The Illusion of Time: Gender Gaps in Job Search and Employment *

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Abstract

The employment rate of college-educated women in South Asia remains low. To understand why, we run surveys and an experiment in collaboration with two of the largest universities in Pakistan. Our sample reflects the country level statistics: six months after graduation, 36.9% of women are working compared to 64.2% of men. Yet, we document that women and men follow the same path from graduation to job offer: they set out with the same aspirations and same preferences for work, they are as likely to send job applications and receive the same number of offers. Instead, what drives the gender employment gap is that women turn down job offers at significantly higher rates than men. We find that application timing underpins this explanation: the probability of accepting a job offer falls over time for women, but not for men. We leverage this new insight to design and experimentally test a policy lever that offers a financial incentive to apply within a month of graduation. This policy shifts applications earlier for both genders but increases employment for women only, leading to a 34% decrease in the gender employment gap. The policy works by increasing the job acceptance rate of women, leaving firm demand unaffected. The experiment also reveals that the reason why timing matters differentially for women lies entirely outside of the labor market: they lack foresight about the rising demands of the marriage market.

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1 Introduction

Large investments in women's education in low and middle income countries have successfully narrowed – and in many cases eliminated – the gender education gap. Yet, women's labor force participation remains extremely low (Addati et al. 2018). This is puzzling because limited access to education was believed to be a major obstacle to women's labor force participation (Heath and Jayachandran 2018). Pakistan offers a compelling illustration of this puzzle: over the past two decades, the share of women with a college degree has nearly doubled, yet only one in three college-educated women is in the labor force. This paper asks why.

Our research design has two phases: diagnostic and experimental, implemented in collaboration with two of the largest universities in Pakistan. For the diagnostic phase we partner with a private university in Lahore, and conduct a series of surveys with a panel of ~ 1,000 students graduating in July 2022. We interview students about their labor market aspirations a month before they graduate, then again two, six, and nine months post-graduation to measure their labor market outcomes. This allows us to diagnose where the pipeline from education to employment leaks. Based on these insights, we design a policy intervention aimed at fixing this leak and assessing its causes. The policy is implemented with a panel of ~ 1,400 students graduating in July 2023 from the largest public university in Pakistan. We track its effect with a new series of surveys, similarly fielded over four waves, between June 2023 and September 2024.

To begin we note that our diagnostic sample reflects the country level statistics: six months after graduation, 36.9% of women are working compared to 64.2% of men. The first hypothesis we test is that there is no pipeline from education to employment at all, that is, women go to college for reasons other than its labor market returns. For instance, Adams and Andrew (2024) document that in India, college degrees enhance marriage prospects. This finding raises the possibility that women want to pursue higher education primarily to improve marital outcomes, rather than labor market ones. At odds with this, the survey we run one month before graduation shows that women's beliefs about their likelihood of working six months post-graduation are comparable to men's, averaging 71.8%. Tacking post-graduation application behavior, we observe that the aspirations women state at baseline are not cheap talk: nearly three out of four women apply to at least one job in the six months following graduation, a share similar to men's.

If women's work aspirations are similar to men's, where does the gender gap in employment come from? We test a wide range of explanations proposed by the existing literature,

extended specifically to the context of college-educated women. We first test whether men and women differ on observable traits and job search behaviors and whether such differences can explain the employment gap. Second, we test whether *the returns* to these traits and behaviors differ across genders. The first exercise shows that most supply-side characteristics, such as GPA, major, industry of search, wage and non-wage preferences, are similar between genders and controlling for them reduces the gender employment gap by only 1.9 ppt (7.0%). Job search behavior is also similar across genders: women send nearly as many applications as men, and do so no later than them, such that further controlling for search effort has no impact on the gender employment gap. Turning to the demand-side, we find limited evidence that a lack of firm demand for women explains the gender employment gap: women receive as many job interviews as men, and more job offers than them, albeit at lower wages. After accounting for all the aforementioned supply and demand side factors, the employment gap remains large, at 18.1 ppt. Given that women and men follow the same path all the way to the offer stage the sole explanation left is that the gender employment gap is driven by the fact that women are much more likely to reject job offers than men. The second exercise uncovers that women's rejection rates are correlated with the timing of job applications: accounting for the total number of applications sent, women who start applying within two months of graduation are 17.1 ppt more likely to have accepted a job offer six months later than women who do not. In contrast, application timings do not correlate with men's employment.

The fact that application timing is so strongly correlated with women's employment potentially adds new policy levers to foster female labor force participation. We design and implement an experiment to evaluate one such lever, specifically an incentive scheme that rewards early applications. The treatment consists of a small monetary reward paid to those who apply to jobs within one month of graduation.[1] It has a significant effect on the timing of applications: 56.7% of women in the treatment group apply to at least one job by August 15th, compared to 31.1% in the control group. We observe similar effects on application timing for men. As a result, the experiment allows us to estimate

1. To correct workers' misperceptions, recent research has honed in on information experiments (Aloud et al. 2020; Jäger et al. 2024; Roussille 2024). Most related to the misperception we study, Alfonsi, Namubiru, and Spaziani (2024) find that debiasing overly optimistic job-seekers in Uganda increases their likelihood of being in the labor force by 27% three months after the intervention. However, in our context, trying to fix misperceptions by providing information would most likely be to no avail. While women in our sample overestimate their own chances of working, they are largely aware of aggregate labor force statistics, predicting a more accurate likelihood of working six months post-graduation for their female peers. Therefore, rather than attempting to correct misperception with market-level information, we design an intervention to directly address the resulting job search distortions.

two parameters of interest, that is, the causal effect of the incentive policy on employment and the causal effect of early applications on employment for the compliers.

We find large intent-to-treat effects on women's employment: six months later, 41.1% of women assigned to treatment are working, compared to 33.6% of control women (a 7.5 ppt or 22.3% difference, p = 0.015). Fourteen months later, the gap between treated and control women remains substantial, at 6.9 ppt (p=0.046). Since, in low income countries, working on a self-employed basis indicates lower labor market attachment and earnings potential (Breza, Kaur, and Shamdasani 2021), we also consider the impact of our treatment on employment for a firm and find stronger effects there: six months later, only 25.3% of control women work for a firm, compared to to 35.5% of treated women (a 10.2 ppt or 40.3% increase, p=0.001). This treatment effect also persists over time, at 9.5 ppt (p=0.006) fourteen months later. In contrast, and consistent with our correlational evidence, we find no treatment effects on the labor market outcomes of men at either the six or fourteen-month follow-up. As a result, the incentive policy leads to a 34% decrease in the gender employment gap.

The incentive policy can also be used to recover the local average treatment effect of early applications on employment. Using treatment assignment as an instrument for early applications, we find that applying within a month of graduation has a significant impact on women's employment outcomes, with 2SLS estimates indicating a 38.2 ppt increase in female firm employment (vs. 23.6 ppt with OLS), at the six month follow-up. Similar effects are estimated at the fourteen-month follow-up. In contrast, the 2SLS estimates show that there is no impact of early applications on male compliers, confirming that timing matters only for women.

Through what channel does the treatment operate? Studying the pipeline to employment, we find that the treatment increases the number of applications women have sent by the fourteen month mark, but it has no downstream effect on the number of offers than women in the treatment group receive, relative to the control group. Since women in the control group are as likely as women in the treated group to receive a job offer by endline, the treatment effect on employment can only operate through an increase in the likelihood that women accept one of the job offers they have received. This is consistent with our correlational evidence, showing that earlier applications are associated with higher acceptance rates.

Finally, we explore why earlier applications lead to higher chances of accepting a job offer for women. We first note that the size of the employment effect relative to the modest

reduction in delay caused by a small incentive suggests that there must be a tipping point of which women are not aware. In other words, women must have biased beliefs about *some* time-varying parameter of the job search process. Hence, we explore the role of factors that are plausibly (i) unanticipated and (ii) change over time. We first test for changes in women's preferences for work: it could be that women unexpectedly revise downwards their preferences for work over time. However, we find no supporting evidence for this channel. Instead, we propose that unexpected changes in the marriage market drive lower acceptance rates for late appliers. This stems from the sharp difference in treatment effects between women who expect to marry late, that is after the median age of 25, and those who expect to marry early. Indeed, treatment effects on working for a firm are much stronger for women who expect to marry late (past age 25), at 17.4 percentage points versus only 5 percentage points for those expecting early marriage (p-value of the difference = 0.022). In line with our interpretation of biased beliefs about time varying parameters, we find that women who expected to marry late at baseline revise their expectation downwards at the six month mark, while those who expect to marry early do not. This completes the argument.

This paper contributes to a growing literature on behavioral job search, which highlights the role of biased beliefs about labor market prospects in the determination of employment and wages. Recent survey data reveals an optimistic bias among job seekers regarding their job finding rate (Spinnewijn 2015; Mueller, Spinnewijn, and Topa 2021; Abebe et al. 2024). In line with those papers we show that biased beliefs affect job search in a way that cannot be undone, so that small differences between applicants at baseline set them on different equilibrium paths leading to very different outcomes. We build on this literature by showing evidence that biased beliefs about the outside option (here housewifery) have similar consequences, implying that rational expectations about labor market prospects are not sufficient to eliminate path dependence and multiple equilibria. Our paper complements two studies that further layer in a gender perspective. First, Kuziemko et al. (2018) show that, in the U.S., young women overestimate their chances of going back to work after childbirth. Similarly, we find that college-graduating women in Pakistan overestimate their near-future labor supply. Second, Cortés et al. (2023) find that, among U.S. college graduates, women accept jobs earlier than men because they are more risk-averse and less over-optimistic. Our paper complements this study by describing the role of application timing in a context with low female labor force participation, where college-graduating women's labor supply decisions are made as much at the extensive

margin (whether to work) as at the intensive margin (which job to choose).

We also contribute to a literature that documents barriers to female labor force participation, and interventions to remove them. On the labor supply side, social norms and intra-household constraints are the leading explanations (Bertrand, Goldin, and Katz 2010; Bursztyn, González, and Yanagizawa-Drott 2020; Jayachandran 2021; Kleven, Landais, and Leite-Mariante 2023; Bursztyn et al. 2023; Agte and Bernhardt 2024). On the labor demand side, firm gender preferences have been shown to contribute to gender gaps in employment (Goldin and Rouse 2000; Kuhn and Shen 2023; Card, Colella, and Lalive 2021; Gentile et al. 2023). In our diagnostic phase, we draw from this literature to document each step of the female pipeline from college education to employment and test its effect on the gender employment gap. In our context, the main leak in the pipeline appears to be on the supply side and occurs at the very last stage of the job search process: the decision to accept a job offer. A growing experimental literature further focuses on testing interventions that remove potential barriers to women's labor market access (Field and Vyborny 2022; Ahmed et al. 2024; Cheema et al. 2022; McKelway 2024; Ho, Jalota, and Karandikar 2023). Many of these papers test labor demand interventions, such as offering more flexible jobs, safer workplaces, or improved transportation. While these avenues hold tremendous promise, they may be hard to scale absent heavy infrastructure investments. Instead, our intervention nudges the supply side only and does not require any changes in firms' behavior.

2 Background

2.1 Context

Gender gaps in college education in Pakistan have shown a remarkable decline over the years. Figure A.1 Panel (a) shows the evolution, over the last twenty years, of the share of women and men (ages 22-35) with a college degree. In 1999, 4.9% of women versus 10.8% of men held a college degree. By 2018, the share of women with a college degree had doubled and the gender education gap had closed by more than half. Despite these large strides in women's educational attainment, Figure A.1 Panel (b) shows that the share of college-educated women (ages 22-35) who are in the labor force has stagnated at around 34% for the past twenty years. This share is not much higher than the average female labor force participation for the same age range (27.8%) and starkly contrasts with

the labor force participation of college-educated men (83.3%). Overall, Pakistan stands out as one of the middle income countries where women's access to college has grown tremendously, yet women's involvement in the labor force remains one of the lowest globally, even in comparison to countries with similar economic development (see Figure A.2).

As the world's 5th most populous nation, Pakistan is interesting to study in its own right. However, the disconnect between a narrowing gender gap in education and a persistent gender gap in labor force participation is not unique to Pakistan: many countries across South Asia, North Africa, and the Middle East face similar challenges (see Jayachandran (2021) and Dinkelman and Ngai (2022) for comprehensive reviews).

In this paper, we study the labor supply decision of women at the time of their college graduation. This choice is motivated by the life cycle of women's labor supply in South Asia, which meaningfully differs from that in higher income countries. Figure A.3 plots the labor force participation of men and women by age in 2018, for the United States in Panel (a) and for Pakistan in Panel (b). A standard pattern in higher income countries like the United States is that women's labor market entry rates are similar to men's but female labor force participation falls in childbearing years. In contrast, the life cycle of women's labor supply in Pakistan is essentially flat: rather than dropping out in childbearing ages, women in Pakistan rarely enter the labor market in the first place. Similar patterns can be observed if we restrict the analysis sample to college graduates (see Panel (c) and (d) of Figure A.3).[2] Since women do not enter the labor market from the onset of their adult life in Pakistan, understanding their labor supply decision right at the point of college graduation is essential.

We partner with two of the most prominent universities in Pakistan to survey their students. To ensure broad coverage and external validity of our results, we select a large, mid-tier private university, and the largest and oldest public university in the country. The private university primarily enrolls students from Lahore, the second largest city in Pakistan, while the public university draws students from around the country.

2.2 Two-Stage Strategy

This project can be separated into two distinct stages: diagnostic and experimental. This section describes the reasons behind this two-stage approach. We illustrate the setting

2. Figure A.3 does not account for cohort effects. It is therefore all the more striking that the labor force participation of young Pakistani women in 2018 is the same as that of older cohorts.

and timeline corresponding to each of the phases in Figure A.4.

Diagnostic Stage We run a series of surveys at the private university, with their cohort graduating in 2022. Details on the recruitment of students for these surveys, as well as descriptive statistics on this diagnostic sample are provided in Sections 3.1 and 3.2. Our goals for this exercise are threefold. First, we want to measure men and women's labor market expectations at the time they graduate from college. To do so, we run an in-person baseline survey in June, one month before students' college graduation. We describe our results in Section 3.3. Our second goal is to diagnose whether the pipeline from labor market beliefs to labor market entry breaks and, if so, where. To do so, we run three follow-up phone surveys with the same students in September 2022 (two months after graduation), in January 2023 (six months after graduation) and in April 2023 (nine months after graduation). The results comparing beliefs with realized labor market outcomes are described in Section 3.4. Third, we seek to provide evidence on the determinants of women's labor supply decisions. In particular, we test which characteristics are predictive of women's employment. We draw our list of potential predictors from the large literature on determinants of female labor force participation. We cover the variables we collect and construct, as well as their predictive power, in Section 4.

Experimental Stage Armed with insights from the diagnostic surveys, we identify a labor market behavior that is both highly predictive of women's employment, and plausibly receptive to change: the timing of their job applications. To test whether policy can leverage timing to increase women's labor supply, we run an intervention that financially encourages a random subset of students to apply to jobs earlier, this time with the graduating cohort of 2023 at Pakistan's largest public university. The main reason for switching to a new university is to verify that the insights from our diagnostic sample generalize to a different context, particularly one with a more diverse student body representing various regions and economic backgrounds across the country. Here as well, we run an in-person baseline survey a month before graduation, as well as two-, six-, and fourteen-month follow-up surveys over the phone. The design and results are detailed in Section 5, while the underlying mechanisms are explored in Section 6.

3 Labor Market: Beliefs and Outcomes

3.1 Recruitment and Balance

Recruitment We invite all 2,872 graduating students (1,146 female and 1,726 male) at the private university to participate one month prior to their graduation. Of these, 2,238 participate in our baseline survey (a response rate of 77.9%).[3] Since we are interested in labor market beliefs and outcomes, we exclude from our sample students who reported during the survey that they already registered for a graduate program since we are mostly interested in. This leaves us with a sample of 1,494 students in our baseline sample.

Attrition and Balance Of the 1,494 students in our baseline sample, 1,029 respond to our six-month survey and 886 respond to our nine-month survey. The six-month and nine-month response rates are therefore 68.9% and 59.3%. These response rates are considerably higher than what is typical in the literature for phone surveys.[4] Table B.1 shows that the baseline, six-month, and nine-month samples have similar observables.[5]

Diagnostic Sample Since our analysis systematically compares baseline beliefs with later realized outcomes, we define our diagnostic sample as the 1,029 students who respond to both the baseline and six-month follow-up surveys.

3. The response rate for our baseline survey is high compared to that of other surveys conducted in university settings. For instance, the response rate of Questrom graduating students in Cortés et al. (2024) was 20%, the response rate for Bertrand, Goldin, and Katz (2010)'s survey of University of Chicago MBA students was 31%, and the response rate was 10-12% across the 28 universities that participated in the recent Global COVID-19 Student Survey Jaeger et al. (2021). We think this high response rate was encouraged by the reward we offered for responding to the survey: a KFC meal. See Figure A.5 for a picture of our food stand.

4. We achieve this by calling students many (at least three) times, systematically recording and varying the day/hour of the call to maximize our chances of response, and recording contact numbers of family members in case the student's own contact details change.

5. Among the many we test, a few observables display differences across waves that are statistically significant. For instance, the average GPA of non-attritors at the six-month follow-up is 3.09, while that of attritors is 3.03. This difference is statistically significant but economically small. We also note that there are no systematic patterns in attrition across waves: most differences that appear in the six-month survey are eliminated at the nine-month survey, and vice versa. For readability, we also exclude the two-month follow-up from the attrition table, as we ended up only using this survey for the definition of one variable in our analysis. The response rate at the two-month follow-up is higher than at the later follow-ups and attrition no different either.

3.2 Descriptive Statistics

The baseline characteristics of our diagnostic sample are shown in Table 1. The last column of the table reports the p-value associated with the test of equal means across gender. Women make up 42.7% of the sample, with 439 female and 590 male respondents. Men and women are both about $22^{1/2}$ years-old, on average. Women's GPAs are about 6.7% higher than men's on average, and this difference is statistically significant. Men are more likely to major in Engineering and Computer Science (39.2% vs. 8.9%), whereas women are more likely to major in Life Sciences (21.6% vs. 5.1%) and Sciences (23.2% vs. 5.8%). Humanities, Languages and Education are moderately more popular among women than men (18.5% vs. 13.4%), while Social Sciences attract a higher proportion of men than women (36.6% vs. 27.8%). Only 6.8% of women and 2.4% of men are married at the time they graduate from college, a similar fraction is engaged (7.5% of women and 5.9% of men). Finally, men and women come from similar familial backgrounds. On average, 41.0% of students have a college-educated mother, and 53.2% have a college-educated father, with no significant gender differences. Additionally, Figure A.6 shows that the students in our diagnostic sample have more liberal gender norms compared to national averages. Men in our sample are 18.3 ppt less likely to agree that being a housewife is just as fulfilling as being a working woman than the average male college student in Pakistan. Similarly, women are 26.5 ppt less like to agree that being a housewife is just as fulfilling as being a working woman than the average female college student in Pakistan. Both men and women in our sample are about 30 ppt less like to agree that when jobs are scarce, men have more right to a job than women.

3.3 Baseline Beliefs about Labor Market Outcomes

We begin our investigation of the education-to-employment pipeline by examining whether women, as they approach college graduation, expect that they will work in the near future. Indeed, it could be that college degrees serve purposes entirely outside of labor market considerations-notably, they also enhance marriage prospects, as documented in Adams and Andrew (2024). This raises the possibility that women want to pursue higher education primarily to improve marital outcomes rather than labor market positioning, potentially explaining the low labor force participation among college-educated women.

Belief about Self: Elicitation In the baseline survey, we ask two main questions to measure students' beliefs about their future labor force participation. The first question is about their reservation wage for their preferred job title across four work schedules (Full-time onsite, Part-time onsite, Full-time remote, Part-time remote). We allow them to reject the job if they would not be willing to work in a given schedule for any wage.[6] We consider that the student expects to be in the labor force at baseline if they provide a reservation wage for at least one of the schedules. The second question is probabilistic: "On a scale from 0 (very unlikely) to 100 (very likely), how likely is it that you will be working within six months of graduating? Work includes working for a private firm or government, running your own business or your family business."

Beliefs about Self: Results Across a wide range of measures, we find that, at the time they graduate, the majority of women expect to work. Virtually all women and men provide us with a reservation wage for at least one work schedule. Additionally, 95.0% of women provide a reservation wage for the full-time, onsite schedule. Importantly, as illustrated in Figure A.7, the distribution of women's reservation and expected wages lie to the left of men's, even after controlling for GPA, major, and industry of search. This suggests that women do not seek unreasonably high wages. Turning to the probabilistic question, the first two bars of Figure 1 Panel (a) show that women report a 71.8% likelihood of working within six months of graduation, only 5.2 ppt lower than men. Beyond expecting to work, most women express a preference for working over being a housewife: Figure A.6 Panel (a) shows that 60.9% of women in our sample report that being a housewife is not as fulfilling as being a working woman. Finally, one may worry that stated beliefs at baseline may just be cheap talk (or the result of demand effects). Two pieces of evidence assuage this concern. First, we do not find any difference in women's responses to questions about their work preferences or adherence to traditional gender norms by the gender of the enumerator. This rules out concerns about demand effects due to the

6. The exact wording of the question is: Imagine that you have graduated from your current degree and are offered a job with 4 possible schedules, which corresponds to [preferred job title]. The four possible schedules are: Full-time (40 hours per week, 9am to 5pm, Monday to Friday) onsite, Part-time (25 hours per week, 9am to 2pm, Monday to Friday) onsite, Full-time remote, Part-time remote. There are no additional jobs currently available that are of interest to you so if you reject this job, you will be unemployed for the foreseeable future. What is the minimum monthly starting salary for which you would be willing to work for any of the following work schedules? Note: you may reject any or all schedules if you would not work on that schedule for any salary. Consider that in all options, the job and the employer are identical in all respects except the schedule, and the job is located in your preferred city. The job is a 20 minute drive away from your house and is representative of other similar jobs in the industry in terms of career growth opportunities, non-wage benefits etc.

enumerator's gender, (e.g., women may be more inclined to abide by traditional gender norms when answering a man than when surveyed by a woman). Second, women's post-graduation actions support their baseline expectations: Figure A.8 Panel (b) shows that 78.4% of women apply for at least one job within six months of graduating, a share similar to men, at 75.1%.[7]

Beliefs about Peers: Elicitation We ask students their beliefs about the future employment of their peers to test whether students' beliefs about themselves differ from their beliefs about their peers. Specifically, we ask: "Think of women in your cohort at [the university] who are not pursuing further education after graduating. Out of 100 randomly selected female students in this sample, how many of them do you think would be employed within six months after graduating?" We repeat the question replacing "female" with "male."

Beliefs about Peers: Results Even though women have high labor market expectations for themselves, both male and female students have much lower expectations about the employment of other women in their cohort. Figure 2 shows that men estimate that their male peers have a 63.5% chance of being employed six months after graduation, while they believe their female peers have a 50.2% chance. Similarly, women estimate that their male peers have a 68.4% chance of employment, compared to a 51.5% chance for their female peers. Notably, women estimate their own likelihood of employment at 71.8%, which is not only much higher than their estimate for other women, but also comparable to their belief about men's chances (68.4%). Thus, women see themselves as much more likely to work than their female peers, and on par with men.

3.4 Beliefs Meet Reality

Beliefs About Self Meet Reality While men and women have similar beliefs about their employment likelihood, the third and fourth bars in Figure 1 Panel (a) reveal a large gender employment gap: 64.2% of men but only 36.9% of women were employed six months after graduation. Validating the representativeness of our sample, the share of

7. We collect further evidence in the experimental sample by administering additional measures of baseline work intentions. Across all these measures, we find that nearly all women, irrespective of their family's wealth, want to work for at least two years after graduation. For more details, see Section C.

working women closely aligns with the national average labor force participation rate for young college-educated women, which is 33.9% in 2018 as shown in Figure A.1 Panel (b). Comparing realized outcomes to the baseline beliefs represented in the first two bars of Figure 1 Panel (a), we find that on average men overestimate their likelihood of working by 12.8 ppt (16.6%), while women overestimate it by 34.9 ppt (48.6%).[8]

Figure 1 Panel (b) shows the relationship between baseline employment beliefs and realized employment six months post-graduation. The benchmark of accurate beliefs would manifest as observations on the 45-degree line.[9] The figure illustrates that, relative to this benchmark, both men and women have inaccurate beliefs about their future employment. Specifically, for both genders the slope of the relationship between their baseline beliefs and realized outcomes is similar and closer to zero than to one (0.35 for men and 0.31 for women). However, the intercept is drastically different across genders: 14.7 ppt for women, and 37.2 ppt for men. Taken together, the slopes and intercepts imply that women overestimate their chances of working along most of the distribution of baseline beliefs, and do so significantly more than men. For example, among those who report a 80.0% chance of working six months post-graduation, only 32.6% of women, vs. 61.7% of men, end up working. In sum, despite striking gender similarities in intended employment documented at the onset of job search, we uncover large gender gaps in employment rates six months post-graduation.

We also conduct a shorter survey nine months post-graduation to track students' employment outcomes. Figure A.9 shows that while women's employment levels rise substantially by 10.8 ppt (from 26.1% to 36.9%) between the two- and and six-month follow-up surveys, there is almost no change in employment levels for women between six months and nine months. The nine-month employment rate is 38.8% for women, only 1.9 ppt higher than the six-month employment rate. Additionally, the employment rates at both six and nine months closely align with the national average of 33.9% for college-educated women in Pakistan. This strongly suggests that employment for women stabilizes around the six-month to one-year mark. The next significant shifts in these outcomes may occur around major life events such as marriage or the birth of a first child.

8. Illing, Schmieder, and Trenkle (2024) also find that men and women who are similar at baseline can experience different outcomes. The study compares men and women who are displaced from similar jobs by applying an event study design combined with propensity score matching and reweighing to administrative data from Germany. After a mass layoff, women's earnings losses are about 35% higher than men's.

9. Deviations from this benchmark take two forms. Observations above the 45-degree line correspond to students underestimating their chances of working. Conversely, observations below the 45-degree line imply students overestimate their chances.

However, tracking these later transitions is beyond the scope of this study, as the average age of marriage for college-educated women in Pakistan is around 25— three years after graduation.

Beliefs About Others Meet Reality Both men and women accurately estimate their male peers' employment outcomes. Men predict 63.5% for other men, and women predict 68.4% for men, close to the 64.2% actual employment rate for men. For female peers, men estimate 50.2% and women estimate 51.5%. While these predictions are higher than women's realized employment at six months (36.9%), they are much more accurate than women's belief about their own likelihood of working (which averages 71.8%).

4 Diagnosing the Gender Gaps

Sections 3.3 and 3.4 reveal significant gender disparities in labor market outcomes six months post-graduation. We now look into various commonly suggested explanations to account for these disparities. We first assess gender differences in relevant endowments (e.g., GPA, major, or search effort) and analyze if these differences explain the gender gaps, following the logic of a Oaxaca decomposition. We then test whether men and women receive different returns on their endowments (e.g., are labor market returns to a higher GPA different for men and women?), and whether potential differences in returns further explain the observed gaps. Before we proceed further, a quick note of caution: in this section we present diagnostic correlations without making causal claims.

Level Differences I: The Usual Supply-Side Suspects A leading explanation for low female labor force participation is that women are primarily responsible for household management (Veerle 2011). This may imply a higher opportunity cost of working, and result in higher reservation wages or a preference for flexible or part-time work (Mas and Pallais 2017; Maestas et al. 2023). As a result, women may pursue fewer or rarer jobs than men, despite similar qualifications and expectations. However, as discussed in Section 3.3, women's reservation wages are lower than men's, conditional or unconditional on covariates. Turning to non-wage amenities, Figure A.10 shows no gender differences in preferred work hours (averaging 6.4 per day for both men and women), or preferences for remote work (about three-fourths of both genders prefer on-site jobs). We also explore gender differences in GPA to assess if disparities in human capital contribute to these gaps.

Figure A.8 Panel (a) illustrates that women have higher GPAs than men, and this holds even after controlling for their major.[10] Finally, another plausible explanation for the gender gap in employment is gender differences in job search (Cortés et al. 2023; Fluchtmann et al. 2024). For instance, if women apply to fewer jobs or apply later than men, they may be less likely to work. Figure A.8 Panel (b) presents the cumulative distributions of the number of job applications by gender. It shows that, at the extensive margin, women are as likely as men to apply to any job. Additionally, the median number of applications, 4, is the same for men and women. While, on average, women apply to 2.8 fewer jobs than men, when adjusted for other observables, such as GPA, major and industry of search, the residualized gender gap in applications is null. Regarding application timing, we define "applying early" as sending at least one job application within two months of graduation. We find that women are as likely as men to apply early (70.1% vs. 69.0%). Overall, college-graduating men and women are more alike in job preferences and search behavior than we anticipated based on the existing literature.

To formally examine how student characteristics affect the gender employment gap, we regress a six-month employment indicator on a female indicator, adding controls progressively in Figure 3. The initial gap of 27.3 ppt decreases by 1.1-2.8 ppt as controls are added for GPA and major (Row 2), industry of search (Row 3), reservation wage and expected wage (Row 4), preferences for work hours and remote work (Row 5), as well as baseline beliefs about one's chances of working six months post-graduation (Row 6). In the final model of supply-side factors (Row 7), we add controls for search effort and past internship experience which only moderately decrease the gap to 22.5 ppt. This suggests that supply-side factors do not play a substantial role in the gender employment gap .

Level Differences II: Demand-Side Factors The literature highlights a number of demand-side factors that may alternatively explain gender gaps in employment, such as statistical, taste-based, and paternalistic gender discrimination (Goldin and Rouse 2000; Bertrand 2011; Kuhn and Shen 2013; Goldin 2014; Kline, Rose, and Walters 2022; Buchmann, Meyer, and Sullivan 2024). To investigate whether demand-side factors explain women's lower employment rates, we collect detailed information on the number of interviews, the number of job offers, and the salary offers received by both men and women. Figure A.11 shows the cumulative distributions of the number of job interviews in Panel (a) and

10. The distribution of men and women across majors differ, as described in Table 1. However, we later show in Figure 3 that gender differences in major choices do not drive the gender employment gap.

the number of job offers received in Panel (b), presented separately for men and women. Strikingly, a similar share of men and women get at least one interview and at least one job offer. We also find that there is no significant gender gap in the number of interviews students receive, or in the number of job offers they receive. When we further control for student baseline observables (e.g., GPA, major, industry of search, as well as wage and non-wage preferences), women get 0.7 more job offers than men. Finally, consistent with Brown (2022), we find in Figure A.11 Panel (c) that firms offer women lower wages, even after controlling for student baseline observables, including reservation and expected wages.[11]

To formally examine whether demand-side factors explain lower female employment rates, we extend the existing model in Figure 3 by incrementally adding controls for students' number of interviews (Row 8) and number of job offers received (Row 9). The gender disparities in employment remain largely unaffected by these additional controls.[12] Finally, in Row 10, we control for offered wage. This last variable has the most bite, reflecting the fact that women receive lower wage offers. Yet, the unexplained gender gap in employment remains very large, at 18.1 ppt. Even after holding job preferences, search behaviors, and the number of offers constant across men and women, women remain significantly less likely to be employed, indicating that the gender gap emerges at an even later stage: job acceptance. Indeed, we find in Figure A.12 that upon receiving a job offer, women are 27.7 ppt less likely than men to be employed six months after graduation. Even after we control for the supply-side factors detailed above, the number of interviews and offers received, and the wage offered by the firm, women remain 21.4 ppt less likely than men to have accepted an offer six months post-graduation.

Differences in Returns Controlling for student characteristics does not shrink gender gaps in a pooled regression, but a given individual characteristic may uniquely predict men or women's future employment. To test for this, we regress employment outcomes six months post-graduation separately for men and women on the supply-side variables we used as controls in Figure 3. Figure 4 shows the results of this exercise in a multivariate

11. We construct the offered wage as equal to the current wage for individuals who are working, the highest rejected wage for individuals who are not working but have received a job offer in the past. In the regression on Row 10 of Figure 3 we set the offered wage to zero for all individuals who are not working and have not receive a job offer in the past.

12. While none of these variables affects the gender employment gap, they do increase the adjusted R^2, confirming their expected relevance to students' labor market outcomes

regression, while Figure A.13 shows the bivariate models. Only two variables, early application and internship experience, are meaningfully predictive of differences in men's and women's employment. All other variables, including baseline beliefs about employment and number of job applications, are not differentially predictive. For example, a one-standard deviation increase in baseline belief about employment probability is associated with a 7.4 ppt increase in men's likelihood of working six months later, compared to a 4.9 ppt increase for women. Similarly, after controlling for all supply-side variables, the number of applications also has no different impact. In contrast, early application timing uniquely matters for women: those applying within two months of graduation are, all else equal, 17.1 ppt more likely to be employed six months later, while early job applications have no effect on men's employment. Additionally, internship experience increases employment probability for both men and women, but the effect is stronger for women (21.6 ppt compared to 13.0 ppt for men). Moving forward, we narrow in on the effect of timing on the employment likelihood of women, as the focus of this paper is on job search rather than pre-graduation characteristics (e.g., doing an internship during college).

5 Experimental Evidence on the Timing of Job Search

5.1 Experimental Design and Implementation

Motivation The finding that early labor market engagement is strongly correlated with women's employment potentially adds new policy levers to foster female labor force participation. We design and implement an experiment to evaluate one such lever, specifically an incentive scheme that rewards early applications. Two points are of note. The first is that we incentivize applications rather than employment. This is because we want to study the effect of application timing on the probability of employment and we do not want to distort labor supply by incentivizing our outcome of interest (employment). Second, we had a choice both on the nature of the policy lever and on its type. For instance, we could have offered an internship program instead of incentivizing earlier applications. We chose the latter because it only requires students, not firms, to change their behavior. This makes it easier to scale compared to demand-side interventions requiring buy-in from firms. Conveniently, our intervention is also simpler and cheaper to implement.[13]

13. We note that our experiment does not identify the average causal effect of timing on employment. To do that we would need to randomize applicants into different application timings, which would make some

Our null hypothesis is that applying early has no impact on subsequent employment. There are two scenarios under which the null holds. First, there is no causal link between timing and employment, and the observed correlation reflects individual heterogeneity that affects both variables independently. Second, there is a causal link between timing and employment, but it is fully internalized so the incentives will not affect the optimal timing of job search. If we reject the null it must be that there is a causal link between timing and employment, and women have biased beliefs about *some* factor whose influence on employment changes over time, so that the same woman applying for jobs at time t and $t+1$ faces different probabilities of accepting an offer. The fact that job seekers have biased beliefs that can lead to unemployment is at the core of the recent literature on behavioral job search (Spinnewijn 2015; Mueller, Spinnewijn, and Topa 2021; Abebe et al. 2024) and motivates our test and interpretation of the findings.

Design To incentivize early applications we randomly assign students to treatment and control groups. The treatment consists of a small monetary reward paid to those who apply to jobs within one month of graduation. The experiment allows us to estimate two parameters of interest, that is the causal effect of the incentive policy on employment β_{ITT} and the causal effect of early applications on employment for the compliers β_{LATE}. To identify β_{ITT} two assumptions need to hold: (i) that treatment is orthogonal to individual characteristics correlated with employment and (ii) the stable unit treatment value assumption (SUTVA). A successful randomization guarantees (i), and Table B.2 Columns 1 to 4 show that, at baseline, the treatment and control groups are balanced on all of the key baseline variables. Violations of SUTVA are unlikely because students from both the treatment and the control group apply to jobs in the broader labor market and compete with other graduates from all over Lahore, the capital and largest city of the Pakistani province of Punjab. This implies that our treatment group can be considered as atomistic in this labor market.[14] To identify β_{LATE} we need the additional assumption that treatment

apply later than they would have done in the absence of the experiment. This would be unethical as we would jeopardize their chance of ever finding a job. More importantly, this experiment would be irrelevant for the design of policy. Instead, we can identify the causal effect of early applications on compliers.

14. As an alternative research design, we contemplated the idea of sharing information about the correlation between employment and application timing in the experiment. However, we decided against it for two reasons. First, because it may be misleading to disclose a correlation when we do not know whether the relationship is causal: we did not want to mislead students into believing that applying early will necessarily be beneficial to them. Second, one central finding in our diagnostic sample is that female students are broadly aware of the barriers other women face to entering the labor market, but tend to think that they are different. Therefore, providing aggregate statistics about the relationship between employment and

affects employment only through its effect on the timing of applications. This is the exclusion restriction for treatment to be a valid instrument for early applications. It is likely to hold because the financial reward itself cannot generate meaningful income effects on labor supply.

Implementation We field the experiment at the public university in Lahore in June 2023. The subjects of the experiment are ~ 2,000 students due to graduate in mid-July 2023. A randomly selected 50% of the sample is offered a monetary reward on condition that they apply to at least four relevant jobs by August 15th (about a month after their graduation). A job is relevant if it matches their skill set and, to claim their reward, they have to provide proof of their applications to the research team through a brief online questionnaire, attaching screenshots that include the application date and job title.[15] We condition the award on sending at least four applications as four was the median number of applications early appliers had sent by the two-months follow-up in the diagnostic sample. The magnitude of the incentive is PKR 5,000 (~$18 USD or $89 USD at Purchasing Power Parity), which is equivalent to 10% of pay at the median monthly salary in our diagnostic sample at the six-month follow-up. To insure against the risk of low take-up, we offer a much higher reward—PKR 20,000—to 10% of the sample.[16] Ex-post this risk did not materialize and the two treatments have similar effects on applications and employment, thus we pool them in the analysis that follows.

For transparency and to ensure that students do not perceive the assignment to treatment as a signal of their labor market prospects we tell them explicitly that assignment is done by lottery. Specifically, students are told "You have now reached the last part of the survey which is experimental. At this stage, whether you are shown two modules or just one module will be randomly determined by a lottery." Then, a wheel spins in front of them on the tablet with its outcome jointly observed by the student and the enumerator (see Figure A.14 for a visual of the wheel). Then, in the event the student is not selected into treatment, he/she is told that "The lottery has decided that you will skip directly to the last module of the survey." We run three follow-up surveys. First, we re-survey

application timing may not result in any behavioral change if women do not internalize these statistics as relevant to them.

15. Our research team reviewed all the screenshots to ensure students applied to real jobs that are relevant to their skill set and found that all students who took up treatment had complied with the terms of the reward.

16. We obtain PPP estimates from the World Bank: https://data.worldbank.org/indicator/PA.NUS.PPP?year=2023..

students in early September 2023 (a couple of weeks after the deadline to receive the treatment incentive) to measure whether we have a first stage, that is a treatment effect on the number of early applications. We then re-survey students in early January 2024 to measure treatment effects on our outcome of interest: employment. We re-survey students a final time in September 2024, fourteen months after graduation to measure persistence of the employment outcomes. The timeline is illustrated in Figure A.4.

5.2 Recruitment, Balance and Take-up

Recruitment Based on budget and power calculations, we target a sample of about 2,000 students for our baseline survey. We stratify our sample by major and gender. Specifically, we over-sample women (65%) since that is our population of interest for the experiment. For majors, we stratify to be representative of the full spectrum of majors at the university. The only exceptions are majors with fewer than 25 students, which we exclude, and a cap of 200 female and 100 male students per major to ensure broad representation in the final sample. This cap is binding for a few majors, in which case sub-groups of students in the major are randomly and incrementally invited to participate until the target is reached. Within this sampling frame, each male and female student have a 50% chance of being randomized into treatment. We receive 2,468 responses at baseline. Since we are interested in labor market beliefs and outcomes, we exclude 223 (9.0%) students who are enrolled in graduate school as well as 299 (12.1%) students who have already secured a job[17] After these adjustments we obtain a baseline sample of 1,946 students who will join the labor force (or not).

Balance and Attrition Table B.2 Columns 1 to 4 show that, at baseline, the treatment and control groups are balanced on all of the key baseline variables, confirming the success of our randomization procedure. Specifically, no significant differences are observed in gender composition, GPA, the distribution of majors, marital or familial backgrounds, and key outcomes between treatment and control groups. The remaining columns of Table B.2 show that balance on observables between treatment arms is maintained in the

17. The share of students that secured a job before graduation (12.1%) is much lower than in some higher-income countries. For instance, in the United States, many college students interview and receive job offers in the year preceding their graduation (Cortés et al. 2023). This low rate of pre-graduation job acceptance informs the design of our experiment: offering financial incentives to apply the month preceding graduation can meaningfully impact students' application timeline as the vast majority has yet to start their job search.

six-month (Columns 5 to 8) and fourteen-month follow-ups (Columns 9 to 12). Table B.3 further investigates whether attrition is systematically correlated with treatment status or baseline characteristics. Attrition is 25.9% and 37.4% at six- and fourteen-months post-graduation, with sample sizes of 1,442 and 1,218 students, respectively. There is no differential attrition by treatment status in the six- or fourteen-month follow-ups. Columns 5 to 12 of Table B.3 show no evidence of differential attrition by treatment status at either follow-up. Similarly, attrition is not driven in either wave by a specific major, type of marital or familial profile, or differences in baseline values of key outcomes. An exception is that women are slightly overrepresented among those lost to attrition. However, Table B.2 confirms that the share of women remains balanced across treatment arms in both waves, indicating that this pattern is unrelated to treatment assignment. GPA is the only other characteristic systematically different between attritors and non-attritors. On average, individuals who remain in the panel have a GPA that is 0.05 points higher than those who leave. However, this difference is economically negligible (1.5%) and unlikely to meaningfully affect our results.

Treatment Take-up Take up, that is the share of respondents in the treatment group that claim and receive the financial award, is 48.2% and 45.1% for women and men, respectively. Figure A.15 correlates an indicator for take-up with students' baseline characteristics. It shows that both male and female students who take up treatment are more likely to major in engineering or computer science and less likely to major in Humanities. Second, women that are already engaged or married are, directionally, less likely to take up the treatment. Third, both women's and men's compliance is positively correlated with baseline beliefs about own employment at six months, as well as baseline beliefs about the employment of same-gender peers at six months. Last, both for women and men, take-up is not correlated with gender norms, as measured by the World Value Survey questions. We also want to test for the "relevance" assumption, namely that the financial incentives leads some women to start applying earlier. To do so, we ask respondents, at the six- and fourteen- month follow-up, the date of their first job application. As shown in Table 2, Column 1, we find that 56.7% of women in the treatment group have sent at least one job application by August 15th (the application deadline), compared to 31.1% in the control group. We observe similar effects on application timing for men: 54.7% of men in the treatment group have sent at least one early application, compared to 35.8% in the control group.

Descriptive Statistics Table 3 presents descriptive statistics for the six-months experimental sample, i.e. students who respond to both the baseline and six-month follow-up surveys. The last column of the table reports the p-value associated with the test of equal means across gender. Women make up 64.2% of the sample, with 926 female and 516 male respondents. On average, women are $22^{1/2}$ and men are 23 years-old. Like in the diagnostic sample, women's GPAs are slightly higher ($\sim$ 5%) than men's on average and this difference is statistically significant. Unlike the diagnostic sample, where men and women tend to major in different fields, the experimental sample shows no systematic gender differences in the distribution of majors. Men and women also share similar backgrounds in terms of parental education and indicators of familial wealth. Only around 4% of both men or women are married at the time they graduate from college, and a similar fraction is engaged (4.3% of women and 3.1% of men).

External Validity of Diagnostic Findings Appendix C shows that the main diagnostic findings, derived from private university students, replicate using the control group of the experimental sample, drawn from a large public university. This validates the relevance of our diagnostic insights to a broad spectrum of college graduates.

5.3 Results

Intent-to-Treat: Specification To estimate the effect of our intervention on students' labor market outcomes, we run the following, intent-to-treat analysis:

$$Y_{it} = \alpha_0 + \alpha_1 Male_i + \alpha_2 T_i + \alpha_3 (T_i \times Male_i) + \alpha_4 X_i + \epsilon_{it} \tag{1}$$

where Y_{it} denotes the outcome of interest for individual i at time t. The coefficient α_1 captures the gender difference in outcomes within the control group, indicating the extent to which outcomes for male students differ from those of female students. The coefficient α_2 is the primary parameter of interest and measures the intent-to-treat effect of the intervention on women assigned to the treatment group ($T_i = 1$). α_3 represents the additional effect of the treatment on male students assigned to the treatment group. For interpretational ease, in our results table we show the treatment effect on male students as $\beta_1 + \alpha_3$, instead of α_3. In our main specification, X_i is a vector of individual covariates

measured at baseline and selected on the basis of their ability to predict the primary outcomes to improve statistical power (McKenzie 2012)[18]. We show treatment effects separately for two periods t, the six-month and fourteen-month follow-up. All standard errors are robust to heteroskedasticity.

Intent-to-Treat: Results Table 2 shows results from our estimation of Equation 1. Panel A describes the treatment effect for women, while Panel B shows the treatment effects for men. In Panel A Column 2, we observe that treated women are 7.5 ppt (22.3%, p=0.015) more likely to be employed six months post-graduation than control women. This increase in women's employment at the six-month follow-up is equivalent to $\sim$ 35% decrease in the gender employment gap, which amounts to 21.5 ppt in the control group. As shown in Column 4, treatment effects on employment persist in the fourteen-month follow-up, where treatment increases the likelihood of work for women by 6.9 ppt (p=0.046). Notably, this represents a nearly identical 34% reduction in the gender employment gap relative to the six-month follow-up, indicating that the effect remains stable over time. We further examine the likelihood of working for a positive wage at a firm (as opposed being self-employed, working in a household enterprise, working for no wage, or being unemployed). Whether women take up firm work is an important outcome for two reasons. First, firm work is, at baseline, the preferred mode of working for the vast majority of women in our sample.[19] Second, in low income countries, working informally for the family firm or on a self-employed basis is associated with lower labor force attachment and earnings potential. For instance, Breza, Kaur, and Shamdasani (2021) show that a large fraction of self-employment in India is in fact "disguised" or "hidden" unemployment, resulting from labor rationing. The World Bank's *World Development Report 2012* further argues that the disproportionate representation of women in self-employment is one of the primary drivers of gender gaps in earnings (World Bank 2021).[20] In Panel A Column 3, we show

18. We adapt the post-double-selection approach set forth by Belloni, Chernozhukov, and Hansen (2014). We show that our results are robust to the exclusion of these controls.

19. We ask women who told us they planned to work at baseline: "What type of work would you prefer to do after you graduate?". The options were "Work for a private firm (or government)","Work in my family-owned business", "Be self-employed" or "Be an intern at a firm". Strikingly, 94.1% of our female respondents said they prefer to work for a private firm.

20. World Bank (2021) reviews extensive data and literature, showing that women in low-income countries are predominantly employed in low-productivity, low-wage jobs, such as small-scale farming, running small firms, and engaging in casual or piece-rate work. It also highlights that most female-headed enterprises are home-based and more often driven by "necessity" than by "opportunity". Reinforcing these findings, Ashraf, Delfino, and Glaeser (2022) reveals that female entrepreneurs typically earn less and are concentrated in low-return industries. Similarly, Our World in Data (2023) notes that most women in paid work in low

that our treatment increases women's probability of working for a firm six months after graduation by 10.2 ppt (40.3%, p=0.001). Column 5 shows that this effect persists fourteen months after graduation: while control women have a 41.6% likelihood of working for a firm, the likelihood for treated women is 9.5 ppt higher (p=0.006). We interpret these stronger effects on firm work as evidence that the treatment not only changes women's chances of working but also the composition of their work. This shift in composition is consistent with the fact that our intervention induces women to apply for positions in the formal labor market, and thus does not have a channel through which it may influence self-employment prospects. The persistence of our effects more than a year after the incentive is awarded indicates that the intervention does not just prompt women who were already likely to work to start a job sooner. Rather, it sustainably increases levels of employment for women. Turning to men in Panel B, we detect no treatment effect on either men's likelihood of working overall, or of working for a firm. These results are consistent with our correlational findings of a positive association with early applications for women, but not for men.[21]

Dynamics of Female Labor Supply Figure 5 examines the treatment effects on firm employment over time. Specifically, Panel a) presents the female treatment effect on having ever worked at a firm by a given date, Panel a) repeats the exercise for men.[22] By May 2023, the month before we announce our treatment, there is no difference in employment between the control and treatment group. For women, treatment effects progressively rise in the months following the announcement of the intervention, becoming marginally significant by the deadline for incentive payment (mid-August 2023) and stabilize around 10 ppt by January 2024 (about six months post-graduation). The treatment effects then remain stable for the following 8 months. In contrast, the intervention has no effect on men's employment at any point in time. Since the results are so stable after six months post-graduation, we do not pursue further data collection after the fourteen-months follow-up.

and middle-income countries are employed within the informal economy. Together, these studies and meta-analyses emphasize how the types of economic activities women engage in contribute to persistent gender disparities in earnings and productivity. Therefore, the shift in the composition of work induced by our treatment holds substantial socioeconomic value for women.

21. Appendix Table B.4 shows results from our estimation of Equation 1 without the controls selected by the post-double-selection procedure. These results are a little less precise than in our main specification but the magnitudes are similar and the female results remain statistically significant at the 5% level for all but the 14 month female employment estimate (Column 3), which is still significant at the 10% level.

22. To get a start date on the first job that a respondent ever held, at the fourteen months, we ask respondents about the start date of their first job. We only ask those who tell us they have worked at some point post-graduation.

We also ask working women, at fourteen months, how long they expect to continue in their *current* job: the average answer is 3.6 years (similar in both treatment and control). Given this, we consider the fourteen-month mark a relevant stopping point to study the post-graduation employment effects of the treatment. However, women's labor supply decisions may still change after marriage (which on average occurs at age 25 for college-educated women, that is about three years after college graduation). As a result, we cautiously consider this study as testing for the effect of early applications on women's pre-marriage labor supply. We consider early labor market experience to be an important object of interest by itself, as various studies show that it shapes women's lifelong labor supply. For instance, Jensen (2012) shows that entering the workforce early increases young Indian women's aspirations to long-term, post-marriage careers. Working early also facilitates women's return to work post-child, as past co-worker networks play an important role in informing the job search of mothers Henke, Schmieder, and Berge (2021). In the context of our experiment, we directly ask working women about their long-term labor supply and find that the vast majority of them intend to pursue employment in the long-run. Specifically, we ask women in the six month survey: "Do you intend to work (for a firm or in your own business) after getting married and having your first child?" 85.5% of working women answer "Yes" to this question. While these responses may reflect women's biases about their future labor supply, they provide evidence that women intend to pursue long-term employment.

Treatment on the Treated We show in Table B.5 the effect of treatment on the treated (the students who were offered the treatment and took it up) and on the non-treated (students who were offered the treatment but did not take it up), relative to the control group. We find that, for women (Panel A), the employment of the treated group is 13.6 ppt higher (p=0.000) than the control group's at 6 months, and 11.6 ppt higher (p=0.003) at 14 months. By contrast, the employment of the non-treated is only marginally higher than in the control group, reflecting limited selection patterns into treatment take-up. For men (Panel B), the treatment effect on the treated is also positive (7.9-10.3 ppt in both follow-ups). However, the treatment effects on the non-treated men are of similar magnitude as the effects on the treated men, but opposite sign. This reflects selection patterns into treatment take-up and explains that, in aggregate, the male intent-to-treat estimates are null.

Local Average Treatment Effects Beyond the intent-to-treat effects of our intervention, we are also interested in the effect of applying early itself. Not everyone selected by our lottery ended up sending early applications and some students in the control group applied early, even absent the financial incentive. Therefore, we use a standard instrumental-variable approach with lottery selection as an instrument for applying early to estimate a local average treatment effect. Formally, we estimate the following model with 2SLS:

$$Early_i = \beta_0 + \beta_1 Male_i + \beta_2 T_i + \beta_3 T_i \times Male_i + \epsilon_i \quad \text{(2: 1st Stage)}$$

$$Y_{it} = \delta_0 + \delta_1 Male_i + \delta_2 \widehat{Early_i} + \nu_{it}. \quad \text{(3: 2nd Stage)}$$

where $Early_i$ denotes whether the student has sent an early application. In our first stage, the coefficients β_2 and β_3 capture the effect of the financial incentive (treatment) on the likelihood of applying early respectively for women and men. Our second stage estimates the effects of applying early, as instrumented by the treatment indicator interacted with the student's gender, on labor market outcomes (e.g., employment). Empirically, we define applying early as a dummy equal to one is one has sent their first application before August 15th (the application deadline to receive our financial incentive).[23]

Local Average Treatment Effects: Results In Table 4, we compare the magnitudes of our descriptive OLS and experimental 2SLS estimates to better understand the relative importance of selection into early applications, versus the effect of our treatment. For women, the OLS estimate in Column 1 suggests that early applications are associated with a 23.6 ppt increase in the probability of working for a firm. The 2SLS estimate in Column 2 is higher than the OLS one, at 38.2 ppt. These effects persist at the fourteen-month follow-up, with the 2SLS estimate at 30.8 ppt. The OLS and 2SLS coefficients differ for several reasons. The OLS is upward biased because it captures the effect of selection—individuals who are more eager to work apply earlier—but downward biased because of measurement error. In contrast, the IV measures the causal effect of early application on the compliers, that is, individuals whose application behavior changes because of the financial incentives. For women, the causal effect of applying early (the 2SLS coefficient) is larger than the OLS. In contrast, for men (Panel B), the point estimates in the 2SLS estimation (in Columns 2 and 4) are small (ranging from -0.03 ppt to 0.05

23. This definition is more granular than in the diagnostic part of the paper, where applied early was defined as where one had sent an application by the second follow-up. By design, we can specify an exact date for the experimental section (August 15) based on the incentive deadline.

ppt) and only statistically significant for the OLS estimates in Columns 1 and 3. This implies that, for men, early applications are not a strong determinant of firm employment outcomes, suggesting that their job search process is less sensitive to timing incentives.

Lack of Anticipation about the Role of Timing As explained in Section 5.1, the fact that we find a positive treatment effect on women's employment not only demonstrates that there is policy space to close the gender employment gap, but also implies that women hold biased beliefs about *some* time-varying parameter of the job search process. However, we find direct empirical evidence that women in our treatment group do not anticipate the causal effect of timing. At baseline, after randomizing respondents into being offered treatment, we ask them about their job search timing and employment expectations. On search timing, we ask them both when they think they will send their first job application and how many applications they think they will have sent by August 15th (the deadline to apply to four relevant jobs in order to get the reward we offer). On employment, we ask them our probabilistic question about their likelihood of working six months post-graduation. The latter question is worded the same way as for the diagnostic sample (see Section 3.3). Table 5 shows the intent-to-treat effects on these variables. We find that treatment shifts women's beliefs about when they will start applying earlier by about 20 days (p=0.000). Being assigned to treatment also increases the number of applications women expect to make by August 15th by 5.93 ppt (p=0.067). However, we find no significant treatment effect on women's beliefs about their likelihood of working (p=0.391). This provides direct evidence that treated women did not anticipate the role of timing in employment.

Discussion We find that a small financial incentive to send a few applications right after graduation has a large and persisting effect on women's employment. In the next section, we dive into the mechanisms driving our results, which will help make sense of the magnitudes. As a preamble to this analysis, we note that the few months around graduation are a critical juncture in the personal and professional lives of the women we study. Most of them have no work experience such that their post-graduation job search is not informed by past labor market exposure. During their college years, women spend their days at school and may live away from their parents. As Table 1 and Table 3 highlight, very few of them are married or even engaged during college. But, at the time they graduate, women suddenly return to their parents' home and/or spend significantly

more time at home as school ended. At around the same time, parents ramp up the search for a suitable marriage match (Calvi, Farooqi, and Kandpal 2024), which we discuss in more details in Section 6.2. During this pivotal period, even a small behavioral change can plausibly generate large, path-dependent, effects on women's labor market outcomes. The next section explores the channels through which these large effects operate.

6 Why and How Does Timing Matter for Employment?

As explained in Section 5.1, the fact that we find a positive treatment effect on women's employment not only demonstrates that there is policy space to close the gender employment gap, but also implies that women hold biased beliefs about *some* time-varying parameter of the job search process. This section explores *which* time-varying parameter these biased beliefs are about. To do so, we first identify demand and supply-side determinants of labor market outcomes that can plausibly change over time. We then provide empirical evidence on which of these determinants drive our experiment results, and the channels through which they do so.

6.1 Changes in Labor Demand

One possible explanation for our treatment effects is that labor demand slows down over time, and women do not anticipate it. This hypothesis is motivated by a well-established literature documenting that longer unemployment spells result in worse labor market outcomes (Schmieder, Wachter, and Bender 2016), as well as a growing literature showing that workers do not anticipate this (Mueller, Spinnewijn, and Topa 2021). We observe three facts that, together, rule out this hypothesis in our context. The first is that there is no slowdown in labor demand for men. As shown in the previous section, our treatment has a similar effect on application timing for both genders but only affects employment outcomes for women, implying that men's vacancy creation and offer arrival rates do not decay with time. Thus, our treatment effects are unlikely to be driven by diminishing labor demand over time for the occupations that employ both men and women. Additionally, Table 6 shows treatment effects on intermediate labor market outcomes that ultimately result in employment: number of applications and number of job offers. While treated women send more applications than control women at the six and fourteen months marks (Column 1 and 3), the number of job offers received is the same for treated and control

women at the six and fourteen months marks (Column 2 and Column 4). These results have two implications. First, treatment-induced changes in search effort are unlikely to explain our results since they do not translate into a higher number of job offers. Second, since the group that does not apply early (control) receives the same number of offers as the group applying early (treatment), the lower employment rate in the control group has to be driven by lower job acceptance rates, rather than by a slowdown in demand. In Appendix Table B.6, we also show results on applications and job offers at the extensive margin (i.e. whether or not a student sends at least one job application and receives at least one job offer). Reflecting the results on number of applications and offers, we find that the treatment increases the likelihood of sending at least one application even by the fourteen month mark (14 months) but has no effect on the likelihood of getting at least one offer by the fourteen-month follow-up. Overall, the evidence does not support a labor demand slowdown as the reason for our treatment effects on employment.

One last dimension we study is the effect of our treatment on the composition of jobs (and corresponding wages). Indeed, it could be that the control group is as likely as the treatment group to secure a job offer, but they may receive lower wage offers or end up in different occupations. Considering the top 3 occupations women most frequently work in, Panel A of Table B.7 shows that the share of women in a given occupation is similar across treatment and control groups at the fourteen-month follow-up. For example, teaching is the most common job among women, and plausibly sensitive to seasonal changes in demand. If the peak hiring period in teaching coincides with our deadline to the treatment group for applying early, we may expect that earlier applications lead treated women to disproportionately sort into teaching. However, treated and control women are equally likely to work as teachers—23.8% of women in the treatment group become teachers relative to 24.1% of women in the control group, a difference which is not statistically significant ((p-value of the difference = 0.916). This suggests that the positive employment effects of applying and receiving job offers earlier are not driven by women sorting into a different category of jobs. Further, Figure A.16 presents the distribution of current wages in Panel (a) and offered wages in Panel (b) for control and treated women at the fourteen-month follow-up. The distributions for both current and offered wages are similar across treatment groups, as indicated by an absolute z-score below one. This finding contradicts the idea that control women face a different demand curve than treated women.

6.2 Changes in Labor Supply

In this section, we examine supply-side barriers to women's employment. As explained in Section 5.1, our treatment effects can only be rationalized if such barriers intensify over time, but women underestimate their incidence at baseline. We therefore jointly explore the existence of barriers and the beliefs women hold about them. We start by looking into whether women's preferences for work change over time and if so, whether women anticipate these changes.

Change in Preferences Just as in the diagnostic sample, at baseline women in the experimental sample perceive their likelihood of employment as high. For instance, as shown in Figure C.1, control women estimate an 81.6% chance of working six months post-graduation. However, only 33.6% of them are actually employed by the six-month mark. This stark gap between expectations and reality points to two supply-side factors as potential explanations for our treatment effects: either women unexpectedly revise downwards their preferences for work over time, or they encounter unanticipated constraints that limit their ability to work. To disentangle these two explanations we field a direct question about women's preference for working in the near-future at the six-month follow-up: "Do you want to work in the coming 12 months?".[24] 87.6% of all women, and 83.4% of unemployed women, answer yes to this question, with no treatment effects on the response. This suggests that unanticipated constraints, rather than changes in women's preferences for work, are driving lower employment rates in our control group.

Change in Labor Market Factors There is a longstanding literature on how biased beliefs about wages and job offer arrival rates influences the labor market outcomes of job seekers (Spinnewijn 2015; Mueller, Spinnewijn, and Topa 2021; Abebe et al. 2024). This literature also engages with time-varying factors: job seekers with optimistic bias tend to turn down early offers in the hope of getting better offers later on. While these workers adjust their wage expectations over time, they often do so too slowly such that they end up long-term unemployed. Motivated by this literature, we test whether treatment effects are heterogeneous across baseline labor market beliefs.[25] In Figure 6 Panel (a), we show that

24. We purposefully made the wording about preference for work, rather than expectations to work, to ensure that we are isolating women's desire to work, outside of external factors that could impact their ability to work.

25. To maximize power, we pool data from the six- and fourteen-month survey waves, with wave fixed effects, and cluster errors at the individual level.

treatment effects on employment are the same for individuals with, at baseline, above median vs. below median reservation wages, expected wage offers and beliefs about market wages. Figure A.17 Panel (a) tests for heterogeneity in treatment effects by these same wage variables, this time on whether one applies early and also shows that there is no difference. We take away from this that the role of timing in our experiment is not channeled through differences in beliefs and expectations about wages. Figure 6 Panel (a) also display no heterogeneity by women's expectations about their own likelihood to work, or the likelihood to work of their female peers, indicating that the role of timing in our experiment is not channeled through differences in beliefs about employment.

Change in Family-Related Factors Following a large and growing literature emphasizing the role of families in shaping female, but not male, labor supply (Jayachandran 2021; Dean and Jayachandran 2019; Bursztyn, González, and Yanagizawa-Drott 2020; Lowe and McKelway 2024), we create a separate category for family-related factors. These are particularly relevant in Pakistan, where 79% of women from a representative sample of urban households report that the head of the family decides (unilaterally or in consultation with her) whether she should work (Junaid et al. 2021). Several other papers point to the role of families in restricting women's labor supply in Pakistan: Field and Vyborny (2016) document that 40% of non-working women in Pakistan cite lack of permission from their husbands or fathers as the main reason for not working. In an experiment on women in Lahore with similar age, marital and education profiles as our sample, Subramanian (2024) also finds that increasing the salience of family discussions about job search led to a 60% decrease in job applications to positions with male supervisors, compared to the control group where family opinions were not highlighted.

This literature leads us to consider heterogeneous treatment effects by family involvement in job search. Specifically, we ask all respondents in our baseline survey: "Whom do you consult when making decisions on a job?" We consider that parents are involved in women's job search if their response is either that they consult their mother, their father, or both.[26] We find that 62.5% of women say that they consult their parents (vs. 36.6% of men). We conceptualize looking for heterogeneity by this variable as a test of the hypothesis that time-varying preferences of parents can explain our result. If timing only matters in situations where women consult their parents about job decisions, this

26. The full list of options is Friends, Mother, Father, Brother(s), Sister(s), Cousin(s), Husband or fiancé, Rest of family, Teachers (or career office, career councilor, university website), Classmates enrolled in my course / seniors, No one, Other.

suggests that families, rather than the women themselves, are the ones whose preferences shift over time, especially given our earlier finding that women's own preferences do not change. Figure 6 Panel (b) presents treatment heterogeneity results by this variable. While treatment effects on early applications are similar across women who do and do not rely on their parents to decide on jobs (as shown in Figure A.17), treatment effects on firm employment differ. In families where daughters do not consult their parents about job offers, the treatment effect on firm employment is smaller than average, at 6.7 ppt. In contrast, in families where parents play a role in women's job search decisions, the treatment effect is larger, at 15.6 ppt (p=0.000)— close to a 3-fold increase compared to women's who do not involve their parents. The fact that timing matters more for women who involve their parents in their job search points to time-varying preferences among parents about their daughter's work. For these time-varying preferences to explain our treatment effects, they must be unanticipated. In support of this, the left panel of Figure C.2 shows that only 20% of women express that they may struggle to work after graduation due to "family reasons," such as not receiving approval from their families or being pressured to prioritize finding a marriage match. In contrast, 91% of women recognize that *other* women will face those obstacles. Further, confirming women's lack of foresight about parents' opposition, we find no relationship between stating that parents are involved in their job search process and recognizing that families may be an obstacle to one's own work. In sum, while women acknowledge that parents generally play a significant role in restricting daughters from working, they do not view their own families as a factor limiting their own employment. This contrast between self-beliefs and beliefs about others is in line with the tension we find between women's high expectations of own work but low expectations about other women's chances of employment. Together, these observations draw a picture in which women are aware of the barriers the "typical" woman faces, but consider these barriers do not apply to them.

Why Would Families' Preferences Vary over Time? Families not only shape women's labor supply decisions but also arrange marriages for their daughters.[27] In the marriage market, timing plays a key role in shaping women's prospects, with families believing that these prospects quickly deteriorate with age once a daughter is out of school (Adams

27. According to a survey conducted by Gallup & Gilani Pakistan in 2024 carried out among a sample of 548 men and women in urban and rural areas of all four provinces of the country, among married Pakistanis, 81% have an arranged marriage. There were also no differences between the choice in marriage experienced by rural and urban residents.

and Andrew 2024). Further, experimental evidence from an online marriage matching platform shows that working women receive fewer expressions of interest from men, suggesting a marriage market penalty for working (Afridi et al. 2023).[28] Combining these existing findings, we posit the following hypothesis for why timing matters: as families' attention progressively turns to marriage post-graduation, opposition to daughters' work unexpectedly increases. Because we only survey students (not their parents), we can only test this hypothesis indirectly. We propose the following strategy: if timing matters because of an unexpected shift towards the marriage market, we should see that our treatment effects on employment are driven by women who lack foresight about the competing forces of the marriage market.

To test whether this holds in our data, we leverage the fact that, both at baseline and at the six-month follow-up, we ask "When do you expect to get married? Please answer in months or years from now." Adding women's response to this question to their current age, we can evaluate the age at which they expect to get married and whether than changes over time. Figure 7 illustrates the relationship between baseline beliefs about age at marriage (x-axis) and updated beliefs, six months post-graduation (y-axis), separately for control and treated women. The 45 degree line represents the benchmark of time-invariant beliefs. While there is a positive slope (of ~ 0.6), it is significantly below 1, suggesting that women who initially expect to marry later are likely to revise their expectations downward. For instance, women who believe at baseline that they would get married at age 26 have converged, by the six-month mark, to believing they will get married a year earlier, at age 25. In contrast, women who initially anticipated marrying sooner (e.g., by age 24) have near-stable expectations. The fact that women who expected to marry later are the ones who update their beliefs the most, suggests that they held incorrect beliefs at baseline, and were exposed to an earlier onset of marriage-related activities than they had expected. Consistent with a convergence of beliefs towards the truth, the beliefs of women who initially thought they would marry late update downwards towards age 25, the national median age at marriage for educated women. It is also worth noting that the treatment has no effect on these marriage timeline beliefs.

28. In the context of high income countries, there is also evidence of a tradeoff between the marriage and the labor market.Bursztyn, Fujiwara, and Pallais (2017) show that unmarried women in an MBA program avoid career-enhancing actions when their actions are observed by unmarried male classmates. This is because women fear sending undesirable marriage market signals to potential marriage matches in their cohort. Bertrand et al. (2021) document a marriage/work trade-off across many developed countries which is especially binding for more educated women, and its intensity is driven by the strength of local gender norms.

Having established that women who initially thought they would marry late lack foresight about the speed of the marriage market, we turn to testing whether these same women are driving our treatment effects on employment. Panel (b) of Figure 6 tests for heterogeneity of our treatment effects by baseline marriage beliefs, separating women who initially think they will marry earlier than age 25 (63.3% of our sample) vs. later (37.0% of our sample). We find that our treatment effects on working for a firm are much stronger for women who expect to marry late (past age 25), at 17.4 percentage points versus only 5 percentage points for those expecting early marriage (p-value of the difference = 0.022). In sum, consistent with our main hypothesis that timing matters because of an unexpected shift towards the marriage market, our treatment effects on employment are driven by women who lack foresight about the imminence of the marriage market. Together with the evidence on parental involvement, this result provides insight into how the treatment operates: in the treatment group, women start searching for jobs earlier and, as a result, consult their parents on job offers at a time where the marriage market has yet to unfold, such that parents are more inclined to let their daughter start a job.

Treatment Effects on Marriage Matches Given that our treatment persistently shifts women into working, an interesting avenue for future research would be to leverage experimental shifts in employment to study the consequences of working on marriage matches. Ex ante, it is not obvious what the marriage market consequences of working are. While the existing literature points to a marriage market cost of working, so far the only experimental evidence on the topic focuses on early signs of interest on an online matching platform, not marriage matches (Dhar 2021; Afridi et al. 2023). Therefore, whether working women receive fewer marriage offers or, down the road, whether their marriage match is worse, remains unknown. It would also be interesting to study whether the effects of women's work on their marriage matches depends on the share of women who enter the labor force. Indeed, there may be enough progressive men to absorb the additional women our treatment shifted into work but, if we scale our experiment such that the share of working women increases substantially, then working could generate a marriage market penalty. At the limit, if all women started working, men may have no choice but to adapt to women's employment status and the marriage penalty would go away. While we think these research topics are fascinating, they remain beyond the scope of this paper. Indeed, marriage is on average three years post-graduation and, to obtain the marriage matches for all the women (not just the average woman) in our sample, we

would need to follow these women for at least five years post-graduation. Beyond the fact that this would require four more years of data collection, we fear that the changes happening in women's lives around marriage (e.g., moving in with their in-laws) would pose an attrition challenge. What we can still offer is evidence of treatment effects on early marriage offers, which we take as a signal of longer term outcomes. Indeed, we ask women about the number of marriage offers they have received in each of our survey waves, as well as the highest education achieved among these offers, as a proxy for the quality of the marriage offer pool, in the six-month follow-up. In Figure A.19, we document that, while marriage is still several years out, marriage market activities ramp up quickly after graduation for women: close to 50% of women receive at least one marriage offer within six months of graduation, a share that rises to nearly 70% at the fourteen-month mark.[29] The negative correlation between the share of women who received a marriage offer and the share of women working by the fourteen month follow up if they have applied in a given month is quite striking, especially in the first few months following graduation. Second, we show that our treatment works not by delaying the launch of the marriage market but by inducing the labor market to unfold before the marriage market. Panel A of Table B.8 Column 1 and 4 show that women in the treatment group are no less likely to get married or engaged than control women in the first six and fourteen months post-graduation. Column 2 and 5 also show that women in the treatment group receive the same number of marriage proposals as women in the control group at both the six and fourteen months marks. Finally, Column 3 shows that the quality of marriage offers—as proxied by the highest education level in the pool of received marriage offers—is also no different by treatment at six months (we kept our fourteen months survey shorter and did not ask that question then). We consider these results as suggestive evidence that marriage is still a few years out for most women, since the majority indicates that they are unlikely to marry any of the men they have so far received a marriage offer from.

Discussion While there is existing evidence on the fact that parental norms may prevent daughters to work (Field and Vyborny 2016; Subramanian 2024), our paper points to the impermanence of these norms: parents' preferences for their daughters' work change over time, decreasing with the rise of the marriage market. One interesting aspect to note here is that women in our treatment group continue to work after the marriage

29. This rapid unfolding of marriage offers is consistent with the finding in Adams and Andrew (2024) that families in South Asia believe that marriage-market prospects quickly deteriorate with age once a daughter is out of school.

market pressures rise. This means that, conditional on starting work early, parents do not force their daughters to stop working, at least not within more than fourteen months post-graduation. While it is beyond the scope of this paper to provide definitive evidence on why this holds, we can offer several plausible explanations. One is that parents hold incorrect beliefs about the marriage penalty for working, such that the daughters of working women receive satisfactory marriage offers and, as a result, parents do not ask their daughters to stop working. Another explanation is that marriage offers are endogenous to a woman's work status: once a woman works she attracts progressive men that are happy with her working, while the longer she waits to start working the more she may draw marriage offers from men that do not want her to work. This would generate a self-fulfilling prophecy: women who do not start working early indeed incur a marriage cost if they start working late, as they would lose the marriage offers they already have. Meanwhile, working women receive offers from more progressive men and are able to keep working.

7 Conclusion

This study provides new evidence that college-educated women in Pakistan strongly expect to work at graduation, yet most remain unemployed six months later. Traditional supply-side explanations fail to account for this gender employment gap: women have higher GPAs (conditional on major choice), lower reservation wages, and similar preferences for non-wage amenities as their male peers. Firm demand is also not the limiting factor, as women are just as likely as men to receive interviews and job offers—though at lower wages. Instead, the gap is primarily driven by women rejecting job offers at significantly higher rates than men.

This raises the question: why do women's employment outcomes fall short of their expectations? Our analysis reveals that the timing of job search is the strongest predictor of gender differences in employment. Women who apply for jobs within two months of graduation are 17.1 percentage points more likely to be employed than those who apply later, while men experience no such returns to earlier applications. Motivated by this finding, we design an experiment offering a small financial incentive to randomly selected students to encourage earlier job search. While the incentive prompts both men and women to apply sooner, it significantly increases employment only among women. These findings suggest that women hold biased beliefs about some time-varying aspect of job

search, causing them to delay applications more than they should.

We show that beliefs on standard labor market outcomes and preferences do not change over time and do not predict the strength of the treatment effect. In contrast, the expected age at marriage falls over time and women who, mistakenly, expected to marry later than the national average age of 25, are less likely to apply early and therefore remain unemployed. Consequently, the treatment effect is strongest for this group as the incentive effectively contort the bias and makes them apply early.

These findings imply that policies that lead to marginal changes on one dimension –here the timing of applications–can have large impacts if selection is driven by a second variable –in our case expected age at marriage. The findings also imply that policies designed to achieve labor market outcomes must take into account the effect on the outside option, whatever that may be.

The open question is why age at marriage binds on average three years before the marriage takes place. Figure A.19 provides some suggestive evidence that the largest drop in job acceptance rates, in the first few months post-graduation, coincides with the largest increase in marriage offers arrival rates. Applying in September instead of August lowers the employment rate by 12.8 pp at the same time marriage offers increase by 13. 3 pp. While this is purely correlational, the timing of the two variables is remarkably synchronised to be dismissed as entirely coincidental. One possible explanation is that marriage offers are endogenous to a woman's work status: once a woman works she attracts progressive men that are happy with her working, while the longer she waits to start working the more she may draw marriage offers from men that do not want her to work. This would generate a self-fulfilling prophecy: women who do not start working early would indeed incur a marriage cost if they start working late, as they would lose the marriage offers they already have, such that they decide not to work. Meanwhile, working women receive offers from more progressive men and are able to keep working. Another possibility is that, while men may be indifferent to their wives' employment status, there is a significant penalty imposed on the man and his family if this is perceived as a necessity rather than a choice. That is, the groom's family will suffer a reputational loss if people believe they need their daughters-in-law to work. Therefore, applying for jobs at the same time as the marriage offers are made creates a possible confusion as to which action came first, that is, the application for jobs might be seen as a consequence of the type of marriage offer. In all cases, gender norms and beliefs about them, around marriage and work play a very important role in shaping women's employment and this must be taken into account

to understand women's labor force participation and to design policies to change it, if so desired.

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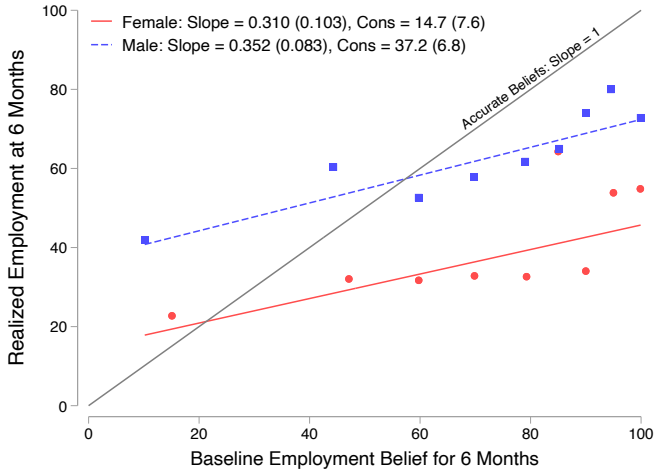
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Figures

Figure 1: Baseline Employment Beliefs vs. Realized Employment Outcomes



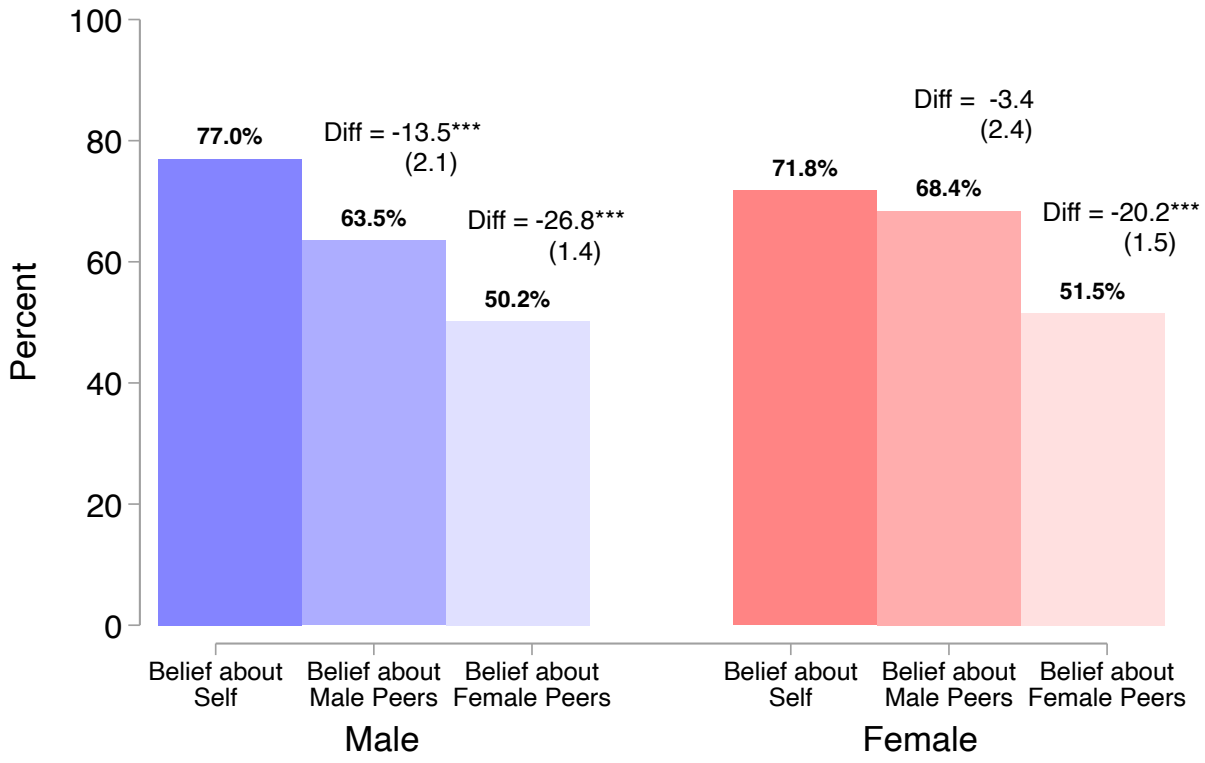
(a) Mean Levels: Intended vs. Realized Employment



(b) Binned Scatter: Intended vs. Realized Employment

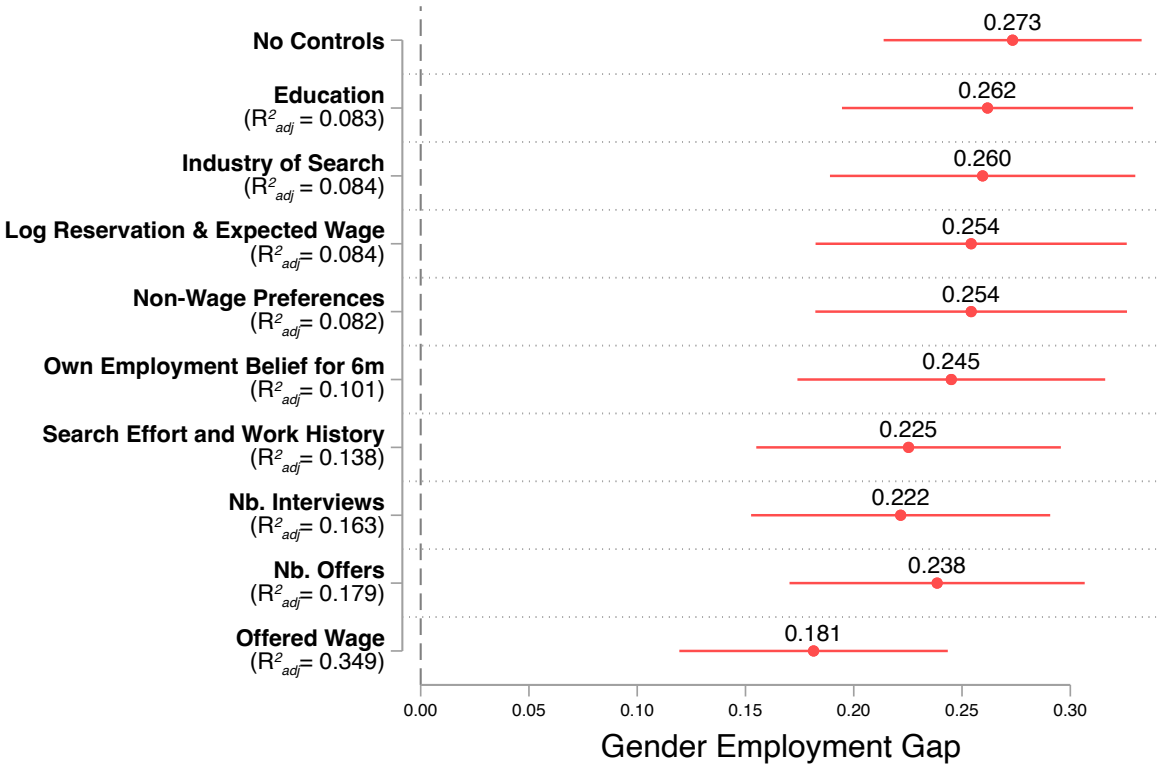
Notes: This figure compares baseline beliefs about one's future employment with realized employment. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Panel (a) contrasts the average baseline belief of students about their own chances of working within six months of graduation (left cluster of two bars) with the same students' realized employment at the six months mark (right cluster of two bars), separately for men (bars 1 and 3) and women (bars 2 and 4). The gender gap in responses is shown directly above the female bar. The average within-gender difference between baseline beliefs and realized employment is shown above the top square brackets. Panel (b) shows a binned scatter plot of baseline employment beliefs against realized employment, separately for men (dashed blue line with square markers) and women (solid red line with circular markers). The 45-degree line represents accurate beliefs, points above (below) the line indicate underestimation (overestimation) of employment chances. In panel (a): * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2: Employment Beliefs about Self vs. Employment Beliefs about Peers



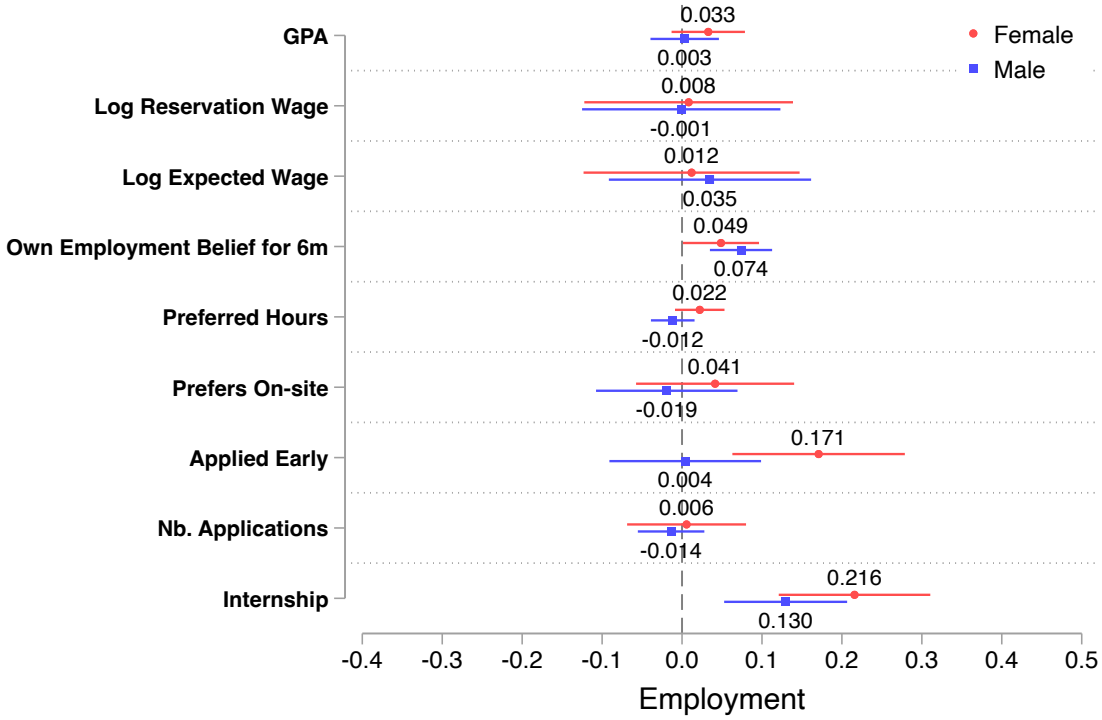
Notes: This figure presents respondent' beliefs about their own employment likelihood relative to beliefs about their peers' employment likelihood, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Male beliefs are represented by the blue cluster of bars on the left. Female beliefs are represented by the red cluster of bars on the right. Bars 1 and 4 show average baseline beliefs about one's own employment likelihood. Bars 2 and 5 show average baseline beliefs about one's male peers' employment likelihood. Bars 3 and 6 show average baseline beliefs about one's female peers' employment likelihood. The average difference between beliefs about self and beliefs about male peers is shown directly above the second bar in each cluster. The average difference between beliefs about self and beliefs about female peers is shown directly above the third bar in each cluster. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3: Explaining the Gender Employment Gap



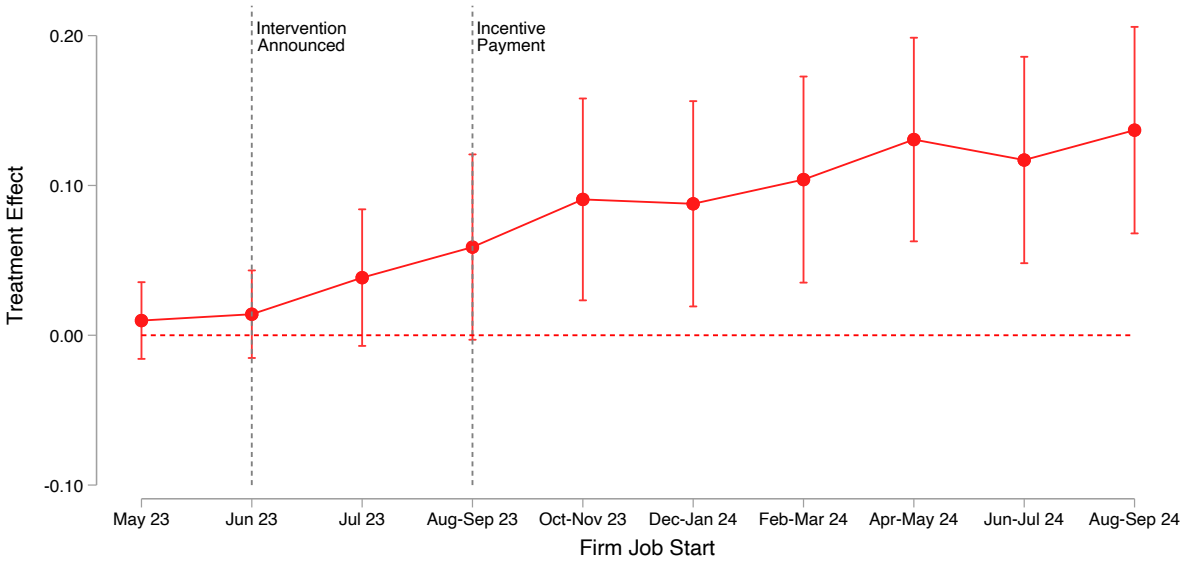
Notes: This figure presents the difference between male and female employment six months post-graduation, with baseline controls for observable characteristics added incrementally. The sample consists of students in the diagnostic sample (see Section 3.1 for details). The Education controls include cumulative GPA and major fixed effects. The Industry of Search controls are fixed effects based on the SOC (Standard Occupational Classification) of a respondent's text-entry baseline responses about what job they are searching for. The Non-Wage Preferences controls include baseline preferences regarding onsite vs. remote work and full-tiem vs part-time work. The Own Employment Belief for 6 Months control includes baseline belief about one's own probability of employment six months later. The Search Effort and Work History controls include the total number of job applications sent by the six-month follow-up, an indicator for applying early (that is for having sent at least one application by the two-months follow-up), and an indicator for internship experience. The Nb. Interviews (Offers) control includes the number of interviews (offers) received by the six-month follow-up. The Offered Wage control includes current wage if the respondent is working, or the highest rejected wage offer if the respondent is not working. All unbounded continuous variables are winsorized at the 2% level. Each coefficient is from a multivariate regression that includes all preceding rows' variables as controls. Adjusted R-squared values are shown for each row. The horizontal bars show 95% confidence intervals.

Figure 4: The Determinants of Gender-Specific Labor Supply

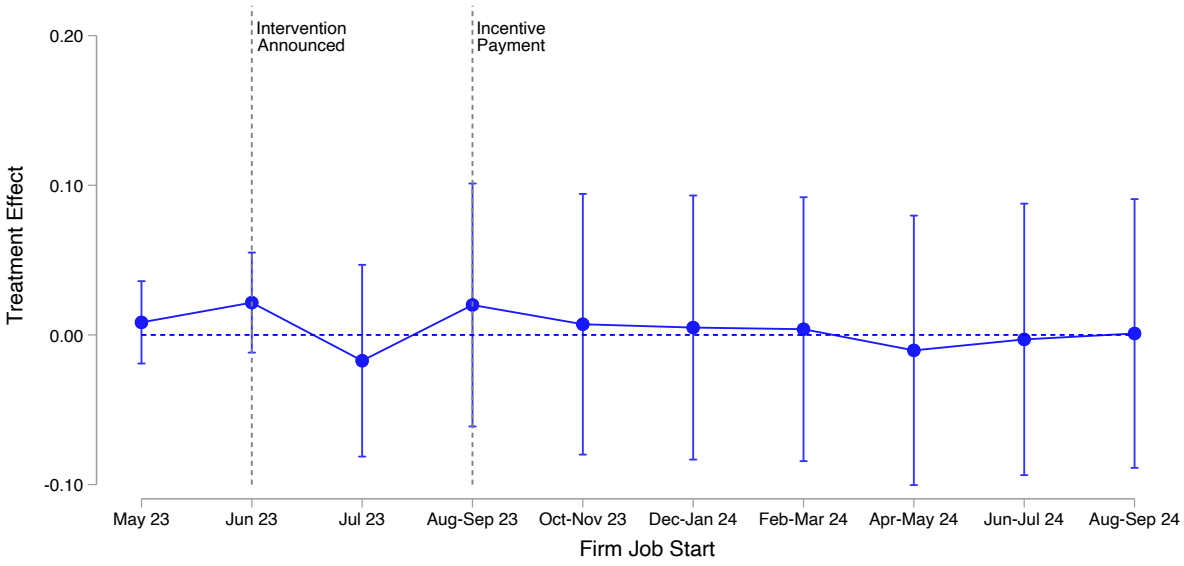


Notes: This figure presents coefficients from a regression of one's employment six months post-graduation on a set of independent variables, separately by gender. Each coefficient is from a multivariate regression conducted separately for men and women, in which all other listed variables are included as controls. The sample consists of students in the diagnostic sample (see Section 3.1 for details). The variables include cumulative GPA (measured in standard deviations), baseline reservation wage, baseline wage expectations, baseline belief about one's own probability of employment (transformed on a 0-1 scale and measured in standard deviations), preferred number of daily work hours, preference for onsite vs. remote work, an indicator for applying early (i.e. by the two-months follow-up), the total number of job applications submitted by the six-month follow-up (measured in standard deviations), and an indicator for having internship experience. All unbounded continuous variables are winsorized at the 2% level. Figure A.13 presents the results of bivariate regressions. The horizontal bars show 95% confidence intervals. Corresponding means and standard deviations for the independent variables shown in the figure are provided in Table B.9.

Figure 5: Dynamic Treatment Effects on Firm Employment



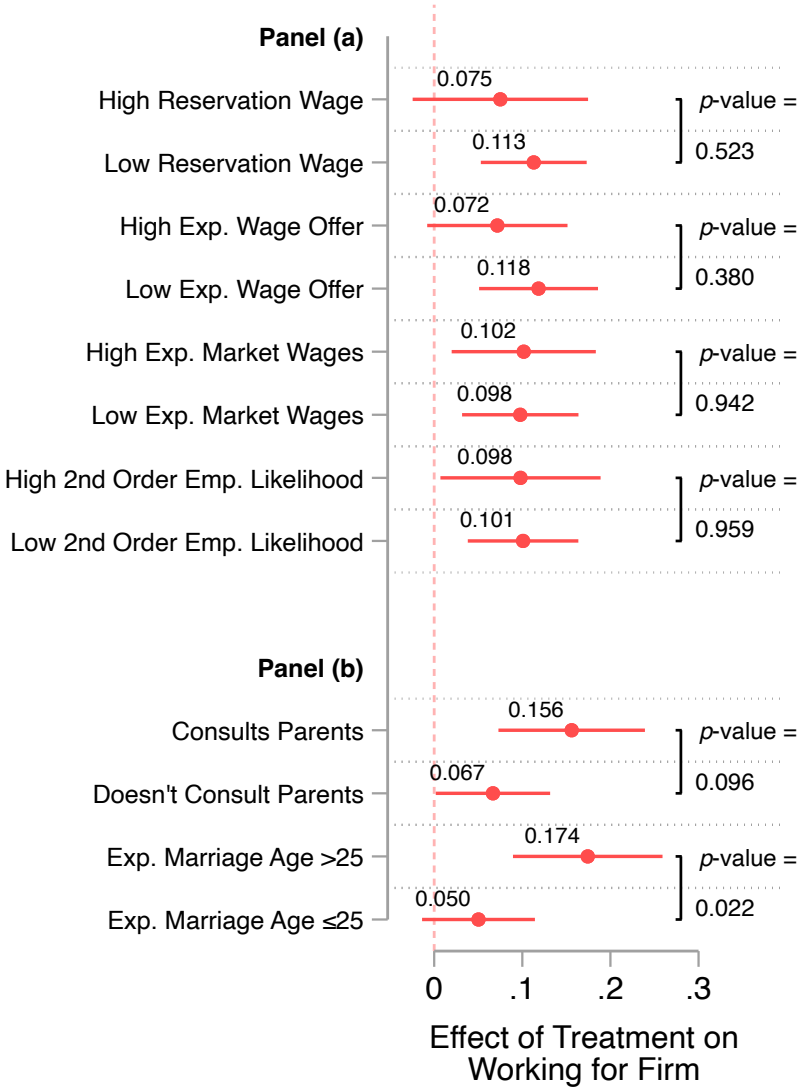
(a) Female: Treatment Effects on Firm Employment



(b) Male: Treatment Effects on Firm Employment

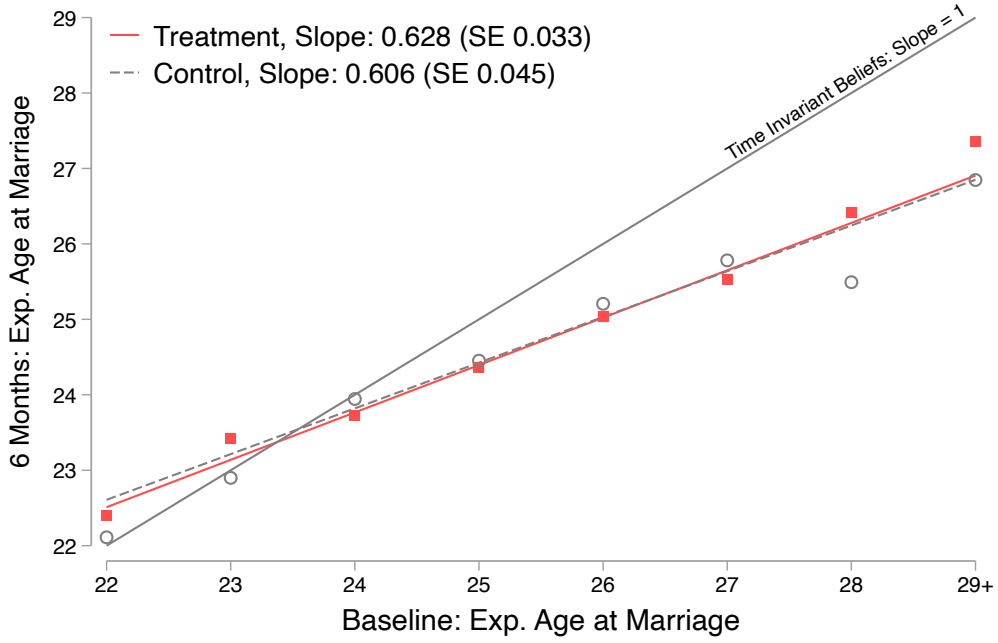
Notes: This figure presents the treatment effect on having ever worked (post-graduation) at a firm by a given date. Panel (a) shows treatment effects for women, while Panel (b) does the same for men. For instance the last coefficient on the right in Panel (a) is the treatment effect on whether a female respondent has ever held a post-graduation firm job by the month of September 2024. The sample consists of students in the experimental sample (see Section 5.1 for details). In both panels, the first dashed vertical line indicates when the intervention was announced, and the second dashed vertical line indicates the deadline by which treated students were required to submit proof of early applications. Both panels include a dashed horizontal line indicating where 0 lies on the y-axis. Vertical bars represent 95 % confidence intervals.

Figure 6: Heterogeneous Treatment Effects on Firm Employment



Notes: This figure presents heterogeneous treatment effects on women's likelihood of working for a firm, where firm employment excludes self-employment and unpaid work. The sample consists of female students in the experimental sample (see Section 5.1 for details). Panel (a) examines heterogeneity based on women's baseline labor market beliefs, including their reservation wage, expected wage offer, and second-order beliefs about peers' expected wages and employment likelihood. Each variable is classified as "High" (above the median) or "Low" (below the median) after winsorizing at the 2% level for unbounded continuous variables. Panel (b) explores heterogeneity based on familial involvement in job search, and marital expectations. Specifically, it includes whether women consult their parents during job search and whether they expect to marry after age 25 (the national median for college-educated women). Responses are pooled from the six- and fourteen-month survey waves, with wave fixed effects, and standard errors are clustered at the individual level. Horizontal bars represent 95% confidence intervals, while the dashed vertical line marks zero on the x-axis. Vertical brackets indicate statistical significance tests between complementary groups, with the corresponding *p*-values reported.

Figure 7: Women's Belief Updating About Expected Age at Marriage



Notes: This figure presents the relationship between women' expected age of marriage at baseline and their updated expected age of marriage at six months, separately by treatment status. The sample consists of female students in the experimental sample who were not already married or engaged by baseline (see Section 5.1 for details). Expected age at marriage is winsorized at the 2% level. Women in the treatment group are represented by the solid red line with square markers. Women in the control group are represented by the dashed gray line with circular markers. The solid gray 45-degree line represents time-invariant beliefs, indicating that the expected age of marriage is unchanged between baseline and the six-month follow-up.

Tables

Table 1: Descriptive Statistics for the Diagnostic Sample

	All	Male	Female	Diff.	P-value
	(1)	(2)	(3)	(4)	(5)
Nb. Obs.	1,029	590	439		
Age	22.5	22.7	22.2	0.5	0.00
GPA	3.1	3.0	3.2	-0.3	0.00
Married	4.3	2.4	6.8	-4.5	0.00
Engaged	6.6	5.9	7.5	-1.6	0.32
Majors:					
Engineering / Computer Science	26.2	39.2	8.9	30.3	0.00
Humanities, Languages and Education	15.5	13.4	18.5	-5.1	0.03
Life Sciences / Pharmacy	12.1	5.1	21.6	-16.6	0.00
Sciences	13.2	5.8	23.2	-17.5	0.00
Social Sciences (inc. Business and Law Degrees)	32.8	36.6	27.8	8.8	0.00
Parental Background:					
College-Educated Mother	41.0	40.7	41.5	-0.8	0.80
College-Educated Father	53.2	52.0	54.7	-2.6	0.40

Notes: This table presents baseline descriptive statistics for respondents in the diagnostic sample (see Section 3.1 for details). Column 1 presents statistics for all respondents. Columns 2 and 3 provide statistics for male and female respondents, respectively. Column 4 shows the difference between genders (calculated as the male - female difference), and Column 5 provides the p-value from a test for equality of means between genders. The first row reports the number of observations in the sample. The rows for Age and GPA report mean values. The remaining rows report the share of students in each category. For instance, the share of all students that are married is 4.3%,and the share of male students in an engineering major is 39.2%. Age is winsorized at the 2% level.

Table 2: Treatment Effects on Employment

	August 15	6 Months		14 Months	
	Has Applied	**Working**	**Working for Firm**	**Working**	**Working for Firm**
	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
Treatment	0.256***	0.075**	0.102***	0.069**	0.095***
	(0.031)	(0.031)	(0.029)	(0.035)	(0.034)
Female Control Mean	0.311	0.336	0.253	0.518	0.416
Panel B: Male					
Treatment	0.189***	0.001	0.012	-0.019	-0.005
	(0.041)	(0.042)	(0.042)	(0.040)	(0.045)
Male Control Mean	0.358	0.551	0.378	0.719	0.561
Nb. Obs.	1,442	1,442	1,442	1,218	1,218

Notes: This table presents the treatment effects on labor market outcomes for students in the six- and fourteen-months experimental sample (see Section 5.1 for details). The sample at fourteen months is restricted to students who also answered the six-month follow-up survey. Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment effect on a respondent's likelihood of applying to at least one job by August 15th. Column 2 reports the treatment effect on employment at six months. Column 3 reports the treatment effect on firm employment at six months. Columns 4 and 5 report the same outcomes as Column 2 and 3, respectively, but at fourteen months. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Table B.4 shows the results without the LASSO-selected controls. Control means are provided separately for each gender. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Descriptive Statistics for the Experimental Sample

	All	Male	Female	Diff.	P-value
	(1)	(2)	(3)	(4)	(5)
Nb. Obs.	1,442	516	926		
Age	22.7	23.2	22.5	0.7	0.00
GPA	3.3	3.2	3.4	-0.2	0.00
Married	4.4	4.3	4.4	-0.2	0.88
Engaged	3.9	3.1	4.3	-1.2	0.23
Majors:					
Engineering / Computer Science	7.1	6.4	7.5	-1.1	0.44
Humanities, Languages and Education	26.3	27.9	25.4	2.5	0.30
Life Sciences / Pharmacy	12.6	10.1	14.0	-4.0	0.02
Sciences	27.0	29.7	25.6	4.1	0.10
Social Sciences (inc. Business and Law Degrees)	27.0	26.0	27.5	-1.6	0.52
Parental Background:					
College-Educated Mother	27.9	18.8	32.9	-14.1	0.00
College-Educated Father	42.6	36.4	46.1	-9.7	0.00
Working Mother	6.9	5.6	7.6	-1.9	0.15
Working Father	86.0	84.9	86.6	-1.7	0.43
Family Owns Car	49.3	44.4	51.9	-7.4	0.02
Family Owns Motorbike	93.3	93.0	93.5	-0.5	0.73
Family has Internet	86.7	80.3	90.1	-9.8	0.00
Family has Laptop	84.9	84.7	85.0	-0.3	0.88
Family has Smartphone	99.6	99.5	99.6	-0.1	0.81

Notes: This table presents baseline descriptive statistics for respondents in the six-month experimental sample (see Section 5.1 for details). Column 1 presents statistics for all respondents. Columns 2 and 3 provide statistics for male and female respondents, respectively. Column 4 shows the difference between genders (calculated as the male - female difference), and Column 5 provides the p-value from a test for equality of means between genders. The first row reports the number of observations in the sample. The rows for Age and GPA report mean values. The remaining rows report the share of students in each category. For instance, the share of all students that are married is 4.4%,and the share of male students in an engineering major is 6.4%. Age is winsorized at the 2% level.

Table 4: OLS and IV Estimates of Early Applications on Employment

	6 Months		14 Months	
	OLS Working for Firm	**2SLS Working for Firm**	**OLS Working for Firm**	**2SLS Working for Firm**
	(1)	(2)	(3)	(4)
Panel A: Female				
Applied Early (by Aug. 15th)	0.236***	0.382***	0.184***	0.308***
	(0.030)	(0.111)	(0.035)	(0.110)
Female, Not Applied Early, Mean	0.189	0.189	0.355	0.355
Panel B: Male				
Applied Early (by Aug. 15th)	0.211***	0.053	0.115**	-0.031
	(0.043)	(0.221)	(0.045)	(0.199)
Male, Not Applied Early, Mean	0.277	0.277	0.481	0.481
Nb. Observations	1,442	1,442	1,218	1,218

Notes: This table presents OLS and 2SLS treatment effects on early job application and firm employment. The sample consists of students in the experimental sample (see Section 5.1 for details). The sample at fourteen months is restricted to students who also answered the six-month follow-up survey. Panel A shows results for women, and Panel B shows results for men. Column 1 reports the OLS estimates from regressing employment at six months on whether a respondent applied early. Column 2 uses the exogenous treatment as an instrumental variable and reports the 2SLS estimates of the effect of applying early on employment at six months. Columns 3 and 4 report the same outcomes as Columns 1 and 2, respectively, but at fourteen months. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations.

Table 5: Treatment Effects on Labor Market Intentions

	Intended Nb. Apps	Intended Search Start (Days)	Emp. Likelihood in 6 Months
	(1)	(2)	(3)
Panel A: Female			
Treatment	0.593*	-20.375***	-0.885
	(0.324)	(2.660)	(1.031)
Female Control Mean	5.586	50.213	79.802
Panel B: Male			
Treatment	-0.580	-12.647***	0.743
	(0.559)	(3.632)	(1.271)
Male Control Mean	7.366	43.748	81.618
Nb. Obs.	1,417	1,417	1,442

Notes: This table presents treatment effects on self-reported job search intentions and employment expectations from the baseline survey. Responses were collected after the treatment group was informed about their eligibility for a financial incentive for submitting four early applications. The sample consists of students in the experimental sample (see Section 5.1 for details). Panel A shows results for women, while Panel B shows results for men. Column 1 reports the treatment effect on the intended number of job applications. Column 2 reports the effect on the intended job search start date, recorded as the number of days from the survey date until the student plans to begin applying. Column 3 reports the treatment effect on the respondent's self-reported likelihood of being employed in six months. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Treatment Effects on Applications and Offers

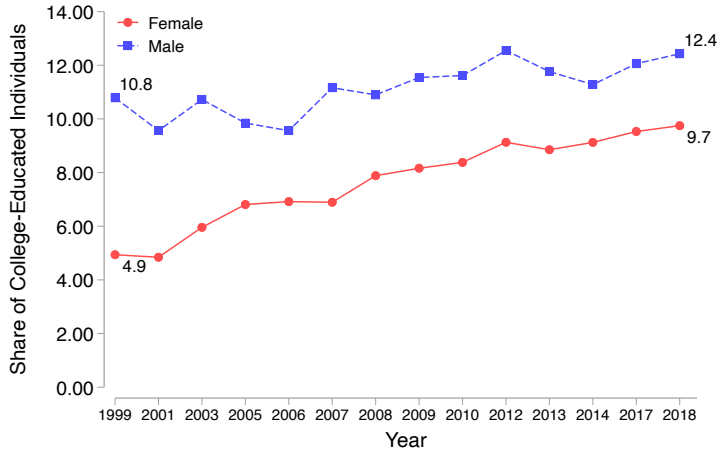
	6 Months		14 Months	
	Nb. Apps	**Nb. Offers**	**Nb. Apps**	**Nb. Offers**
	(1)	(2)	(3)	(4)
Panel A: Female				
Treatment	1.459**	0.162	1.663**	-0.004
	(0.739)	(0.165)	(0.714)	(0.097)
Female Control Mean	8.163	2.007	4.739	0.902
Panel B: Male				
Treatment	0.497	0.132	-0.404	-0.011
	(1.052)	(0.204)	(0.967)	(0.120)
Male Control Mean	9.530	1.909	6.541	0.959
Nb. Obs.	1,433	1,433	1,207	1,207

Notes: This table presents the treatment effects on intermediate labor market outcomes for students in the experimental sample (see Section 5.1 for details). The sample at fourteen months is restricted to students who also answered the six-month follow-up survey. Panel A shows results for women, and Panel B shows results for men. Column 1 reports the number of applications sent between graduation and the six-month follow up. Column 2 reports the number of job offers received between graduation and the six-month follow-up. Column 3 reports the number of applications sent in the six-months prior to the fourteen-month follow-up. Column 4 reports the number of job offers received in the in the six-months prior to the fourteen-month follow-up. Number of applications and number of offers are winsorized at the 2% level. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations. There are fewer observations in this table relative to Table 2 because the analysis is limited to cases with non-missing values for number of applications and offers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

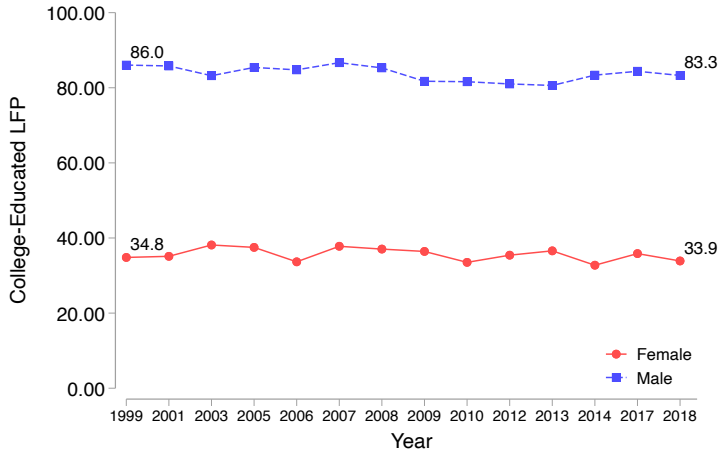
Appendix

A Appendix Figures

Figure A.1: College Education and Labor Force Participation in Pakistan



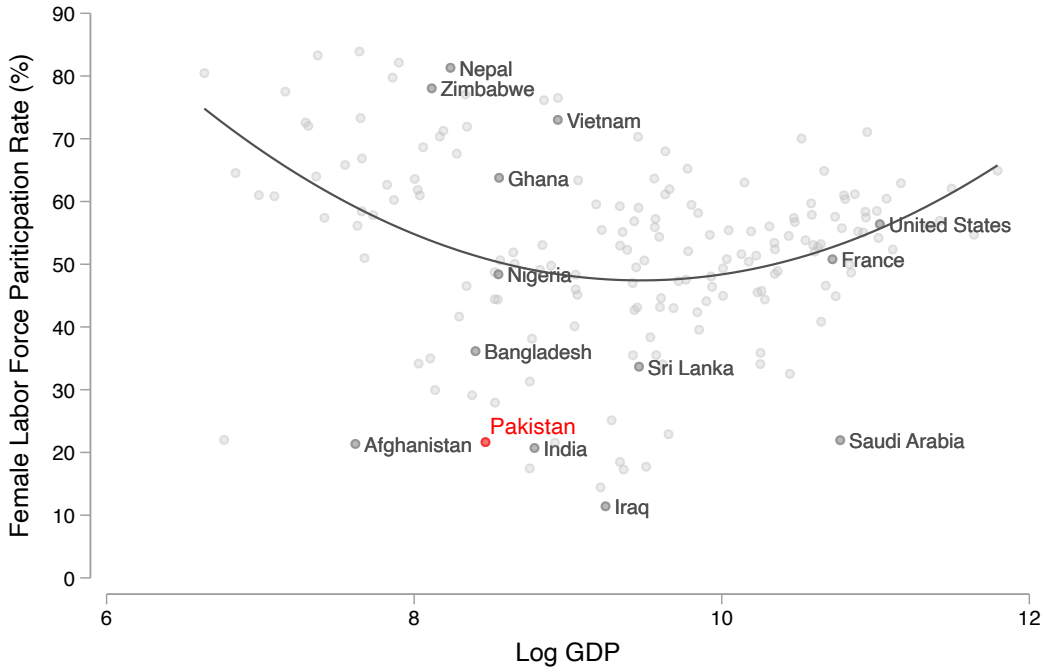
(a) Gender Gaps in College Education



(b) Gender Gaps in College-Educated Labor Force Participation

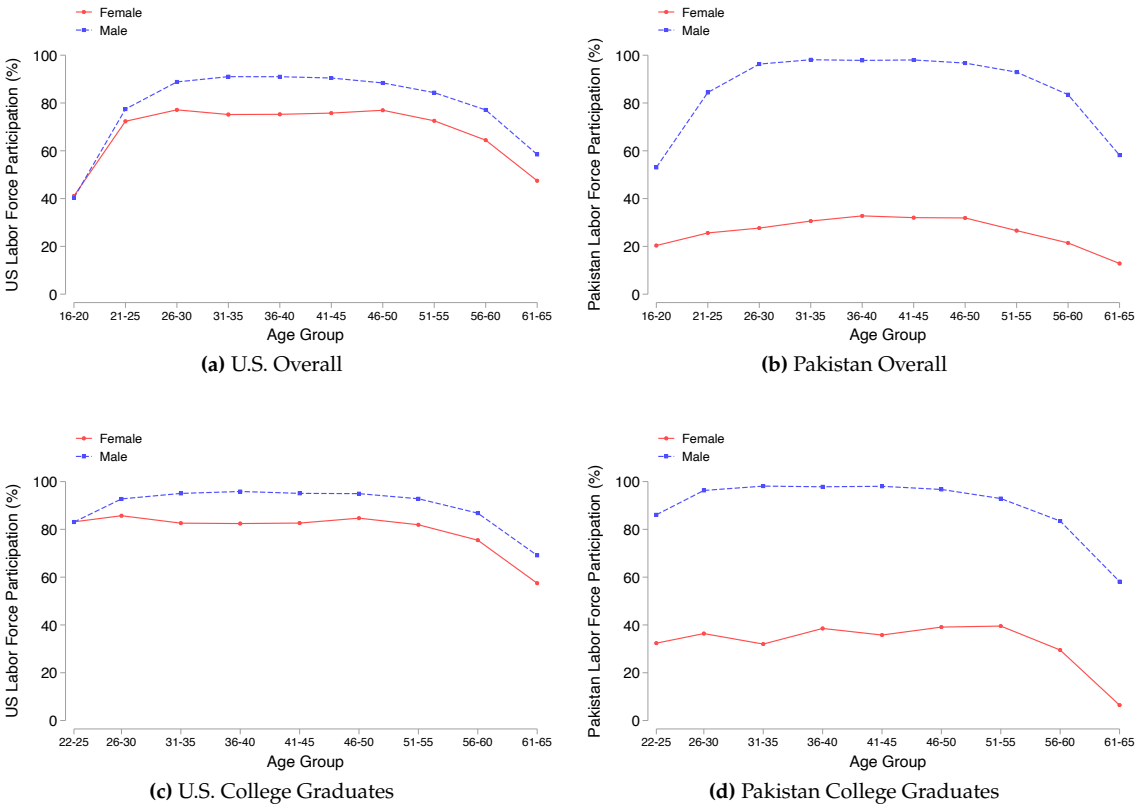
Notes: This figure presents trends in college education and labor force participation in Pakistan between 1999 and 2018. Panel (a) shows the share of individuals aged 22–35 who are college-educated, separately by gender. Panel (b) shows the labor force participation rates for college-educated individuals in the same age group, separately by gender. In both panels, men are represented by a dashed blue line with square markers, and women are represented by a solid red line with circular markers. Data for both panels is obtained from the Pakistan Labor Force Surveys.

Figure A.2: Female Labor Force Participation vs. (Log) GDP per Capita by Country (2018)



Notes: This figure compares log GDP per capita and female labor force participation across several countries, with Pakistan highlighted in red. The U-shaped relationship between GDP and female labor force participation is represented by a solid black line. Countries that lie directly on the U-shaped line are shown in gray (for example, Nigeria and France). Countries with similar levels of GDP per capita to Pakistan (for example, Nepal and Ghana) or similar levels of female labor force participation (for example, Saudi Arabia and India) are also shown in gray. Data are obtained from the World Bank (2018).

Figure A.3: Labor Force Participation by Age and Gender, US vs. Pakistan (2018)



(a) U.S. Overall

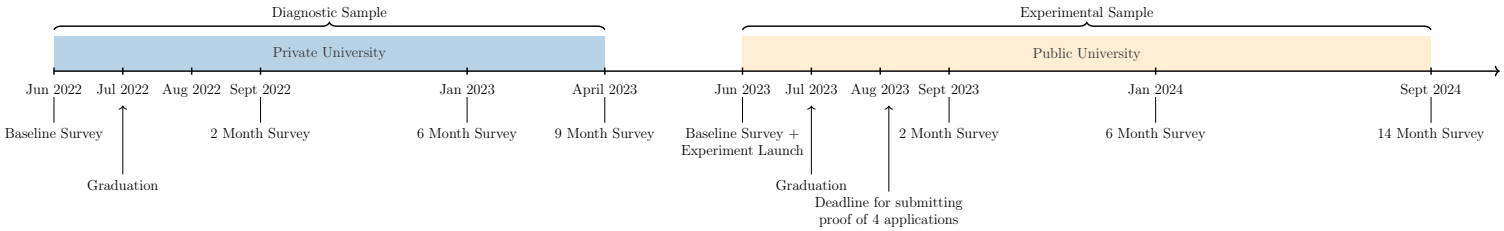
(b) Pakistan Overall

(c) U.S. College Graduates

(d) Pakistan College Graduates

Notes: This figure compares age, education, and labor force participation in the United States and Pakistan, separately by gender. Panels (a) and (b) show labor force participation for men and women aged 16 to 65 in the United States and Pakistan, respectively. Panels (c) and (d) show labor force participation for college-educated men and women aged 22 to 65 in the United States and Pakistan, respectively. In all panels, men are represented by a dashed blue line with circular markers and women are represented by a solid red line with circular markers. Data for the United States is obtained from the Current Population Survey (2018) and data for Pakistan is obtained from the Pakistan Labor Force Surveys (2018).

Figure A.4: Research Timeline



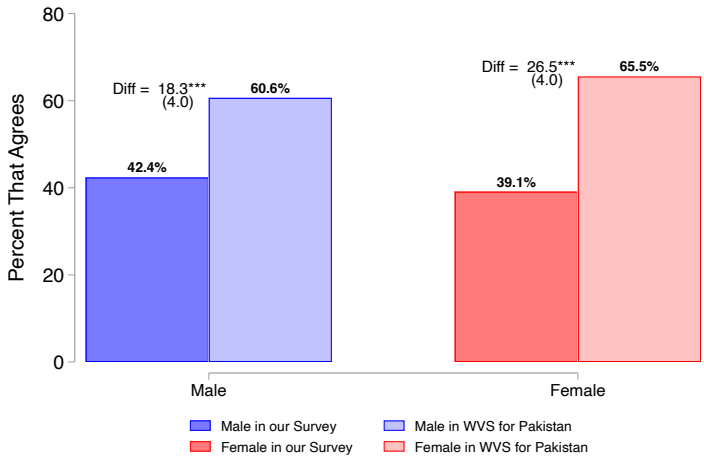
Notes: This figure presents the timing of research surveys relative to students' graduation timeline. The first surveys (represented in blue on the timeline) were conducted with the diagnostic sample described in Section 3.1 at the private university. The baseline survey was conducted in June 2022, one month prior to the end of the academic term. This is noted on the timeline as "graduation", although convocation ceremonies were scheduled at different times by different departments. This cohort of students was followed-up with two, six, and nine months later, in September 2022, January 2023, and April 2023, respectively. Insights from these follow-ups informed the intervention implemented one year later in the experimental sample described in Section 5.1 at the public university. These surveys are represented in yellow on the timeline. The baseline survey and experiment were fielded in June 2023 at this university, one month prior to end of the academic term in July 2023. This is noted again as "graduation" on the timeline. The deadline given to the treatment group to show proof of 4 applications was August 15, 2023. This cohort of students was followed-up with two, six, and fourteen months later, in September 2023, January 2024, and September 2024, respectively.

Figure A.5: Survey Incentives

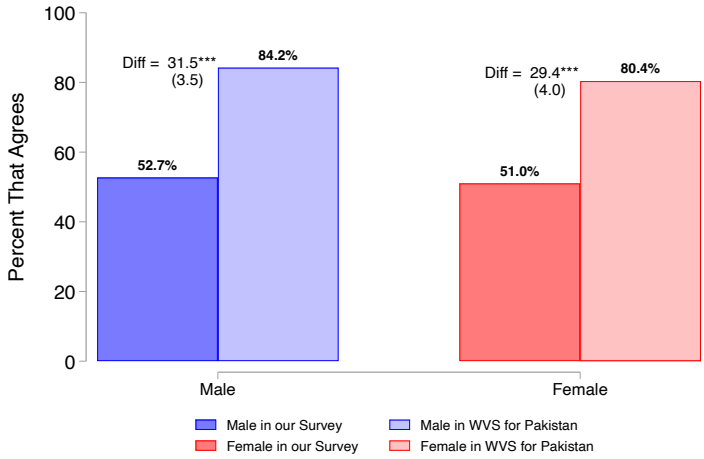


Notes: This figure presents a photograph taken on June 9, 2022 at the private university in Lahore, Pakistan. It shows the setup of one of our food stands during baseline data collection. All students who completed the survey were given vouchers to redeem KFC meals and a bakery item from the food stand.

Figure A.6: Social Norms in Our Sample Relative to National Average



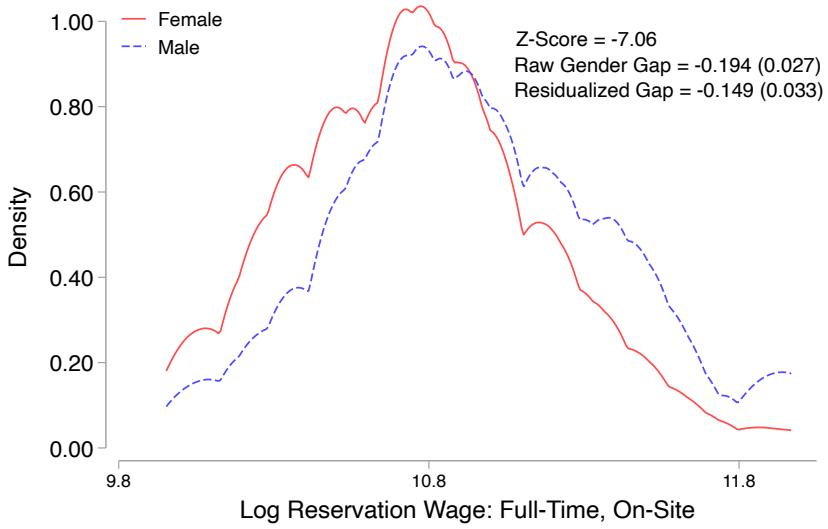
(a) Being a Housewife is as Fulfilling as Working



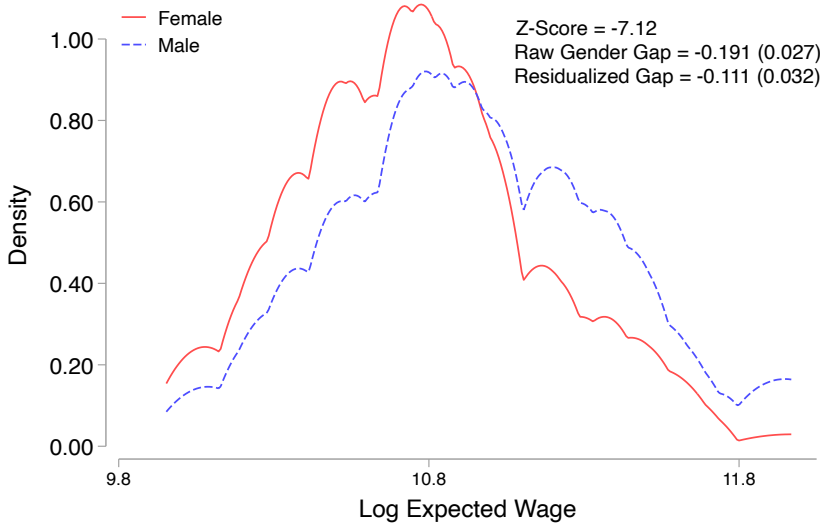
(b) When Jobs are Scarce, Men Have More Right to a Job

Notes: This figure compares baseline beliefs about social norms among students in the diagnostic sample (see Section 3.1 for details) with national average responses, separately for men and women. Panel (a) shows the percentage of male respondents (left cluster of two bars) and female respondents (right cluster of two bars) that agree with the statement, "Being a housewife is just as fulfilling as working for pay." Panel (b) shows the percentage of male respondents (left cluster of two bars) and female respondents (right cluster of two bars) that agree with the statement, "When jobs are scarce, men should have more right to a job than women." In both panels, men are represented in blue (bars 1 and 2) and women are represented in red (bars 3 and 4). The darker bars (bars 1 and 3) in each panel represent respondents in the diagnostic sample, while the lighter bars (bars 2 and 4) represent respondents in the World Value Survey (WVS) for Pakistan. The average difference between respondents in the diagnostic sample and respondents in the WVS sample is shown directly above the darker bar for each gender. Data is obtained from the WVS (Wave 7: 2017-21), which is a nationally representative sample. We restrict WVS data to individuals under age 29. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7: Supply-Side Factors I: Reservation Wage and Expected Wage



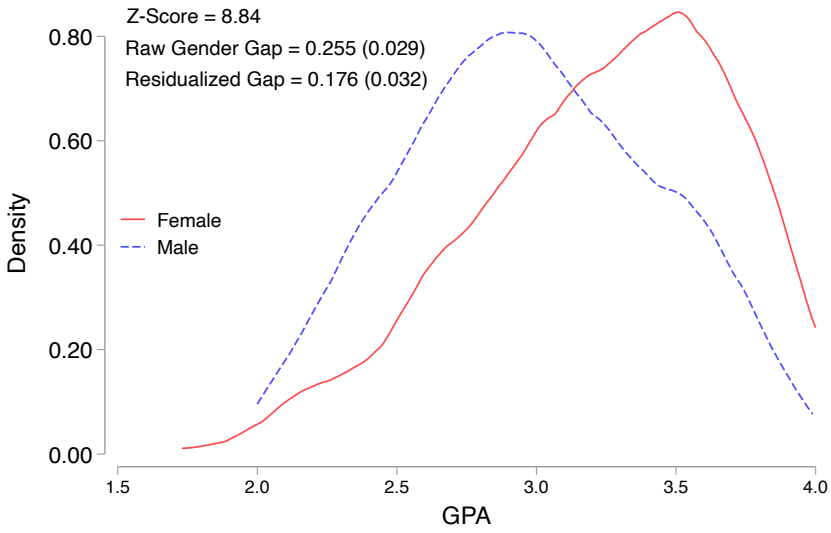
(a) Kernel Density: Log Reservation Wage



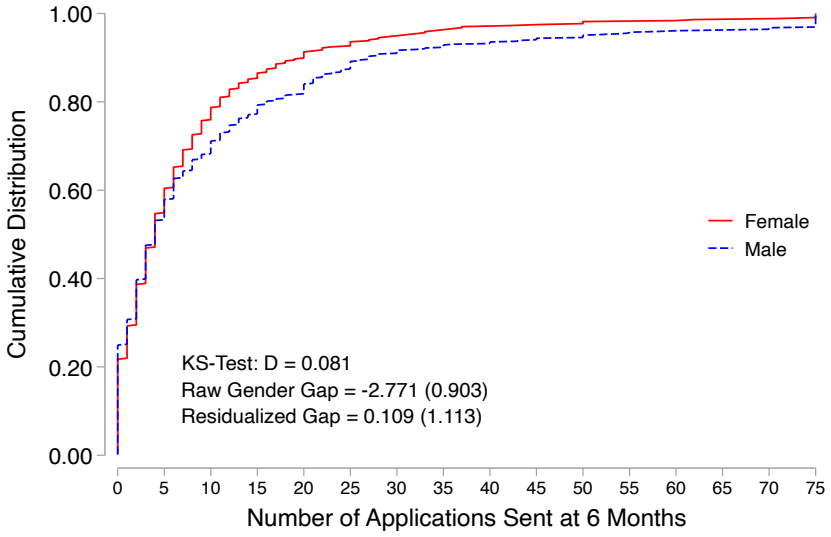
(b) Kernel Density: Log Expected Wage

Notes: This figure presents the distribution of baseline reservation and expected wages, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Panel (a) shows the kernel density of log reservation wages for a full-time, on-site job. Panel (b) shows the kernel density of log expected wages for a full-time, on-site job for the respondent's preferred job title. Reservation and expected wages are winsorized at the 2% level. In both panels, women are represented by a solid red line, and men are represented by a dashed blue line. Both panels show raw and residualized gender gaps, calculated as the female - male difference, and the z-score for the difference between women and men. The residualized estimate controls for cumulative GPA, major, industry of search, preference for onsite vs. remote work, number of preferred daily work hours, and internship experience.

Figure A.8: Supply-Side Factors II: GPA and Search Effort



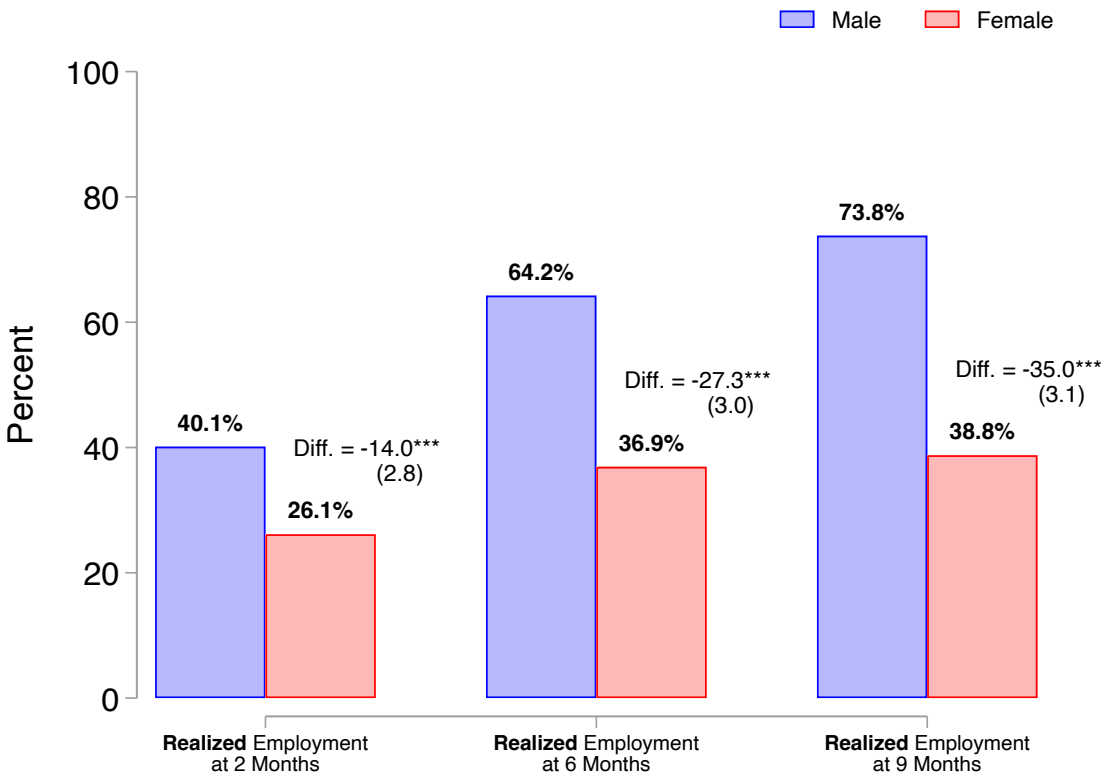
(a) Kernel Density: GPA



(b) CDF: Job Applications at Six Months

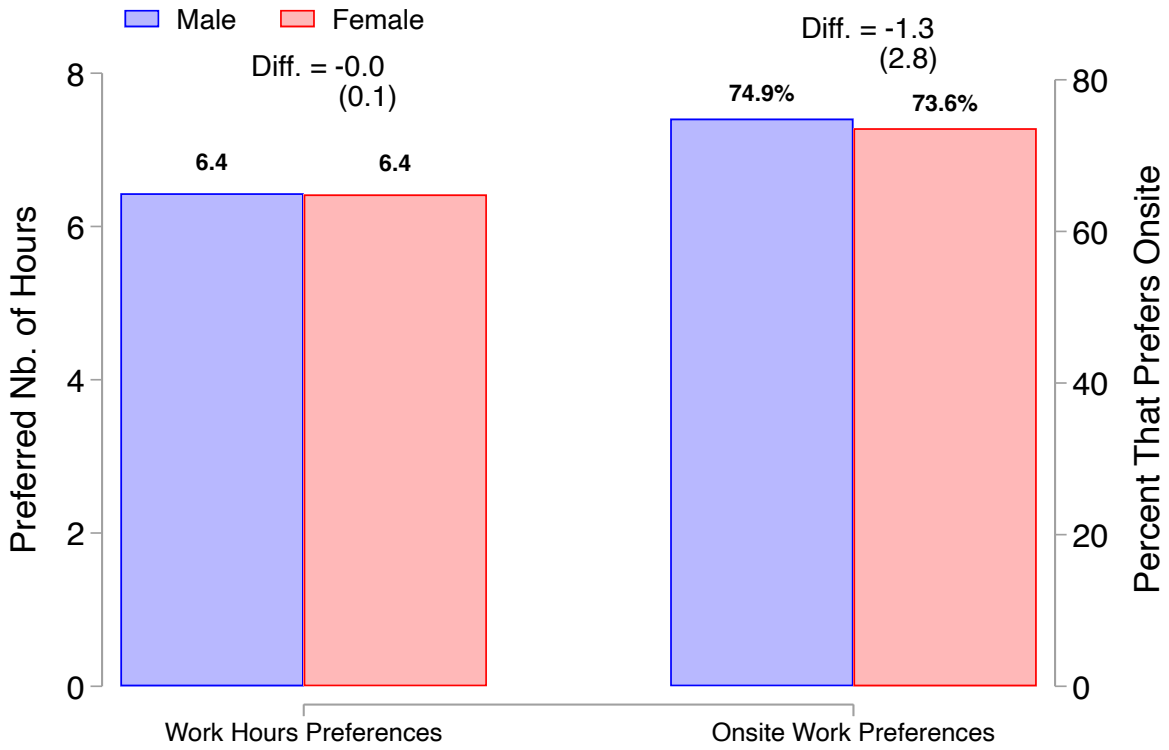
Notes: This figure presents the distribution of baseline GPA and number of job applications sent by the six-month follow-up, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Panel (a) shows the kernel density of cumulative GPA. Panel (b) shows the cumulative distribution of the number of job applications sent by the six-month follow-up. Number of job applications is winsorized at the 2% level. In both panels, women are represented by a solid red line, and men are represented by a dashed blue line. Both panels show raw and residualized gender gaps, calculated as the female - male difference, and the z-score for the difference between women and men. The residualized estimate in Panel (a) controls for major. The residualized estimate in Panel (b) controls for cumulative GPA, major, industry of search, preference for onsite vs. remote work, number of preferred daily work hours, and internship experience.

Figure A.9: Employment Rates By Gender Across Survey Waves



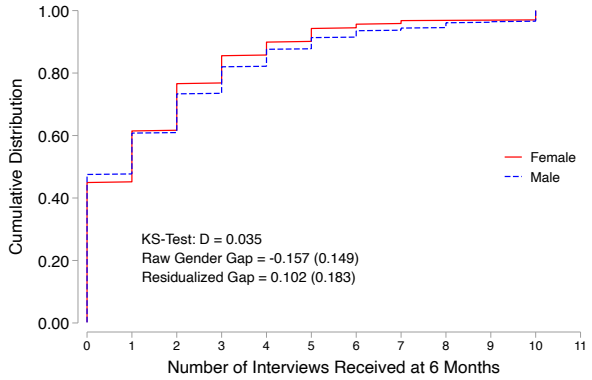
Notes: This figure presents employment rates, separately by gender and survey wave. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Employment is shown for the two, six, and nine-month follow-up surveys by the left, middle, and right clusters of bars, respectively. Men are represented in blue (bars 1, 3, and 5) and women are represented in red (bars 2, 4, and 6). The average difference between male and female employment is shown directly above the female bar for each follow-up survey. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.10: Supply-Side Factors III: Preferred Work Arrangements

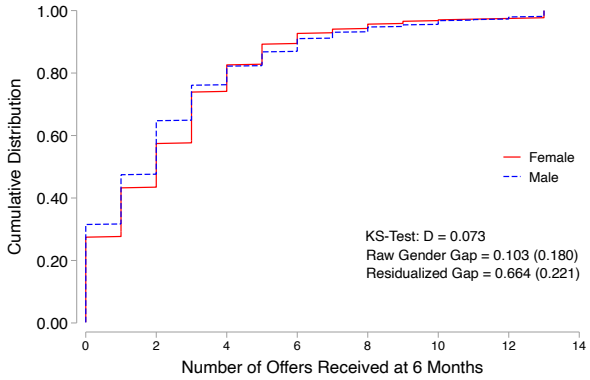


Notes: The figure presents information on baseline preferred work arrangements, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). The left cluster of two bars shows the average number of preferred work hours. The right cluster of two bars shows the percentage of respondents that prefer to work onsite rather than work remotely. Men are represented in blue (bars 1 and 3) and women are represented in red (bars 2 and 4). The average difference between male and female responses is shown directly above the female bar. The variable for preferred hours of work in a day is winsorized at the 2% level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.11: Demand-Side Factors: Interviews, Offers and Offered Wages



(a) CDF: Job Interviews at Six Months



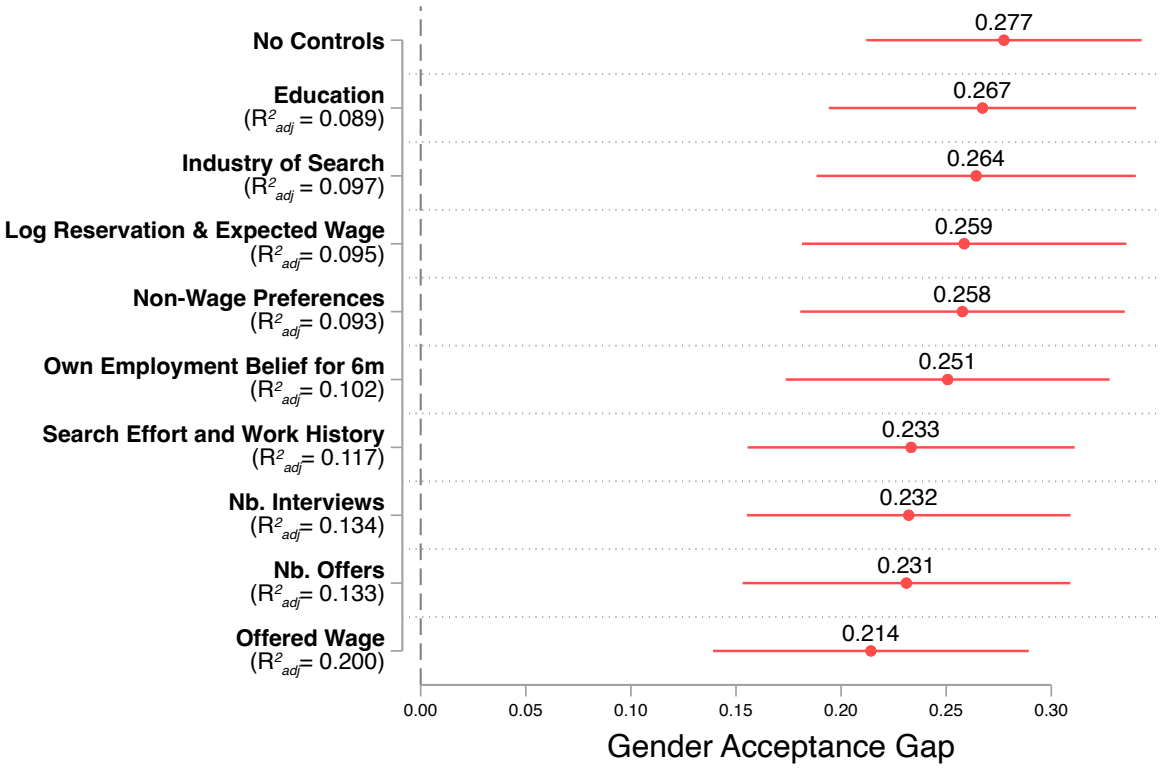
(b) CDF: Job Offers at Six Months



(c) Kernel Density: Log Offered Wages at Six Months

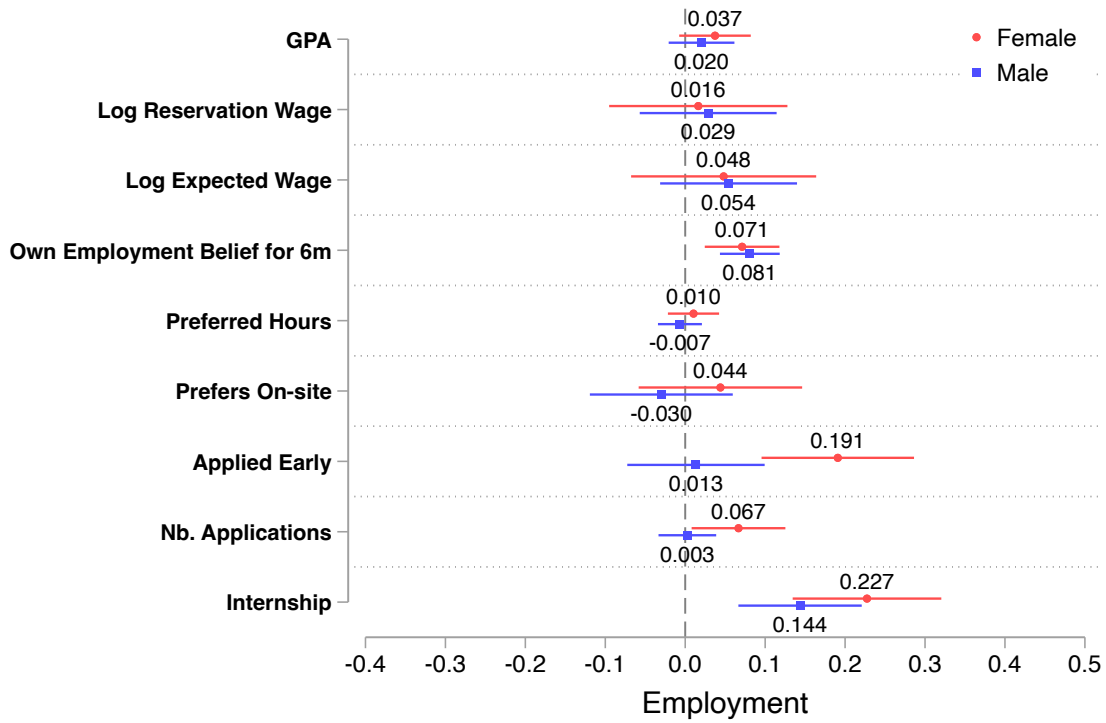
Notes: The figure presents the distribution of job interviews, job offers, and offered wages received by the six-month follow-up, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Panel (a) shows the cumulative distribution of the number of job interviews received by the six-month follow-up. Panel (b) shows the cumulative distribution of the number of job offers received by the six-month follow-up. Panel (c) shows the kernel density of log offered wage at six months for respondents who reported at least one job offer. Number of interviews, number of offers, and offered wage are winsorized at the 2% level. In all three panels, women are represented by a solid red line, and men are represented by a dashed blue line. All three panels show raw and residualized gender gaps, calculated as the female - male difference. Panels (a) and (b) show the KS-test for differences in the raw distributions of female and male interviews and offers, respectively. Panel (c) reports the z-score for the difference in mean log offered wages between women and men. The residualized estimate in all panels controls for cumulative GPA, major, industry of search, preference for onsite vs. remote work, number of preferred daily work hours, internship experience, reservation wage, and expected wage.

Figure A.12: Explaining the Gender Acceptance Gap Six Months After Graduation



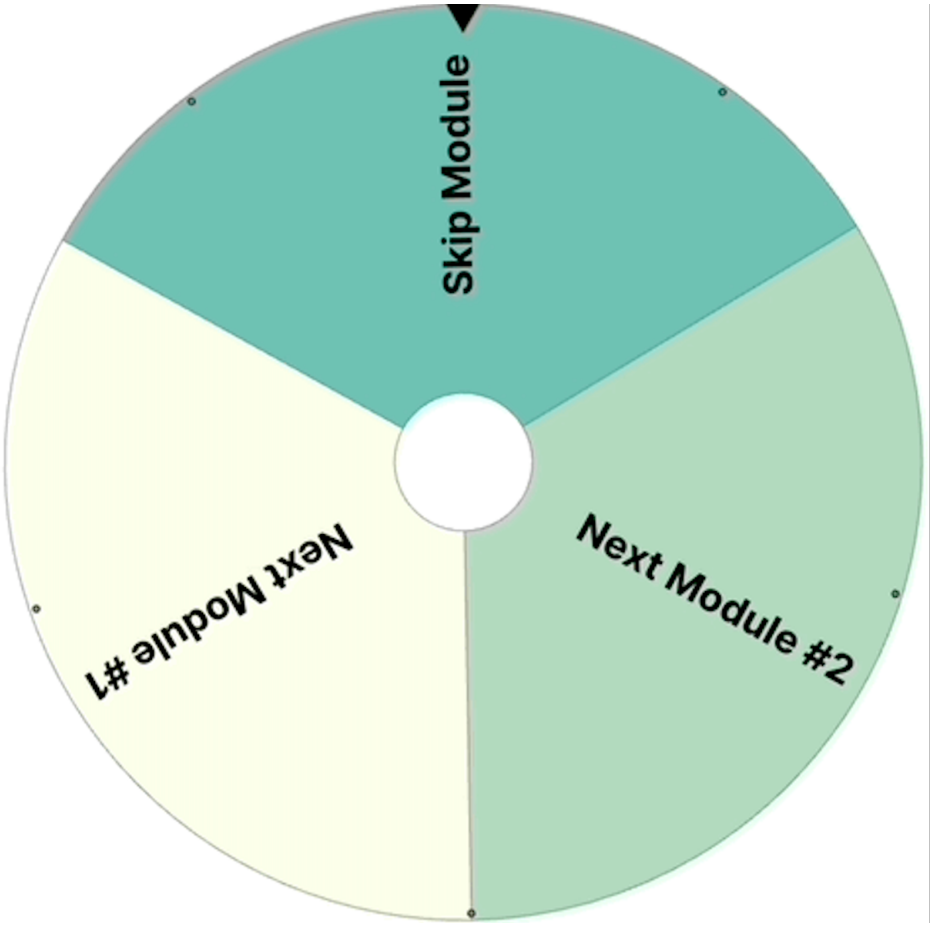
Notes: This figure presents the difference between male and female likelihood of having accepted a job offer six months post-graduation, with controls for observable characteristics added incrementally. The sample consists of students in the diagnostic sample (see Section 3.1 for details). Each row reports the gap between male and female job offer acceptance after controlling for the variable listed in that row and all rows above. The Education controls include cumulative GPA and major fixed effects. The Industry of Search controls incorporate fixed effects derived from the semantic classification of a respondent's preferred job title into Standard Occupational Classification (SOC) codes. The Reservation and Expected Wage controls include respondents' wage expectations at baseline. The Non-Wage Preferences controls include preferences regarding onsite vs. remote work and the number of preferred daily work hours. The Own Employment Belief for 6 Months control includes baseline belief about one's probability of employment. The Search Effort and Work History controls include the total number of job applications sent by the six-month follow-up, an indicator for applying early, and an indicator for internship experience. The Nb. Interviews control includes the number of interviews received by the six-month follow-up. The Nb. Offers control includes the number of job offers received by the six-month follow-up. The Offered Wage control includes current wage if the respondent is working, or the highest rejected wage offer if the respondent is not working. All unbounded continuous variables are winsorized at the 2% level. Each coefficient (except for the first row) is from a multivariate regression that includes all preceding rows' variables as controls. The first row presents the coefficient from a bivariate regression of an indicator for accepting a job offer on the female indicator. Adjusted R-squared values are shown for each row. The horizontal bars show 95% confidence intervals. The mean acceptance rate for men is 73.6%.

Figure A.13: Timing Distinctively Predicts Women's Employment (Bivariate Estimates)



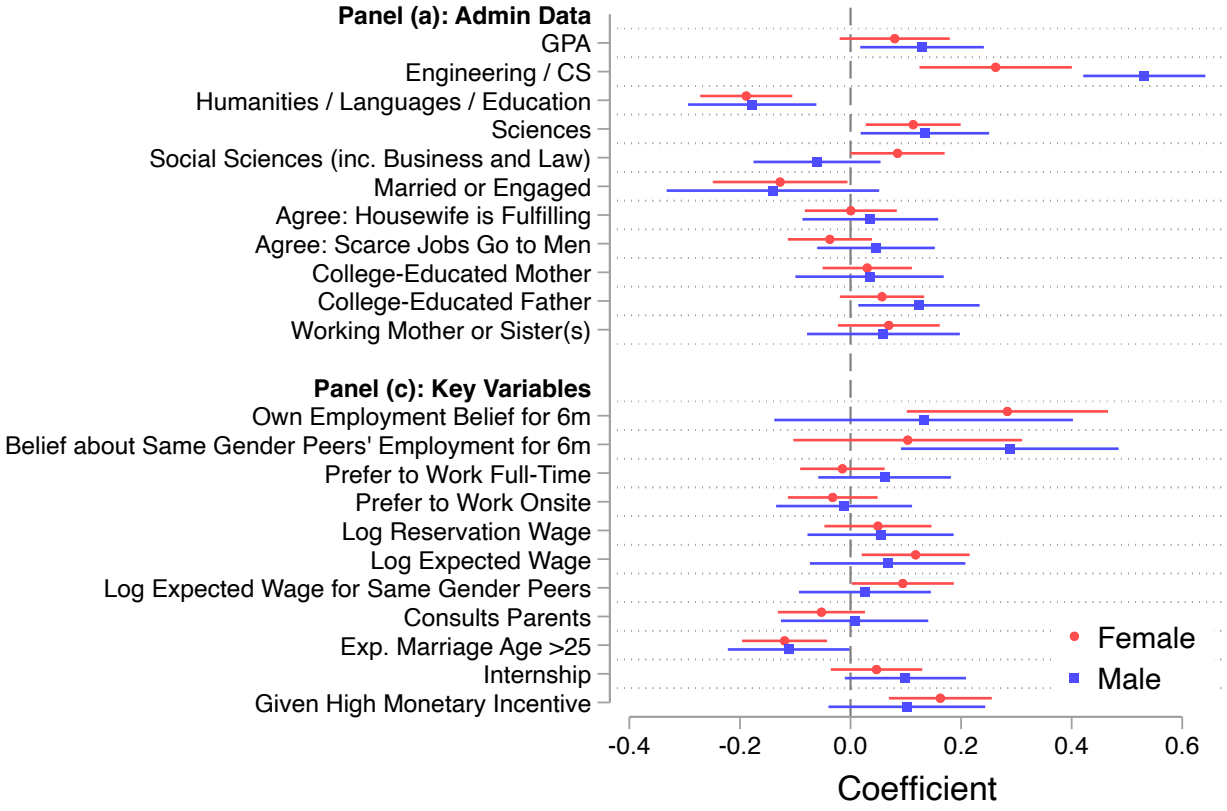
Notes: This figure presents the probability of employment six months post-graduation as explained by a set of independent variables, separately by gender. The sample consists of students in the diagnostic sample (see Section 3.1 for details). The predictors include cumulative GPA (measured in standard deviations), baseline wage expectations, baseline belief about the probability of employment (on a 0-1 scale, measured in standard deviations), preferred daily work hours, preference for onsite vs. remote work, an indicator for applying early, the total number of job applications submitted by the six-month follow-up (measured in standard deviations), and an indicator for having internship experience. All unbounded continuous variables are winsorized at the 2% level. Each coefficient is from a bivariate regression conducted separately for men and women. Figure 4 presents the results of a multivariate regression for each predictor of employment, rather than bivariate regressions. The horizontal bars show 95% confidence intervals. Corresponding means and standard deviations for the independent variables shown in the figure are provided in Table B.9.

Figure A.14: Wheel Shown to Students in the Experimental Sample



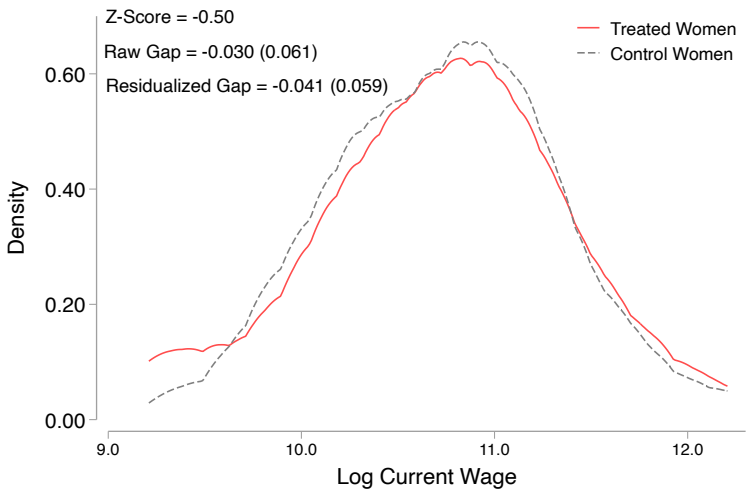
Notes: This figure presents the wheel shown to students during the baseline survey in the experimental sample described in Section 5.1 at the public university. The wheel was spun on a tablet, with both the student and the enumerator able to observe the outcome. The wheel randomly assigned students to one of two treatment groups or the control group. Students in the control group were informed that the survey would proceed to the final module, while those in the treatment groups were informed about the incentives for early application.

Figure A.15: Characteristics of the Treated

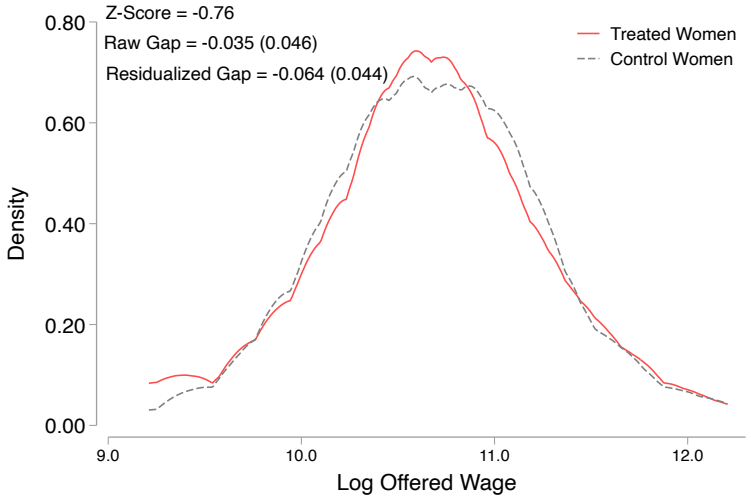


Notes: This figure compares observable characteristics of students who were offered and took up treatment and those who were offered but did not take up treatment, separately by gender. The sample consists of students in the experimental sample (see Section 5.1 for details). Panel (a) shows administrative data, such as GPA and college major. Panel (b) shows survey responses about demographic background, such as marital status, agreement with two statements that reflect gender values, parental education, and female family members' work status. Panel (c) shows survey responses which may determine of labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, wage expectations, and whether the student was offered the high-monetary incentive. All unbounded continuous variables are winsorized at the 2% level. Each coefficient is from a bivariate regression conducted separately for men and women. The horizontal bars show 95% confidence intervals.

Figure A.16: Wage Distribution for Treated and Control Women



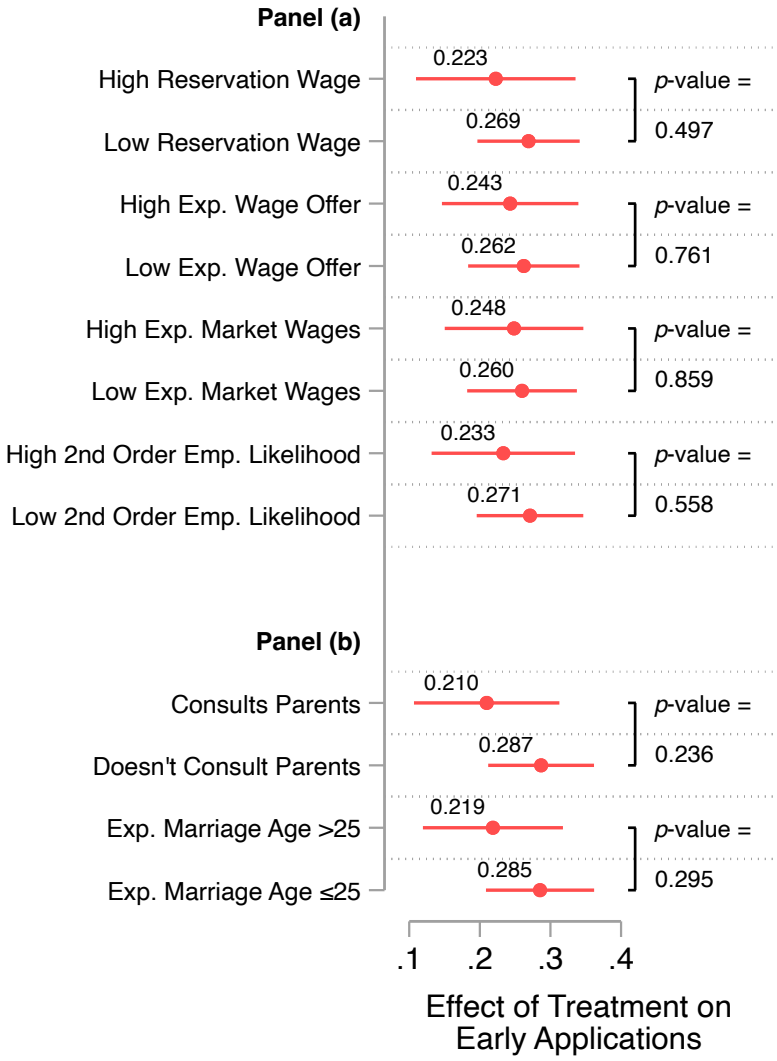
(a) Log Current Wage by Treatment



(b) Log Offered Wage by Treatment

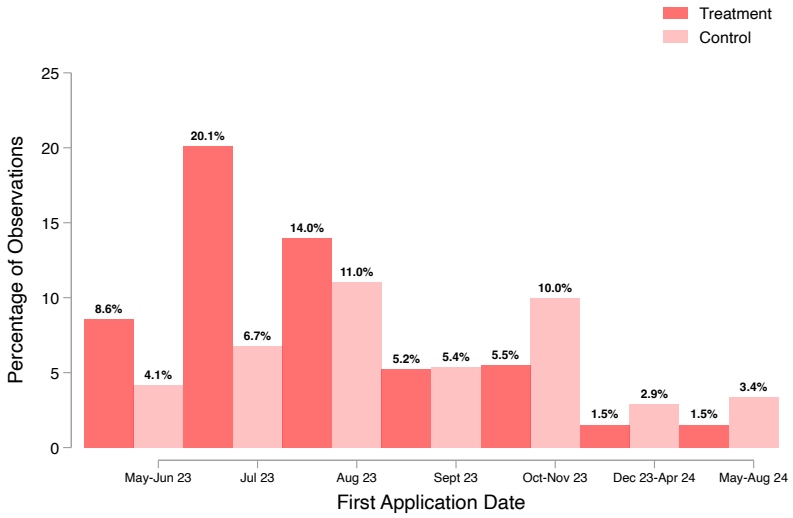
Notes: This figure presents the distribution of current and offered wages for women at the fourteen-month follow-up, separately by treatment status. The sample consists of students in the experimental sample (see Section 5.1 for details) who provided a current or offered wage, respectively. Panel (a) shows kernel density of log current wage and Panel (b) shows kernel density of log offered wage. Current wage and offered wage are winsorized at the 2% level. In both panels, treated women are represented by a solid red line, and control women are represented by a dashed gray line. Both panels show raw and residualized gaps, calculated as the treatment - control difference, and the z-score for the difference between treated women and control women. The residualized estimate controls for cumulative GPA, major, industry of search, preference for onsite vs. remote work, number of preferred daily work hours, internship experience, reservation wage, and expected wage.

Figure A.17: Heterogeneous Treatment Effects on Early Application

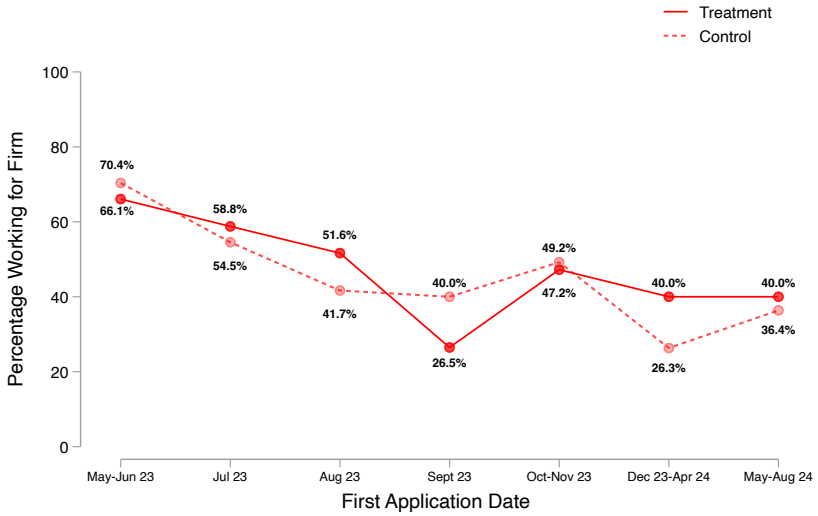


Notes: This figure presents heterogeneous treatment effects on women's likelihood of applying to jobs early, defined as submitting at least one application by August 15—the deadline for treated students to qualify for the financial reward. The sample consists of female students in the experimental sample (see Section 5.1 for details). Panel (a) shows heterogeneity based on women's baseline labor market beliefs, including their reservation wage, expected wage offer, and second-order beliefs about peers' expected wages and employment likelihood.Each variable is classified as "High" (above the median) or "Low" (below the median) after winsorizing at the 2% level for unbounded continuous variables. Panel (b) shows heterogeneity based on familial involvement in job search, and marital expectations. Specifically, it includes whether women consult their parents during job search and whether they expect to marry after age 25 (the national median for college-educated women). Responses are pooled from the six- and fourteen-month survey waves, with wave fixed effects, and standard errors are clustered at the individual level. Horizontal bars represent 95% confidence intervals, while the dashed vertical line marks zero on the x-axis. Vertical brackets indicate statistical significance tests between complementary groups, with the corresponding *p*-values reported.

Figure A.18: Female First Application Date and Firm Employment



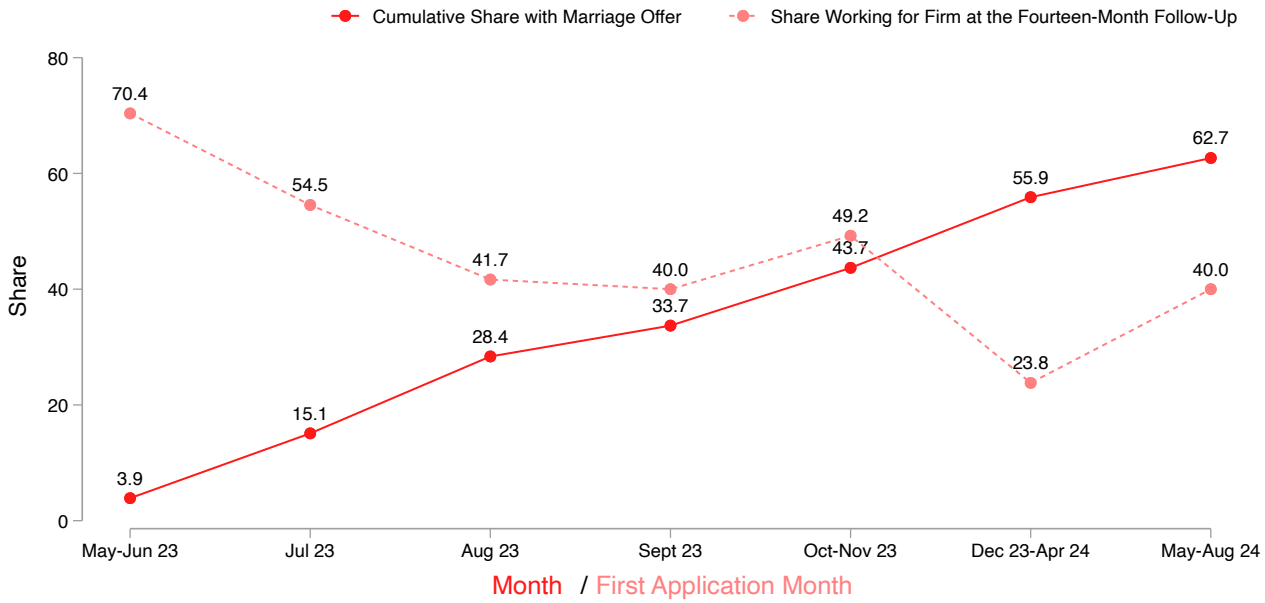
(a) Distribution of First Application Date



(b) Percent Working for Firm by First Application Date

Notes: This figure presents the distribution of first application dates and the share of women working for a firm at the fourteen-month follow-up, separately by treatment status. The sample consists of students in the experimental sample (see Section 5.1 for details) who provided the date of least one job application. Panel (a) presents a histogram of first application dates, while Panel (B) shows the share of women in treatment and control (who provided at least one job application date) who are working for a firm by the month of their first job application. In Panel (a), treated women are represented by the darker red bars on the left side of each cluster of two bars, and control women are represented by the lighter red bars on the right side of each cluster. In Panel (b), treated women are represented by the solid, dark red line and control women are represented by the dashed, light red line.

Figure A.19: Month of First Job Application Relative to Employment and Share with Marriage Offer



Notes: This figure presents the share women with at least one post-graduation marriage offer by each (set of) month(s) and the share of women working for a firm at the fourteen-month follow-up based on whether their first application was sent in that (set of) month(s). The sample consists of females in the control group of the experimental sample (see Section 5.1 for details) for the share working for a firm (lighter red, dashed line), and excluding those who are already married or engaged at baseline for the cumulative share with a marriage offer (darker red, solid line). The numbers along each point represent the estimated share of individuals who have received a post-graduation marriage offer, or who are working at fourteen-months, by the months indicated on the x-axis (either of the offer, or of the first application date).

B Appendix Tables

Table B.1: Attrition in the Diagnostic Sample: Baseline, Six-Month, and Nine-Month Follow-Ups

		6m Follow-Up				9m Follow-Up			
	Baseline	Non-Attritors	Attritors	Diff.	P-value	Non-Attritors	Attritors	Diff.	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nb. Obs.	1,494	1,029	465			886	608		
Panel A: Administrative Data									
Female	43.98	42.66	46.88	-4.22	0.13	42.44	46.22	-3.78	0.15
GPA	3.07	3.09	3.03	0.06	0.02	3.07	3.07	-0.00	0.79
Age	22.44	22.47	22.39	0.08	0.26	22.46	22.42	0.04	0.62
Majors:									
Engineering / Computer Science	25.10	26.24	22.58	3.66	0.29	24.38	26.15	-1.77	0.17
Humanities / Languages / Education	13.32	15.55	8.39	7.16	0.00	11.63	15.79	-4.16	0.03
Life Sciences / Pharmacy	14.59	12.15	20.00	-7.85	0.00	12.87	17.11	-4.24	0.05
Sciences	13.32	13.22	13.55	-0.33	0.86	16.03	9.38	6.65	0.00
Social Sciences (inc. Business and Law)	33.67	32.85	35.48	-2.64	0.25	35.10	31.58	3.52	0.20
Panel B: Survey Responses (Sample Characteristics)									
Married	4.48	4.28	4.95	-0.67	0.67	4.06	5.10	-1.04	0.42
Engaged	6.89	6.61	7.53	-0.92	0.59	6.32	7.73	-1.41	0.35
College-Educated Mother	40.76	41.01	40.22	0.80	0.77	38.94	43.42	-4.48	0.08
College-Educated Father	53.75	53.16	55.05	-1.90	0.52	52.03	56.25	-4.22	0.11
Panel C: Survey Responses (Key Variables)									
Own Employment Belief for 6m	74.20	74.77	72.95	1.81	0.21	74.71	73.47	1.25	0.38
Belief about Female Peers' Employment for 6m	50.88	50.81	51.04	-0.23	0.92	50.77	51.05	-0.28	0.88
Prefer to Work Full-Time	41.58	39.92	45.26	-5.34	0.08	39.71	44.32	-4.61	0.11
Prefer to Work Onsite	72.44	74.33	68.26	6.07	0.02	74.80	69.00	5.80	0.02
Log Reservation Wage	10.81	10.82	10.80	0.02	0.66	10.80	10.82	-0.01	0.35
Log Expected Wage	10.80	10.81	10.78	0.04	0.22	10.81	10.79	0.02	0.60

Notes: This table compares attritors and non-attritors in the diagnostic sample (see Section 3.1 for details). The first row reports the number of observations at baseline, the six-month follow-up, and the nine-month follow-up, separately by attrition status. Panel A shows administrative data such as GPA, age, and college major. Panel B shows survey responses about demographic background such as marital status and parental education. Panel C shows survey responses which may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. All unbounded continuous variables are winsorized at the 2% level. Column 1 reports the distribution of characteristics at baseline for the entire diagnostic sample. Columns 2 and 3 report the distribution for respondents who answered the six-month follow-up survey ("non-attritors") and those who did not ("attritors"). Column 4 reports the differences between the two groups, and Column 5 reports the p-values from testing the differences after controlling for gender. Columns 6 through 9 show the same analyses as Columns 2 through 5, respectively, for the nine-month follow-up survey.

Table B.2: Experimental Sample Treatment Balance: Baseline, Six-Month, and Fourteen-Month Follow-Ups

	Baseline				6m Follow-Up				14m Follow-Up			
	Control (1)	Treatment (2)	Diff. (3)	P-value (4)	Control (5)	Treatment (6)	Diff. (7)	P-value (8)	Control (9)	Treatment (10)	Diff. (11)	P-value (12)
Nb. Obs.	938	1,008			688	754			726	771		
Panel A: Administrative Data												
Female	65.14	66.27	-1.13	0.60	63.08	65.25	-2.17	0.39	63.22	64.98	-1.76	0.48
GPA	3.31	3.31	0.00	0.92	3.32	3.33	-0.01	0.84	3.33	3.32	0.01	0.67
Majors:												
Engineering / Computer Science	8.21	6.35	1.86	0.12	7.56	6.63	0.93	0.48	7.99	6.23	1.76	0.18
Humanities / Languages / Education	28.04	26.09	1.95	0.34	28.49	24.27	4.22	0.07	26.58	25.16	1.42	0.55
Life Sciences / Pharmacy	12.69	11.90	0.78	0.58	13.08	12.20	0.88	0.58	13.77	11.28	2.49	0.13
Sciences	25.16	27.38	-2.22	0.26	25.15	28.78	-3.63	0.11	26.03	28.02	-1.98	0.37
Social Sciences (inc. Business and Law)	25.91	28.27	-2.37	0.24	25.73	28.12	-2.39	0.31	25.62	29.31	-3.69	0.11
Panel B: Survey Responses (Sample Characteristics)												
Married	4.37	5.36	-0.99	0.32	3.92	4.77	-0.85	0.43	4.13	4.93	-0.80	0.47
Engaged	5.01	3.87	1.14	0.21	4.65	3.18	1.47	0.14	4.55	3.24	1.30	0.18
College-Educated Mother	28.46	28.57	-0.11	0.98	27.62	28.12	-0.50	0.93	27.13	28.79	-1.66	0.54
College-Educated Father	44.03	42.56	1.47	0.49	43.17	42.18	0.99	0.64	42.42	41.25	1.18	0.60
Panel C: Survey Responses (Key Variables)												
Own Employment Belief for 6m	79.99	79.54	0.46	0.65	80.47	80.14	0.33	0.82	80.03	79.66	0.37	0.78
Belief about Female Peers' Employment for 6m	51.23	50.70	0.52	0.54	51.15	50.08	1.07	0.28	51.29	50.21	1.09	0.27
Prefer to Work Full-Time	59.70	61.21	-1.51	0.42	59.74	61.14	-1.40	0.45	61.02	60.44	0.58	0.95
Prefer to Work Onsite	69.26	67.49	1.76	0.44	69.95	67.81	2.14	0.45	70.13	66.58	3.55	0.17
Reservation Wage	53.51	52.52	0.99	0.41	53.02	52.72	0.30	0.92	52.68	52.26	0.42	0.81
Expected Wage	62.06	60.54	1.52	0.25	62.47	60.85	1.63	0.33	61.67	60.90	0.78	0.67

Notes: This table compares treatment and control groups in the experimental sample (see Section 5.1 for details). The first row reports the number of observations at baseline, the six-month follow-up, and the fourteen-month follow-up, separately by treatment status. Panel A shows administrative data such as GPA, age, and college major. Panel B shows survey responses about demographic background such as marital status and parental education. Panel C shows survey responses which may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. All unbounded continuous variables are winsorized at the 2% level. Column 1 reports the distribution of characteristics at baseline for the control group. Column 2 reports the distribution of characteristics at baseline for the treatment group. Column 3 reports the difference between the two groups, and Column 4 reports the p-values from testing the differences after controlling for gender. Columns 5 through 8 and Columns 9 through 12 show the same analyses as Columns 1 through 4 for the six-month and nine-month follow-up surveys, respectively.

Table B.3: Attrition in the Experimental Sample: Baseline, Six-Month and Fourteen-Month Follow-Ups

		6m Follow-Up				14m Follow-Up			
	Baseline	Non-Attritors	Attritors	Diff.	P-value	Non-Attritors	Attritors	Diff.	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nb. Obs.	1,946	1,442	504			1,218	728		
Percentage Treated	51.75	52.29	50.20	2.09	0.40	52.22	50.96	1.26	0.56
Panel A: Administrative data									
Female	65.78	64.22	70.24	-6.02	0.01	62.97	70.47	-7.49	0.00
GPA	3.31	3.33	3.27	0.05	0.00	3.33	3.28	0.05	0.00
Age	22.73	22.74	22.70	0.04	0.99	22.71	22.76	-0.05	0.17
Majors:									
Engineering / Computer Science	7.30	7.07	7.94	-0.86	0.53	7.31	7.28	0.03	0.99
Humanities / Languages / Education	27.03	26.28	29.17	-2.88	0.21	25.62	29.40	-3.78	0.07
Life Sciences / Pharmacy	12.23	12.62	11.11	1.51	0.28	12.32	12.09	0.23	0.71
Sciences	26.26	27.05	24.01	3.04	0.20	27.91	23.49	4.43	0.04
Social Sciences (inc. Business and Law)	27.18	26.98	27.78	-0.80	0.72	26.85	27.75	-0.90	0.65
Panel B: Survey Responses (Sample Characteristics)									
Married	4.83	4.37	6.15	-1.78	0.14	4.19	5.91	-1.72	0.11
Engaged	4.42	3.88	5.95	-2.07	0.10	3.78	5.49	-1.72	0.12
College-Educated Mother	28.52	27.88	30.36	-2.48	0.47	27.34	30.49	-3.15	0.30
College-Educated Father	43.22	42.65	44.84	-2.19	0.50	41.13	46.70	-5.57	0.03
Panel C: Survey Responses (Key Variables)									
Own Employment Belief for 6m	79.77	80.30	78.26	2.04	0.09	80.34	78.82	1.52	0.20
Belief about Female Peers' Employment for 6m	50.96	50.59	52.03	-1.44	0.22	50.61	51.55	-0.95	0.42
Prefer to Work Full-Time	60.43	60.47	60.32	0.15	0.64	61.49	58.65	2.84	0.60
Prefer to Work Onsite	68.29	68.76	66.94	1.82	0.62	68.40	68.10	0.30	0.84
Log Reservation Wage	10.79	10.79	10.79	-0.00	0.56	10.79	10.79	-0.01	0.28
Log Expected Wage	10.94	10.94	10.92	0.03	0.41	10.95	10.92	0.03	0.48

Notes: This table compares attritors and non-attritors in the experimental sample (see Section 5.1 for details). The first row reports the number of observations at baseline, the six-month follow-up, and the nine-month follow-up, separately by attrition status. Panel A shows administrative data such as GPA, age, and college major. Panel B shows survey responses about demographic background such as marital status and parental education. Panel C shows survey responses which may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. All unbounded continuous variables are winsorized at the 2% level. Column 1 reports the distribution of characteristics at baseline for the entire experimental sample. Columns 2 and 3 report the distribution for respondents who answered the six-month follow-up survey ("non-attritors") and those who did not ("attritors"). Column 4 reports the differences between the two groups, and Column 5 reports the p-values from testing the differences after controlling for gender. Columns 6 through 9 show the same analyses as Columns 2 through 5, respectively, for the fourteen-month follow-up survey.

Table B.4: Treatment Effects on Employment (without Lasso Controls)

	6 Months		14 Months	
	Working	**Working for Firm**	**Working**	**Working for Firm**
	(1)	(2)	(3)	(4)
Panel A: Female				
Treatment	0.066**	0.098***	0.061*	0.087**
	(0.032)	(0.030)	(0.036)	(0.036)
Female Control Mean	0.336	0.253	0.518	0.416
Panel B: Male				
Treatment	0.006	0.015	-0.011	0.004
	(0.044)	(0.043)	(0.043)	(0.047)
Male Control Mean	0.551	0.378	0.719	0.561
Nb. Obs.	1,442	1,442	1,218	1,218

Notes: This table presents the treatment effects on labor market outcomes for students in the six and fourteen-months experimental sample (see Section 5.1 for details). Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment effect on employment at 6 months. Column 2 reports the treatment effect on firm employment at six months. Columns 3 and 4 report the same outcomes as Column 1 and 2, respectively, but at fourteen months. Coefficients in the panels are estimated together in a single regression (pooling men and women) and are estimated without controlling for the LASSO-selected variables (such that the only independent variables are gender, treatment and their interaction). Table 2 shows the results with the LASSO-selected controls. Control means are provided separately for each gender. Control means are provided separately for each gender. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Treatment Effects of the Experiment on Treated vs. Non-Treated

	6 Months		14 Months	
	Working	**Working for Firm**	**Working**	**Working for Firm**
	(1)	(2)	(3)	(4)
Panel A: Female				
Treatment on Treated	0.136***	0.173***	0.116***	0.152***
	(0.037)	(0.036)	(0.039)	(0.040)
Treatment on Non-Treated	0.002	0.019	0.005	-0.001
	(0.038)	(0.036)	(0.046)	(0.045)
Female Control Mean	0.336	0.253	0.518	0.416
Panel B: Male				
Treatment on Treated	0.079	0.103**	0.041	0.081
	(0.051)	(0.052)	(0.045)	(0.052)
Treatment on Non-Treated	-0.073	-0.073	-0.085	-0.104*
	(0.053)	(0.050)	(0.053)	(0.057)
Male Control Mean	0.551	0.378	0.719	0.561
Nb. Obs.	1,442	1,442	1,218	1,218

Notes: This table presents the treatment effects on labor market outcomes, separately by whether the student was offered treatment and took it up (treated) or was offered treatment but did not take it up (non-treated). The sample consists of students in the experimental sample (see Section 5.1 for details). Panel A shows results for women, separately for treated and non-treated, and Panel B shows results for men, separately for treated and non-treated. Column 1 reports the treatment effect on employment at 6 months. Column 2 reports the treatment effect on (paid) firm employment at six months. Columns 3 and 4, respectively, report the same outcomes as Column 1 and 2, but at fourteen months. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations. Table B.4 shows the same table with overall treatment effects rather than treatment effects by take-up status. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Treatment Effects on Applications at the Extensive Margin

	6 Months		14 Months	
	Has Applied	**Has Offer**	**Has Applied**	**Has Offer**
	(1)	(2)	(3)	(4)
Panel A: Female				
Treatment	0.105***	0.064**	0.090***	0.034
	(0.026)	(0.031)	(0.021)	(0.030)
Female Control Mean	0.748	0.615	0.854	0.739
Panel B: Male				
Treatment	0.037	0.009	0.023	-0.012
	(0.033)	(0.041)	(0.025)	(0.038)
Male Control Mean	0.806	0.640	0.917	0.794
Nb. Obs.	1,433	1,433	1,207	1,207

Notes: This table presents the treatment effects on applications at the extensive margin for students in the experimental sample (see Section 5.1 for details). The sample at fourteen months is restricted to students who also answered the six-month follow-up survey. Panel A shows results for women, and Panel B shows results for men. Columns 1 and 2 report the treatment effect on a respondent's likelihood of applying for at least one job and receiving at least one job offer by the six-month follow-up, respectively. Columns 3 and 4 show the same outcomes as Columns 1 and 2, respectively, but at the fourteen-month follow-up. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations. There are fewer observations in this table relative to Table 2 because the analysis is limited to cases with non-missing values for number of applications and offers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Distribution Across Top Three Occupations by Gender and Treatment

	Treatment (1)	**Control** (2)	**Diff** (3)	**P-value** (4)
Panel A: Women				
Teachers	23.80	24.11	-0.31	0.92
Software and I.T.	12.23	12.89	-0.66	0.77
Marketing and Sales	9.17	9.31	-0.14	0.94
Panel B: Men				
Software and I.T.	14.67	15.76	-1.09	0.77
Teachers	14.67	15.22	-0.54	0.88
Marketing and Sales	9.24	10.33	-1.09	0.73

Notes: This table presents the three most common occupations at the fourteen-month follow-up, separately by gender and treatment status. The sample consists of students in the experimental sample (see Section 5.1 for details) who are employed by the six-month follow-up survey. Panel A shows the top three occupations for women. Panel B shows the top three occupations for men. Column 1 reports the share of respondents in the treatment group in each occupation. Column 2 reports the share of respondents in the control group in each occupation. Column 3 reports the differences between the two groups, and Column 4 reports the p-values from testing the differences.

Table B.8: Treatment Effects of the Experiment on Marriage Outcome

	6 Months			14 Months	
	Married or Engaged	**Number of Marriage Offers**	**Highly-Educated Groom**	**Married or Engaged**	**Number of Marriage Offers**
	(1)	(2)	(3)	(4)	(5)
Panel A: Female					
Treatment	0.012	0.054	0.009	0.024	-0.059
	(0.021)	(0.161)	(0.033)	(0.029)	(0.307)
Female Control Mean	0.098	1.545	0.293	0.175	3.266
Panel B: Male					
Treatment	0.032	0.100		0.010	0.642**
	(0.023)	(0.163)		(0.032)	(0.286)
Male Control Mean	0.049	0.860		0.116	1.495
Nb. Obs.	1,270	1,196	741	1,111	971

Notes: This table presents the estimated effects of the treatment on marriage outcomes. The sample consists of students in the experimental sample (see Section 5.1 for details), excluding those who are already married or engaged at baseline. Panel A shows results for women. Panel B shows results for men. Column 1 reports the treatment effects on being married or engaged by the six-month follow-up. Column 2 reports the treatment effects on number of marriage offers received by the six-month follow-up. Column 3 reports the treatment effects for women only on the "quality of marriage offers", measured by an indicator for whether the highest education level among all received offers is a Master's degree or higher. Columns 4 and 5 show the same outcomes as Columns 1 and 2, respectively, but at the fourteen-month follow-up. There is no equivalent version of Column 3 because the question was not asked at the fourteen-month follow-up. Number of marriage offers is winsorized at the 2% level. Coefficients in the panels are estimated together in a single regression (pooling men and women) and all regressions control for the variables selected following the post-double-selection LASSO procedure. Control means are provided separately for each gender. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Means and Standard Deviations for Diagnostic Predictors of Employment

	Female		Male	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
GPA	3.23	0.46	2.98	0.45
Log Reservation Wage	10.70	0.42	10.90	0.46
Log Expected Wage	10.71	0.40	10.89	0.46
Own Employment Beliefs for 6m	0.72	0.22	0.77	0.24
Preferred Hours	6.42	1.46	6.43	1.54
Prefers On-site	0.74	0.44	0.75	0.43
Applied Early	0.70	0.46	0.69	0.46
Nb. Applications	7.55	10.96	9.94	14.78
Internship	0.38	0.49	0.52	0.50

Notes: This table presents the means and standard deviations for the diagnostic predictors of employment shown in Figure 4 and Figure A.13. The sample consists of students in the diagnostic sample (see Section 3.1 for details). All unbounded continuous variables are winsorized at the 2% level.

C External Validity of Diagnostic Results

In this section we establish the external validity of our diagnostic findings from the private university by replicating them at Pakistan's oldest and largest public university. This new setting attracts students from more diverse socioeconomic and geographic background than the private university, making it an attractive setting for testing external validity. We establish external validity by showing that our diagnostic insights from Figures 1-3 and A.6 hold when produced using the control group in our experimental sample.[30] We also present additional data suggesting that women not only expect to work post-graduation, but want to.

Figure C.1 Panel (a) compares baseline employment expectations with realized outcomes by gender in the control group of the experimental sample, replicating the analysis from Figure 1 Panel (a). Consistent with the patterns observed in the diagnostic sample, men and women in the control group of the experimental sample exhibit high and similar expectations for future employment at baseline: 80.4% of women and 82.7% of men expect to be employed within six months of graduation. The modest gender gap in expectations (2.3 ppt) is comparable to the gap in the diagnostic sample (5.2 ppt), where employment expectations were similarly high (71.8% for women, 77.0% for men). Additionally, the realized outcomes for women diverge sharply from their initial expectations in both samples. In the experimental sample, only 33.6% of women in the control group are employed six months after graduation—46.8 ppt below their expectations, and 21.6 ppt lower than men's realized employment rate. This overestimation of future employment among women mirrors the diagnostic sample, where 36.9% of women are employed six months post-graduation, 34.9 ppt below their average baseline expectations and 27.3 ppt lower than men's realized employment rate.

Figure C.1 Panel (b) shows that the relationship between baseline employment beliefs and realized outcomes in the experimental sample mirrors the analysis in Figure 1 Panel (b): both genders have inaccurate beliefs across the full distribution, and markedly different intercepts. Slopes are higher in the experimental sample than the diagnostic sample, but remain far from 1 (0.48 for women and 0.65 for men in the experimental sample, versus 0.31 for women and 0.35 for men in the diagnostic sample). Slopes are also less precisely

30. The treatment group is excluded as our treatment directly impacts some of the outcomes of interest, such as realized employment.

estimated, due to a smaller sample size, which results from restricting our analysis to the control group.

Figure C.3 compares the baseline first and second order employment beliefs of men and women in the experimental sample, replicating insights from Figure 2. In the diagnostic sample, we saw that even though men and women have inaccurate beliefs about their own future employment, they predict their peers' future labor supply more accurately. Specifically, both men and women correctly predict that their male peers' chances of employment are relatively high, estimated at 63.5% by men, and 68.5% by women in the diagnostic sample. Similar responses were provided by the control group of the experimental sample, where men estimated other men's employment prospects at 68.1%, while women estimated them at 73.0%. Similarly, both genders correctly assess that women have relatively lower chances of working six months later, estimated in the control experimental sample at 51.0% by men and 51.2% by women. This is remarkably close the second order beliefs reported in the diagnostic sample (50.2% by men and 51.6% by women).

Figure C.4 follows Figure 3 in analyzing whether common demand- and supply-side barriers to female employment explain the gender employment gap observed six months after graduation. In the diagnostic sample, the raw gender gap in employment was 28.9 ppt. In the control group of the experimental sample, the employment gap is smaller but still substantially large at 21.6 ppt. As in Figure 3, gradually adding controls for education (GPA and major), job search industry, reservation wage, preferences for work hours and remote work, and baseline beliefs about employment prospects reduces the employment gap in the control group of the experimental sample only modestly, by 2.9 ppt. Adding controls for job search effort and work history further narrows the gap by just 0.9 ppt. Finally, accounting for demand-side factors (number of interviews, job offers, and offered wages) reduces the gap by another 1.5 ppt. Taken together, these controls only reduce the raw gap by 5.3 ppt. This is similar to the diagnostic sample, where the gap shrinks from 28.9 ppt to 20.1 ppt (8.8 ppt), such that the key takeaway remains: even after controlling for student characteristics, job preferences, and demand-side factors (especially the number of job offers), the gender employment gap persists.

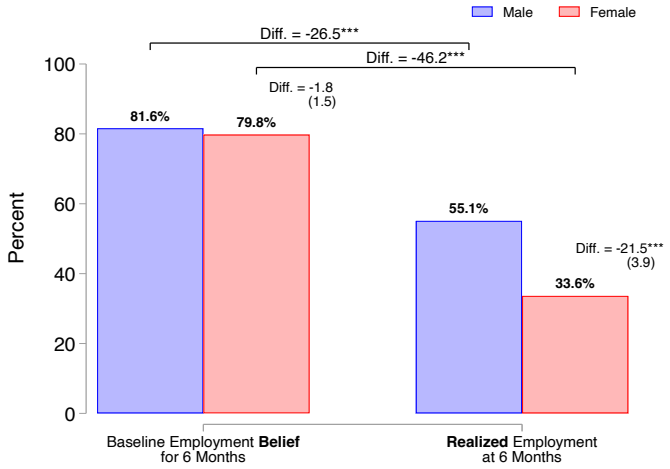
Beyond replication of the patterns already documented at the private university, we collect additional data at the public university in support of the fact that women at the time they

graduate from college *want* to work. First, we explicitly ask women if they want to work on a paid basis within six months of graduation and, separately, two years after graduation.[31] Of the women surveyed, 97.6% and 98.4% reported that they want to be working both six months and two years after graduation, respectively. This suggests that women want to start working soon after graduation and they also want to continue working for a while after graduation. We also ask women who reported less than a 100% likelihood of working within six months, why they think they may not work. The first panel of Figure C.2 titled "Self" reports the distribution of their responses. The most prevalent barrier, cited by 37% of women, was poor macroeconomic conditions that may limit job availability. Importantly, only 11% told us that they may not work because they may not *want* to work six months from now. Even when considering respondents' beliefs about other women (second panel in Figure C.2 titled "Other Women"), only 15% of women reported that other women may not work post-graduation because they may not want to work. Finally, we find that there is no meaningful difference in women's stated likelihood of working in six months by their levels of familial wealth, suggesting that financial necessity may not be the primary driver of women's intention to work. At baseline, we measure ownership of five assets and amenities: car, motorbike, internet connection, laptop and smartphone. As shown in Table 3, most families own all of these assets, but there is more variation in car ownership across households. Accordingly, Figure C.5 shows baseline beliefs about work separately by whether a woman's family owns a car. There are no systematic differences in women's responses by family car ownership (78.5% and 78.3%). There are also no significant differences in realized employment outcomes six months later by car ownership. This suggests that financial constraints are not the primary reason driving women's willingness to work and that other motives (e.g., independence, desire for a career; bargaining power etc...) prevail.

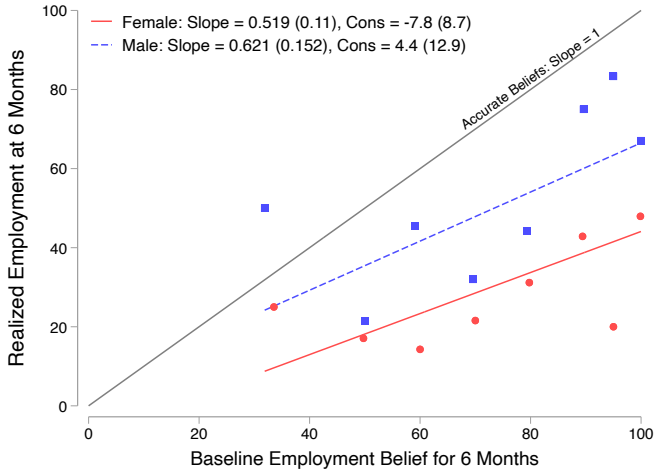
31. The exact questions were: "Do you want to be working (e.g., for a firm or in your own/family business) in the next **six months** after you graduate?" and "Do you want to be working (e.g., for a firm or in your own/family business) on a paid basis **2 years** from now?"

External Validity Figures

Figure C.1: Baseline Employment Belief vs. Realized Employment: Experiment Control Sample



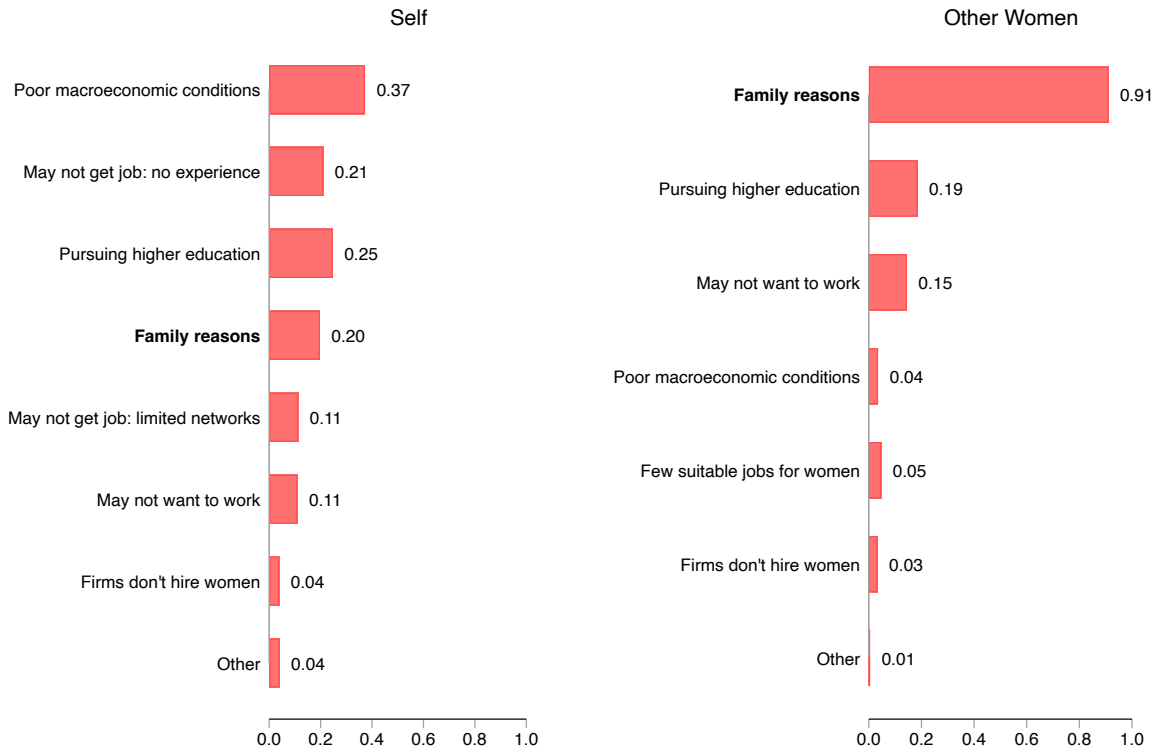
(a) Mean Levels: Intended vs. Realized Employment



(b) Binned Scatter: Intended vs. Realized Employment

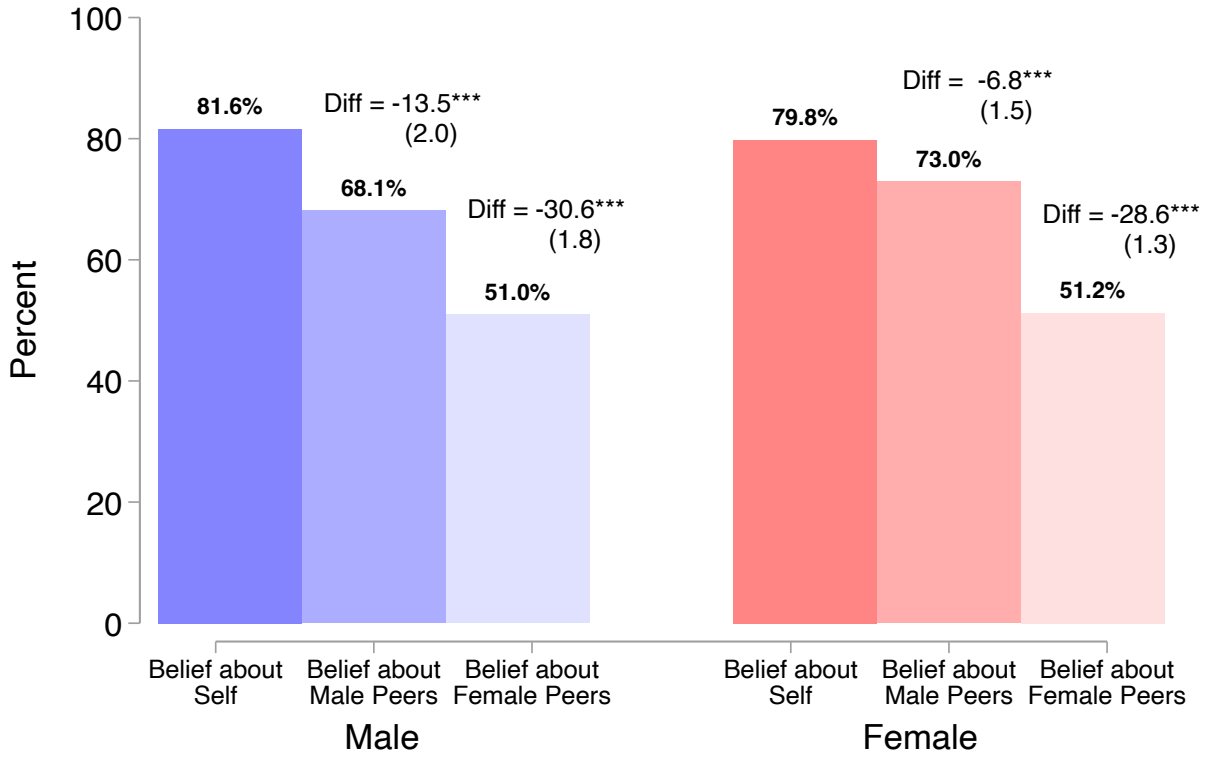
Notes: This figure replicates Figure 1 with the control group of the experimental sample (see Section 5.1 for details). Panel (a) shows the average self-assessed likelihood of employment six months after graduation (left cluster of two bars) and realized employment at six months (right cluster of two bars), separately by gender. Men are represented in blue (bars 1 and 3) and women are represented in red (bars 2 and 4). Panel (b) shows a binned scatter plot of baseline employment beliefs against realized employment, separately by gender. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.2: Potential Reasons for Remaining Unemployed: Self vs. Peers



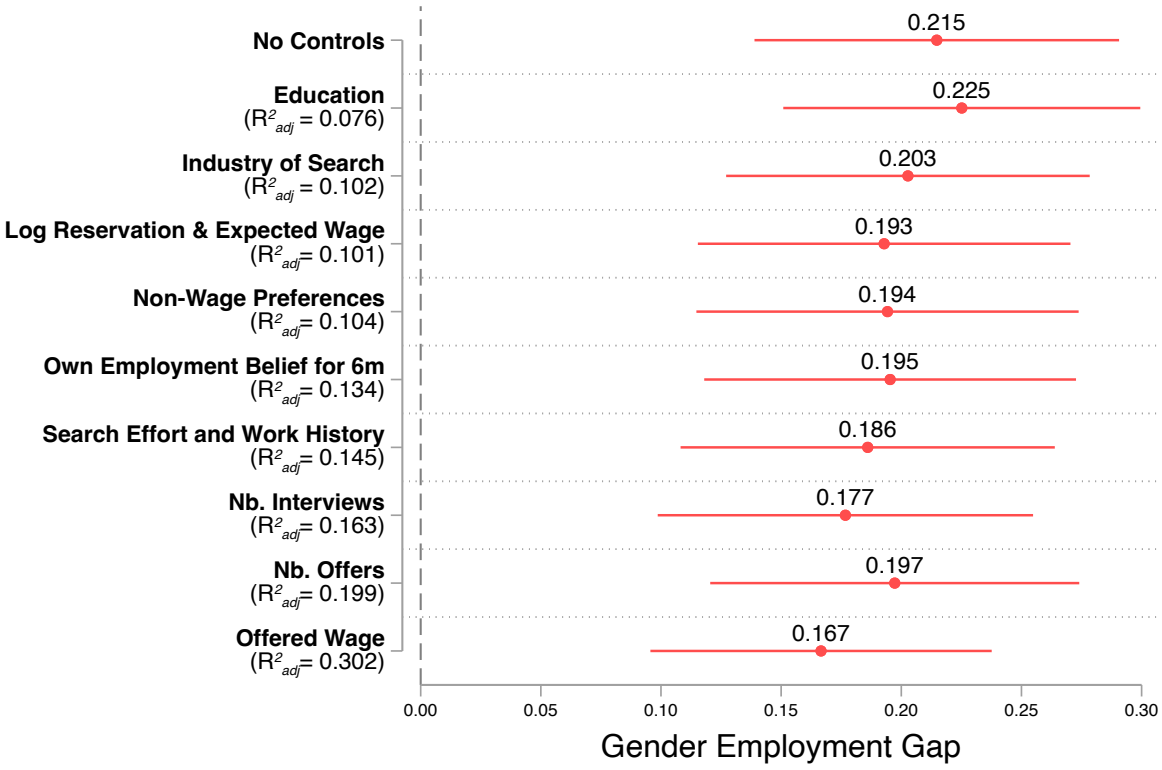
Notes: This figure presents women's beliefs at baseline about why they and other women in their class may not work in the future. The sample consists of all female students in the control group at the public university (see Section 5.1 for details). The left panel ("Self") reports responses to the question: "Why do you think there is a chance you may not work?" This question was asked to all women who reported less than a 100% likelihood of being employed six months after graduation (75.6% of respondents). The right panel ("Other women") presents responses to the question: "Out of the remaining XX women, why do you think they are not working?" This question was asked to all women who previously reported expecting a non-zero share of their female peers to be unemployed (97.0% of respondents). Respondents provided open-ended answers, which enumerators then categorized into pre-defined bins or coded under "Other" if none applied. Enumerators could select multiple responses on behalf of respondents. An answer was coded as "Family reasons" if it corresponded to the responses: "I may not get permission from family to work" or "I am getting married, have a baby, or focus on my family."

Figure C.3: Employment Beliefs about Self vs. Peers: Experiment Control Sample



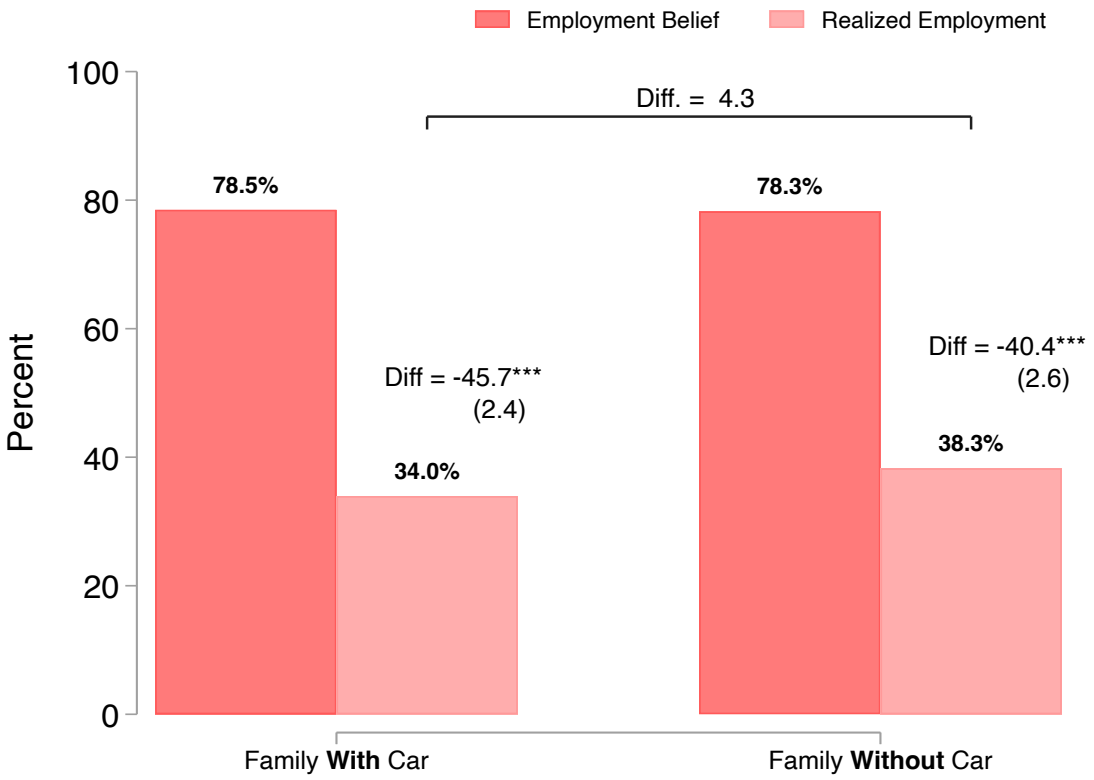
Notes: This figure replicates Figure 2 with data from the control group of the experimental sample (see Section 5.1 for details). Male beliefs are represented by the blue cluster of bars on the left. Female beliefs are represented by the red cluster of bars on the right. Bars 1 and 4 show average baseline beliefs about oneself. Bars 2 and 5 show average baseline beliefs about male peers. Bars 3 and 6 show average baseline beliefs about female peers. The average difference between beliefs about self and beliefs about male peers is shown directly above the second bar in each cluster. The average difference between beliefs about self and beliefs about female peers is shown directly above the third bar in each cluster. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.4: Explaining the Employment Gap at Six Months: Experiment Control Sample



Notes: This figure replicates Figure 3 using data from the control group of the experimental sample (see Section 5.1 for details). Each row reports the gap between male and female employment after controlling for the variable listed in that row and all rows above. The Education controls include cumulative GPA and major fixed effects. The Industry of Search controls incorporate fixed effects derived from the semantic classification of a respondent's preferred job title into Standard Occupational Classification (SOC) codes. The Reservation and Expected Wage controls include respondents' wage expectations at baseline. The Non-Wage Preferences controls include preferences regarding onsite vs. remote work and the number of preferred daily work hours. The Own Employment Belief for 6 Months control includes baseline belief about one's probability of employment. The Search Effort and Work History controls include the total number of job applications sent by the six-month follow-up, an indicator for applying early, and an indicator for internship experience. The Nb. Interviews control includes the number of interviews received by the six-month follow-up. The Nb. Offers control includes the number of job offers received by the six-month follow-up. The Offered Wage control includes current wage if the respondent is working, or the highest rejected wage offer if the respondent is not working. All unbounded continuous variables are winsorized at the 2% level. Adjusted R-squared values are shown for each row. The horizontal bars show 95% confidence intervals.

Figure C.5: Employment Beliefs and Realized Outcomes by Wealth



Notes: This figure presents heterogeneity by familial wealth in women's beliefs about employment in six months, and their realized employment in six months. The sample consists of all female students in the control group (see Section 5.1 for details). Women whose families own a car are represented by the left cluster of two bars, and women whose families do not are represented by the right cluster of two bars. The darker red bars (bars 1 and 3) represent employment beliefs, and the lighter red bars (bars 2 and 4) represent realized employment. The average difference between employment beliefs and realized employment for each group of women is shown directly above the realized employment bar in each cluster. The average difference in realized employment for women whose families do and do not own a car is shown above the brackets at the top of the figure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.