Screening Women Out?
Experimenting with Salary Disclosure in Job Ads

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Abstract: Firm wage premiums can widen gender pay gaps if women face barriers to accessing high paying firms, or negotiating the available surplus. This paper examines whether the absence of salary information in job ads restricts women's access to high paying firms. I find that firms are more likely to hide salaries when they are higher, for otherwise comparable jobs. In particular, large, well-paying firms use salary non-disclosure to reduce costly screening by encouraging applicants to self-screen. This practice has disproportionate costs for women, who, like men, apply more to higher paying jobs when salaries are visible, but, unlike men, do not direct search when they are concealed. To investigate, I conduct an experiment on Pakistan's largest job search platform with around 14,000 jobs and 6,300 firms. Treated jobs are required to disclose salary ranges, while control jobs retain the option to hide. The intervention has limited effects on salaries, but increases applications by 54%, especially to large firms whose higher salaries are newly revealed. The reallocation of search from small to large firms is 37 percentage-points higher for women, eliminating existing gender gaps in sorting. While the applicant pool slightly declines in average quality, top applicants to treated jobs are higher ability and 4.8% more likely to be female. A trade-off underlies these findings: salary non-disclosure modestly deters unqualified applicants but additionally screens out the highest ability women.

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1 Introduction

Large gender pay gaps persist globally, affecting not just the earnings of women in the workforce, but also the entry decisions of those outside. About 38% of the gender pay gap remains unexplained even after accounting for gender differences in occupation, industry, location, education, experience, race, and unionization (Blau and Kahn, 2017). An important, yet often overlooked factor is the role firms play in shaping these gaps. Extensive research shows that wages contain a firm-specific component, causing similar workers in similar jobs to earn different salaries depending on their employer (Goux and Maurin, 1999; Gruetter and Lalive, 2009; Card et al., 2013, 2018). Firm-level pay differences may widen gender gaps if gendered barriers limit women's access to high paying firms, or their ability to negotiate the available premiums. Card et al. (2016) show that firm wage premiums explain 20% of Portugal's gender pay gap, with women's sorting into lower-paying firms accounting for three-fourths of this effect.

Since firms vary in pay, how workers direct search to firms shapes their labor market outcomes. Job-seekers commonly rely on stated salary information in job ads to guide their decisions about where to apply, and how much to bargain for (Dal Bó et al., 2013; Belot et al., 2022; Banfi and Villena-Roldán, 2019). Consequently, advertised salaries directly influence contracted pay (Menzio, 2007; Skoda, 2022). Yet, salary information is typically missing in job ads worldwide. For instance, more than 80% of job ads in Chile, China, Ethiopia, Germany, Slovenia, and the U.S. contain no salary information (Brenčič, 2012; Banfi and Villena-Roldán, 2019; Kuhn and Shen, 2013; Batra et al., 2023; Indeed Hiring Lab, 2023b). This lack of transparency may be more costly for women, who often have smaller and less supportive professional networks (Beaman et al., 2018; Ductor et al., 2023), and fewer years of experience, making it harder to extract wage signals from job descriptions. Their higher risk and ambiguity aversion (Bertrand, 2011) and greater search costs due to gendered care responsibilities (Jayachandran, 2021b) may further deter women from applying to jobs with undisclosed pay.

This paper considers whether the lack of salary information in job ads prevents women from targeting high paying firms. The study is based in Pakistan, where just a quarter of all working age women are in the labor force, and the ILO-estimated gender pay gaps – 34% raw and 36% adjusted – are the highest globally (International Labour Organization, 2018). In this setting, I run a large-scale field experiment on Pakistan's leading online job search platform. Treated jobs in the experiment are required to reveal salary ranges publicly, while control jobs retain the option to hide. Around 14,000 jobs, 247,000 job-seekers and 6,300 firms have been exposed to the experiment over the course of 5 months. The intervention enables me to test whether mandating salary range disclosure affects advertised salaries, gender gaps in directed search to

high paying firms, and applicant quality. In an upcoming workers' survey, I also measure effects on employment and the gender pay gap, in addition to the mechanisms that drive gender gaps in sorting.

The platform's design provides unique access to both revealed and hidden salaries, offering a rare opportunity to study selection into salary disclosure. While firms are required to report salary ranges to the platform, they can choose to hide them from job seekers. About 55% of job ads omit salary information. Using baseline data on both revealed and hidden salaries – incluing 27 million job applications, 300,000 jobs, and 90,000 firms – I start by studying the predictors of salary disclosure. The findings indicate that while jobs with hidden salaries are more complex, holding job characteristics fixed, salary is more likely to be hidden when the job is higher paying than other similar jobs. Moreover, an extensive set of job characteristics (e.g., salary, occupation, city, job title, and industry fixed effects, skills, education and experience requirements, job schedule, and career-level) collectively explain only 12.7% of the variation in the hiding decision. Meanwhile, firm fixed effects alone explain over half of the variation. In particular, the hiding decision is strongly correlated with firm size and premiums: firms that hide salaries more are larger, better paying, and control a more sizeable share of job applications.

To investigate why firms offering higher salaries conceal this information, despite its potential to attract more talent, I turn to a model of job search, and firm surveys. The model suggests that revealing higher salaries invariably attracts high ability workers, but has ambiguous impacts on applications from low ability workers: either these applications increase because they are drawn by the higher wage, or decrease because they are deterred by increased competition from higher ability workers. Thus, it is theoretically ambiguous whether salary non-disclosure is a dominant strategy for firms. However, firm surveys reveal that firms believe in the latter scenario: among firms that hide salaries, 63% believe that revealing their salaries will strictly increase the total number of applications, while 72% believe it will weakly lower the average quality (with 40% believing it will strictly lower the average quality). This preference for fewer, better-matched applicants over a larger pool, that requires filtering out unsuitable candidates, suggests that screening costs are substantial. Thus, firms who hide salaries do so strategically to exclusively attract 'suitable' workers – those who can infer wage from non-wage information and optimally choose to apply. Meanwhile, the absence of salary information can deter otherwise unsuitable workers who apply solely because the salary is high, thereby preventing average quality from declining.

Existing theoretical evidence suggests that strategic salary non-disclosure is a rational response by firms in environments with a high risk of adverse selection (Michelacci and Suarez, 2006), which

is especially likely in developing countries. In these countries, economic growth has expanded the supply of educated and experienced workers, but the quality of education and experience remain widely heterogenous (World Bank, 2018; Muralidharan and Singh, 2023; Bandiera et al., 2024b). As a result, stated resume characteristics provide weak signals of true ability (Bertrand et al., 2024). In such settings, having choice over more workers is only favorable for firms if their screening ability grows in parallel. On my partner platform, the number of seemingly qualified applicants is high: 89% of applicants to the average job meet its education requirements, and 76% meet the experience criteria. Thus, to meaningfully filter applicants, firms must go beyond resumes, investing resources in time-intensive interviews or hiring tests. Additionally, as more job posts have moved to online platforms, the marginal cost of sending an additional application has fallen because these platforms are expressly designed to make it easier for workers to apply to jobs (Autor, 2001). Reflecting this, applicants on the platform spend an average of only two minutes per job application. Given the growing volume of seemingly similar applications, firms face a difficult signal extraction problem. To navigate costly screening and the risk of adverse selection, they have been shown to resort to hiring within familiar social networks (Jayachandran, 2021a; Chandrasekhar et al., 2020). This paper sheds light on another adjustment margin globally used by firms – especially larger, better-paying ones – to overcome screening costs: self-screening through salary non-disclosure.

While salary non-disclosure may seem rational for firms, it can exclude women if women rely more on stated salary information to shape their job search. Using baseline administrative data, I show that both men and women send more applications to higher paying jobs when the salary is visible. In fact, this elasticity is higher for women, revealing greater sensitivity to salaries. But when the salary is invisible in otherwise comparable jobs, women lose the ability to direct search to high paying jobs. Meanwhile, men still direct search to higher paying jobs when salaries are hidden – though to a smaller extent than when they are visible. Since jobs with hidden salaries pay more than comparable jobs with disclosed salaries, in applying less to jobs with hidden salaries, women are effectively self-selecting out of the best opportunities.

While the descriptive evidence suggests that salary information is key, the results may instead be driven by unobserved differences in jobs that do and do not hide salaries, rather than by salary hiding itself. To investigate the descriptive patterns causally, I conduct a field experiment on Pakistan's leading job platform. The experiment requires treated ads to disclose salary ranges, while control ads retain the option to hide them. The intervention raises salary disclosure in job ads by 41 percentage points. Firms are allowed to opt out, but they must contact platform representatives, confirm their preference, and await manual processing. All requests are granted, but non-compliant firms still privately disclose salaries, allowing me to study selection

into non-compliance. Non-compliance is minimal (3%), occurring predemoninantly among large firms.[1] Firms neither exit the platform nor reduce job postings in response to the intervention, highlighting the market power of the platform. I estimate intent-to-treat effects in this setting, which provide a lower bound, allowing for some non-compliers in the treatment group, and many voluntary disclosers in the control group. In particular, I assess impacts on log minimum and maximum advertised salaries, job views and applications, applicant quality, and potential 'shortlists'. Since firms have no incentives to report hiring outcomes once a suitable candidate has been identified, I am unfortunately unable to study these.

I begin by examining the demand side. The impact of salary disclosure mandates on advertised salary levels is a priori ambiguous. These requirements may drive wages up by increasing competition for talent. Alternatively, they can lead to wage compression if firms collude or fear that incumbent workers will demand raises.[2] The experiment reveals that mandating salary disclosure modestly increases log minimum salaries by 3%, but has no effect on maximum salaries, resulting in narrower salary ranges. This increase is driven by smaller firms, likely reflecting competitive pressures from their larger counterparts, whose higher salaries have now become visible.

On the supply side, if workers already know hidden salaries or do not rely on advertised salaries to guide their search, salary disclosure should have no effect on applications. However, the experiment increases job views on treated ads by 49.9% and applications by 53.8%, implying that salary information matters for search, and was previously less accessible. Given this, salary disclosure should generate more interest in jobs whose salaries were previously harder to learn but are now revealed to be higher. As pre-registered, jobs at large firms fit this pattern exactly. In the control group, jobs at large firms are 20 percentage points more likely to hide salaries. These jobs also pay more: the minimum salary in control jobs at large firms is 30% higher than in small firms, and the maximum is 18% higher. Treatment has no effect on the salaries of large firms. Thus, they remain higher when treated, and have a narrower range. Since large firms previously hid salaries more often but are now revealed to be higher paying, the increase in job applications is primarily driven by greater interest in these firms. Specifically, jobs at large firms experience a 78.1% increase in applications, compared to only 20.9% for jobs at small firms. This shift reflects both an extensive margin increase—more applications overall—and an intensive margin reallocation: the increased search activity is mainly directed to large firms.

[1] Large firms are defined as those with over 50 employees. The split at 50 ensures balanced job ads between small and large firms.

[2] However, firms report in the survey that this is a risky strategy, as workers may anchor their expectations to the now higher maximum.

Turning now to the key question of interest: does salary disclosure disproportionately affect women's ability to access high paying firms? On average, the intervention has stronger effects on women, increasing men's applications to treated jobs by 50.3% and women's by 68.1% (the gender difference is significant at p=0.03). Consistent with stylized facts, women in the control group are less able to direct search in the absence of salary information than men. Control jobs at large firms receive 64.3% more male applications than control jobs at small firms, but only 40.5% more female applications. Treatment increases men's applications to large firms by 69.7% relative to control large firms, and women's by 115.5%. This increase in application to large firms (more than) closes the gender gap in directed search observed among control jobs. Specifically, treated jobs at large firms receive 164.5% more applications from women than treated jobs at small firms, whereas they receive 127.5% more applications from men (a 37 percentage point gender difference in favor of women).

Since firms that hide salaries believe the increase in application quantity is not worth the potential loss in quality, I next examine the impact on applicant quality. I find that average applicant quality declines in line with firm beliefs, but modestly. While the share of applicants meeting experience requirements remains stable on average, small firms experience a 1 percentage point decline among male and female candidates. The share of candidates who meet education requirements also declines by 1 percentage point. Notably, most candidates in the control group meet experience and education requirements (76% for experience and 89% for education) underscoring the problem of excess, seemingly similar applications. Thus, salary disclosure does not seem to dramatically alter the quality of the average applicant. However, large firms do experience a sharper decline in the share of applicants who meet the skills requirements of the job: in the control group 39% of female and 46% of male applicants meet all skills requirements. This share drops by 6.5% for male and 5.1% for female applicants to treated jobs. While these impacts on candidates' observable qualities appear to be small, there may be additional negative impacts on unobservables that are known to firms. Thus, I take this evidence to be consistent with firms' beliefs in the survey: salary disclosure imposes costs on large firms by increasing the average quantity but reducing the quality of applications.

While average applicant quality influences screening effort, hiring outcomes are ultimately determined by the quality of the top candidates. Given this, I study selection into the applicant pool by identifying top candidates in the broader labor market based on their expected salary, GPA, years of experience, and management experience. Next, I consider the likelihood that they apply to a given job. I find that 'high-ability' men apply broadly, with 82-91% of control jobs already having at least one high-ability man, whereas high-ability women are more selective. Control jobs have a 51-55% likelihood that a high ability woman applies to their job. Treatment

modestly increases high-ability men's applications to large firms by 1-3%, but increases high-ability women's applications by 11-18%. However, this comes with a cost: treatment also draws in more low-quality applicants, both male and female. Notably, women in the lowest percentiles of GPA and experience apply more broadly as well: they have a 60-79% likelihood of being in the applicant pool of control jobs (83-97% for low-ability men). Treatment increases low ability men's applications by 1-3%, while it raises low ability women's applications by 5-14%.

These results suggest that firms design their hiring processes around the most common applicant behavior—where high-ability candidates, who are predominantly men, apply broadly even without salary information, while lower-ability candidates are somewhat deterred by its absence. Given this prevailing pattern, firms' hiring strategies may seem reasonable. However, they overlook a key factor: high-ability women search for jobs differently than the typical applicant. This could stem from a lack of awareness among firms about gendered search behavior. Alternatively, firms may be aware of this difference but remain unconcerned—either because male and female workers are close substitutes, or because the role offers limited returns to attracting top talent.

To further assess whether treatment improves the quality of those most likely to be hired, I examine the top applicants in each job's applicant pool. I construct a potential shortlist of these candidates, and compare their quality across treatment and control jobs. The results show that top candidates in the treatment group have 0.07–0.12 standard deviations higher ability, measured by their level of education, years of experience, GPA, and management experience. Crucially, treatment jobs experience a 3 percentage point (5.2%) increase in the likelihood that the top applicants include at least one woman, reinforcing the positive selection effects of salary transparency on female applications.

The positive selection of women into treated jobs is further reflected in data on firms' engagement with the applications. In treated jobs, firms review and download a smaller share (9.5–10.7%) of the CVs received. Since these jobs attract significantly more applications than control jobs, this suggests that firms have fixed screening capacity, and face diminishing returns to evaluating additional candidates. Despite this, the female share of reviewed CVs rises by approximately 9% in treated jobs, even as male applications increase and the overall share of applications reviewed declines. This indicates that firms are disproportionately considering female candidates.

While treated jobs receive higher ability workers, the surge in applications—particularly at large firms—heightens the screening burden, making it harder to identify these candidates. While previous findings show that top applicants in treated jobs tend to be more qualified, especially at large firms, this improvement is reflected only in the CVs reviewed by small firms. Large

firms, despite receiving higher quality applications for treated than control jobs, review CVs of similar quality across both groups, and are no more likely than control firms to consider female candidates. These results underscore a key tradeoff: salary disclosure attracts high-ability workers, but firms' screening constraints may prevent them from effectively identifying top talent in a larger applicant pool. As a result, employers prefer a smaller, pre-screened set of applications rather than an overwhelming volume of candidates. These findings highlight the need for better screening technologies to help firms effectively identify and capitalize on the highest-quality applicants available to them.

2 Context

2.1 Pakistan

This research is based in Pakistan, a country that ranks 142nd out of 146 on the Global Gender Gap Index, reflecting one of the largest levels of gender disparity worldwide (World Economic Forum, 2023).[3] Pakistan's female labor force participation rate is 24.4%, which is far below that of other countries at similar income levels (Our World in Data, 2024). In contrast, the male labor force participation rate is 81.0% (International Labor Organization, 2024). Even among women with a college education, labor force participation and employment rates remain in line with the national average (Bandiera et al., 2024a). Moreover, large gender gaps persist not just in extensive margin entry into the labor force, but also within the labor force. Pakistan's raw gender pay gap is one of the largest at 34%, second only to India at 34.5%, while the adjusted gender pay gap is the highest at 36.3% (International Labour Organization, 2018).[4] Furthermore, despite near gender parity in tertiary education, only 6% of firms in Pakistan have women in top management roles (Bandiera et al., 2024a; World Economic Forum, 2023).

2.2 Job platform

In this setting, I partner with the largest job search platform in Pakistan. Over the course of my baseline data period (2019-2024), there are 29.5 million job applications. In addition, 90,640 firms are registered on the platform, of which 69% posted at least one ad, and the average firm posted 3.6 job ads.

[3]The Global Gender Gap Index annually assesses gender parity across four dimensions: economic participation and opportunity, educational attainment, health and survival, and political empowerment.

[4]The adjusted gap accounts for education, age, full-time versus part-time work status, and private-sector versus public-sector employment

Jobs. The platform typically receives at least 100 new job postings daily, resulting in 326,145 job ads from January 2019 to April 2024. The average job gets 75.5 applications. A majority of job postings (81.6%) require a Bachelor's degree and are typically classified as entry-level (29%) or mid-career roles (65%). The platform supports a wide variety of jobs, spanning 63 industries and 63 occupations. Details on the top 10 industries and occupations can be found in Appendix Table B.2. The platform's diversity is further illustrated by the job title word clouds shown in Appendix Figure A.2.

Job-seekers. About 3.1 million job-seekers are registered on the platform in this period, of which 26.9% are women. Of the registered job-seekers, 74.2% applied to at least one job during the study period, submitting an average of 8.8 applications. Job-seekers are usually in their late 20s or early 30s, with a median age of 27 and an average of 28. They tend to have high education levels: 53.3% hold a Bachelor's degree, and 25.9% have a Master's degree. Figure A.1 highlights gender differences among job-seekers. Women are, on average, 1.6 years younger than men but still have similar years of work experience. Moreover, they are more educated – women are 10.9 percentage points (47.6%) more likely than men to have a Masters degree. Despite this, women are also 13.9 percentage points (28.3%) more likely to remain confined to entry level jobs, earning on average 25% less than men, accounting for occupation fixed effects. Their expected salary is also lower than men's by 19% (conditional on occupation). The average woman submits 7.4 (49.1%) fewer job applications than their male counterparts, and the maximum stated salary of the average job women apply to is 17% lower than the average job men apply to, highlighting the potentially large contribution of gender differences in application to gender differences in pay.

2.3 Salary disclosure in job ads

Global context. Salary is a fundamental characteristic of jobs. Nonetheless, salary information is largely missing in job ads around the world. Figure 1 shows that regardless of the regional and economic characteristics of the country, salary non-disclosure is widely prevalent around the world. One exception is Slovakia where 83.2% of ads reveal the salary in ads but Slovakia has a law mandating disclosure of minimum salaries in job ads (Skoda, 2022).

Salary transparency laws. In recent years, there has been a large global shift toward wage transparency laws mandating employers to state salary information in job ads. In the United States, as of 2024, 14 states have enacted such laws. In March 2023, the Salary Transparency Act was also introduced in Congress, which if passed, would require US employers across the country to disclose salary ranges in job ads. In Europe, several countries—including Austria, Denmark, Iceland, Finland, Germany, Norway, and Sweden—have implemented similar measures, while

the United Kingdom is piloting the reform with a group of volunteering firms. These reforms are part of a broader trend toward pay transparency, with 71% of OECD countries having enacted laws addressing some aspect of salary transparency over the past two decades (Cullen, 2024). These include prohibitions against penalizing colleagues who share salary information, requirements for firms to disclose internal pay data, and mandates for public reporting of pay disparities. As these policies become more widespread, evaluating their effectiveness and broader economic impacts has become increasingly relevant.

3 Data

Administrative data. The job platform generates data on registered job-seekers, job postings, firms and applications. Job characteristics are described in Appendix Table B.1. It shows that visible salaries range from a minimum of PKR 42,517 (SD: 43,895) to a maximum of PKR 68,183 (SD: 67,561), while hidden salaries are generally higher, with a minimum of PKR 56,152 (SD: 61,529) and a maximum of PKR 98,143 (SD: 107,424). Jobs typically require less than one year of prior experience on average (Mean: 0.90 years, SD: 1.89). Each job attracts an average of 75.5 applications (SD: 270.02) and the average job require around three skills (Mean: 3.25, SD: 2.44). A majority of the positions are full-time (94%) with daytime schedules (79%). Only 5% of jobs mandate screening questions. Most jobs target mid-career professionals (65%), followed by entry-level positions (29%), while a small fraction are available for interns or students (4%) and department heads (1%). Bachelor's degrees are the most common educational requirement, listed for 65% of the jobs, while higher qualifications like Master's degrees are specified in 9% of postings. A notable proportion of jobs require no more than an intermediate-level education (16%), and 7% are open to candidates with matriculation or less. Firms vary in size, with small businesses (1–50 employees) accounting for about half the postings (54%). Appendix Table B.3 also shows job seeker characteristics.

Job-seeker characteristics are described in Appendix Table B.3. The average age is 28.1 years (SD: 6.93), and candidates typically possess 3.27 years of work experience (SD: 5.01). Academic performance, measured by GPA, averages 2.85 (SD: 0.80). Jobseekers submit around 8.84 applications (SD: 46.14). The workforce skews male, with women comprising 27% of jobseekers. In terms of compensation, the average current salary is PKR 45,998 (SD: 52,795), while expected salaries are slightly higher, averaging PKR 49,441 (SD: 54,151). Mid-career professionals make up the largest group (41%), followed by entry-level candidates (29%) and interns or students (26%). Senior-level roles, such as department heads (3%) and executives (1%), represent a smaller fraction of jobseekers. Educationally, over half of jobseekers hold a Bachelor's degree (53%), with

an additional 26% possessing a Master's degree. High school or less accounts for a small share (2%), while 7% hold a certificate or diploma, and 1% have earned a PhD.

Firm surveys. I conduct baseline surveys with key decision-makers in over 300 firms. These firms are randomly sampled from the platform's registered list, conditional on the firm having posted at least one job in the past year and a minimum of five in the past three years. The sample is stratfied such that two-thirds of the firms hide salaries while one-thirds do not. In the survey, 81% of respondents have the authority to unilaterally modify their firms' job ads, 90% are involved in setting salaries, and the median respondent has 6 years of hiring experience. A third of respondents are from human resources, 41% are from general administration (e.g., CEOs), and the remainder are department heads. Although the response rate is low (15%), it is not systematically different across firm size, industry, salary non-disclosure frequency, market share of jobs and applications, mean salary, female share of applicants, and other characteristics (see Appendix Figure A.4)

4 Salary non-disclosure: Facts and theoretical framework

4.1 Determinants of salary hiding

More complex jobs are more likely to hide salaries. Using baseline administrative data, I find that as jobs become more advanced in career level and require higher education and experience, they are more likely to conceal salary information from job seekers. Figure 2 illustrates this pattern: as experience and education requirements rise, the likelihood of salary non-disclosure also increases. Similarly, jobs at higher career levels are less likely to disclose salary ranges. These trends are consistent with findings from the U.S. and Chile (Batra et al., 2023; Banfi and Villena-Roldán, 2019). The following section extends this literature by moving beyond comparisons of different types of jobs, to explore implications when job characteristics are held constant.

Holding job characteristics fixed, salary is more likely to be hidden when it is higher. A novel feature of the platform is that salary ranges are mandatory to report to the platform, but optional to reveal to job-seekers. Firms have strong incentives to report accurate salary ranges, as doing so grants them access to market salary comparisons. Additionally, once applications are received, firms can use the platform's filtering tools to screen out candidates whose expected or current salaries fall outside their specified range. While previous research has explored which types of jobs are more likely to hide salary information, this feature allows me to go further by examining whether salary levels vary with disclosure status within jobs of similar types. One may expect that when salaries are higher, firms are more inclined to reveal them in order to

attract the best talent. Surprisingly, I find the opposite: for observationally similar jobs, salaries are more likely to be hidden when they are higher. Figure 3 shows that the minimum, midpoint, and maximum of the salary range are increasing in the probability of salary non-disclosure, conditional on industry, occupation, and city fixed effects, as well as several job characteristics such as experience, skills and education requirements, career level, number of vacancies, and job schedule. Specifically, a one-log-unit increase in the minimum, median, and maximum salary of the range is associated with a 0.5, 7.0, and 8.1 percentage point increase, respectively, in the likelihood of salary being hidden. This suggests that the full distribution of salaries for otherwise comparable jobs is shifted to the right when the salary is hidden.

Salary non-disclosure is driven by firm – not job – characteristics with large firms hiding salaries more. While salary hiding is correlated with job characteristics, job characteristics explain only a small share of the variation in salary disclosure. Figure 4 demonstrates that controlling for a rich set of job characteristics such as the number of required and desired skills, education and experience requirements, stated gender preferences, job schedule, career level, number of job openings, midpoint of the salary range, and fixed effects for occupation, industry, city, and job title collectively explains no more than 12.7% of the variation. In contrast, firm fixed effects alone explain 53.4% of the variation in salary disclosure. Similarly, Appendix Figure A.3, which evaluates the role of the same covariates but using the Bayesian Information Criterion (BIC), shows that firm effects play the most important role in minimizing BIC. Given the importance of firm fixed effects, I next investigate which types of firms are more likely to hide salaries. Figure 5 illustrates that large, well paying firms are less likely to disclose salaries. The first sub-figure uses firm-level data to show that, among firms posting more than one ad (65.9%), the proportion of jobs where the salary is hidden increases with firm size. Specifically, firms with 1-10 employees hide salaries in 35% of their ads, while firms with over 50 employees do so in 41-46% of their ads. The second sub-figure uses the same sample, and shows that the share of firm jobs with hidden salary is increasing in the premiums paid by the firm. Firm premiums are measured as the residuals from regressing the average of maximum salaries advertised by the firm on industry fixed effects, and then split into quartiles. While firms in the bottom quartile hide 35% of their salaries, firms in the top quartile hide 40% of their salaries. The third graph further reveals that salary non-disclosure becomes more likely as firms control a higher quartile of the application market share, where firm market share is measured by splitting jobs into occupation-industry-year clusters and measuring the market share of jobs and applications controlled by a given firm in these 'markets', with errors clustered at the firm level. Firms in the bottom quartile 38% likely to hide salaries, while firms in the top quartile at 59% likely.

4.2 Why do large firms hide attractive salaries?

Advertising high salaries plausibly draws the best talent to a job. Why then do large firms hide their appealing salaries from job ads? To understand this, I first develop a job search model that highlights the potential costs to firms of advertising high salaries, and then link its predictions to firm survey data to rationalize firms' hiding behavior. The model considers how a higher adverstised wage changes the composition of the applicant pool, drawing on insights from Ashraf et al. (2020). Later, I extend it to consider why hiding these higher wages may be rational for a firm.

Model setup. Consider a one-sector, static world where a firm is seeking to recruit a worker for a job. Workers have job-specific ability θ, drawn from a common distribution with CDF $F(\theta)$ and PDF $f(\theta)$ that is known to firms and workers. Note that the same worker may have different θ for different types of jobs, but here job type is held fixed. Workers' ability in a job is thus considered by firms to be a measure of their 'fit' for the job. However, workers' θ is their private information initially, and it is revealed to firms when they invite workers for an interview.

Firms make wage announcements and receive applications from workers. In turn, they face a cost $C(n)$ for advertising a vacancy and processing applications, which is increasing in n, the expected number of applications. Firms post a wage w, and workers earn this wage if hired, regardless of their θ. The match produces surplus θ if formed, and firms get a pay-off $\theta - w$.

Hiring a worker with $\theta < \theta_{\min}$ results in a negative expected payoff. Thus, a firm only hires an applicant if their ability (θ) meets or exceeds a threshold $\theta_{\min}$. The firm selects the best applicant from its pool of n applicants, where the best applicant's ability is $\bar{\theta} \equiv \max\{\theta_1, \ldots, \theta_n\}$. Thus, the firm's hiring probability is the probability that at least one applicant meets the threshold, which is equivalent to the probability that the best applicant satisfies $\bar{\theta} \geq \theta_{\min}$. The probability that a single applicant has $\theta < \theta_{\min}$ is $Pr(\theta < \theta_{\min}) = F(\theta_{\min})$. Since applicants are independent, the probability that all n applicants have $\theta < \theta_{\min}$ is $Pr(\bar{\theta} < \theta_{\min}) = [F(\theta_{\min})]^n$. Therefore, the probability that at least one applicant meets the hiring threshold—and hence that the firm successfully hires the best worker—is:

$$Q(n, \theta_{min}) \equiv Pr(\bar{\theta} \geq \theta_{\min}) = 1 - [F(\theta_{\min})]^n$$

This matching probability is increasing in n and $\bar{\theta}$ as shown in Appendix Section A.3.

Workers' matching probability contains two components: the probability that no other worker with higher ability applied, and the probability that worker's own ability exceeds the firm's

cut-off ($\theta \geq \theta_{min}$). The probability that any given worker has ability at most θ is $F(\theta)$. Since there are $n-1$ other applicants, the probability that all of them have $\theta' < \theta$ is $[F(\theta)]^{n-1}$. The probability that the worker's own ability meets the hiring threshold is $1 - F(\theta_{min})$. The workers' matching probability is then:

$$P(n, \theta) \equiv [F(\theta)^{n-1}] \cdot (1 - F(\theta_{min}))$$

which decreases with n and increases with θ as shown in Appendix Section A.4.

Both firms and workers face uncertainty over matching. Firms also face uncertainty over workers' θ. As a result, both sides make entry decisions based on rational forecasts over $n(w)$, the number of applications a job will draw for each w (increasing in w), and $\bar{\theta}(w)$, the best applicant's expected ability in the applicant pool. The latter also increases in w , as higher wages compensate workers for their outside options.

Firms. The firm chooses w to maximize profits:

$$\pi(w) = [1 - F(\theta_{\min})^{n(w)}] \left(\bar{\theta}(w) - w\right) - c(n(w)) \tag{1}$$

where $\theta_{min} = \frac{c(n(w))+w}{1-F(\theta_{\min})^{n(w)}}$ ensures non-negative profits.

Workers. Workers apply if their expected utility from applying is weakly positive:

$$U_\theta = F(\theta)^{n-1}[1 - F(\theta_{min})] (\lambda \theta_i + w) - V(\theta) - s \geq 0 \tag{2}$$

where workers receive a wage w if employed. They have an outside option $V(\theta)$, increasing in θ, and pay a search cost s. Workers derive non-pecuniary enjoyment from working, which depends on how well matched they are with the job. Specifically, they get $\lambda\theta$ from working, where $0 \leq \lambda < 1$.

Matching. Matching occurs in three stages. In Stage 1, firm choose w to maximize profits. In Stage 2, workers make application decisions given w. In the third stage, not modeled explicitly but anticipated in stages 1 and 2, firms pick the best worker.

Workers apply to a job with wage w if their θ falls in a given range. There is a threshold $\underline{\theta}(w)$ below which workers do not apply because their expected utility from working relative to the search cost is too low. There is an upper threshold $\bar{\theta}(w)$ beyond which workers with $\theta \geq \bar{\theta}(w)$

do not apply because the expected payoff is below their outside option. These thresholds can be seen in Panel (a) of Figure 6 .

Impact of advertising a high wage. Higher wages increase $\bar{\theta}(w)$ by compensating high-ability workers for their higher outside option. But, as shown in Panel (b) of Figure 6, they have two opposite impacts on $\underline{\theta}(w)$, making the net result ambiguous. First, they decrease $\underline{\theta}(w)$ by compensating low-ability workers for their lower enjoyment of work relative to the application cost, inducing workers with lower ability to apply. Second, they increase total demand for the job, reducing the likelihood that any individual worker gets hired, thereby discouraging applications (proof in Appendix Section A.5):

$$\frac{\partial\big[P(n(w),\theta)\big]}{\partial w} < 0,$$

But this effect is stronger for low-ability workers because higher ability workers are now selecting into the applicant pool, reducing the likelihood that low ability workers get hired (proof in Appendix Section A.6):

$$\frac{\partial^2\big[P(n(w),\theta\big]}{\partial w\,\partial\theta} > 0,$$

As a result, higher wages may increase $\underline{\theta}(w)$ because lower ability workers now experience tougher competition.

Result: Upper threshold is increasing in w (i.e., $\frac{\partial\bar{\theta}(w)}{\partial w} > 0$). But lower threshold may be increasing or decreasing in w. For details see Sections A.7 and A.8.

Firm beliefs. The model predicts that disclosing high salaries in job ads has ambiguous impacts on the average quantity and quality of the applicant pool, depending empirically on whether the higher wage offsets the lower likelihood of being hired amongst low ability workers. Firm surveys reveal that firms who hide salaries overwhelmingly believe in one of these two possibilities. Figure 7 shows that 63% of firms who hide salaries believe that revealing their salaries in job ads will draw a higher total number of applications, and 72% further believe that it will weakly diminish the average applicant quality .

Costly screening. Firms should generally seek to maximize the total number of applications as it increases the probability of finding a match. Meanwhile, the unsuitable applicants can simply be filtered out. However, having more choice over applicants is only favorable as long as firms are able to screen out lower quality applicants at a reasonable cost. The fact that a potential decline in applicant quality instead drives firms to hide salaries implies that screening is costly. Theoretical work confirms that salary non-disclosure in job ads is more likely in settings where workers are

more dispersed in ability and the risk of adverse selection is high (Michelacci and Suarez, 2006). This may be especially the case in developing countries where the supply of human capital is growing but traditional resume characteristics offer weak signals of true ability. Over the last two decades, the number of educational institutions, and levels of educational attainment have risen rapidly in developing countries. However, the quality of education is vastly heteregenous, and often uncorrelated with learning outcomes (Muralidharan and Singh, 2023; Bandiera et al., 2024b). Moreover, as many workers move out of agriculture, their experience of working in manufacturing and services based firms is on the rise. But given large heterogeneity in the nature of jobs, and higher turnover in developing countries, the relevance of experience in determining worker quality remains ambiguous (Alfonsi et al., 2024). Finally, as job posts and applications move online, digital job search platforms – which are expressly designed to make it easier for workers to apply to many jobs – are generating even more applications (Autor, 2001).

These patterns are highly relevant in my setting where the average job receives a large number of applications (75.5), and the average applicant spends only ~2 minutes sending out the job application. On paper, most applicants look similarly qualified for the job: 89% meet the education requirements while 76% meet the experience requirements of the job . To meaningfully filter applicants that are poor fits, a firm may need to invest considerable resources interviewing candidates. These screening costs are likely to be even more substantial for large firms who receive more applications, and face more institutional barriers to terminating the contract of a worker ex-post revealed to be a poor fit. In light of costly screening and the risk of adverse selection, research has shown that firms often limit their hiring to familiar social networks (Jayachandran, 2021a; Chandrasekhar et al., 2020). In this paper, I document that salary non-disclosure is another coping mechanism similarly employed by firms in response to costly screening.

How salary non-disclosure can self-screen. If firms do not post wages, workers form expectations over wages: $\tilde{w} = w + \epsilon$ where $\epsilon \sim N(0, \sigma^2)$. Accessing wage information when it is hidden is more costly for workers with lower θ because they lack the experience or skills in the relevant role that would enable them to extract wage signals from job posts, or are less well connected to relevant networks. Alternatively, they have to spend more time researching a firm and its specific job. As a result, application cost is heterogeneous under this regime, with $s_\theta = s + \frac{1}{\theta_i}$ where the cost rises as the fit with the job declines. Workers apply if:

$$F(\theta)^{n-1}[1 - F(\theta_{min})]\,(\lambda\theta_i + \tilde{w}) - V_\theta - s - \frac{1}{\theta_i} \leq 0.$$

Wage hiding is, thus, a rational response by firms who believe that as θ falls, the cost of application rises prohibitively, deterring lower ability workers from applying and raising $\underline{\theta}$. This means that

the process of learning wages when they are hidden is a screening ordeal that disproportionately affects workers who are worse fits, leading them to self-screen out of the applicant pool while the right type of worker optimally chooses to apply. By contrast, a law that mandates salary range disclosure in job ads eliminates $\frac{1}{\theta}$, all workers of all types equal access to the job.

Prediction. As $\theta \to 0$, the cost of application grows, deterring lower-ability workers, and raising the threshold $\underline{\theta}(w)$. Thus, hiding wages may reduce the total number of applicants, while the quality of the applicant pool increases.

4.3 Gender impacts of salary non-disclosure

Salary hiding is favorable for match quality if it screens purely on workers' fit with the job. However, there may be some gender-specific barriers to job search that it imposes, which are orthogonal to fit. To investigate this, Figure 8 shows the relationship between number of applications and the salary of a job by gender, controling for industry, occupation and city fixed effects, and job characteristics such as experience and education requirements, career level of the job, number of vacancies corresponding to the ad, number of required skills and the schedule of the job. Panel (a) shows the application counts, while Panel (b) presents mean-adjusted application counts to account for there being more male applications at each salary level, which stems partly from there being more men in the labor market, and partly from the average man sending about 7 more applications than the average woman. When the salary is visible, a job receives 15.3 more applications from men with each log unit increase in the maximum advertised salary. Meanwhile, it receives 4.2 more female applications. Accounting for gender differences in application levels, Panel (b) shows that women are slightly *more* responsive to salary information than men so long as the salary is visible. Specifically, their application rate rises by 28% with each log unit increase in salary, while men's rises by 20%. However, when the salary information is hidden, women lose the ability to direct search in response to salary. The number of female applications a job receives has no relationship with the salary of the job in this case. By contrast, men still retain some ability to direct search: they send on average about 2 more applications for each log unit increase in salaries. Since jobs with hidden salaries are higher paying, an inability to target them implies women effectively self-select out of the best paying opportunities.

This suggests that salary non-disclosure imposes costs on job search that are disproportionate for women. This may be because women lack access to relevant professional networks, or the work experience required to infer wages from non-wage information. Alternatively, women may have a higher opportunity cost of job search. In considering applying to a job, they may account for the time cost not just of the initial application but subsequent stages of hiring as well, and may

not wish to enter this process without more certain information about their likelihood of success. Thus, women may be more averse to ambiguity due to familial gender norms that shape their time use and job search. However, it may also be the case that despite controlling for various job characteristics, jobs that hide salaries are unobservably different in other regards that makes women less likely to apply to them. To consider whether salary hiding makes a difference or whether jobs with hidden salaries are different, I turn to an experiment where jobs are randomly induced to reveal salaries.

Experiment Design

In partnership with Pakistan's largest online job search platform, I run an experiment on over 14,000 jobs and 6,354 firms where randomly selected ads are required to reveal salaries while control ads retain choice over whether to disclose this information. Specifically, at the time that a new job ad is being uploaded by a firm, a random number is generated at the back end which determines the treatment assignment of a given ad. Firms posting jobs in the control group continue being able to choose to hide this information from job-seekers, as shown in Appendix Figure 9 Panel (a). Meanwhile, treated ads are unable to access the hiding button, and as shown in Panel (b) of Figure 9, they are told instead, *"To find you the best match, the salary for this will **displayed** in the ad, as part of a reform. Click here to learn more."* Clicking on the provided link generates a pop-up shown in Figure A.5 Panel (a), which informs firms that the platform anticipates that salary disclosure in job ads will improve matching, and to test this, some jobs are being randomly selected to disclose salary ranges. This makes it known to firms that they are part of an on-going experiment. Firms posting treated ads are also shown a pop-up message before they finalize the job ad, reminding them that the salaries they have entered will be publicly revealed. This is message is shown in Figure A.5 Panel (b).

Compliance. Firms that wish to opt out of the experiment may contact platform representatives, listen to an explanation of the experiment, confirm their preference to opt out, and wait for manual processing. As was the case at baseline, non-compliant firms are required to privately disclose salaries to the platform, allowing me to examine selection into non-compliance. This is crucial because existing studies on wage transparency laws highlight substantial non-compliance but cannot analyze selection into compliance due to the inaccessibility of hidden salaries for both workers *and* researchers. For example, despite legal requirements, 30% of job ads in Colorado fail to include salary information (Arnold et al., 2022). Since randomization is conducted at the job ad level, firms cannot avoid treatment by refreshing the webpage or reposting the job with the same title later. The platform ensures consistent treatment assignment by linking the treatment status

to the first attempt of posting the job, even if it was left incomplete by the firm and resumed later. Additionally, the platform employs a large sales team that reviews all ads daily before they go live. If a firm attempts to evade treatment by making minor changes to the job title while posting fundamentally the same job, the sales team intervenes. They contact the firm, standardize the job title with the earlier post, and the platform reassigns the original treatment status to the updated ad. This mechanism ensures compliance with the experiment's design.

Empirical Approach

I assess intent to treat impacts on log salaries and applicant quality using the following OLS specification.

$$Y_j = \alpha + \beta T_j + \epsilon_j \tag{3}$$

Y_j are the outcomes of interest for a given job while T_j is an indicator that equals 1 if the ad was assigned to treatment, and 0 otherwise – regardless of whether the ad complies with treatment. Since some ads in the treatment group may not disclose salaries while others in the control group may disclose salaries, the results presented in the following section are lower bound estimates.

To estimate treatment effects on counts data (views, applications) I run the following poisson specification and report incident rate ratios:

$$Y_j = exp(\alpha + \beta T_j) \tag{4}$$

This is helpful not only because the poisson distribution is better suited to counts data, but also because it allows me to estimate percentage changes which account for baseline differences in the number of male and female applications.

Results

First stage and compliance. Figure 10 shows that about 50-55% of ads at baseline did not show salary range information publicly. Treatment increases the likelihood of salary range disclosure by 41 percentage points. Compliance with the treatment is high overall, with an average non-compliance rate of 3%. However, non-compliance is more common among large firms, where 6.6% of treated job postings do not disclose salary this requirements.[5] In comparison, only 0.02% of job postings from smaller firms are non-compliant. Additionally, Figure A.6 shows that the

[5]Large firms are those with over 50 employees. The split at 50 ensures that the number of job ads corresponding to small and large firms are roughly even.

number of job postings and active firms remained stable following the treatment, suggesting that the mandate for salary disclosure did not lead to a reduction in platform participation. The low rates of non-compliance and firm exits should not be interpreted as evidence that salary disclosure is costless for firms. Instead, they underscore the bargaining power of the platform. On its webpages, the platform pitches the disclosure requirement as a mandatory condition for posting the ad. Most firms accept this among many other platform requirements as a necessary pre-requisite for accessing the country's largest online market of job-seekers. Thus, firms trade off the potential costs of salary disclosure with the opporunity cost of losing access to this labor market. Large treated firms have more leverage over the platform as they can undermine the appeal of the platform to jobseekers if they decide to exit. As a result, such firms feel better positioned to negotiate an exception to disclosure requirements (even though an exception is granted to everyone who requests it, conditional on them taking the initiative to ask). Therefore, non-compliance is much higher among large firms relative to small firms. However, large firms with exceptional market power over the platform are limited in number, allowing the platform to maintain good enforcement of its disclosure requirements regardless.

Impact on advertised salaries. The requirement to disclose salary ranges in job ads can have both positive and negative impacts on advertised salaries. On the one hand, salaries may increase as firms compete to attract the best talent, particularly if, as seen in baseline data, firms that previously withheld salary information were paying higher wages and are now driven by the experiment to reveal these salaries. On the other hand, salary levels may decrease if firms, having greater visibility into their workers' outside options, implicitly or explicitly collude to suppress wages. Additionally, salary levels could drop if firms reduce the salaries for new hires due to pressure from incumbent workers, who now have easier access to pay information and may demand higher wages. In addition to salary levels, the intervention may affect the width of the salary range. Firms that wish to avoid disclosing specific salaries may opt to broaden the range, providing a less precise signal of the worker's potential wage. Widening the range is thus another form of strategic non-compliance with the intended reform.

Table 1 considers treatment effects on the log minimum and maximum adverstised salaries, as well as the size of the salary range, computed as the maximum minus minimum salary, divided by the midpoint of the range. Column 1 shows that the effect of the treatment on the log of the maximum advertised salary is null. Column 2 examines the treatment's impact on the log of the minimum advertised salary. The results indicate that treatment leads to a 3% increase in the minimum salary (significant at the 5% level). The treatment has a negative and statistically significant effect of -0.04 (p<0.01), indicating that firms tend to post narrower salary ranges in response to the disclosure requirement. This is contrary to the expectation that

firms would widen their ranges to avoid providing meaningful information to jobseekers. This finding aligns with evidence from the firm survey, in which firms report that applicants anchor their wage expectations to the maximum salary. Widening of salary ranges and the resulting higher maximum salaries may therefore lead to tougher salary demands from applicants during negotiations. I take these results to suggest that on the demand-side, the intervention has no or modest impacts on salary levels, especially among large firms.

Impact on job search. Salary range disclosure in job ads should have no impact on workers' search behavior if there are no information frictions that salary transparency resolves, or if workers do not adjust their job search based on salary information. To test whether salary information matters, I consider treatment impacts on job views and applications. Views capture whether workers click on job summaries to access its details. These summaries, examples of which are shown in Appendix Figure A.7, include salary range information when available, and thus, an applicant choosing to view further details of the job may be responding to the salary information. Table 2 shows that views on job ads with salary range information increase by 50% (Panel A, Column 1) while job applications increase by 54% (Panel A, Column 4). The treatment effect on applications is 18 percentage points larger for women (Panel A, Column 6) than for men (Panel A, Column 6), with the difference significant at $p = 0.03$, as reported in Panel A, Column 6. This suggests that salary information plays an important role in determining where job-seekers direct search, particularly shaping women's search decisions.

Large firms. If salary information matters for directing search, it should be the case that impacts are largest for jobs where the salary was previously harder to infer, but is ex-post revealed to be high. As specified in the pre-analysis plan, jobs at large firms match these characteristics exactly, and should experience larger treatment effects.[6] Table 3 Panel A, Columns 2-3 show that while views on treated jobs increase by 20%, they increase by 70% for jobs at large firms, with the difference significant at p-value=0.01. Similarly, Columns 5-6 show that applications to jobs at small firms increase by 21% but they increase by 78% for large firms. Why is it the case that treatment effects are driven by jobs at large firms? In line with the descriptive statistics, Table B.4 Column 2 shows that in steady state, it is harder to access wage information for large firms because large firms are 20 percentage points (31.3%) more likely to conceal it from job-seekers. The treatment increases salary range disclosure of large firms by 48 percentage points. Second, Table 4 shows that large firms pay more. Column 1 reveals that the maxmium salary of large firms in the control group is 18% higher than that of small firms. Treatment has no impact

[6] A firm is characterized as large if it has over 50 employees, and ads at firms with fewer than 50 employees constitute 54% of all jobs so the split at 50 roughly divides the sample in half (see Appendix Table B.1 for the distribution of the firm size variable).

on these salary levels and thus, it remains the case that large firms pay more in the treatment group. Similarly, Column 2 shows that in the control group, the minimum salary advertised by large firms is 30% higher than that advertised by small firms. Since treatment does not affect the minimum salaries of large firms, and raises the minimum salaries of small firms by only 3%, it remains the case that large firms have higher minimum salaries in the treatment group. Moreover, the treatment effect on small firms indicates that they may have adjusted their salary levels in response to the higher salaries now publicly disclosed by large firms. Column 3 also shows that the size of the range advertised by large firms is narrower than that of small firms, in both the treatment and control groups. Taken together, these results highlight that large firms have salaries that were previously harder to access, but are ex-post revealed to be higher. As a result, workers allocate more of their search efforts towards these firms.

Women. On the supply side, if salary information influences job search behavior, salary transparency is likely to have the greatest impact on individuals who are particularly sensitive to this information but face barriers to accessing it when it is not publicly available. As pre-registered and based on baseline patterns, women appear to be the primary beneficiaries of such a reform. They are highly responsive to salary information but face greater difficulty inferring wage signals from job postings when transparency is lacking. Figure 11 illustrates these dynamics. Panel (a) shows that in the control group, jobs at large firms attract 64.3% more applications compared to jobs at small firms, but only 40.5% more applications from women. The resulting gender gap of 23.8 percentage points is significant at p=0.02, highlighting baseline differences in the ability to target higher paying opportunities when salary information is potentially unavailable. Panel (b) demonstrates that in the treatment group, where salary transparency is introduced, jobs at large firms receive 69.9% more applications from men, and 115.5% more applications from women, with the gender difference significant at the 1% level. Finally, Panel (c) reveals that the baseline gender gap observed in Panel (a) not only closes under the treatment but reverses in favor of women. The reform prompts a stronger reallocation of search efforts from small to large firms among women compared to men. Specifically, jobs at large firms receive 127.5% more applications from men than jobs at smaller firms. By contrast, they receive 164.5% more applications from women. This gender difference is significant with a p-value of 0.01, underscoring how salary transparency shifts search dynamics, disproportionately benefiting women. Corresponding results on job views are in Appendix Figure A.11 while a tabular version of results on both views and applications is presented in Appendix Table B.8.

Average applicant quality. While firms recognize that salary disclosure can increase the number of applicants, they are concerned that average applicant quality may decline to the extent that the benefits of having a larger pool are outweighed by the additional screening costs. Table

5 examines whether concerns about the decline in average quality are substantiated empirically. Panel A reports the share of applicants who meet the experience requirements for a job. The results show largely null effects, with the exception of a modest decline of 1 percentage point for jobs posted by small firms. Notably, even in the control group, 62–81% of male and female applicants to small and large firms meet the experience requirements, so this decline represents only a 1.2% relative change in the treatment group's average experience profile. Panel B evaluates the share of applicants who meet the education requirements. Similar to experience, there is a 1 percentage point average decline for jobs at both small and large firms. Given the high control means of 88–91%, this translates to at most a 1.1% relative change in the education profile of the average applicant. These high control means underscore the descriptive evidence that most applicants seem to be a good match for jobs based on traditional resume characteristics, and further distinguishing applicants' true abilities remains a challenge, regardless of salary disclosure. Panel C examines the share of applicants who meet all skill requirements for a job. Skills show greater variation in applicant quality. In the control group, 39–48% of male and female applicants to small and large firms meet all skill requirements. Under treatment, this likelihood declines for jobs at large firms by 3 percentage points among male applicants and 2 percentage points among female applicants. Relative to control jobs, this represents a decline in skill match quality of 6.5% for men and 5.1% for women. These findings capture effects on observable resume characteristics and suggest only modest declines in average applicant quality. However, they may signal more significant declines in unobservable traits. Since this aligns with firm survey responses and predictions from the job search model, I interpret this as evidence that salary transparency in job ads lowers the average quality of applicants.

Selection into the applicant pool. While average applicant quality reflects screening costs, it is less relevant for assessing match quality, as firms hire the best – not the average – candidate in their applicant pool (as modeled in Section 4.2). To consider selection into the applicant pool, Table 6 examines how salary range disclosure affects the likelihood that the highest- or lowest-ability workers in the market apply to jobs at large firms. Appendix Table B.5 presents corresponding results for small firms. This analysis considers the entire labor market, classifying workers as high- or low-ability based on their position in the relevant percentiles of the distribution. Panels A and B focus on applicants in the top decile of the expected salary distribution, treating expected salary as a potential proxy for applicant quality. Panels C and D, by contrast, examine applicants in the bottom decile. Recognizing that expected salary may be influenced by gender biases and reflect more than ability, Columns 2 through 4 introduce alternative measures of applicant quality. Column 2 identifies applicants in the top or bottom quartile of GPA. Column 3 focuses on applicants in the top or bottom decile of years of experience. Column 4 considers whether applicants have ever managed a team – about half of all job-seekers have team

management experience. The pattern of results described below remains consistent regardless of the measure of quality used.

A key takeaway from Table 6, Panels A and B, is that control jobs are almost guaranteed to attract at least one high-ability man, with the likelihood ranging from 82% to 91%. This is despite the fact that no restrictions are imposed on the relevance of a given job to these male applicants. In contrast, the likelihood of attracting a high-ability woman is significantly lower, at just 51% to 55%. This disparity arises from two factors: first, the labor market has more men, resulting in a larger pool of men in the top quartiles or deciles of ability distributions. Second, high-ability women apply to fewer jobs on average—submitting 4–5 fewer applications than their male counterparts, as detailed in Appendix Table B.6. As a result, for high-ability men, salary range transparency has a modest effect. Panel A shows that transparency increases the likelihood of application by men in the top decile of expected salary by 2.4% (Column 1). Similarly, men in the top GPA quartile are 3.3% more likely to apply (Column 2), those in the top decile of years of experience are 3.7% more likely (Column 3), and men with management experience are 2.2% more likely to apply (Column 4). By comparison, salary range transparency has a much stronger impact on high-ability women. Panel B shows that transparency increases the likelihood of application by women in the top decile of expected salary by 10.9% (Column 1). Women in the top GPA quartile are 17.3% more likely to apply (Column 2), those in the top decile of years of experience are 17.6% more likely (Column 3), and women with management experience are 13.2% more likely to apply (Column 4). Each of the gender differences in a given column, across Panels A and B are statistically significant. These results underscore how salary range transparency disproportionately benefits high-ability women, improving their representation in applicant pools and narrowing the gender gap in access to higher-quality opportunities. By using salary non-disclosure as a screening tool, firms are effectively screening these high-ability women out of their applicant pools

However, Panels C and D of Table 6 reveal a trade-off in using salary disclosure to attract high-ability applicants. Among control jobs, the likelihood of having at least one low-ability man in the applicant pool is high, ranging from 83% to 97% across different measures of ability. This reinforces that men, regardless of ability apply broadly. Moreover, low-ability women, as measured by GPA, years of experience, or management experience, also apply more broadly than high ability women. For control jobs, the likelihood the job has at least one low-ability woman ranges from 60% to 79%. Panel C shows that salary transparency increases the likelihood of application by men in the bottom decile of expected salary by 3.6% (Column 1). Similarly, low-ability men in the bottom GPA quartile (Column 2) and those in the bottom decile of years of experience (Column 3) are 2.2% and 1.0% more likely to apply respectively. Finally, men who

have never managed a team are also 1.0% more likely to apply to treated jobs at large firms. In comparison, Panel D shows that low ability women in the bottom decile of expected salary are 13.6% more likely to apply (Column 1). Those in the bottom quartile of GPA are 10% more likely to apply (Column 2) while those in the bottom decile of years of experience are 5.5% more likely to apply (Column 3). Finally, those who have never managed a team are 6.3% more likely to apply. With the exception of results on expected salary, all of these effects are smaller for low than high ability women. Nonetheless, they underscore an important dimension of the cost of salary range disclosure: to attract high ability women, firms must tolerate applications low ability women as well.

Quality of top candidates. If higher-quality applicants from the labor market are drawn to treated jobs, the quality of a firm's potential shortlist should improve. To test for this, I now consider whether the top candidates applying to treated jobs are higher quality than the top candidates applying to control jobs. To identify top candidates, the top three values in each applicant pool are first determined for five key attributes: expected salary, education, experience, GPA, and team size managed. Applicants who rank in the top three for any of these attributes are flagged accordingly. Next, a score is constructed for each applicant, representing the proportion of these five attributes in which they rank among the top three. Finally, applicants are classified as the best in the pool if their score is among the top three in their applicant pool. Table 7 presents the results of this analysis, with expected salary, education level, years of experience, GPA, and team size managed normalized using the mean and standard deviation of the control group. Column 1 shows that the average expected salary of these top candidates is no different in the treatment group compared to the control group. However, across Columns 2-5, we see that the education level, years of experience, GPA, and team size managed by these top candidates are 0.07-.0.12 SDs higher in treatment than control. Moreover, Column 5 shows that the likelihood that the top candidates include at least one woman is also 3 percentage points (5.2%) higher in treatment than in control. These effects are stable across small and large firms (Panels B and C respectively), but especially pronounced for large firms.

Firm responses to applications. While the results above consider a potential shortlist based on observed resume characteristices, firms may evaluate candidates using different criteria, or fail to identify the best candidates due to the noise generated by a higher volume of applications in treatment. Thus, I now consider the candidates whose CVs are viewed or downloaded by firm representatives as a proxy for firms' hiring choices. These firm responses are captured through firms' clicks on the application dashboard of the platform, where firms are presented with summarized profiles of each applicant, in addition to a link to their CV and the option to download the CV. This information on clicks is missing for firms who bulk-download CVs via

email, or engage with applicants via a phone-based app. I observe these CV views and downloads for about one-third of the jobs. Access to this information is not differential by treatment status, as shown in Appendix Table B.7. Using these data on clicks, I track whether an applicant's CV was viewed or downloaded. Table 8 shows that firms review and download a smaller proportion (9.5–10.7%) of CVs for treated jobs. Since these jobs receive significantly more applications than control jobs, this suggests that firms encounter higher screening costs and diminishing returns to evaluating additional candidates. Despite this, the share of female CVs viewed or downloaded increases by approximately 9% in treatment jobs. This occurs even as male applications rise in parallel and the overall review rate declines, indicating that firms are placing greater relative consideration on female candidates.

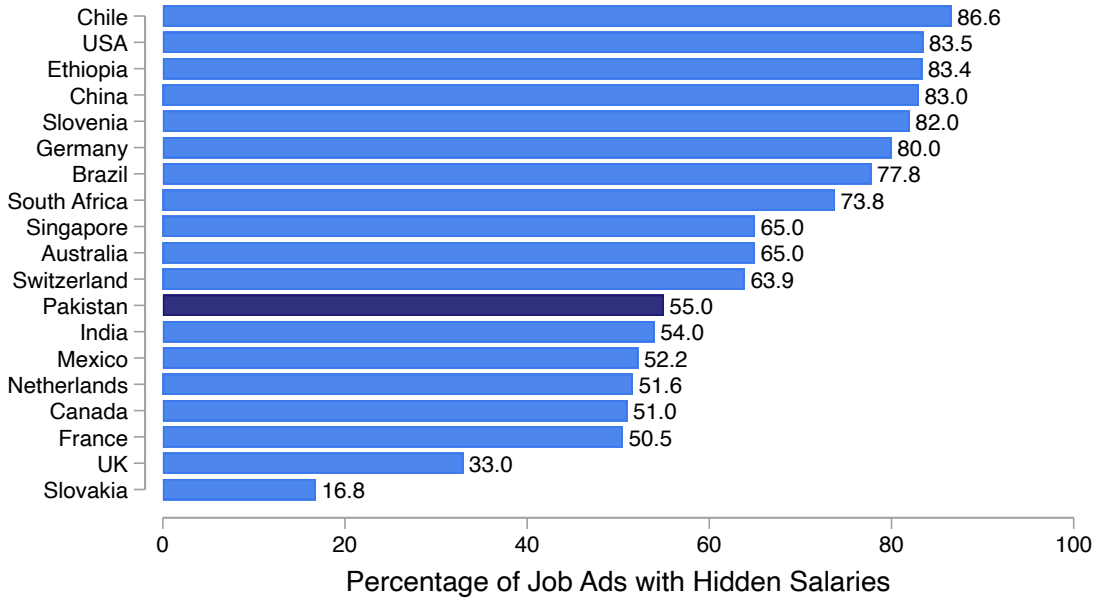
Quality of candidates considered by firms. Treated firms receive 53.8% more applications than control firms, driven primarily by large firms, which see a 78.1% increase. This surge in applications heightens the screening burden on treated jobs, and may introduce noise, making it harder to discern ability signals. While the earlier discussion highlighted that top applicants—particularly at large firms—are of higher quality in treated jobs (Table 7), I now assess whether the CVs that firms actually review reflect this quality improvement. Table 9 examines the impact of treatment on the average quality of applicants whose CVs were viewed or downloaded by firms, with views and downloads serving as proxies for shortlisting. As in Table 7, expected salary, education level, years of experience, GPA, and team size managed are normalized using the mean and standard deviation of the control group. Column 1 shows that the average expected salary of considered candidates is similar between treatment and control. However, Columns 2 and 3 indicate that treated firms review candidates with higher education levels (0.10 SDs) and more experience (0.06 SDs) than those in the control group. Columns 4 and 5 show positive but statistically insignificant impacts on GPA and team size managed. Column 6 further shows that the likelihood that at least one considered candidate is female is 3 percentage points (4.8%) higher in treatment than in control. Panels B and C reveal that these effects are driven by small firms. For small firms (Panel B), treatment increases the education and experience levels of considered candidates by 0.08 and 0.10 SDs, respectively, with a 5 percentage point increase in the likelihood of considering at least one female applicant. In contrast, for large firms (Panel C), while the education level of considered candidates increases by 0.11 SDs, effects on other characteristics are more muted. Taken together with Table 7, these results suggest that the higher volume of applications received by large firms weakens their ability to identify high-quality candidates within their applicant pool. These results highlight a key tradeoff: while salary disclosure attracts high-ability workers, employers' screening limitations may make it difficult to distinguish them amid the large influx of lower-ability applicants.

Conclusion

This experiment demonstrates that salary non-disclosure imposes higher search costs on women. High-ability women, who are particularly sensitive to the absence of salary information, self-select out of nearly half of all job opportunities when salaries are hidden. In contrast, men and lower-ability women apply broadly regardless of transparency, while salary disclosure increases high-ability women's likelihood of applying to large, high-paying firms by 11–18%. As a result, the female share of CVs viewed or downloaded by firms rises, even as the overall application volume grows and firms review a smaller proportion of received CVs. These findings reveal a critical trade-off: while salary non-disclosure may help filter out less-qualified applicants, it also screens out highly skilled women. However, attracting these applicants comes at a cost. When the applicant pool becomes too large, the signal of ability is diluted by noise, making it harder for large firms to identify top candidates. Crucially, relying on salary non-disclosure as a screening tool fails to account for the distinct job search behaviors of high-ability women—an oversight that can be costly for roles where attracting top talent is essential and where men and women are not perfect substitutes. Ashraf et al. (2024) show that in countries with low female labor force participation, such as Pakistan, high-ability women are more positively selected than men, leading to productivity gains for the same wage bill.

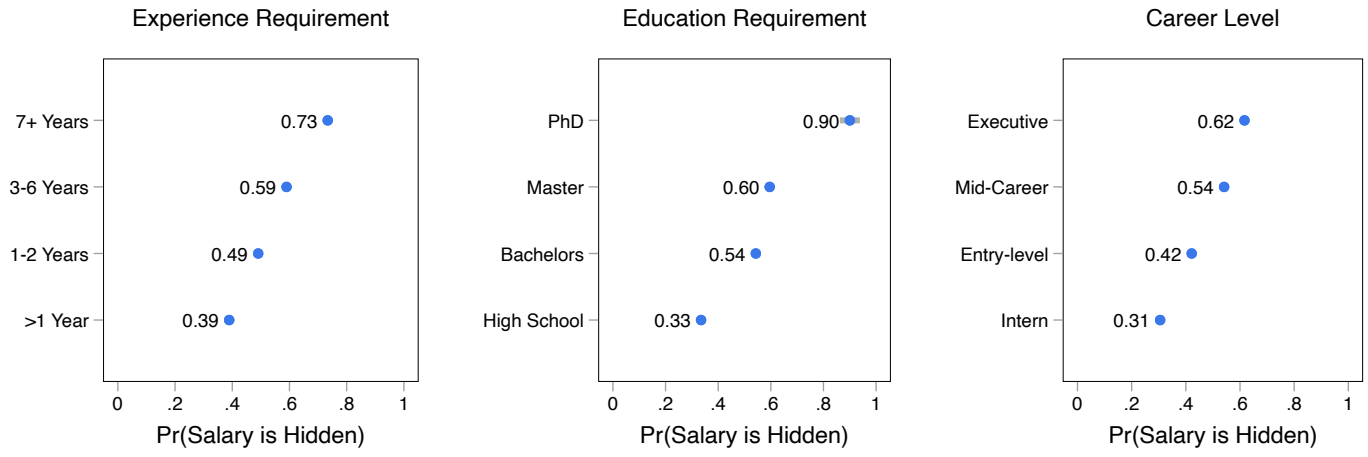
Figures

Figure 1: Salary Non-Disclosure Globally



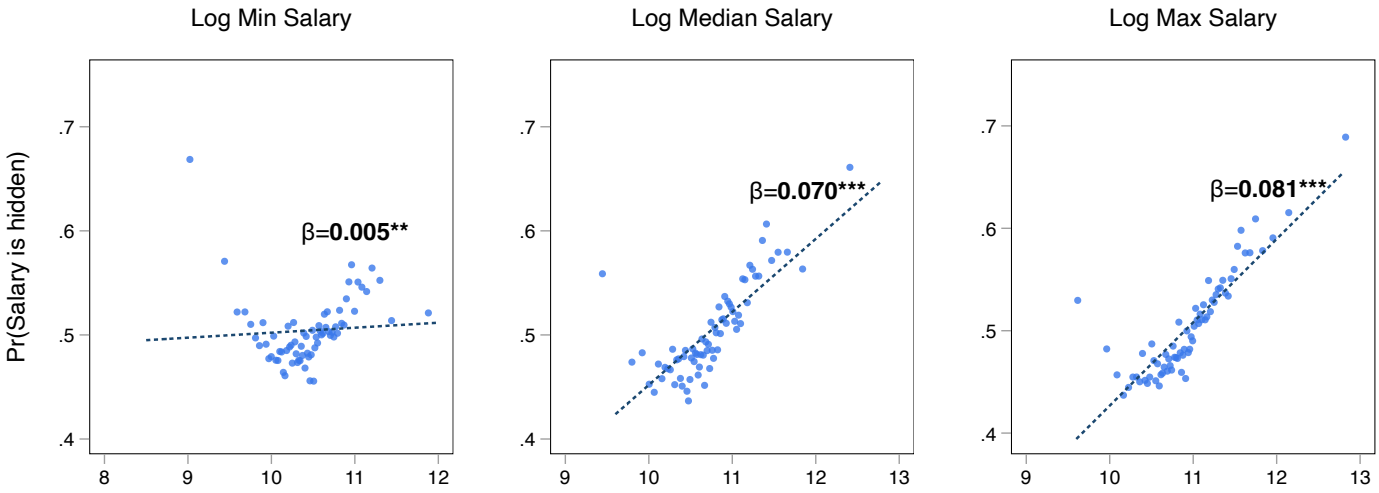
Notes: The figure shows percentage of job ads across different countries in which no salary information is stated. This information has been gathered from the following sources: Banfi and Villena-Roldán (2019); Batra et al. (2023); Brenčič (2012); Kuhn and Shen (2013); Skoda (2022); Indeed Hiring Lab (2023a, 2024, 2023b); HRD Asia (2023); People Matters (2023); AfriWorket (2024); Adzuna (2022) [Return to page 9]

Figure 2: Jobs that hide salaries are more complex



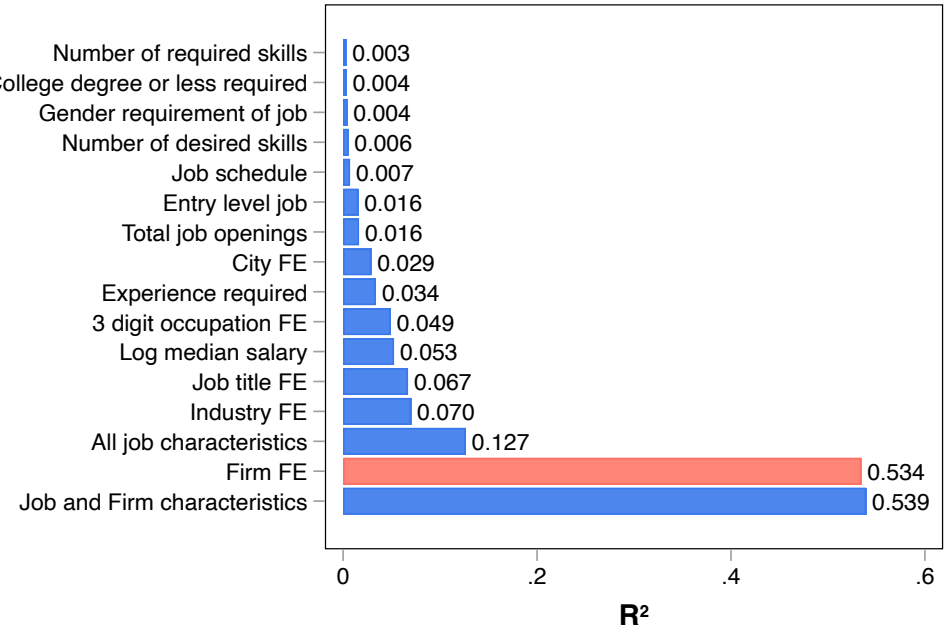
Notes: The figure shows correlations at the job level between an indicator for whether the salary is hidden, and various job characteristics. The sample consists of all baseline jobs. [Return to page 11]

Figure 3: Comparable jobs with hidden salaries pay more



Notes: The figure shows the job-level relationship between an indicator for whether the salary of the job is hidden, and the log minimum, median and maximum salary of the job, residualized on industry, occupation and city fixed effects, and job characteristics (experience requirement, education requirement, career level of job, number of vacancies corresponding to the ad, number of required skills and job schedule). The median salary corresponds to the midpoint of the range. The sample consists of all baseline jobs. [Return to page 12]

Figure 4: Firm effects explain most of the variation in hiding



Notes: The figure shows R^2 from a job-level regression of an indicator for whether the salary of the job is hidden on each characteristic of the job, one at a time, until the third-last row in which all job characteristics are entered together. In the second to last row, firm fixed effects are controlled for by themselves, and the final row includes firm effects together with job characteristics. The sample consists of all baseline jobs. [Return to page 12]

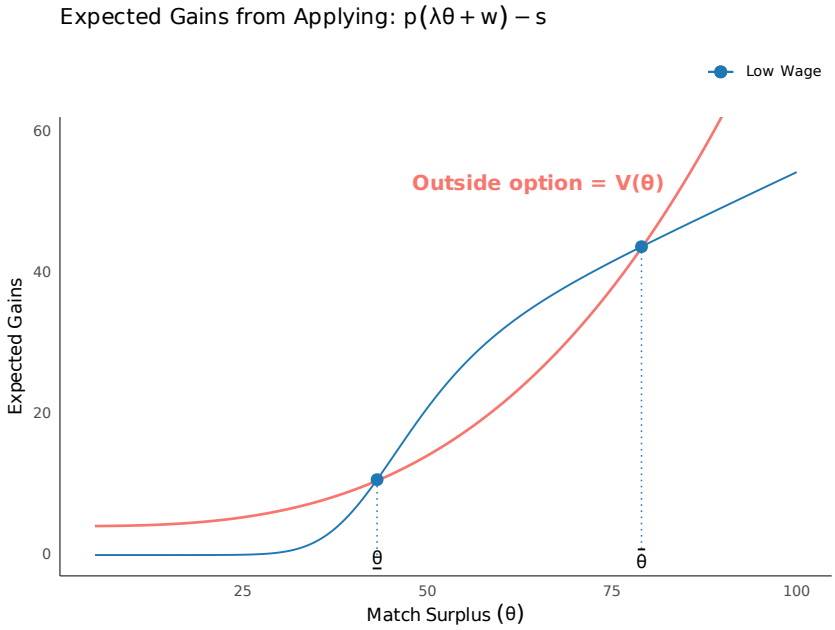
Figure 5: Firms that hide more are larger and better paying



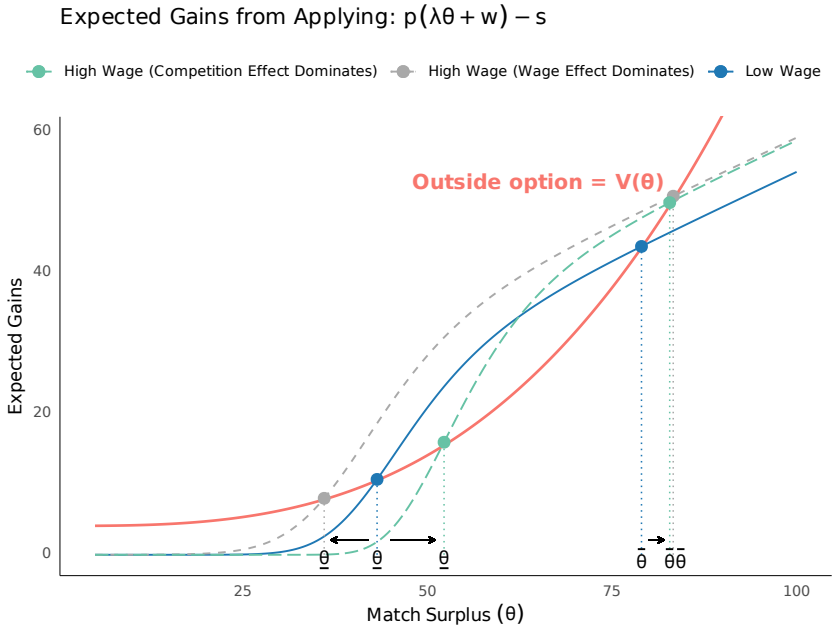
Notes: The first figure shows firm-level relationship between the share of jobs a firm posted that had salary hidden, and the number of employees in the firm. The sample consists of all firms that posted more than one ad, which corresponds to 65.9% of the firms in this period. The second graph is based on the same sample, and considers the relationship between firm premiums and proportion of salaries hidden among the jobs advertised by a firm. Firm premiums are measured as the residuals from regressing the average of maximum salaries advertised by the firm on industry fixed effects. The third figure is at the job-level. It shows the relationship between the quartile of market share of applications and vacancies that a given firm has, and whether the salary of the job is hidden. A market consists of all job ads in the same occupation-industry-year cluster. In these job-level graphs, errors are clustered at the firm level. The sample consists of all baseline jobs, and the firms associated with these jobs. [Return to page 12]

Figure 6: Theoretical framework: Application thresholds

(a) Selection into Application

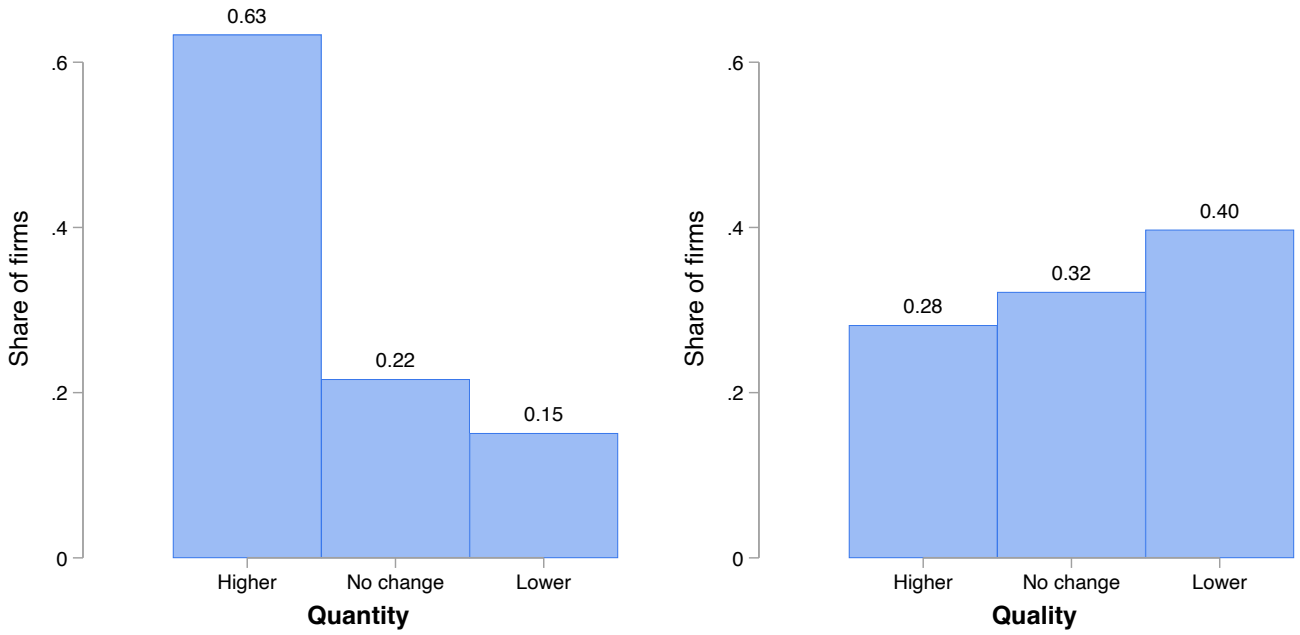


(b) Increase in advertised wage



Notes: This figure illustrates the relationship between worker ability θ, the expected gains from applying to a job (solid blue line), and the outside option $V(\theta)$ (solid red line). The intersections of these two curves define the lower and upper application thresholds, denoted as $\underline{\theta}$ and $\bar{\theta}$, respectively. The expected gains from applying are determined by the hiring probability and the expected wage, adjusted for search costs. Specifically, it is: $P(n, \theta) \cdot (\lambda\theta + w) - s$. Panel (b) shows two counterfactuals when a higher wage (w) is advertised. In one case, the competition effect dominates, and in the other, the wage effect dominates. [Return to page 15]

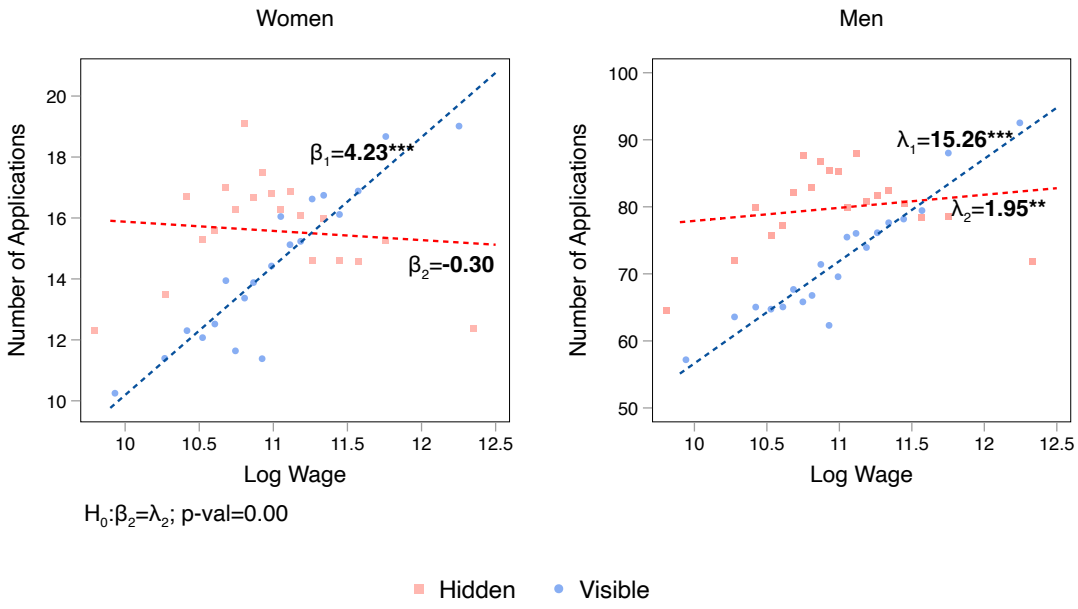
Figure 7: Firms expect higher quantity, weakly lower quality if salary hiding policy is reversed



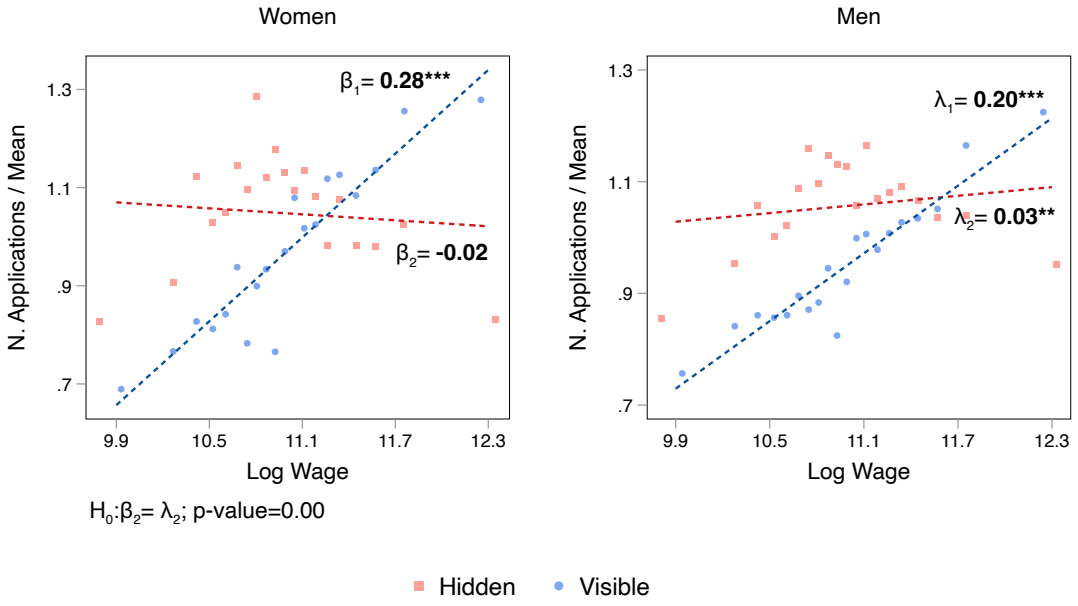
Notes: The figure shows firm responses to the question: "What do you think will happen to the quantity and quality of applications if you revealed the salary?" The sample consists of 203 firms that hide salary information. [Return to page 15]

Figure 8: Women direct search as long as salary is visible

(a) Number of applications sent and log wage



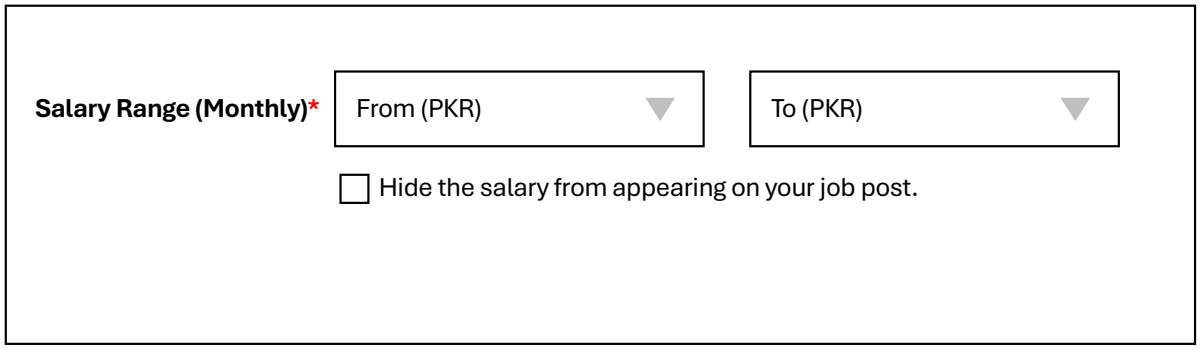
(b) Number of applications re-scaled by gender-specific mean, and log wage



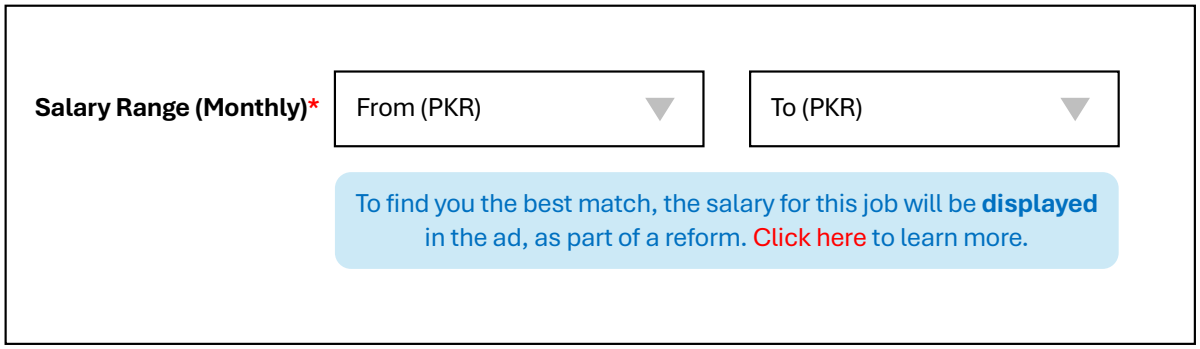
Notes: The graph in panel (a) shows the relationship between the number of applications sent by men and women to a job, and the log maximum wage of the job, separately by whether the salary of the job is hidden or visible to the job-seeker. It controls for industry, occupation and city fixed effects, and job characteristics (experience requirement, education requirement, career level of job, number of vacancies corresponding to the ad, number of required skills and job schedule). The graph in panel (b) shows the same information, but re-scales the y-axis by dividing number of applications with the gender-specific mean number of applications. The average number of applications sent to a job by men is 75.6 and by women is 14.9. [Return to page 17]

Figure 9: Experiment Design

(a) Control Ads

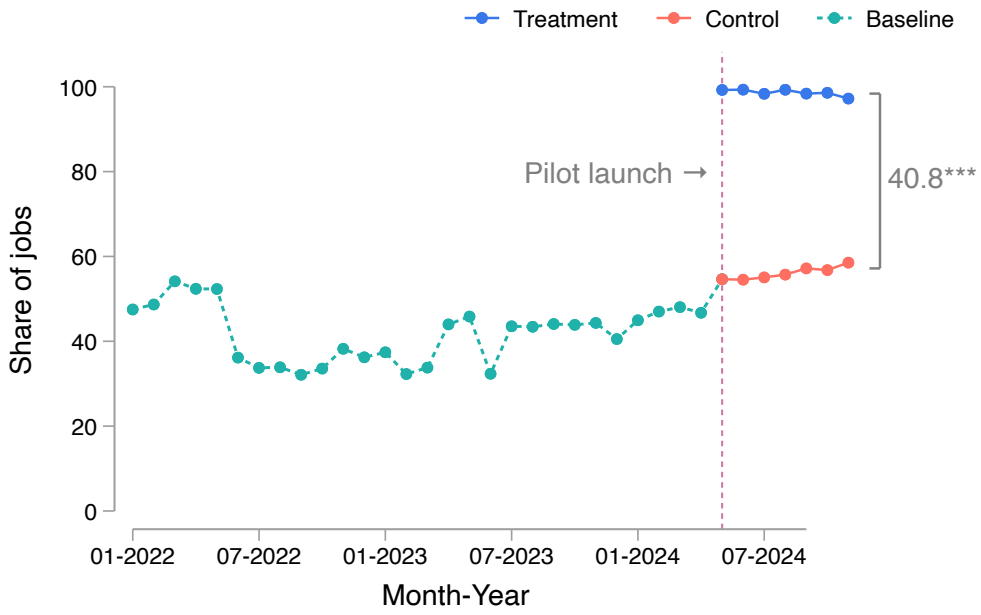


(b) Treatment Ads



Notes: Panel (a) Control shows the standard job posting interface for specifying salary ranges. Employers can optionally check a box to hide the salary range from appearing in the job post. Panel (b) Treatment shows the modified interface for the treatment group, where salary ranges are displayed by default. Employers are informed via a notification that this transparency is part of a reform to improve job matches. Employers in this version cannot hide the salary range. [Return to page 18]

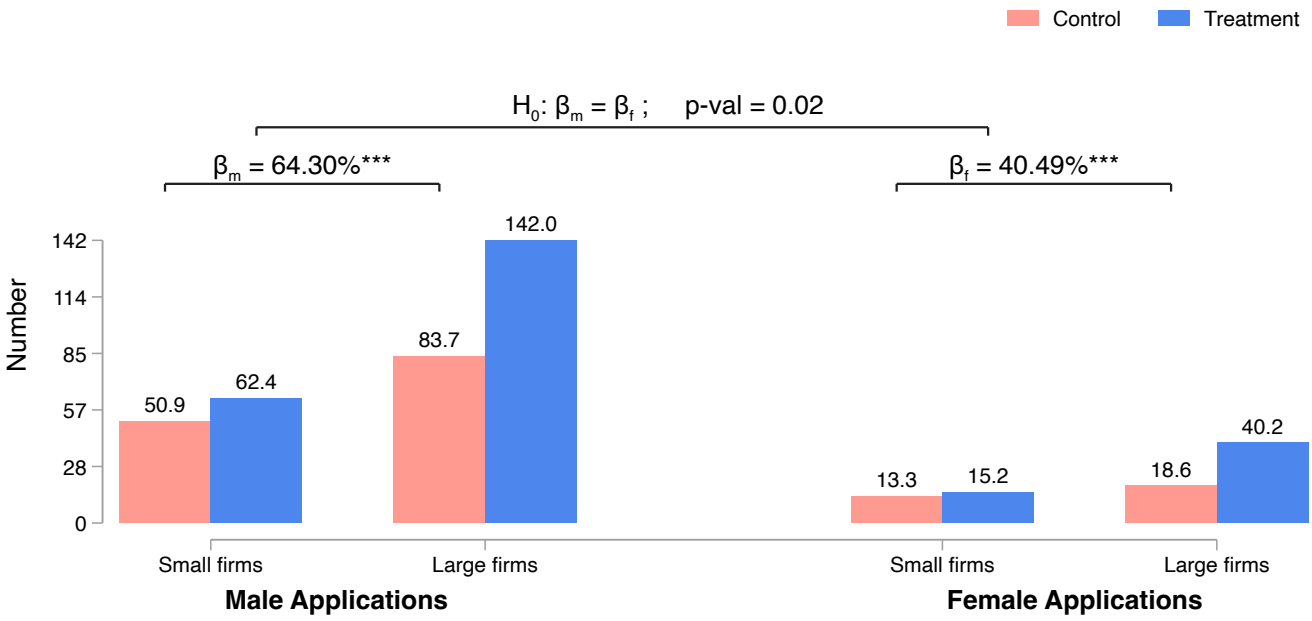
Figure 10: First stage: Share of jobs with visible salaries



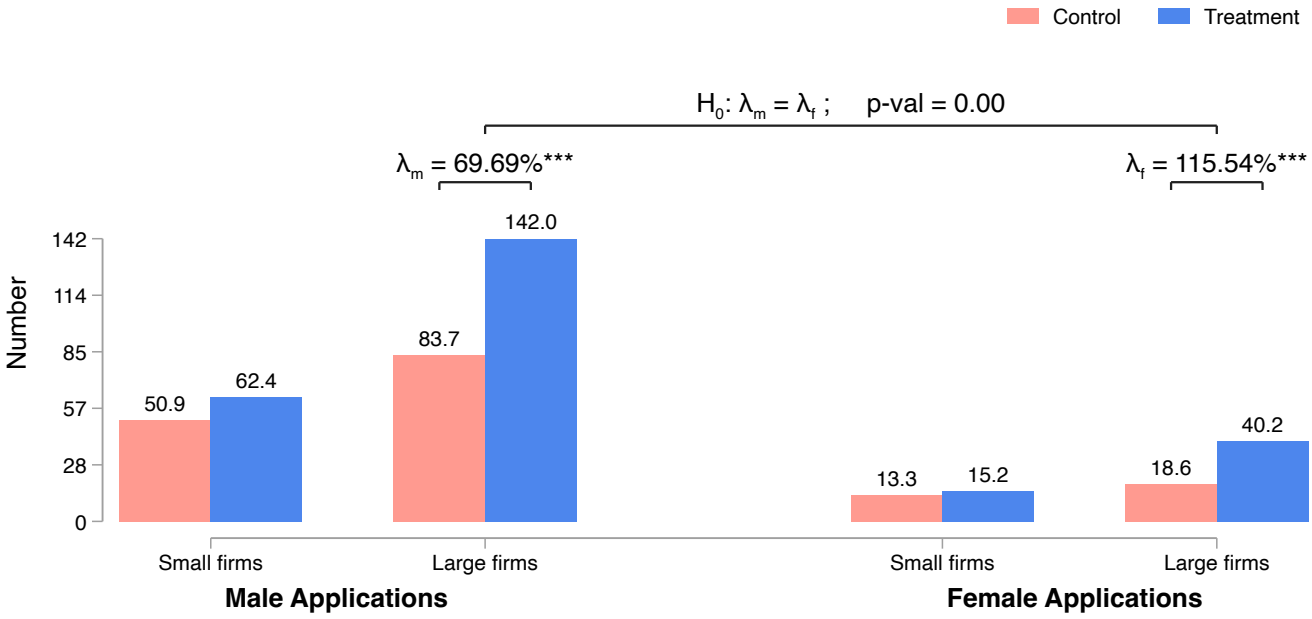
Notes: The figure illustrates the share of jobs with hidden salaries across treatment and control groups over time, with the vertical dashed line indicating the pilot launch in May 2024. The blue line represents the treatment group, the red line represents the control group, and the purple line indicates baseline trends. Following the launch, a significant increase of 0.41 percentage points (p<0.01) in salary disclosure is observed in the treatment group compared to the control. [Return to page 19]

Figure 11: Treatment impacts on job applications by gender (corresponding Table: B.8)

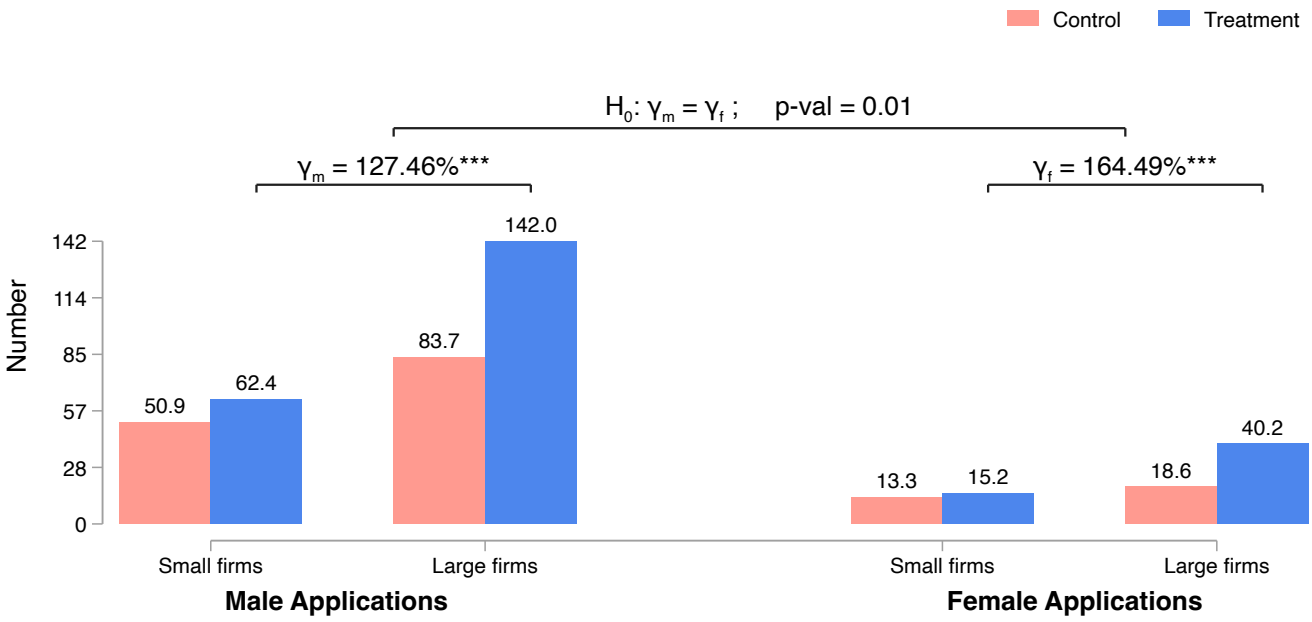
(a) Women direct search to large firms to a lesser extent than men



(b) Reallocation of search is larger for women



(c) Treatment closes gender gaps



Notes: The figure shows the treatment effects on applications with heterogeneity by firm size and gender. Corresponding graphs on **job views** can be found in Appendix **Figure** A.11 while a tabular version can be found in Appendix **Table** B.8. A firm is defined as large if it has more than 50 employees. The bars represent control and treatment group means, while the bottom brackets represent percentage change from a poisson regression. The top brackets test whether the gender difference in percentages is significantly different. Panel (a) compares control group differences between men and women in directing search to large firms. Panel (b) shows whether treatment increases the number of applications to treated jobs at large firms relative to control jobs at large firms, and whether the relative gender differences are significant. Panel (c) shows whether treatment induces a reallocation of search within the treatment group from small to large firms, and whether the magnitudes of reallocation are significantly different by gender. [Return to page 22]

Tables

Table 1: Treatment effects on salaries

	(1)	(2)	(3)
	Log Max Salary	**Log Min Salary**	**Salary Range: (Max-Min)/Median**
Treated Job	-0.01	0.03**	-0.04***
	(0.01)	(0.01)	(0.01)
Constant	11.24	10.77	0.44
Observations	13,637	13,637	13,637

Notes: The sample consists of all jobs in the experiment. Column 1 shows log maximum advertised salary. Column 2 shows log minimum advertised salary. Column 3 shows the width of the salary range by subtracting minimum from maximum salary and dividing by the mid-point of the range. Observations are missing for a handful of firms who do not report salaries to the platform because job ads are pulled from those firms' internal job posting sites where this information is not mandatory to report. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. [Return to page 20]

Table 2: Treatment effects on workers' job search

Panel A: *Treatment effect on Incidence Rate Ratios (IRR) using Poisson*

	IRR: Views			**IRR: Applications**		
	(1) All	(2) Male (β_m)	(3) Female (β_f)	(4) All	(5) Male (β_m)	(6) Female (β_f)
Treated Job	1.50***	1.50***	1.58***	1.54***	1.50***	1.68***
	(0.11)	(0.10)	(0.16)	(0.12)	(0.11)	(0.20)
Observations	13,791	13,791	13,791	13,791	13,791	13,791
H_0: $\beta_f = \beta_m$; p-value			0.23			0.03

Panel B: *Treatment effect on counts using OLS*

	N. Views			**N. Applications**		
	(1) All	(2) Male (β_m)	(3) Female (β_f)	(4) All	(5) Male (β_m)	(6) Female (β_f)
Treated Job	54.62***	37.55***	14.45***	43.05***	32.46***	10.56***
	(11.49)	(7.41)	(3.62)	(9.08)	(6.39)	(2.74)
Control job mean	109.40	75.25	24.87	80.08	64.53	15.51

Notes: This table presents the treatment effects on workers' job search behavior, measured in terms of job views and applications. **Panel A** presents incidence rate ratios (IRR) estimated using a Poisson model (described in Equaltion 4), capturing the proportional change in views and applications due to treatment. An IRR greater than 1 indicates an increase in job search activity relative to control jobs, e.g., Column 1 suggests a 50% increase in views due to treatment. **Panel B** reports the estimated effects on the number of views and applications using ordinary least squares (OLS) as described in Equation 3. Columns 1 shows the treatment effect on total number of views, while Columns 2 and 3 show these effects separately for male (β_m) and female (β_f) workers. Columns 4–6 report similar estimates for the total number of applications submitted. The control job mean in each row provides the baseline views and application counts for comparison. The p-value for $H_0 : \beta_f = \beta_m$ tests whether the treatment effects from the Poisson specification differ by gender. Robust standard errors are in parentheses. For a **visual representation** of Columns 1 and 4, see Figure A.8. For similar graphs on gender specific results in Columns 2-3 and Columns 5-6, see Figure A.9. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [Return to page 21]

Table 3: Workers direct search to larger firms

Panel A: *Treatment effect as Incidence Rate Ratios (IRR) using Poisson*

	IRR: Views			**IRR: Applications**		
	(1) All firms	(2) Small firms (β_s)	(3) Large firms (β_l)	(4) All firms	(5) Small firms (β_s)	(6) Large firms (β_l)
Treated Job	1.50***	1.20***	1.70***	1.54***	1.21**	1.78***
	(0.11)	(0.07)	(0.19)	(0.12)	(0.09)	(0.21)
Observations	13,791	7,910	5,880	13,791	7,910	5,880
H_0: $\beta_l = \beta_s$; p-value			0.01			0.01

Panel B: *Treatment effect on counts using OLS*

	N. Views			**N. Applications**		
	(1) All firms	(2) Small firms (β_s)	(3) Large firms (β_l)	(4) All firms	(5) Small firms (β_s)	(6) Large firms (β_l)
Treated Job	54.62***	17.23***	100.71***	43.05***	13.43***	79.90***
	(11.49)	(5.30)	(25.46)	(9.08)	(5.01)	(19.78)
Control job mean	109.40	85.34	143.22	80.08	64.22	102.37

Notes: This table presents heterogeneous treatment effects by firm size on workers' job search behavior, measured in terms of job views and applications. **Panel A** presents incidence rate ratios (IRR) estimated using a Poisson model, capturing the proportional change in job views and applications due to treatment. An IRR greater than 1 indicates an increase in search activity relative to control jobs. For example, in Column 1, treatment increases job views by 50%. The p-value for $H_0 : \beta_l = \beta_s$ tests whether the treatment effects from the Poisson specification differ between small and large firms. **Panel B** reports the estimated effects on the number of views and applications using ordinary least squares (OLS). Column 1 shows the overall treatment effect on job views, while Columns 2 and 3 separate these effects for searches directed at small and large firms, respectively. Columns 4–6 follow the same structure for job applications. The control job mean in each row provides baseline views and application counts. A **visual representation** of the results in Columns 2-3 and 5-6 are in Figure A.10. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [Return to page 21]

Table 4: Treatment effects on salaries by firm size

	(1) **Log Max Salary**	(2) **Log Min Salary**	(3) **Salary Range: (Max-Min)/Median**
Treated Job	-0.03	0.03*	-0.04***
	(0.02)	(0.02)	(0.01)
Large Firm	0.18***	0.30***	-0.10***
	(0.02)	(0.02)	(0.01)
Large Firm × Treated Job	0.03	-0.00	0.03**
	(0.03)	(0.03)	(0.01)
Constant	11.16	10.65	0.48
Observations	13,637	13,637	13,637

Notes: The sample consists of all jobs in the experiment. Column 1 shows log maximum advertised salary. Column 2 shows log minimum advertised salary. Column 3 shows the width of the salary range by subtracting minimum from maximum salary and dividing by the mid-point of the range. Observations are missing for a handful of firms who do not report salaries to the platform because job ads are pulled from those firms' internal job posting sites where this information is not mandatory to report. $*p < 0.1, **p < 0.05, ***p < 0.01$. [Return to page 21]

Table 5: Average applicant quality

Panel A: *Share of applicants who meet* ***experience*** *requirements*

	All Firms		Small Firms		Large Firms	
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female
Treated Job	-0.01	-0.01	-0.01*	-0.01*	0.00	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control Job Mean	0.78	0.69	0.81	0.73	0.73	0.62
Observations	13,599	12,241	7,838	7,075	5,761	5,166

Panel B: *Share of applicants who meet* ***education*** *requirements*

	All Firms		Small Firms		Large Firms	
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female
Treated Job	-0.01***	-0.01	-0.01**	-0.00	-0.01***	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Control Job Mean	0.88	0.91	0.88	0.91	0.88	0.90
Observations	13,602	12,245	7,841	7,078	5,761	5,167

Panel C: *Share of applicants who meet* ***skills*** *requirements*

	All Firms		Small Firms		Large Firms	
	(1) Male	(2) Female	(3) Male	(4) Female	(5) Male	(6) Female
Treated Job	-0.01***	-0.01	-0.00	0.00	-0.03***	-0.02**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Control Job Mean	0.47	0.40	0.48	0.40	0.46	0.39
Observations	13,707	12,354	7,877	7,115	5,830	5,239

Notes: The sample consists of all jobs in the experiment. Observations are missing when either no male or female applicant applied to that job, or all the applicants who applied had the relevant characteristic (experience, education or skills) missing. $*p < 0.1, **p < 0.05, ***p < 0.01$. [Return to page 23]

Table 6: Selection in applications to large firms by high and low ability applicants

Panel A: High Ability Men				
	(1) **Expected Salary Top Decile**	(2) **GPA Top Quartile**	(3) **Years of Experience Top Decile**	(4) **Managed a Team**
Treated Job (β_m)	0.02**	0.03***	0.03***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.83	0.89	0.82	0.90
Panel B: High Ability Women				
	(1)	(2)	(3)	(4)
Treated Job (β_f)	0.06***	0.09***	0.09***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.55	0.52	0.51	0.54
Observations	5,880	5,880	5,880	5,880
H_0: $\beta_f = \beta_m$; p-value	0.01	0.00	0.00	0.00
Panel C: Low Ability Men				
	(1) **Expected Salary Bottom Decile**	(2) **GPA Bottom Quartile**	(3) **Years of Experience Bottom Decile**	(4) **Never managed a Team**
Treated Job (β_m)	0.03***	0.02***	0.01*	0.01**
	(0.01)	(0.01)	(0.01)	(0.00)
Control mean	0.83	0.91	0.93	0.97
Panel D: Low Ability Women				
	(1)	(2)	(3)	(4)
Treated Job (β_f)	0.06***	0.06***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.44	0.60	0.73	0.79
Observations	5,880	5,880	5,880	5,880
H_0: $\beta_f = \beta_m$; p-value	0.04	0.00	0.02	0.00

Notes: The sample consists of job ads posted by large firms. Column 1 of Panels A and B shows likelihood men and women in the top decile of their expected wage applied. Panels C and D show the same for men and women in the bottom decile of expected wage. Column 2 of Panels A and B shows likelihood men and women in the top quartile of GPA applied, while in Panels C and D, the column corresponds to the bottom quartile. Column 3 of Panels A and B shows likelihood men and women in the top decile of years of experience applied, while Panels C and D, the show the same for the bottom decile. Column 4 of Panels A and B shows likelihood men and women who have any management experience applied, while Panels C and D, the show the same for men and women with no management experience. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. [Return to page 24]

Table 7: Characteristics of the top applicants

	(1) Expected Salary (SDs)	(2) Education Level (SDs)	(3) Experience (SDs)	(4) GPA (SDs)	(5) Team Size Managed (SDs)	(6) At least 1 Female
Panel A: All firms						
Treated Job	0.01	0.11***	0.09***	0.07***	0.12***	0.03***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Control Job Mean	0.00	0.00	-0.00	0.00	-0.00	0.58
Observations	13,687	13,686	13,684	13,589	13,641	13,687
Panel B: Small firms						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated Job	-0.01	0.07***	0.06***	0.08***	0.09***	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Control Job Mean	0.00	-0.00	-0.00	0.00	0.00	0.58
Observations	7,874	7,874	7,873	7,819	7,844	7,874
Panel C: Large firms						
	(1)	(2)	(3)	(4)	(5)	(6)
Treated Job	0.01	0.15***	0.11***	0.05**	0.13***	0.04***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Control Job Mean	0.00	-0.00	-0.00	0.00	0.00	0.56
Observations	5,813	5,812	5,811	5,770	5,797	5,813

Notes: The table presents the impact of treatment on the quality of the top applicants for a job. To identify top candidates, the top three values in each applicant pool are first determined for five key attributes: expected salary, education, experience, GPA, and team size managed. Applicants who rank in the top three for any of these attributes are flagged accordingly. Next, a score is constructed for each applicant, representing the proportion of these five attributes in which they rank among the top three. Finally, applicants are classified as the best in the pool if their score is among the top three in their applicant pool. Column 1 shows the average expected salary of these top candidates, Column 2 shows the average years of education, Column 3 shows average years of experience, Column 4 shows average GPA, and Column 5 shows size of the team managed. Each of these are normalized by the mean and standard deviation of the control group. Column 6 shows whether than at least one of the top candidates is a woman. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. [Return to page 26]

Table 8: Firm review of applications

	(1) **Share of CVs Viewed**	(2) **Share of CVs Downloaded**	(3) **Female Share of CV Views**	(4) **Female Share of CV Downloads**
Treated Job	-0.02***	-0.03***	0.02**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Control Job Mean	0.21	0.28	0.23	0.22
Observations	3,493	4,504	3,493	4,504

Notes: The table shows impacts of treatment on the share of CVs viewed and downloaded by firms. Upon receiving applications for a job, firms get access to an applications portal where they may view the CVs of the applicants individually or download these CVs (either altogether or for a specific subset). If a firm bulk downloads all CVs, no views on applications may be observed. The sample consists of firms for which two types of clicks are observed on the platform: CV views, and CV downloads. Firms also get an email containing all the applicant CVs, and in case firms engage only via email with the applications, no clicks are observed. When a firm interacted with the portal only to select all CVs and download them, I observe the download event but no clicks on CVs. Column 1 shows the share of CVs viewed relative to the total application pool. Column 2 shows the share of CVs downloaded relative to the total application pool. Column 3 shows the female share of all CVs viewed. Column 4 shows the female share of all CVs downloaded. $*p < 0.1, **p < 0.05, ***p < 0.01$. [Return to page 26]

Table 9: Average quality of applicants considered by firms

Panel A: All firms

	(1) Expected Salary (SDs)	(2) Education Level (SDs)	(3) Experience (SDs)	(4) GPA (SDs)	(5) Team Size Managed (SDs)	(6) At least 1 Female
Treated Job	0.02	0.10***	0.06**	0.03	0.05	0.03**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Control Job Mean	0.00	-0.00	-0.00	-0.00	-0.00	0.62
Observations	5,323	5,324	5,324	5,324	5,296	4,868

Panel B: Small firms

	(1)	(2)	(3)	(4)	(5)	(6)
Treated Job	0.01	0.08**	0.11***	0.05	0.08**	0.05**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
Control Job Mean	0.00	-0.00	0.00	0.00	0.00	0.64
Observations	2,586	2,587	2,587	2,587	2,575	2,308

Panel C: Large firms

	(1)	(2)	(3)	(4)	(5)	(6)
Treated Job	0.03	0.11***	0.01	0.01	0.01	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
Control Job Mean	0.00	-0.00	0.00	0.00	0.00	0.59
Observations	2,737	2,737	2,737	2,737	2,721	2,560

Notes: The table presents the impact of treatment on the average quality of candidates whose CVs were viewed or downloaded by firms. Column 1 shows the average expected salary of these candidates, Column 2 shows the average years of education, Column 3 shows average years of experience, Column 4 shows average GPA, and Column 5 shows size of the team managed. Each of these are normalized by the mean and standard deviation of the control group. Column 6 shows whether at least one of the candidates is a woman. $*p < 0.1, **p < 0.05, ***p < 0.01$. [Return to page 26]

References

Adzuna, "Adzuna Salary Transparency White Paper," https://www.adzuna.com/blog/wp-content/uploads/2022/11/Adzuna-Salary-Transparency-White-Paper.pdf 2022. Accessed: 2024-12-23. [Return to page 28]

AfriWorket, "AfriWorket: Empowering Africa's Workforce," https://afriworket.com 2024. Accessed: 2024-12-23. [Return to page 28]

Alfonsi, Livia, Vittorio Bassi, Imran Rasul, and Elena Spadini, "The Returns to Skills During the Pandemic: Experimental Evidence from Uganda," Technical Report, University College London October 2024. [Return to page 16]

Arnold, David, Simon Quach, and Bledi Taska, "The Impact of Pay Transparency in Job Postings on the Labor Market," *SSRN Electronic Journal*, August 2022. [Return to page 18]

Ashraf, Nava, Oriana Bandiera, Edward Davenport, and Scott S. Lee, "Losing Prosociality in the Quest for Talent? Sorting, Selection, and Productivity in the Delivery of Public Services," *American Economic Review*, May 2020, *110* (5), 1355–1394. [Return to page 13]

_ , _ , Virginia Minni, and Victor Quintas y Martinez, "Gender Gaps across the Spectrum of Development: Local Talent and Firm Productivity," 2024. [Return to page 27]

Autor, David H., "Wiring the Labor Market," *Journal of Economic Perspectives*, March 2001, *15* (1), 25–40. [Referenced on pages 4 and 16]

Bandiera, Oriana, Amen Jalal, and Nina Roussille, "Timing Matters: Gender Gaps in Job Search and Employment," 2024. Working Paper. [Return to page 8]

_ , Ananya Kotia, Ilse Lindenlaub, Christian Moser, and Andrea Prat, "Meritocracy across Countries," April 2024. 82 pages. Posted: 18 Apr 2024. Multiple versions available. [Referenced on pages 4 and 16]

Banfi, Stefano and Benjamín Villena-Roldán, "Do High-Wage Jobs Attract More Applicants? Directed Search Evidence from the Online Labor Market," *Journal of Labor Economics*, 2019, *37* (3), 715–746. [Referenced on pages 2, 11, and 28]

Batra, Honey, Amanda Michaud, and Simon Mongey, "Online Job Posts Contain Very Little Wage Information," Technical Report 31984, National Bureau of Economic Research December 2023. [Referenced on pages 2, 11, and 28]

Beaman, Lori, Niall Keleher, and Jeremy Magruder, "Do Job Networks Disadvantage Women? Evidence from a Recruitment Experiment in Malawi," *Journal of Labor Economics*, 2018, *36* (1), 121–157. [Return to page 2]

Belot, Michèle, Philipp Kircher, and Paul Muller, "How Wage Announcements Affect Job Search—A Field Experiment," *American Economic Journal: Macroeconomics*, October 2022, *14* (4), 1–67. [Return to page 2]

Bertrand, Marianne, "New Perspectives on Gender," in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 4B, Amsterdam: Elsevier, 2011, pp. 1545–1592. [Return to page 2]

_ , Bruno Crépon, and Stefano Caria, "Improving job seekers' employment and earnings through credible skills signals," 2024. Accessed: 2024-12-23. [Return to page 4]

Blau, Francine D. and Lawrence M. Kahn, "The Gender Wage Gap: Extent, Trends, and Sources," *Journal of Economic Literature*, 2017, *55* (3), 789–865. [Return to page 2]

Brenčič, Vera, "Wage posting: evidence from job ads," *Canadian Journal of Economics/Revue canadienne d'économique*, 2012, *45* (4), 1529–1559. [Referenced on pages 2 **and** 28]

Bó, Ernesto Dal, Frederico Finan, and Martín A. Rossi, "Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service*," *The Quarterly Journal of Economics*, 04 2013, *128* (3), 1169–1218. [Return to page 2]

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *The Quarterly Journal of Economics*, 2016, *131* (2), 633–686. [Return to page 2]

_ , _ , Joerg Heining, and Patrick Kline, "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 2018, *36* (1), S13–S70. [Return to page 2]

_ , Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 2013, *128* (3), 967–1015. [Return to page 2]

Chandrasekhar, Arun G, Melanie Morten, and Alessandra Peter, "Network-based hiring: Local benefits; global costs," Technical Report, National Bureau of Economic Research 2020. [Referenced on pages 4 **and** 16]

Cullen, Zoë B, "Is Pay Transparency Good?," *Journal of Economic Perspectives*, 2024, *38* (1), 153–180. [Return to page 10]

Ductor, Lorenzo, Sanjeev Goyal, and Anja Prummer, "Gender and Collaboration," *The Review of Economics and Statistics*, 2023, *105* (6), 1366–1378. [Return to page 2]

Goux, Dominique and Eric Maurin, "Persistence of interindustry wage differentials: a reexamination using matched worker-firm panel data," *Journal of labor Economics*, 1999, *17* (3), 492–533. [Return to page 2]

Gruetter, Max and Rafael Lalive, "The importance of firms in wage determination," *Labour Economics*, 2009, *16* (2), 149–160. [Return to page 2]

HRD Asia, "Pay transparency: More Singapore job postings including salary offers," June 2023. Accessed: 2024-04-15. [Return to page 28]

Indeed Hiring Lab, "Pay transparency: More Singapore job postings including salary offers," July 2023. Accessed: 2024-04-15. [Return to page 28]

_ , "Salaires dans les offres d'emploi : l'importance croissante de la transparence en Europe," April 2023. Accessed: 2024-04-15. [Referenced on pages 2 and 28]

_ , "Salary Transparency Increasingly the Norm in Canadian Job Postings," March 2024. Accessed: 2024-04-15. [Return to page 28]

International Labor Organization, "Labor Force Participation Rate, Male (% of Male Population Ages 15+), Pakistan," 2024. Accessed: 2024-12-23. [Return to page 8]

International Labour Organization, *Global Wage Report 2018/19: What Lies Behind Gender Pay Gaps*, Geneva: International Labour Office, 2018. [Referenced on pages 2 and 8]

Jayachandran, Seema, "Microentrepreneurship in developing countries," *Handbook of labor, human resources and population economics*, 2021, pp. 1–31. [Referenced on pages 4 and 16]

_ , "Social Norms as a Barrier to Women's Employment in Developing Countries," *IMF Economic Review*, 2021, *69* (3), 576–595. [Return to page 2]

Kuhn, Peter and Kailing Shen, "GENDER DISCRIMINATION IN JOB ADS: EVIDENCE FROM CHINA," *The Quarterly Journal of Economics*, 2013, *128* (1), 287–336. [Referenced on pages 2 and 28]

Marinescu, Ioana and Ronald Wolthoff, "Opening the Black Box of the Matching Function: The Power of Words," *Journal of Labor Economics*, 2020, *38* (2), 535–568. [Return to page 51]

Menzio, Guido, "A Theory of Partially Directed Search," *Journal of Political Economy*, 2007, *115* (5), 748–769. [Return to page 2]

Michelacci, Claudio and Javier Suarez, "Incomplete Wage Posting," *Journal of Political Economy*, 2006, *114* (6), 1098–1123. [Referenced on pages 3 and 16]

Muralidharan, Karthik and Abhijeet Singh, "India's New National Education Policy: Evidence and Challenges," 2023. Accessed via RISE. [Referenced on pages 4 and 16]

Our World in Data, "Female Labor Force Participation Rates by National Per Capita Income," 2024. Accessed: 2024-12-23. [Return to page 8]

People Matters, "Pay transparency on the rise in India, 50postings include salary details," May 2023. Accessed: 2024-04-15. [Return to page 28]

Skoda, Samuel, "Directing Job Search in Practice: Mandating Pay Information in Job Ads," *Job Market Paper*, November 2022. [Referenced on pages 2, 9, and 28]

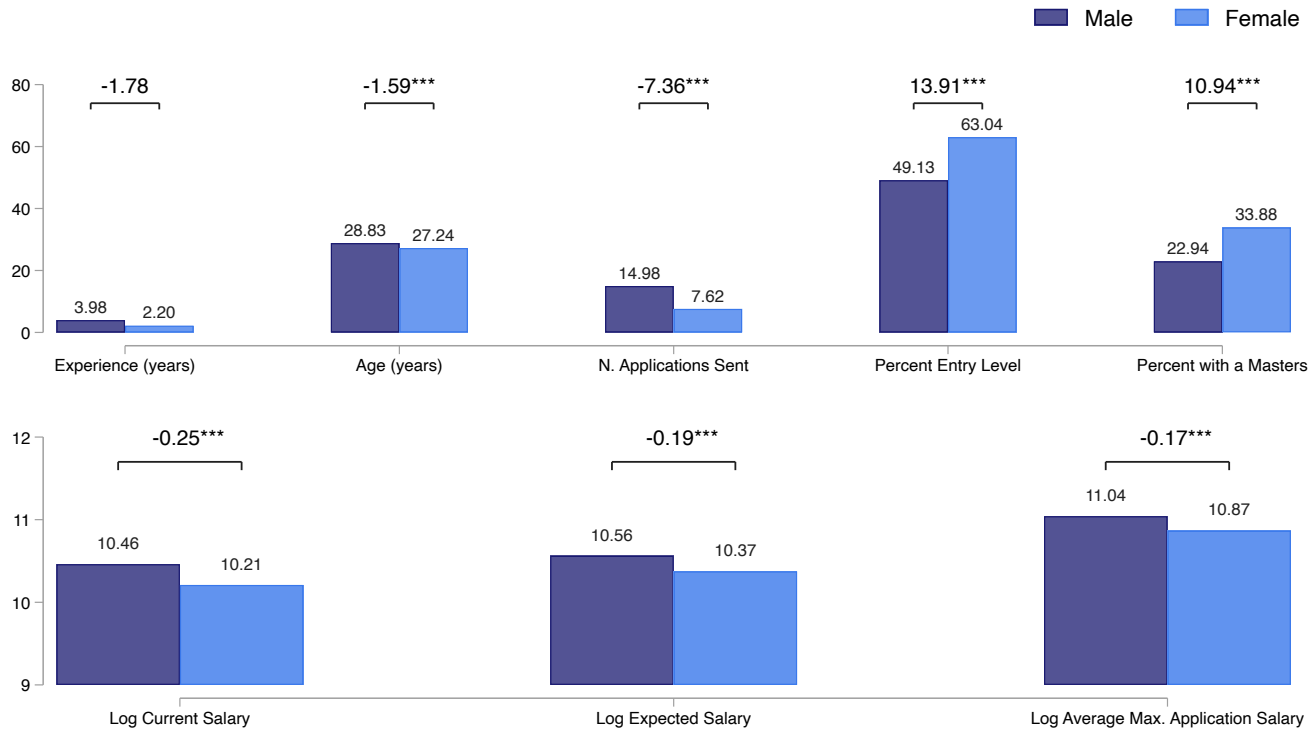
World Bank, *World Development Report 2018: Learning to Realize Education's Promise*, Washington, DC: The World Bank, 2018. [Return to page 4]

World Economic Forum, "Global Gender Gap Report 2023," 2023. Accessed: 2024-12-23. [Return to page 8]

A Appendix

A.1 Appendix Figures

Figure A.1: Gender differences in worker characteristics on the platform



Notes: The figure shows average differences in characteristics between male and female job seekers. The purple bars represent male while blue bars represent female job seekers. The sample consists of 1.9 million job seekers registered on the job platform at baseline. In the first row of the figure, the first two bars examine gender differences in years of experience among job seekers, the next two bars examine differences in age, the following two bars show differences in number of job applications sent by the average male and female worker, the 7th and 8th bars show differences in career levels of the job seekers (specifically whether they self-report their career level to be entry level), while the final two bars in this row show likelihood the job seeker has a Masters degree. The bottom row shows gender differences across three salary dimensions, accounting for industry fixed effects: current salary, expected salary and the max salary of the average job candidates applied to. [Return to page 9]

Figure A.2: First Word of Job Title

(a) Jobs with Hidden Salaries

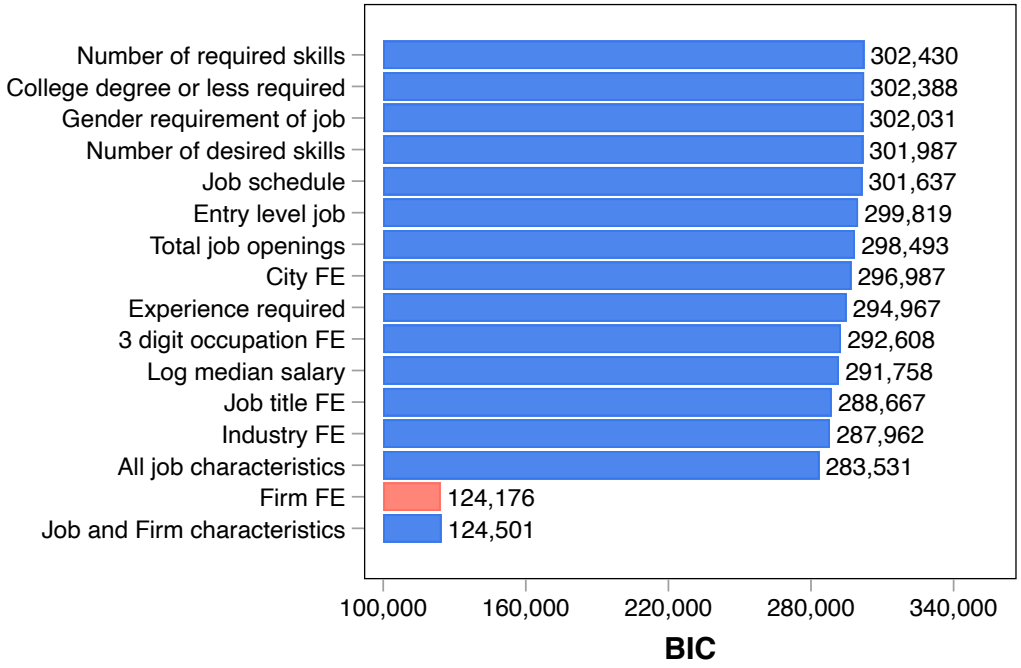


(b) Jobs with Visible Salaries



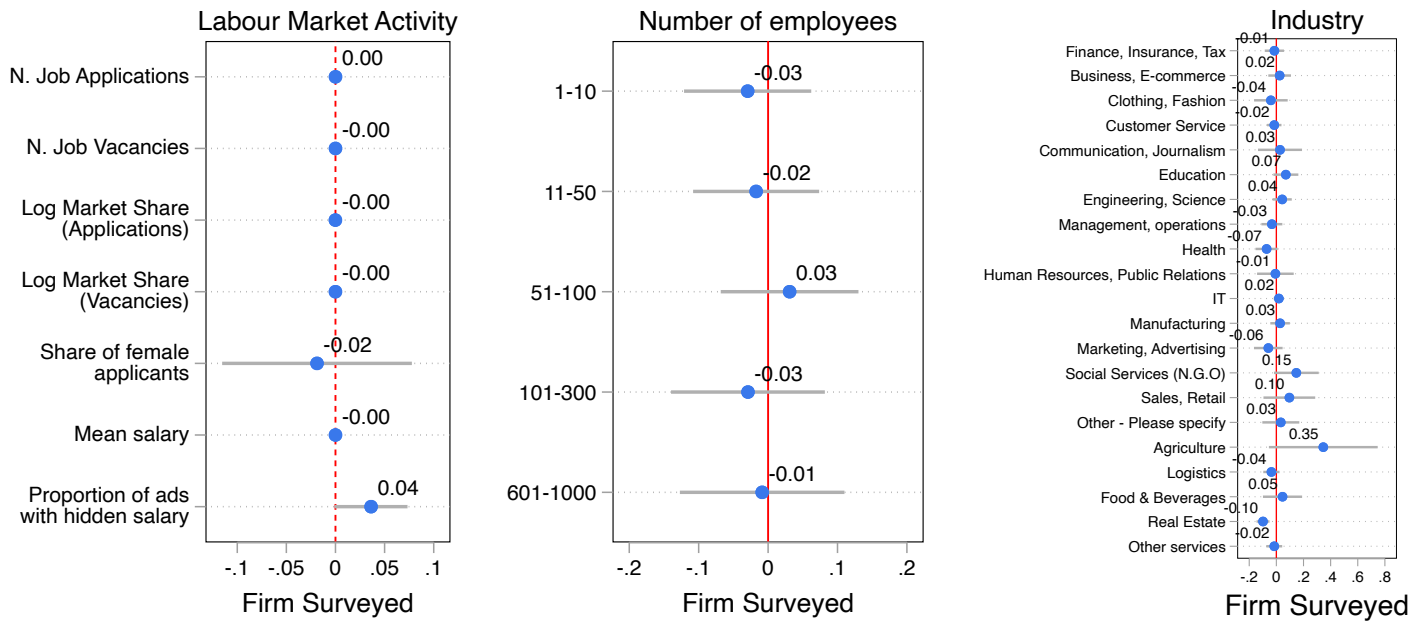
Notes: The figure shows the forst word of job titles separately for jobs with hidden salaries (panel a) and jobs with visible salaries (panel b). The job titles are cleaned following the approach in Marinescu and Wolthoff (2020). [Return to page 9]

Figure A.3: Firm effects explain most of the variation in hiding



Notes: The figure shows the Bayesian Information Criterion (BIC) from a job-level regression of an indicator for whether the salary of the job is hidden on each characteristic of the job, one at a time, until the third-last row in which all job characteristics are entered together. In the second to last row, firm fixed effects are controlled for by themselves, and the final row includes firm effects together with job characteristics. The sample consists of all baseline jobs. [Return to page 12]

Figure A.4: Selection into firm survey

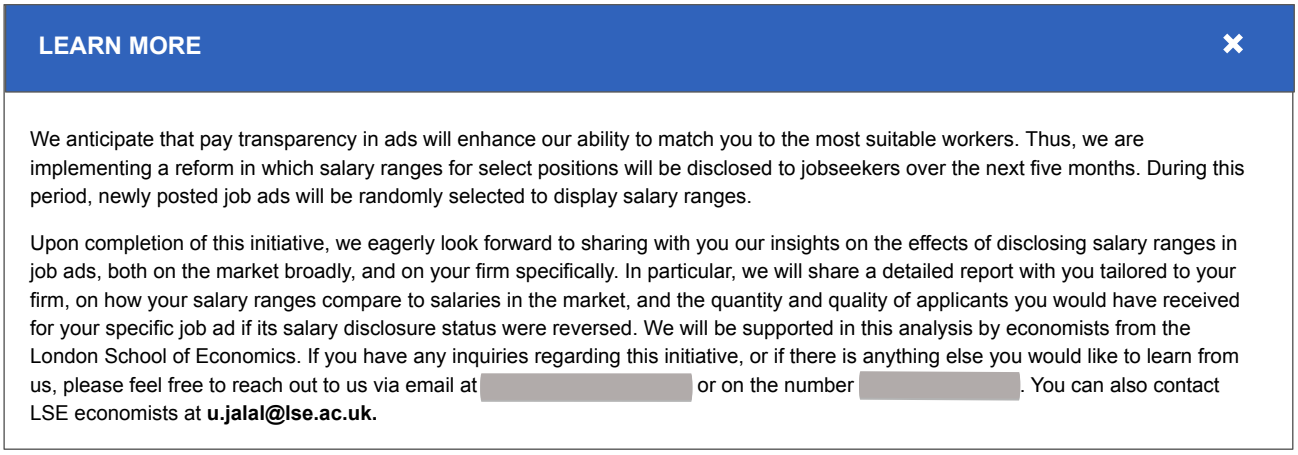


F-test of joint significance: 1.37; p-val=0.07

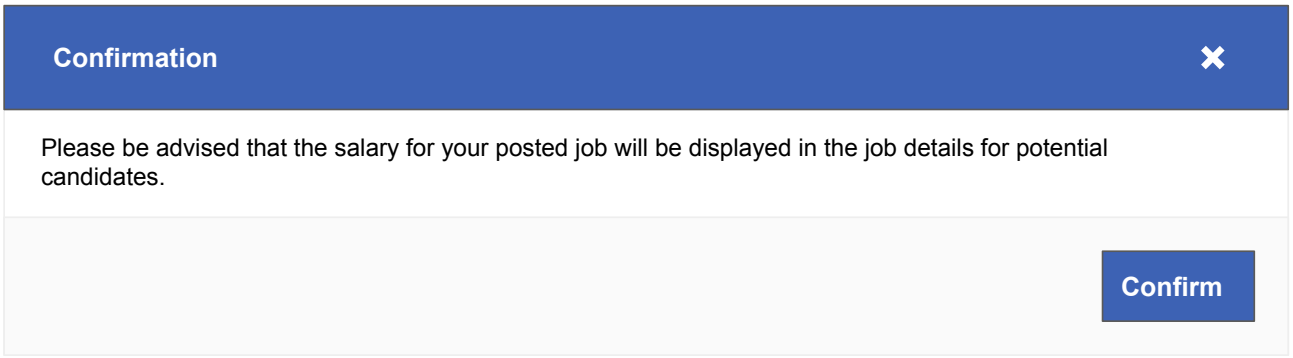
Notes: The figure tests whether there was selection in the firms who consented to participate in the survey. The first subfigure tests whether there is differential selection into the survey by the number of job applications received by the firm, the number of job vacancies, the log market share of applications and vacancies, the share of female applicants, average salary across jobs posted by the firm, and the proportion of jobs at the firm with salary hidden. The second subfigure tests whether response rate varies by firm size. The third sub figure tests whether specific industries are more or less likely to participate in the survey. The figure also reports an F-test of joint significance. [Return to page 12]

Figure A.5: Further information and inattention

(a) Further information for treated ads

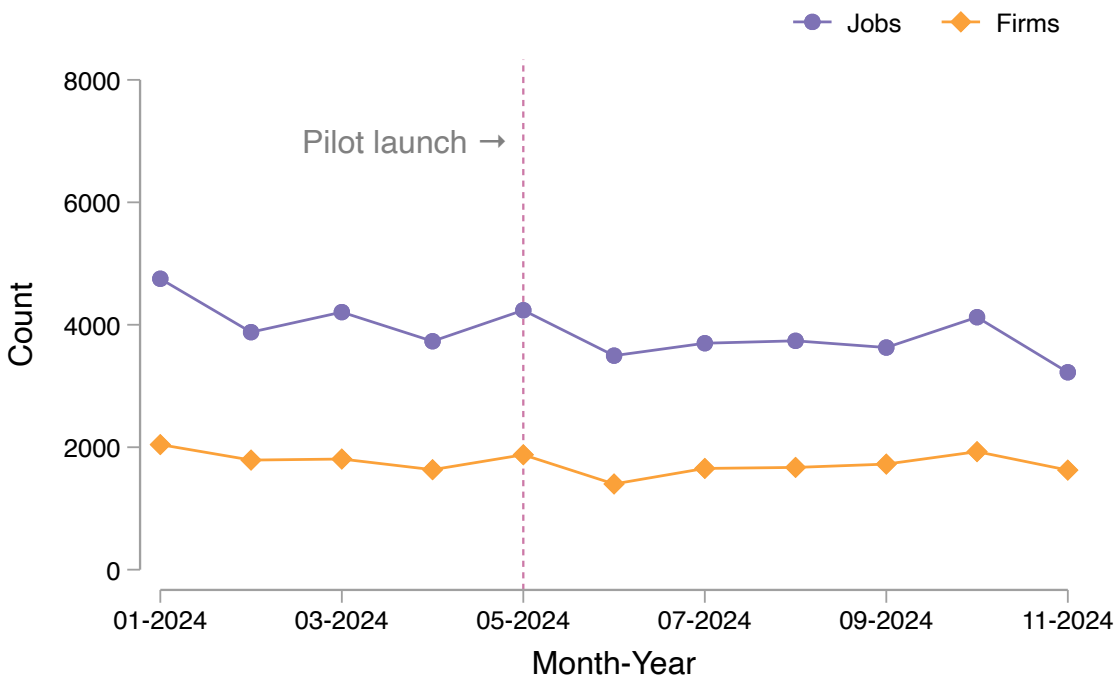


(b) Inattention



Notes: Panel (a) shows the "Learn More" pop-up provided to employers posting treated ads. It details the reform's purpose, emphasizing improved candidate matching and transparency. The pop-up invites employers to reach out with inquiries and mentions the involvement of researchers from the London School of Economics. Panel (b) illustrates an inattention check, where employers in the treatment group receive a confirmation prompt explicitly stating that the salary range will be visible to jobseekers. This ensures employers understand the implications before finalizing their job postings. [Return to page 18]

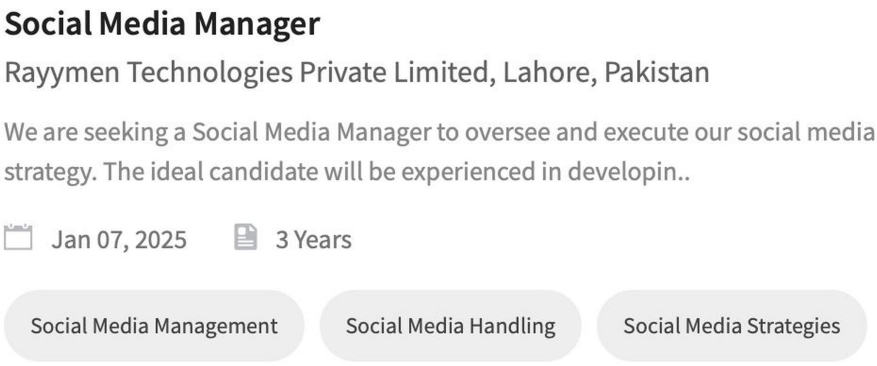
Figure A.6: No evidence of job posting or firm exits following experiment launch



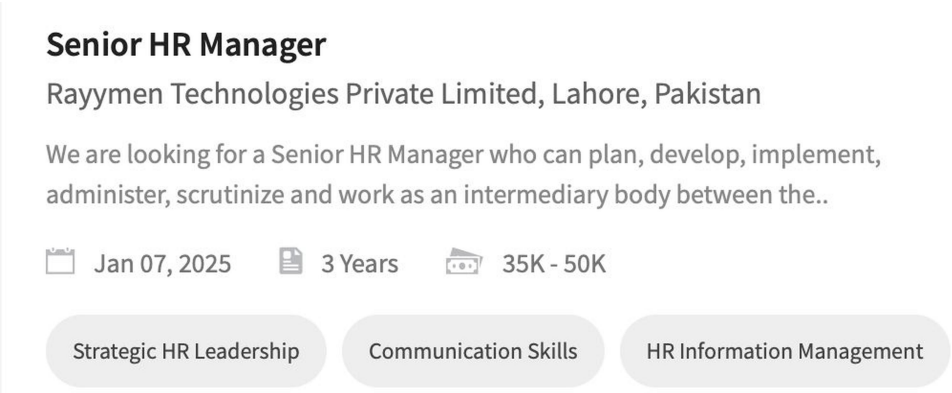
Notes: The figure shows the monthly counts of job postings (purple line) and active firms (orange line) on the platform from January 2024 to November 2024. The vertical dashed line marks the launch of the pilot intervention in May 2024. There is no evidence of a significant decline in the number of job postings or firms following the intervention, indicating no discernible exit of participants from the platform. [Return to page 19]

Figure A.7: Short previews of jobs

(a) Job with hidden salaries

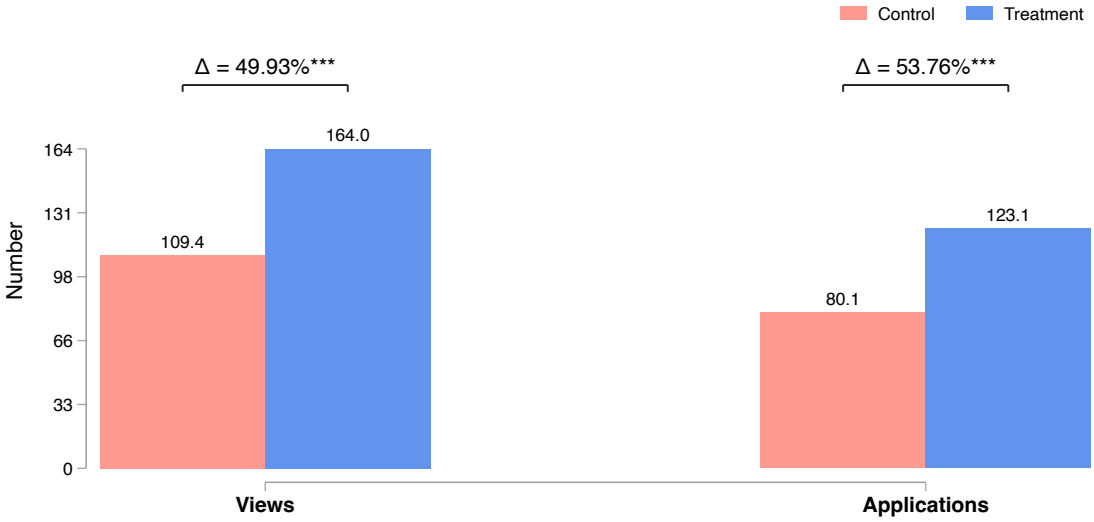


(b) Job with visible salaries



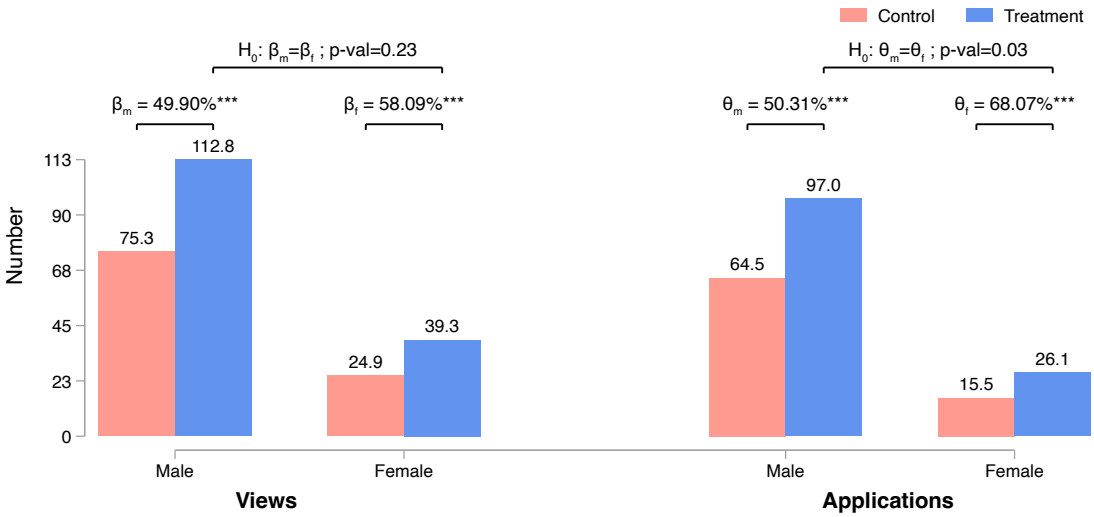
Notes: The figure presents initial previews of job postings on the platform that are visible to workers when they browse for jobs. Panel (a) illustrates a job posting where salary information is hidden, while Panel (b) shows a job posting with visible salary details. Specifically, it shows that the salary range is PKR 35,000 to 50,000. Both job postings are from the same firm and feature the job title, firm name and location, limited description of the job characteristics, application deadline, as well as experience and skills requirements. The placement of each of these details is the same for each job. Workers can click on these vignettes to see full job details which usually span 1-2 pages. [Return to page 21]

Figure A.8: Treatment effect on views and applications



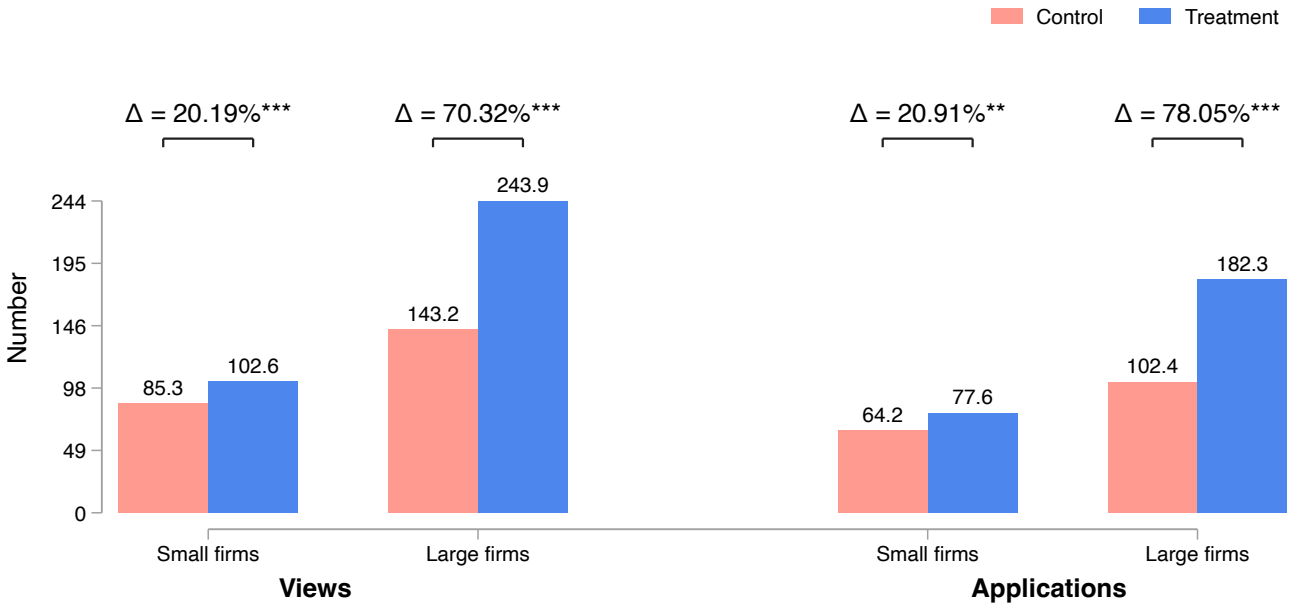
Notes: The figure shows treatment effect on job ad views and applications. The bars represent control and treatment group means, while the brackets represent percentage change from a poisson regression. [Return to page 39]

Figure A.9: Treatment effects by gender on views and applications



Notes: The figure shows treatment effect on job ad views and applications. The bars represent control and treatment group means, while the brackets represent percentage change from a poisson regression. [Return to page 39]

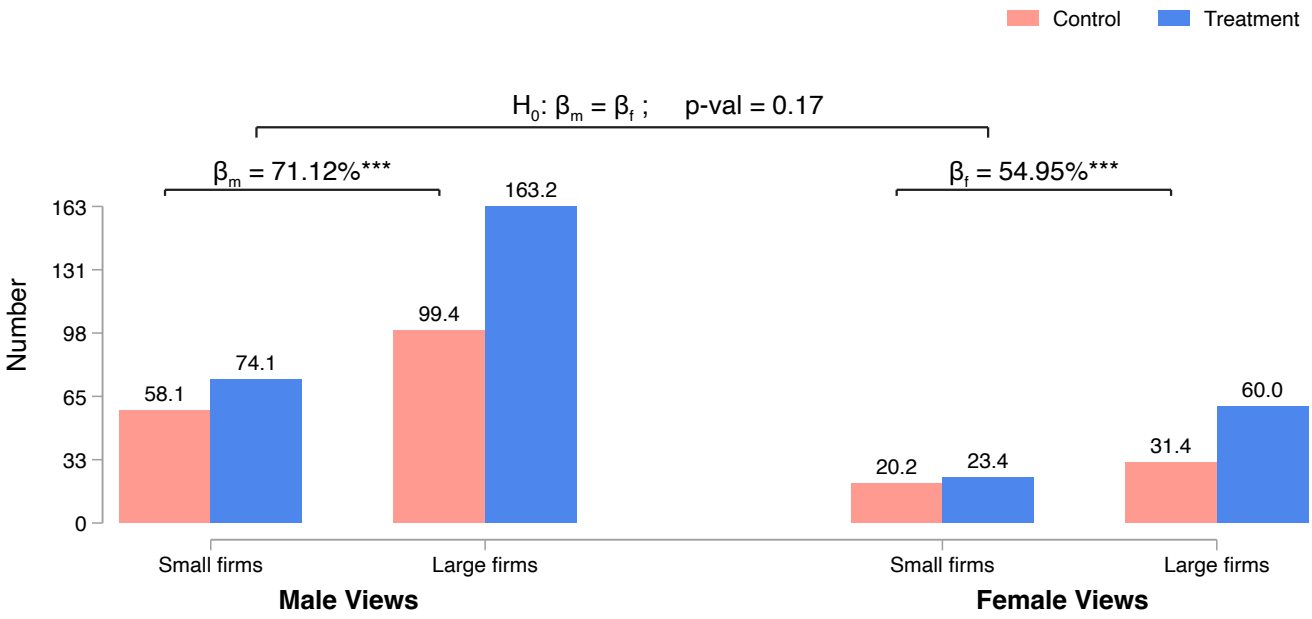
Figure A.10: Treatment effect on views and applications by firm size



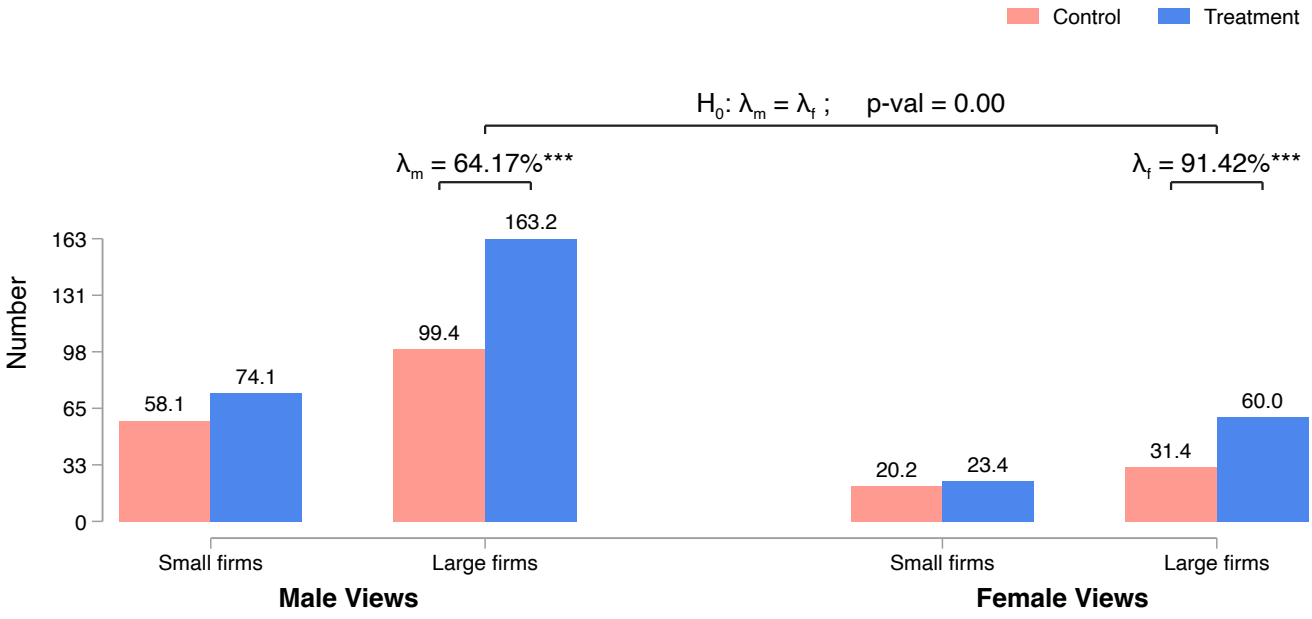
Notes: The figure shows treatment effect on job ad views and applications with heterogeneity by firm size. A firm is defined as large if it has more than 50 employees. The bars represent control and treatment group means, while the brackets represent percentage change from a poisson regression. [Return to page 40]

Figure A.11: Treatment impacts on job views by gender

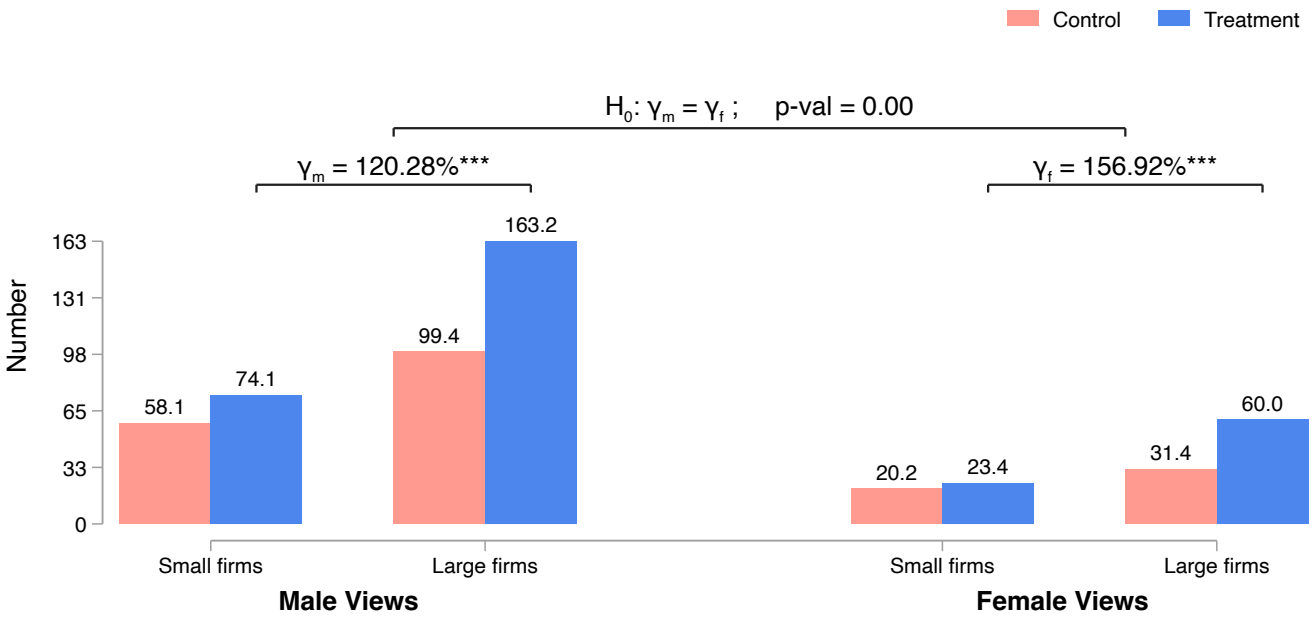
(a) Gender gaps in job views in the control group



(b) Reallocation of search is larger for women



(c) Treatment closes gender gaps



Notes: The figure shows the treatment effects on views with heterogeneity by firm size and gender. A firm is defined as large if it has more than 50 employees. The bars represent control and treatment group means, while the bottom brackets represent percentage change from a poisson regression. The top brackets test whether the gender difference in percentages is significantly different. Panel (a) compares control group differences between men and women in directing search to large firms. Panel (b) shows whether treatment increases the number of views to treated jobs at large firms relative to control jobs at large firms, and whether the relative gender differences are significant. Panel (c) shows whether treatment induces a reallocation of search within the treatment group from small to large firms, and whether the magnitudes of reallocation are significantly different by gender. [Return to page 22 or 37]

A.2 Appendix Tables

Table B.1: Descriptive Statistics: Jobs

	Mean	SD
Salary		
Min Salary - Visible (PKR)	42,517	43,895
Max Salary - Visible (PKR)	68,183	67,561
Min Salary - Hidden (PKR)	56,152	61,529
Max Salary - Hidden (PKR)	98,143	107,424
Years of Experience Required	0.90	1.89
N. Applications Received	75.45	270.02
N. Requred Skills	3.25	2.44
N. Desired Skills	0.61	1.45
Full-time Job	0.94	
Schedule: Day time job	0.79	
Screening Question Required	0.05	
Career Level		
Intern/Student	0.04	
Entry Level	0.29	
Mid-Career/Professional	0.65	
Dept. Head	0.01	
Executive/Top Management	0.00	
Career Level Not Reported	0.01	
Education Requirement		
Matriculation or Less	0.07	
Intermediate	0.16	
Certificate/Diploma	0.03	
Bachelor	0.65	
Master	0.09	
PhD	0.00	
Education Requirement Not Reported	0.01	
Firm Size: N. Employees		
1-10	0.22	
11-50	0.32	
51-100	0.17	
101-200	0.10	
201-300	0.03	
301-600	0.05	
600+	0.12	
Observations	326,145	

Notes: The table shows baseline descriptive statistics of jobs covering the period January 2019-April 2024. Means and standard deviations are reported for averages in Columns 1 and 2, respectively. Standard deviations are omitted where the statistic represents share of jobs. [Return to page 21]

Table B.2: Top 10 Occupations and Industries on the Platform

Rank	Industry	Industry Percent	Occupation	Occupation Percent
1	Information Technology	23.38	Sales and Business Development	14.74
2	Services	7.24	Software and Web Development	12.71
3	N.G.O./Social Services	6.06	Accounts, Finance and Financial Services	8.82
4	Call Center	5.89	Client Services and Customer Support	7.74
5	Education/Training	5.54	Marketing	5.02
6	Manufacturing	5.09	Telemarketing	4.72
7	Real Estate/Property	4.49	Human Resources	4.12
8	Recruitment / Employment Firms	4.05	Teachers/Education, Training and Development	3.63
9	Business Development	3.77	Creative Design	3.58
10	BPO	3.25	Computer Networking	2.92

Notes: The table shows the top 10 industries and occupations on the platform. Column 1 ranks top 10 industries and occupations in order of most to least common. Column 2 lists the industries while column 3 lists the percentage of total jobs the industry corresponds to. Column 4 lists the occupations while column 3 lists the percentage of total jobs the occupation corresponds to. [Return to page 9]

Table B.3: Descriptive Statistics: Job-seekers

	Mean	SD
Age	28.10	6.93
Years of Experience	3.27	5.01
GPA	2.85	0.80
N. Applications Sent	8.84	46.14
Share Female	0.27	
Current Salary (PKR)	45,998	52,795
Expected Salary (PKR)	49,441	54,151
Career Level		
Intern/Student	0.26	
Entry Level	0.29	
Mid-Career/Professional	0.41	
Dept. Head	0.03	
Executive/Top Management	0.01	
Education Level		
High School or Less	0.02	
Intermediate	0.11	
Certificate/Diploma	0.07	
Bachelor	0.53	
Master	0.26	
PhD	0.01	
Observations	3,158,049	

Notes: The table shows baseline descriptive statistics of job-seekers covering the period January 2019-December 2024. Means and standard deviations are reported for averages in Columns 1 and 2, respectively. Standard deviations are omitted where the statistic represents share of job-seekers. [Return to page 9]

Table B.4: First stage by firm size

	Visible Salary	
	(1)	(2)
Treatment	0.408***	0.354***
	(0.007)	(0.008)
Large Firm		-0.198***
		(0.013)
Large Firm × Treated Job		0.133***
		(0.013)
Constant	0.562	0.644
Non-compliance rate in treatment	0.030	
Non-compliance rate in small firms		0.002
Non-compliance rate in large firms		0.066
Observations	13,790	13,790

Notes: This table presents first-stage estimates of salary visibility by firm size. **Column (1)** estimates the impact of treatment on salary visibility, while **Column (2)** accounts for firm size by including an interaction between treatment and large firms. Non-compliance rates indicate the share of firms that were assigned to treatment but did not comply by making salary information visible. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [Return to page 21]

Table B.5: Selection in applications to small firms by high and low ability candidates

Panel A: High Ability Men				
	(1) **Expected Salary Top Decile**	(2) **GPA Top Quartile**	(3) **Years of Experience Top Decile**	(4) **Managed a Team**
Treated Job (β_m)	0.02**	0.04***	0.02**	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.72	0.87	0.73	0.87
Panel B: High Ability Women				
	(1)	(2)	(3)	(4)
Treated Job (β_f)	0.03***	0.04***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.48	0.49	0.44	0.48
Observations	7,910	7,910	7,910	7,910
H_0: $\beta_f = \beta_m$; p-value	0.38	0.69	0.19	0.03
Panel C: Low Ability Men				
	(1) **Expected Salary Bottom Decile**	(2) **GPA Bottom Quartile**	(3) **Years of Experience Bottom Decile**	(4) **Never managed a Team**
Treated Job (β_m)	0.04***	0.01**	0.01**	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Control mean	0.81	0.91	0.95	0.98
Panel D: Low Ability Women				
	(1)	(2)	(3)	(4)
Treated Job (β_f)	0.04***	0.05***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Control mean	0.41	0.55	0.76	0.80
Observations	7,910	7,910	7,910	7,910
H_0: $\beta_f = \beta_m$; p-value	0.75	0.00	0.13	0.00

Notes: The sample consists of job ads posted by small firms. Column 1 of Panels A and B shows likelihood men and women in the top decile of their expected wage applied. Panels C and D show the same for men and women in the bottom decile of expected wage. Column 2 of Panels A and B shows likelihood men and women in the top quartile of GPA applied, while in Panels C and D, the column corresponds to the bottom quartile. Column 3 of Panels A and B shows likelihood men and women in the top decile of years of experience applied, while Panels C and D, the show the same for the bottom decile. Column 4 of Panels A and B shows likelihood men and women who have any management experience applied, while Panels C and D, the show the same for men and women with no management experience. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. [Return to page 23]

Table B.6: Gender gaps in search among high ability job-seekers

	(1) **Expected Salary Top Decile**	(2) **GPA Top Quartile**	(3) **Years of Experience Top Decile**	(4) **Managed a Team**
Female Applications	-4.18***	-4.24***	-4.62***	-4.94***
	(0.25)	(0.19)	(0.26)	(0.18)
Male Applications	13.81	12.17	15.77	12.64
Observations	86,695	105,601	95,696	142,294

Notes: The table considers gender gaps in applications among high ability workers. It shows job-seeker level regressions of number of applications sent by high ability workers on the gender dummy. The row displaying "Male Applications" shows the number of applications sent by men. The row of coefficients pertaining to "Female Applications" shows the difference relative to men in the number of applications sent by female job-seekers. Column 1 shows these gender differences among job-seekers in the top decile of expected salary. Column 2 shows these gender differences among job-seekers in the top quartile of GPA. Column 3 shows these gender differences among job-seekers in the top decile of years of experience. Column 4 of shows these gender differences among job-seekers with management experience. An observation is missing if that characteristic is not observed for a worker since these are not mandatory to report. $*p < 0.1, **p < 0.05, ***p < 0.01$. [Return to page 24]

Table B.7: Firm use of applicant dashboard by treatment status

	(1) **CV views missing**	(2) **CV downloads missing**
Large Firm × Treated Job	0.02	-0.00
	(0.02)	(0.02)
Treated Job	-0.01	-0.01
	(0.01)	(0.01)
Large Firm	-0.05***	-0.13***
	(0.01)	(0.01)
Constant	0.77	0.74
Observations	13,790	13,790

Notes: This table examines the impact of treatment on firms' use of the applicant dashboard, specifically the share of CV views and downloads that are missing from the platform. Firms access applications through a portal where they can individually view CVs or download them in bulk. If a firm downloads all CVs at once, individual views may not be recorded. Additionally, firms receive applicant CVs via email, and engagement through email alone would result in missing dashboard activity. Column (1) reports the share of missing CV views, and Column (2) reports the share of missing CV downloads. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. [Return to page 26]

Table B.8: Treatment impacts by gender and firm size

Panel A: *Treatment effect as Incidence Rate Ratios (IRR) using Poisson*

	IRR: Views		**IRR: Applications**	
	(1) Male (m)	(2) Female (f)	(3) Male (m)	(4) Female (f)
Treated Job (β_1)	1.28***	1.15*	1.23***	1.14
	(0.04)	(0.08)	(0.09)	(0.12)
Large Firm (β_2)	1.71***	1.55***	1.64***	1.40***
	(0.09)	(0.15)	(0.13)	(0.18)
Large Firm × Treated Job (β_3)	1.29**	1.66***	1.38***	1.88***
	(0.15)	(0.27)	(0.17)	(0.37)
Treatment effect on large firms ($\beta_1 \times \beta_3$)	1.64***	1.91***	1.70***	2.16***
	(0.18)	(0.28)	(0.18)	(0.36)
Treatment reallocation from small to large firms ($\beta_2 \times \beta_3$)	2.20***	2.57***	2.27***	2.64***
	(0.22)	(0.34)	(0.22)	(0.39)
H_0: $\beta_{2,f} = \beta_{2,m}$; p-value		0.17		
H_0: $(\beta_{1,f} \times \beta_{3,f}) = (\beta_{1,m} \times \beta_{3,m})$; p-value		0.00		
H_0: $(\beta_{2,f} \times \beta_{3,f}) = (\beta_{2,m} \times \beta_{3,m})$; p-value		0.00		

Panel B: *Treatment effect as counts using OLS*

	N. Views		**N. Applications**	
	(1) Male (m)	(2) Female (f)	(3) Male (m)	(4) Female (f)
Treated Job (β_1)	15.99***	3.13**	11.49***	1.92
	(2.17)	(1.52)	(3.68)	(1.41)
Large Firm (β_2)	41.31***	11.12***	32.74***	5.37***
	(4.66)	(2.45)	(5.02)	(2.04)
Large Firm × Treated Job (β_3)	47.78***	25.55***	46.81***	19.62***
	(16.94)	(8.22)	(14.33)	(6.19)
Treatment effect on large firms ($\beta_1 + \beta_3$)	63.78***	28.68***	58.30***	21.55***
	(16.80)	(8.08)	(13.85)	(6.03)
Treatment reallocation from small to large firms ($\beta_2 + \beta_3$)	89.09***	36.68***	79.55***	25.00***
	(16.29)	(7.85)	(13.43)	(5.85)
Constant	75.25	24.87	64.53	15.51
Observations	13,790	13,790	13,790	13,790

Notes: This table presents the treatment effects on job search behavior, focusing on gender differences in how workers direct search toward small and large firms. **Panel A** reports incidence rate ratios (IRR) estimated using a Poisson model, capturing the proportional change in job views and applications due to treatment. Columns (1)–(2) show the effects on male and female job views, while Columns (3)–(4) report similar estimates for job applications. **Panel B** presents the same analysis using OLS to estimate the treatment effects in levels, showing the absolute increase in job views and applications due to treatment. The corresponding **graphical representation** of these results is provided in Figure A.8 for views, and Figure 11 for applications. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [Return to page 22 or 37]

A.3 Impact of n and $\bar{\theta}$ on firm's hiring probability

The impact of n on the hiring probability can be seen by differentiating it with respect to n:

$$\frac{d}{dn}\left(1-[F(\theta_{\min})]^n\right) = -\ln F(\theta_{\min})\cdot[F(\theta_{\min})]^n.$$

Since $0 \leq F(\theta_{\min}) < 1$, it follows that $\ln F(\theta_{\min}) < 0$, ensuring:

$$\frac{d}{dn}Q(n,\bar{\theta}) > 0$$

The second effect comes from the fact that if the expected maximum ability $\bar{\theta}$ increases, the probability of exceeding any fixed threshold $\theta_{\min}$ also rises. Thus:

$$\frac{d}{d\bar{\theta}}Q(n,\bar{\theta}) > 0$$

A.4 Impact of n and θ on workers' hiring probability

Workers' hiring probability is:

$$P(n,\theta) \equiv [F(\theta)]^{n-1}\cdot(1-F(\theta_{min}))$$

Differentiating with respect to n:

$$\frac{\partial}{\partial n}P(n,\theta) = (1-F(\theta_{\min}))\cdot[F(\theta)]^{n-1}\ln F(\theta).$$

Since $0 \leq F(\theta) \leq 1$, we have $\ln F(\theta) \leq 0$, which implies:

$$\frac{\partial}{\partial n}[F(\theta)]^{n-1} \leq 0.$$

Thus, as n increases, $[F(\theta)]^{n-1}$ decreases, and since $(1-F(\theta_{\min}))$ is independent of n, we conclude:

$$\frac{\partial}{\partial n}P(n,\theta) < 0.$$

Differentiating with respect to θ:

$$\frac{\partial}{\partial \theta}P(n,\theta) = (n-1)[F(\theta)]^{n-2}(1-F(\theta_{min}))f(\theta),$$

which is positive for $n > 1$.

A.5 Hiring probability is decreasing in w: $\frac{\partial P}{\partial w} < 0$

$$P(n(w),\theta) = [F(\theta)]^{n(w)-1}\cdot(1-F(\theta_{\min})).$$

Since the number of applicants $n(w)$ is increasing in w, we differentiate $P(n(w), \theta)$ with respect to w:

$$\frac{\partial}{\partial w} P(n(w), \theta) = \frac{\partial}{\partial n} P(n, \theta) \cdot \frac{dn(w)}{dw}$$

where

$$\frac{\partial}{\partial n} P(n, \theta) = (1 - F(\theta_{\min})) \cdot [F(\theta)]^{n-1} \ln F(\theta),$$

and $\ln F(\theta) \leq 0$ since $0 \leq F(\theta) \leq 1$. This implies:

$$\frac{\partial}{\partial n} P(n, \theta) \leq 0.$$

Since $\frac{dn(w)}{dw} > 0$ (i.e., the number of applicants increases with w), we conclude that:

$$\frac{\partial}{\partial w} P(n(w), \theta) < 0.$$

Thus, as w increases, competition intensifies, reducing the probability that any individual worker matches.

A.6 Impact is smaller for workers with lower θ: $\frac{\partial^2 P}{\partial w \partial \theta} > 0$

$$\frac{\partial^2 P}{\partial w \partial \theta} = \frac{\partial}{\partial \theta} \left([F(\theta)]^{n(w)-1} \ln F(\theta) \cdot \frac{dn(w)}{dw} \right)$$

$$\frac{\partial^2 P}{\partial w \partial \theta} = \frac{dn(w)}{dw} \cdot \left(\frac{\partial}{\partial \theta} \left[[F(\theta)]^{n(w)-1} \ln F(\theta) \right] \right)$$

Now, differentiating the term inside the parentheses:

$$\frac{\partial}{\partial \theta} [F(\theta)]^{n(w)-1} \ln F(\theta) + [F(\theta)]^{n(w)-1} \frac{1}{F(\theta)} f(\theta)$$

where:

$$\frac{\partial}{\partial \theta} [F(\theta)]^{n(w)-1} = (n(w) - 1)[F(\theta)]^{n(w)-2} f(\theta),$$

we get:

$$(n(w) - 1)[F(\theta)]^{n(w)-2} f(\theta) \ln F(\theta) + [F(\theta)]^{n(w)-1} \frac{f(\theta)}{F(\theta)}.$$

Factoring out $f(\theta)$ and $[F(\theta)]^{n(w)-2}$:

$$f(\theta)[F(\theta)]^{n(w)-2} \left[(n(w) - 1) \ln F(\theta) + 1 \right]$$

Thus:

$$\frac{\partial^2 P}{\partial w \partial \theta} = f(\theta)[F(\theta)]^{n(w)-2}\left[(n(w)-1)\ln F(\theta)+1\right]\frac{dn(w)}{dw}.$$

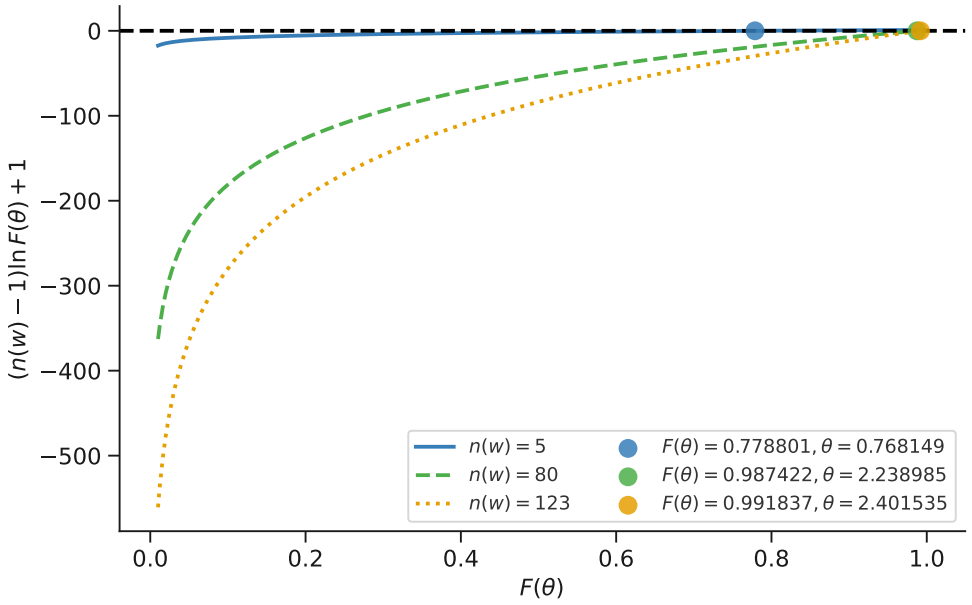
where:

- $f(\theta) > 0$, since it is a probability density function and must be non-negative for all θ.
- $\frac{dn(w)}{dw} > 0$, because an increase in wages attracts more applicants.
- For the expression to be positive, we need $(n(w)-1)\ln F(\theta)+1 > 0$.
  - Rearranging:

$$(n(w)-1)\ln F(\theta) > -1$$
$$\ln F(\theta) > -\frac{1}{n(w)-1}$$
$$F(\theta) > e^{-1/(n(w)-1)}$$

  - This condition is met for finite sufficiently large θ. For larger applicant pools, even moderately high θ values will satisfy this condition as shown in the graph below.

Figure A.12: Threshold values of $F(\theta)$ for which $(n(w)-1)\ln F(\theta)+1 > 0$.



Notes: This figure illustrates the relationship between the cumulative distribution function $F(\theta)$ and the condition $(n(w)-1)\ln F(\theta)+1$. Each line represents a different value of $n(w)$, the number of applications. Circular markers indicate the threshold values where the expression transitions from negative to non-negative. The corresponding θ values, derived from the inverse normal CDF. The legend is structured into two columns: the first listing $n(w)$ values corresponding to each curve, and the second listing threshold values and their associated θ.

Thus, as θ grows we have:

$$\frac{\partial^2 P}{\partial w \partial \theta} > 0.$$

A.7 Upper Threshold: $\bar{\theta}(w)$ increases with w.

Define the function

$$F\big(\theta, w\big) \;=\; P\big(n(w), \theta\big)\,\big[\lambda\,\theta + w\big] \;-\; V(\theta) \;-\; s.$$

The threshold $\bar{\theta}(w)$ is implicitly defined by the condition

$$F\big(\bar{\theta}(w),\, w\big) = 0.$$

Applying the Implicit Function Theorem,

$$\frac{\mathrm{d}}{\mathrm{d}w} F\big(\bar{\theta}(w),\, w\big) \;=\; F_\theta\big(\bar{\theta}(w), w\big)\,\bar{\theta}' \;+\; F_w\big(\bar{\theta}(w), w\big) \;=\; 0 \quad\Longrightarrow\quad \bar{\theta}(w)' \;=\; -\,\frac{F_w}{F_\theta}.$$

Where:

$$F_\theta = \underbrace{P\big(n(w), \bar{\theta}(w)\big)\,\lambda}_{\text{(i)}} \;-\; \underbrace{\frac{\partial V_{\bar{\theta}}}{\partial \theta}}_{\text{(ii)}},$$

$$F_w = \underbrace{\frac{\partial P}{\partial w}\Big[\lambda\,\bar{\theta}(w) + w\Big]}_{\text{(negative since } \frac{\partial P}{\partial w} < 0)} + \underbrace{P\big(n(w), \bar{\theta}(w)\big)}_{\text{(} > 0 \text{ because it's a probability)}} - \underbrace{\frac{\partial V_{\bar{\theta}}}{\partial w}}_{\text{(=0 since } V(\theta) \text{ depends only on } \theta)}$$

Sign conditions:

- $\boldsymbol{F_w > 0}$: A shown in Section A.6, while $\frac{\partial P}{\partial w} < 0$ since more competition lowers hiring probability, its magnitude falls as θ rises, thus the first term becomes smaller. Meanwhile, the hiring probability rises in θ as shown below:

$$P(n, \theta) = (n-1)[F(\theta)]^{n-1}(1 - F(\theta_{min}))$$
$$\frac{\partial P(n, \theta)}{\partial \theta} = (n-1)[F(\theta)]^{n-2}(1 - F(\theta_{min}))f(\theta)$$

  Thus, as θ rises, the magnitude of $P(.)$ dominates, making $F_w > 0$.

- $\boldsymbol{F_\theta < 0}$: As ability θ increases, the outside option $V(\theta)$ grows at rate $\frac{\partial V(\theta)}{\partial \theta}$. Since $P(\cdot)$ is capped at 1 and $\lambda < 1$, we typically have

$$\frac{\partial V(\theta)}{\partial \theta} > P(n(w), \bar{\theta}) \cdot \lambda,$$

  ensuring that $F_\theta < 0$.

Since $F_w > 0$ and $F_\theta < 0$, we conclude:

$$-\frac{F_w}{F_\theta} > 0 \quad \Longrightarrow \quad \bar{\theta}'(w) > 0.$$

Hence, the upper threshold $\bar{\theta}(w)$ increases with the wage.

A.8 Lower Threshold $\underline{\theta}(w)$ has an Ambiguous Relationship w.r.t. w

Similarly, define

$$G\big(\theta, w\big) = P\big(n(w), \underline{\theta}(w)\big)\left[\lambda\,\theta + w\right] - V(\theta) - s.$$

The lower threshold $\underline{\theta}(w)$ is implicitly defined by

$$G\big(\underline{\theta}(w), w\big) = 0.$$

Applying the Implicit Function Theorem,

$$\frac{\mathrm{d}}{\mathrm{d}w} G\big(\underline{\theta}(w),\, w\big) = G_\theta\big(\underline{\theta}(w), w\big)\,\underline{\theta}'(w) + G_w\big(\underline{\theta}(w), w\big) = 0 \quad \Longrightarrow \quad \underline{\theta}'(w) = -\frac{G_w}{G_\theta}.$$

Where:

$$G_\theta = \underbrace{P\big(n(w), \underline{\theta}(w)\big)\,\lambda}_{\text{(i)}} - \underbrace{\frac{\partial V(\theta)}{\partial \theta}}_{\text{(ii)}},$$

$$G_w = \underbrace{\frac{\partial P}{\partial w}\Big[\lambda\,\underline{\theta}(w) + w\Big]}_{\text{(negative if competition effect dominates)}} + \underbrace{P\big(n(w), \underline{\theta}(w)\big)}_{\text{(positive)}}$$

Sign Conditions:

- $G_\theta < 0$: As θ increases, $V(\theta)$ grows at rate $\frac{\partial V(\theta)}{\partial \theta}$. Since $P(\cdot)$ is capped at 1 and $\lambda < 1$,

  $$\frac{\partial V(\theta)}{\partial \theta} > P(n(w), \underline{\theta}(w)) \cdot \lambda$$

  ensures $G_\theta < 0$.

- G_w is ambiguous: The direct wage effect increases $\left[\lambda\,\theta + w\right]$, while competition lowers hiring probability ($\frac{\partial P}{\partial w} < 0$). If $\underline{\theta}(w)$ is low, crowding-out is strong, making $G_w < 0$. If the direct wage effect dominates, then $G_w > 0$.

Hence, we have that:

$$\underline{\theta}'(w) = -\frac{G_w}{G_\theta}$$

- If $G_w > 0$, then $\underline{\theta}'(w) < 0$: More low-$\theta$ workers apply.

- If $G_w < 0$, then $\underline{\theta}'(w) > 0$: The lower threshold rises.

Thus, the effect of w on $\underline{\theta}(w)$ is ambiguous. High wage increases the best applicant's expected ability. Finally, note that $\underline{\theta}(w)$ is defined as the expected maximum (or best) ability in the applicant pool. As w rises, the upper threshold $\bar{\theta}(w)$ strictly increases, expanding the supply of high-ability applicants. Even if $\underline{\theta}(w)$ moves, the distribution's upper support becomes strictly larger. Hence, under standard single-peaked or monotonic hazard assumptions on θ's distribution, the *max* of the drawn pool shifts right in expectation, implying $\underline{\theta}'(w) > 0$.

Conclusion. Higher wages unambiguously *raise* the upper threshold $\bar{\theta}(w)$ and thus *increase* the expected top ability $\underline{\theta}(w)$. They have *opposing* influences on the lower threshold $\underline{\theta}(w)$: A positive wage effect that encourages low-θ types to apply. A negative crowding-out effect that discourages them by lowering $P(n(w), \underline{\theta}(w))$ when $\underline{\theta}(w)$ is large. Thus, a large crowding-out effect can push $\underline{\theta}(w)$ *upward*, reducing the participation of marginal workers, while a small crowding-out effect can drive $\underline{\theta}(w)$ *downward*.