for the vacancy is the largest component of that endowment.

Tables C.3 and C.5 conduct a similar analysis, but focus respectively on the outcomes of whether the jobseeker applied to the given vacancy in the dyad, and whether the jobseeker was interviewed for the given vacancy in the dyad. Unlike in Table 1, these are not conditional on platform-matching or applying, respectively. Rather the sample includes all possible dyads. We additionally include salary of the vacancy, jobseeker's years of education and experience, and jobseeker's socio-economic status index, as further explanatory variables. In Table C.3, we again see that endowments rather than coefficients explain much of the gap in application. In fact, the unexplained portion of the gender gap moves in the opposite direction as expected and would favor women. Similar to the results in Table C.1, we see that the largest magnitude gap in endowments comes from whether the jobseeker qualifies for the vacancy on gender. Men apply for vacancies at an overall higher rate than women, but this is largely coming mechanically through the fact that women qualify for a lower number of vacancies based on gender than men, and are thus not platform-matching to as many vacancies to be able to apply to them. As we show in Table 1, conditional on platform-matching the application gender gap does not favor men. In Table C.5, we show a very similar pattern of results for interviews, but with smaller magnitudes since interviews are a much rarer outcome.

Finally, in Tables C.2, C.4, and C.6, we conduct the decomposition, but omit whether the jobseeker satisfied the gender requirement of the vacancy from the list of explanatory variables. We find that for all three outcomes, when the gender requirement variable is omitted, more of the gender gap in the outcome is unexplained than explained. From these results, we conclude that firm-side gender restrictions are the dominant factor in determining women's access to opportunities on the platform.

Table C.1: Oaxaca-Blinder-Kitagawa Decomposition: Platform-Matched

	overall	explained	unexplained
Men	0.225^{***}		
	[0.000292]		
Women	0.0927^{***}		
	[0.000287]		
difference	0.132^{***}		
	[0.000419]		
explained	0.128^{***}		
	[0.000338]		
unexplained	0.00420^{***}		
	[0.000246]		
Selected occup.		0.00304^{***}	0.132^{***}
		[0.000276]	[0.000276]
Qualify gender		0.100^{***}	0.0115^{***}
		[0.000174]	[0.000505]
Qualify educ		0.000216^{*}	0.121^{***}
		[0.000115]	[0.000499]
Qualify exper.		0.0246^{***}	0.0672^{***}
		[0.0000942]	[0.000565]
Constant			-0.327^{***}
			[0.00101]
Observations	3541932		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.

Table C.2: Oaxaca-Blinder-Kitagawa Decomposition: Platform-Matched - Excluding the Qualify Gender Explanatory Variable

	overall	explained	unexplained
Men	0.225***		
	[0.000284]		
Women	0.0927***		
	[0.000270]		
difference	0.132***		
	[0.000388]		
explained	0.0325***		
	[0.000318]		
unexplained	0.0996***		
	[0.000333]		
Selected occup.		0.00306***	0.128***
		[0.000290]	[0.000321]
Qualify educ		0.000224*	0.143***
		[0.000123]	[0.000493]
Qualify exper.		0.0292***	0.0482***
		[0.000109]	[0.000532]
Constant			-0.220***
			[0.000827]
Observations	3541932		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.

Table C.3: Oaxaca-Blinder-Kitagawa Decomposition: Apply

	overall	explained	unexplained
Men	0.00113***		
	[0.0000200]		
Women	0.000605***		
	[0.0000251]		
difference	0.000524***		
	[0.0000322]		
explained	0.000626***		
	[0.0000142]		
unexplained	-0.000103***		
	[0.0000319]		
Selected occup.		0.0000164***	0.000536***
		[0.00000150]	[0.0000315]
Qualify gender		0.000537***	-0.000212***
		[0.00000913]	[0.0000378]
Qualify educ		0.000000907	0.000139***
		[0.000000659]	[0.0000505]
Qualify exper.		0.000145***	0.000407***
		[0.00000449]	[0.0000415]
Ln(salary)		-0.00000530***	0.000599***
		[0.000000679]	[0.000174]
Years ed		0.00000743**	0.000569***
		[0.00000354]	[0.0000626]
Years of Experience		-0.0000768***	-0.000108***
		[0.0000145]	[0.0000284]
SES Index		0.000000704	-0.00000526***
		[0.000000446]	[0.00000155]
Constant			-0.00203***
			[0.000204]
Observations	3400384		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.

Table C.4: Oaxaca-Blinder-Kitagawa Decomposition: Apply - Excluding the Qualify Gender Explanatory Variable

	overall	explained	unexplained
Men	0.00113***		
	[0.0000229]		
Women	0.000605***		
	[0.0000233]		
difference	0.000524***		
	[0.0000313]		
explained	0.000158***		
	[0.0000127]		
unexplained	0.000365***		
	[0.0000313]		
Selected occup.		0.0000165***	0.000504***
		[0.00000154]	[0.0000315]
Qualify educ		0.000000942	0.000495***
		[0.000000671]	[0.0000419]
Qualify exper.		0.000155***	0.000278***
		[0.00000551]	[0.0000422]
Ln(salary)		-0.00000621***	0.000937***
		[0.000000664]	[0.000163]
Years ed		0.00000170	-0.0000163
		[0.00000368]	[0.0000630]
Years of Experience		-0.0000105	-0.000138***
		[0.0000154]	[0.0000281]
SES Index		0.000000563	-0.00000474***
		[0.000000397]	[0.00000155]
Constant			-0.00169***
			[0.000194]
Observations	3400384		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.

Table C.5: Oaxaca-Blinder-Kitagawa Decomposition: Interview

	overall	explained	unexplained
Men	0.0000845***		
	[0.00000581]		
Women	0.0000623***		
	[0.00000846]		
difference	0.0000222**		
	[0.0000108]		
explained	0.0000487***		
	[0.00000373]		
unexplained	-0.0000265**		
	[0.0000103]		
Selected occup.		0.00000126***	0.0000268***
		[0.000000141]	[0.0000101]
Qualify gender		0.0000442***	-0.0000498***
		[0.00000272]	[0.0000123]
Qualify educ		7.92e-08	-0.0000133
		[5.22e-08]	[0.0000181]
Qualify exper.		0.0000137***	-0.000000742
		[0.00000137]	[0.0000126]
Ln(salary)		-0.000000818***	0.0000894***
		[9.78e-08]	[0.0000294]
Years ed		0.00000322***	0.0000594***
		[0.00000109]	[0.0000215]
Years of Experience		-0.0000131***	0.00000850
		[0.00000419]	[0.00000827]
SES Index		0.000000146	0.000000154
		[0.000000133]	[0.000000477]
Constant			-0.000147***
			[0.0000462]
Observations	3400384		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.

Table C.6: Oaxaca-Blinder-Kitagawa Decomposition: Interview - - Excluding the Qualify Gender Explanatory Variable

	overall	explained	unexplained
Men	0.0000845***		
	[0.00000579]		
Women	0.0000623***		
	[0.00000718]		
difference	0.0000222**		
	[0.00000945]		
explained	0.0000103***		
	[0.00000332]		
unexplained	0.0000119		
	[0.00000860]		
Selected occup.		0.00000128***	0.0000230**
		[0.000000135]	[0.00000938]
Qualify educ		8.21e-08	0.0000209
		[6.20e-08]	[0.0000131]
Qualify exper.		0.0000145***	-0.0000123
		[0.00000145]	[0.0000119]
Ln(salary)		-0.000000892***	0.000118***
		[9.98e-08]	[0.0000310]
Years ed		0.00000275**	-0.000000764
		[0.00000111]	[0.0000168]
Years of Experience		-0.00000761*	0.00000615
		[0.00000442]	[0.00000786]
SES Index		0.000000135	0.000000202
		[0.000000139]	[0.000000458]
Constant			-0.000143***
			[0.0000444]
Observations	3400384		

Notes: Bootstrapped standard errors clustered on jobseeker and vacancy.