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

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Abstract

In countries with low female employment, college-educated women often transition directly from education to homemaking. Does this reflect informed, forward-looking choices or unanticipated constraints? We study this question in Pakistan, where two-thirds of college-educated women remain out of the labor force. Tracking 2,400 college-graduating students, we document that men and women start their search with similar work aspirations, apply at similar rates, and receive comparable numbers of job offers. Yet a 27 pp employment gap emerges within six months post-graduation. This gap stems largely from timing: for women alone, there is a critical window, immediately post-graduation, during which job search is associated with much higher chances of employment. To test whether this relationship is causal, we randomize a modest incentive to apply early. By shifting search into the early window, the intervention raises women's employment by ~ 20% but leaves men's employment unaffected, closing a third of the gender gap. Our evidence suggests that applying early enables women to start working before demands from the marriage market arise. Treatment effects are driven by women who underestimate how quickly these demands materialize, revealing an "illusion of time." This illusion can be persistent since women in our sample recognize the barriers to employment faced by their female peers, but overestimate their own ability to overcome them.

JEL codes: J16, J21, J64, I25, O15

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I Introduction

Gender is a powerful and persistent determinant of how labor is divided between the household and the market. Its influence becomes especially evident at pivotal life stages, when many women exit, or never enter paid work. In some countries, this shift occurs at the birth of the first child; in others, it happens at marriage. In settings with the lowest female labor force participation, women often skip the labor market altogether, transitioning directly from school to homemaking (Kleven, Landais, and Leite-Mariante 2024).

If women do not anticipate these junctures, they may under-invest in navigating them (Kuziemko et al. 2018; Costa-Ramón et al. 2024). As a result, expectations can play a central role in shaping women's ability to remain in the labor force. A gap between expectations and reality also presents a strategic opportunity for policy intervention: either to correct misperceptions or to mitigate the resulting labor market distortions.

In this paper, we study a pivotal juncture: college graduation. Our setting is Pakistan, a country where the gender gap in education has narrowed significantly, yet female labor force participation remains among the lowest in the world.[1] We partner with two universities – a large, mid-tier private institution and the country's oldest and largest public university – and track students from one month before graduation through to the following year. The panel structure of our data allows us to capture a critical window during which labor market expectations are formed and early career decisions are made.

Our research design unfolds in two phases: diagnostic and experimental. In the diagnostic phase, we compare labor market expectations to realized outcomes and identify when and how women exit the pipeline from education to employment. Based on these insights, we design an intervention to enable women to stay on the employment path. The experiment also allows us to test whether women hold accurate beliefs about the factors driving their non-employment.

In the diagnostic phase, we track the full job search of ~1,000 students graduating from the private university. The gender gap in employment emerges quickly and mirrors national trends: six months after graduation, 36.9% of women are working, compared to 64.2% of men. This gap appears largely unanticipated by women: one month before graduation, women report on average a 71.8% likelihood of working within six months of graduation, only 5.2 pp lower than men. Hence, women's low employment is not the deliberate result of forward-looking decisions made before

1. As the world's fifth 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 Figure A.2 for cross-country evidence on female labor force participation, as well as Jayachandran (2021) and Dinkelman and Ngai (2022) for comprehensive reviews).

graduation. Instead, it reflects a mismatch between expectations and reality. Moreover, women's overestimation of their own employment chances is not rooted in misperceptions about the broader labor market. On the contrary, women's beliefs about the employment prospects of their male and female peers are broadly consistent with realized outcomes. Thus, women in our sample recognize that female labor force participation is low in general, but they think this trend does not apply to them.

Beyond beliefs, men and women display remarkably similar job search behavior in the months following graduation. Women are just as likely as their male peers to apply for jobs and receive interview offers. Likewise, job preferences at graduation are largely gender-neutral: a large majority of both men and women in our sample express a preference for full-time, on-site jobs. If anything, the observed differences favor women: they have higher GPAs, report lower reservation wages, and receive more job offers. Taken together, these results suggest that leading explanations for later-life gender gaps in employment – such as preferences for part-time work, flexible hours, or remote work – are not applicable in our sample of college graduates. This suggests that, rather than being innate, such differential preferences likely emerge over time as women adapt to household constraints or social norms.

Since women and men follow nearly identical paths all the way up to the job offer stage, the gender employment gap must arise from differences in job offer acceptance – specifically, from women rejecting all job offers at higher rates than men. This occurs despite parity in personal traits and job search behavior, implying that the employment *returns* to these traits and behaviors differ across genders. Across all observable characteristics, we find only one return that differs meaningfully between women and men: the return to applying early. Specifically, women who begin applying within two months of graduation are 23.1 percentage points (pp) more likely to secure a job within six months (a 133.8% increase) compared to those who delay their search, conditional on other observable characteristics. In contrast, among men, application timing is not correlated with employment.

The link between application timing and employment may reflect unobserved differences among women, rather than a causal effect of timing itself. Even if the relationship is causal, its implications depend on whether women anticipate it. If women are aware that applying early increases their chances of employment, then observed differences in application timing likely reflect intentional trade-offs made to maximize expected utility. If not, women may be operating under an "illusion of time" – delaying job search under the false assumption that timing does not matter, and unintentionally reducing their employment prospects.

To distinguish between these possibilities, we design an experiment that encourages early job search by offering a small cash reward to students who apply to at least four jobs within one month of graduation. The incentive induces a substantial shift in application timing: 57.1% of treated women apply by August 15th, compared to 31.6% in the control group. A similar shift is observed among men. If the incentive also increases employment, this would imply that the link between timing and employment is both causal and unanticipated. In contrast, if students already internalize the benefits of early application, they may apply to some jobs earlier solely to claim the incentive, while the optimal timing of job search, and therefore employment outcomes, remain unchanged.

We find that our intervention has a large and persistent effect on women's employment. Intent-to-treat estimates indicate that, at the six-month follow-up, 41.1% of women assigned to treatment are working, compared to 33.6% in the control group (a 22.3% increase, difference p-value = 0.015). Given that unemployment often disguises as self-employment in low-income countries (Breza, Kaur, and Shamdasani 2021), we also consider the impact of our treatment on firm employment alone and find even stronger results: 35.5% of treated women are working in a firm at six months, compared to 25.3% of control women (a 40.3% increase, difference p-value = 0.001). These effects persist in the fourteen-months follow-up. In contrast, and consistent with our diagnostic findings, we observe no treatment effects on male employment. Consequently, the incentive reduces the gender employment gap by about a third in both follow-ups.

Women's strong employment response to the incentive shows that application timing has a causal and unanticipated effect on their employment. We also collect direct evidence on women's lack of foresight about this effect. At baseline, after introducing the incentive, we ask students when they expect to apply and how likely they are to be employed six months after graduation. While treated women adjust their expected application date earlier, there is no treatment effect on women's expected employment. This disconnect confirms that women fail to anticipate the importance of timing for employment, and thus operate under the "illusion of time".

What, then, drives this "illusion"? Since timing matters uniquely for women, we seek a plausibly gender-specific explanation. Although men and women express similar work preferences and search similarly, their outside options differ: women marry earlier, and marriage may constrain women's labor supply in ways that do not affect men. We provide evidence that this asymmetry helps explain why early applications increase employment for women only.

We show that marriage offers to women surge shortly after graduation, just as job acceptance rates begin to fall. Applying in September instead of June is associated with a 30.4 pp decline in employment, just as the likelihood of receiving a marriage offer rises by 29.8 pp over the same period. Although correlational, this synchronicity suggests the existence of a narrow window – immediately after graduation but before marriage activities intensify – during which entering the labor market is most feasible for women. Notably, we find no evidence that taking a job during this window undermines women's marriage prospects. Though marriage often occurs several years later, we track early signals (timing, number, and quality of marriage offers) and find no treatment effects. This suggests that early labor market entry does not come at a detectable cost in the marriage market.

For marriage market activities to explain the illusion of time, their timing must be unanticipated. Consistent with this, we find that women who initially expect to marry "late" (after the median age, 25) revise their expectations downward within six months of their graduation. For instance, women who expected at baseline to marry at age 26 revise that estimate down to 25 by the six-month follow-up. In contrast, those already expecting early marriage have stable expectations. Correspondingly, the treatment has a much larger impact on employment for women who expect to marry late (17.4 pp vs. 5.6 pp, difference p-value = 0.031). In other words, the treatment effect is concentrated among women who are surprised by how soon marriage will arrive, suggesting that the unexpected timing of the marriage market underlies the illusion of time.

As marriage market activities intensify, women become less likely to accept job offers. One possibility is that their own preferences shift: women may lose interest in working as their focus turns to marriage. Alternatively, women's interest in employment may remain stable, but new external constraints emerge that limit their ability to work. Our data supports the second explanation. Six months after graduation, 87.6% of all women (including 83.4% of unemployed women) report wanting to work. Additionally, reservation wages fall over time (down 14.5 log points at six months and 7.1 at fourteen), which suggests increasing willingness to accept lower-paying jobs . If preferences remain stable, but offer acceptance declines, the constraint must lie elsewhere. We provide evidence consistent with the influence of one particular constraint: women's families. First, existing literature has shown that timing shapes families' perception of marriage market outcomes. For example, Adams and Andrew (2024) find that families in South Asia believe a daughter's marriage-market prospects deteriorate rapidly once she is out of school. Second, treatment effects are concentrated among women who have to involve their parents in their employment decision. At baseline, 60% of women (versus 39% of men) report needing parental approval to work. Among these women, the treatment raises firm employment by 16.3 pp, compared to 6.8 pp for those who do not need parental approval (difference p-value = 0.079). Last, for family involvement to explain our treatment effects, it should come as a surprise to women. In support of this, we find that, at baseline, only 20% of women believe that they may struggle to work after graduation because of family constraints. In contrast, 91% think that *other* women will face these family-related obstacles.

Why might parental support for women's work erode over time? One possibility is that, while we find no marriage penalty for early employment, there may be a penalty for entering the labor force later, beyond the window our intervention targets. Alternatively, there may be no penalty at all, but parents experience confirmation bias: if a non-working daughter receives strong marriage offers, this reinforces the belief that avoiding work pays off. Meanwhile, when a working daughter also receives good marriage offers, it validates the belief that employment is not detrimental to marriage prospects. Though we cannot distinguish between these explanations, the policy implication is the same. Early job search allows women to secure employment before external constraints—whether social, familial, or perceived—arise, opening a window of opportunity that policy can target.

Taken together, our findings show that, at the first critical juncture for labor market entry – college graduation – women hold the same labor market aspirations and preferences as men. Women are also aware of prevailing gender norms and barriers to female employment, but they do not anticipate how quickly and directly these forces will limit their own labor supply. As a result, when the constraints emerge, they do so unexpectedly, creating a wedge between expectations and outcomes. By incentivizing women to begin their job search in the brief but critical window before constraints take hold, our intervention helps narrow the wedge and bring women's labor market outcomes closer to their aspirations.

This paper contributes to a growing literature on behavioral job search, which highlights the role of biased beliefs about labor market prospects in shaping employment and wages. Recent survey and experimental evidence reveals an optimistic bias among job seekers regarding their job-finding rate (Spinnewijn 2015; Mueller, Spinnewijn, and Topa 2021; Bandiera et al. 2023; Banerjee and Sequeira 2023; Abebe et al. 2024; Kelley, Ksoll, and Magruder 2024). Our closest links are to Kuziemko et al. (2018) and Costa-Ramón et al. (2024), who show that in the U.S. and Switzerland, respectively, women underestimate the long-term career costs of motherhood, leading to overoptimistic expectations about their future labor supply prior to childbirth.[2] We extend this insight to a markedly different institutional context and an earlier life stage. In our setting of urban college graduates in Pakistan, women systematically overestimate their near-term labor force participation at college graduation. Our paper also builds on Cortés et al. (2023), which highlights the gendered role of timing in employment among U.S. college graduates. They find that women accept jobs earlier than men because they are more risk-averse and less over-optimistic. We complement their findings by documenting the critical role of application timing in a lower-income country, where college-educated 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).

2. Similarly, Boneva et al. 2024 collect a wide range of women's beliefs about maternal labor supply and show that information provision can shape women's employment intentions.

To correct workers' misperceptions, recent research has honed in on information experiments (Altmann et al. 2018; Belot, Kircher, and Muller 2019; Aloud et al. 2020; Jäger et al. 2024; Roussille 2024). Closest to our setting, Alfonsi, Namubiru, and Spaziani (2024) find that debiasing overly optimistic job seekers in Uganda increases their labor force participation by 27% three months after the intervention. However, our context is different in that 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 well-informed about aggregate labor force statistics, predicting the employment rate of their female peers six months post-graduation much more accurately than their own. This suggests that the misperception is not so much about labor market conditions per se as about how these conditions apply to oneself. Therefore, rather than attempting to provide market-level statistics, we design an intervention that directly addresses the distortions in job search behavior due to this self-belief bias.

We also contribute to an extensive literature on barriers to female labor force participation and interventions to reduce them. Our evidence builds on prior works highlighting the powerful role gender norms play in shaping labor market outcomes (Fernández, Fogli, and Olivetti 2004; Bertrand, Goldin, and Katz 2010; Bursztyn, Fujiwara, and Pallais 2017; Bursztyn, González, and Yanagizawa-Drott 2020; Jayachandran 2021; Kleven 2022; Bursztyn et al. 2023; Agte and Bernhardt 2024; Boelmann, Raute, and Schönberg 2025). In particular, we identify a key mechanism that helps sustain the influence of these norms: the belief among women that norms constrain others but not themselves. This misperception makes women less prepared for and more vulnerable to the very constraints they underestimate, contributing to the persistence of gender gaps in employment. Our findings also suggest that gender differences in preferences for job attributes, such as part-time or remote work, are not intrinsic: most women in our sample want full-time, onsite jobs at college graduation. Instead, women's preferences for flexibility later in life are likely shaped by household or family constraints. This is consistent with Beerli, Hofer, and Schaede (2025), who show that a decline in the availability of part-time jobs reduces labor supply among mothers but not among non-mothers. Finally, our findings offer a new perspective on the absence of a child penalty in many lower-income societies, such as India, Pakistan, and parts of Africa (Kleven, Landais, and Leite-Mariante 2024). The absence of a measurable child penalty does not imply the absence of gendered labor market constraints. Rather, these constraints may simply bind much earlier and in different ways. We show that gender norms begin to shape women's labor market trajectories from the moment they graduate from college, and they lead many women to exit or forgo employment altogether, long before family formation begins.

II Employment Beliefs vs. Outcomes

II.A Our Diagnostic Sample

College Graduates We study the labor supply decision of women (and men) at the time of their college graduation — a critical juncture where many women in Pakistan face a choice between entering employment or assuming domestic responsibilities. Figure A.3 illustrates this by plotting the labor force participation rates of men and women by age in 2018, for the U.S. in Panel (a) and for Pakistan in Panel (b). A standard pattern in high-income countries like the U.S. is that women's participation rates are similar to men's around labor market entry but falls during the childbearing years. In contrast, women's labor supply in Pakistan is essentially flat over the life cycle: rather than dropping out in childbearing ages, women in Pakistan rarely enter the labor market in the first place. This pattern persists even when restricting to college graduates (Panels (c) and (d) of Figure A.3).[3] Since most women in Pakistan do not enter the labor market at any point during their adulthood, understanding their labor supply decision right at the point of college graduation is essential.

Recruitment The timeline of our diagnostic survey is illustrated in blue in Figure A.4. In June 2022, one month before graduation, we invited all 2,872 graduating students (1,146 female and 1,726 male) at a private university to participate in our survey. Of these, 2,238 participate in our baseline survey, yielding a response rate of 77.9%.[4] Since we are interested in labor market beliefs and outcomes, we exclude from our sample students who reported that they had already registered for a graduate program. This leaves us with 1,493 students in our baseline sample.

Attrition Of the 1,493 students in our baseline sample, 1,029 respond to our six-month follow-up survey, and 910 to our nine-month follow-up. The six-month and nine-month response rates are therefore 68.9% and 61.0%. These response rates are considerably higher than those typically reported in the phone survey literature.[5] Table B.1 shows that the baseline, six-month, and

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

4. The response rate for our baseline survey is high compared to other surveys conducted in university settings. For instance, the response rate is 20% among Boston University Questrom graduates in Cortés et al. (2024), 31% among University of Chicago MBAs in Bertrand, Goldin, and Katz (2010), and 10–12% in the Global COVID-19 Student Survey across 28 universities in Jaeger et al. (2021). We believe this high response rate was driven by the incentive we offered for responding to the survey: a KFC meal. See Figure A.5 for a picture of our food stand.

5. We achieve this by calling students multiple times (at least three), systematically varying the day/hour of calls to maximize chances of response.

nine-month samples have similar observable characteristics (all measured at baseline).[6] Since our analysis systematically compares baseline beliefs with later realized outcomes, we define our diagnostic sample as the 1,029 students who responded to both the baseline and the six-month follow-up surveys.

Descriptive Statistics Table I presents the baseline characteristics of our diagnostic sample. The last column reports the p-value from a test of equal means between genders. Women make up 42.7% of the sample, with 439 female and 590 male respondents. Men and women are both about 22 years old on average. Women have significantly higher (6.7%) GPAs than men. 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 somewhat more popular among women (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 graduation, with a similar fraction engaged (7.5% of women and 5.9% of men). Finally, men and women come from similar parental education backgrounds: 41.0% of students have a college-educated mother, and 53.2% have a college-educated father, with no significant gender differences.

II.B Baseline Beliefs about Labor Market Outcomes

We begin studying the education-to-employment pipeline by examining the labor market aspirations of men and women right around their college graduation.

Beliefs about Self: Elicitation In the baseline survey, we elicit students' beliefs about their future labor force participation through two main questions. The first question measures their reservation wage for their preferred job title across four work schedules (Full-time Onsite, Part-time Onsite, Full-time Remote, Part-time Remote). Importantly, for each schedule, respondents have the option to indicate that they are not willing to work at any wage in this schedule.[7] The second question

6. Among many variables, a few have statistically significant but economically negligible differences across waves. For instance, the average GPA among non-attritors (respondents) in the six-month follow-up is 3.09, compared to 3.04 among attritors. We also note that there are no systematic patterns in attrition across waves: most differences that appear in the six-month survey do not appear in the nine-month survey, and vice versa. For readability, we exclude the two-month follow-up from the table, as we used this survey to define only one variable in our analysis. The two-month response rate is higher than that of later follow-ups, and attrition patterns are no different.

7. 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

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 the majority of women expect to work at the time of graduation. Virtually all women and men report a reservation wage for at least one work schedule, and 95.0% of women report a reservation wage for the full-time, onsite schedule. Notably, as shown in Figure A.6, the distribution of women's reservation and expected wages lies to the left of men's, even after controlling for GPA, major, and preferred occupation. This shows that women are willing to work for lower wages than men. Turning to the probabilistic question, the first two bars in Figure I Panel (a) show that women report a 71.8% likelihood of working within six months of graduation, only 5.2 pp lower than men. One potential concern is that these stated intentions may reflect non-committal cheap talk or are influenced by perceived demand effects. Two pieces of evidence alleviate this concern. First, women's post-graduation actions align with the intentions they stated at baseline: Figure A.7 Panel (b) shows that 80.4% of women apply for at least one job within six months of graduation, a rate similar to men's (78.5%).[8] Second, we find no systematic differences in women's reported employment expectations — or in their responses to questions about traditional gender norms — by the gender of the enumerator. This suggests demand effects, such as tailoring their answers to appear more traditional before a male enumerator, are unlikely to be driving the results. Taken together, these results underscore that women's expectations about their own employment prospects are nearly as high as men's at graduation.

Beliefs about Peers: Elicitation We ask students their beliefs about the future employment likelihood 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 will be employed within six months after graduating?"

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.

8. 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.

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. As shown in Figure II, men estimate that 63.5% of their male peers will be employed six months after graduation, versus 50.2% of their female peers. Similarly, women estimate a 68.4% employment rate for their male peers, compared to 51.5% 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 estimate for men (68.4%). In other words, women see themselves as much more likely to work than their female peers, and on par with men.

II.C 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 I Panel (a) reveal a large gender employment gap: 64.2% of men, compared to only 36.9% of women, were employed six months after graduation. This figure for women closely aligns with the national labor force participation rate for young college-educated women in Pakistan, which is 33.9% in 2018 (Figure A.1 Panel (b)). Comparing realized outcomes to baseline beliefs represented in the first two bars of Figure I Panel (a), we find that men overestimate their likelihood of working by 12.8 pp (16.6%) on average, while women overestimate it by 34.9 pp (48.6%).[9]

Figure I Panel (b) plots the relationship between baseline employment beliefs and realized employment six months post-graduation. The 45-degree line represents the benchmark of accurate beliefs.[10] The figure shows that, relative to this benchmark, both men and women have inaccurate beliefs about their future employment. For both genders, the slope of the relationship between 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 markedly different across genders: 37.2 pp for men and only 14.7 pp for women. Taken together, the slopes and intercepts imply that women overestimate their chances of working across most of the distribution of baseline beliefs, and they do so to a

9. Illing, Schmieder, and Trenkle (2024) also find that men and women who are similar at baseline can experience different outcomes. Using German administrative data, the study compares men and women who are displaced from similar jobs through an event study design with propensity score matching. It finds that, after a mass layoff, women's earnings losses are about 35% higher than men's.

10. Deviations from this benchmark can take two forms. Points above the 45-degree reflect underestimation of employment chances, while points below the 45-degree line reflect overestimation.

significantly greater extent than men. For example, among those who report an 80.0% chance of working at baseline, only 32.6% of women end up working six months post-graduation, vs. 61.7% of men. Overall, our results indicate that the gender gap in realized employment is largely unanticipated by women.

We conduct a shorter survey nine months post-graduation to track students' employment outcomes. As shown in Figure A.8, female employment rises substantially (from 29.4% to 36.9%, a 7.5 pp gain) between the two- and six-month follow-up surveys. However, the pace of increase slows considerably thereafter, reaching just 40.1% at nine months (a 3.2 pp gain) and still well below women's baseline expectation of 71.8%. In contrast, the male employment rate rises more sharply both between the two- and six-month surveys (from 44.5% to 64.2%) and between the six-month and nine-month surveys (from 64.2% to 75.1%). By the nine-month mark, male realized employment reaches a level close to their baseline expectation of 77.0%.

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

Taking Stock Our results indicate that women substantially overestimate their own likelihood of working in the months following college graduation. However, these incorrect expectations are not due to misperceptions about overall female labor force participation, as women's second–order beliefs about the employment prospects of their female (and male) peers are broadly consistent with realized outcomes. In other words, women in our sample are aware that female employment rates are low, but they do not expect these statistics to apply to themselves.

III Diagnosing the Gender Employment Gap

Section II shows that, although men and women express similar labor market aspirations at graduation, significant gender disparities emerge in labor market outcomes six months later. We now explore several possible explanations for this gap.

While a vast literature has identified structural, preference-based, and institutional barriers as key drivers of gender gaps in employment, most of these constraints tend to bind *after* women enter the labor market — particularly following marriage and childbirth. They include gender differences in preferences for job flexibility (Mas and Pallais 2017; Maestas et al. 2023; Wiswall and Zafar 2018), job search behavior (Cortés et al. 2023; Fluchtmann et al. 2024), household and childcare responsibilities (Halim, Perova, and Reynolds 2023), as well as discrimination in hiring and pay (Goldin and Rouse 2000; Brown 2022; Bertrand 2011; Kuhn and Shen 2013; Goldin 2014; Kline, Rose, and Walters 2022; Gentile et al. 2023; Buchmann, Meyer, and Sullivan 2024). Together, these factors help explain women's higher exit rates, slower wage growth, and greater selection into part-time or informal employment later in life.

In this section, we examine whether these key determinants also shape gender gaps in employment at the point of labor market entry. Following the logic of a Oaxaca decomposition, we first assess gender differences in relevant, observable endowments (e.g., GPA, major, or search effort) and analyze whether these differences explain the gender gaps. We then test whether men and women receive different returns to their endowments (e.g., whether labor market returns to a high GPA differ by gender), and whether these potential differences in returns further explain the observed gaps. Before proceeding further, we make an important note: analyses in this section are diagnostic and correlational. We do not make causal claims.

III.A Gender Differences in Traditional Factors

Differences in Preferences for Job Amenities A leading explanation for low female labor force participation is that women are primarily responsible for household management (Veerle 2011). This implies a higher opportunity cost of market work and may lead to higher reservation wages or a stronger preference for flexible or part-time employment. As a result, women may apply for fewer jobs or self-select out of more demanding or inflexible roles, even when they have similar qualifications to men. However, such patterns may not yet be operative at the time of labor market entry, since most women at this time are single and childless (only 6.8% of our female respondents are married at baseline). Consistent with this, Figure A.6 shows that women report lower reservation wages (Panel (a)) and expected wage offers (Panel (b)) than men, both unconditionally and conditional on covariates. Turning to non-wage amenities, prior work shows women may place greater value on amenities like flexible hours or remote work (Ho, Jalota, and Karandikar 2023; Field and Vyborny 2022). However, this is not true for our sample of college graduates. As shown in Figure A.9, there are no gender differences in preferred work hours (averaging 6.4 hours per day for both men and women) or preferences for remote work (about three-fourths of both genders prefer on-site jobs). This likely reflects the fact that household and childcare responsibilities, which often constrain women's work schedule, do not yet apply to our sample of single, childless women.

Differences in Human Capital We examine gender differences in GPA to assess whether disparities in human capital contribute to employment gaps. Figure A.7 Panel (a) illustrates that women have higher GPAs than men, a pattern that persists even after controlling for academic major. As documented in Table I, the distribution of majors differs substantially across men and women. However, we later show in Figure III that neither gender differences in major choices nor internship experience drive the gender employment gap.

Differences in Job Search Another well-documented explanation for gender gaps in employment is differences in job search. For instance, if women apply to fewer jobs or apply later than men, they may be less likely to secure a job. Figure A.7 Panel (b) presents the cumulative distribution of the number of job applications by gender. It shows that, at the extensive margin, women are as likely as men to apply to at least one job. Additionally, the median number of applications is the same for men and women (4 applications). While, women apply to 2.8 fewer jobs than men on average, this difference disappears once we adjust for other observables ("residualized gender gap") such as GPA, major. Regarding application timing, we define "applying early" as sending at least one job application within two months of graduation (before our second survey wave). As shown in Row 7 of Table B.2, women are as likely as men to apply early. Overall, the job search behavior in our sample of college-educated men and women exhibits greater similarity than one would expect based on prior research, which highlights the importance of context and sample composition in shaping observed gender differences.

Differences in Firm Demand To investigate whether demand-side factors drive 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.10 shows the cumulative distributions of the number of job interviews (Panel (a)) and job offers (Panel (b)) by gender. Strikingly, a similar share of men and women receive at least one interview and one job offer. Moreover, there is no significant gender differences in the number of interviews attended or the number of job offers received. When we further adjust for baseline observable characteristics (e.g., GPA, major, preferred occupation, as well as wage and non-wage preferences), women receive 0.6 more job offers than men. However, consistent with Brown (2022), we do find a gender gap in salary offers. As shown in Figure A.10 Panel (c), women receive lower wage offers from firms than men, even after controlling for cumulative GPA, major, and preferred occupation.[11] These lower

11. We define the offered wage as the highest wage offer received by a student for a job (regardless of whether they have accepted it).

wage offers mirror women's lower expected wages, such that women are no more likely than men to receive an offer below their expected wage. In sum, while firm demand factors may play a key role in constraining women's labor market outcomes later in life, they do not appear to be a major driver of the gender employment gap in our sample of college-graduating women.

III.B The Limited Role of Traditional Factors in Explaining the Gender Employment Gap

Differences in Levels To formally examine how student characteristics affect the gender employment gap, we regress a six-month employment indicator on a female dummy while progressively adding controls for the observable characteristics described above. Results are presented in Figure III. The initial gender employment gap — at 27.3 pp — decreases by no more than 2.8 pp as we sequentially add controls for GPA and major (Row 2), preferred occupation (Row 3), reservation and expected wages (Row 4), preferences for work hours and remote work (Row 5), and baseline employment beliefs (Row 6). In the final model of supply-side factors (Row 7), we add search effort and past internship experience, which shrinks the gap only moderately to 22.8 pp. These results show that supply-side factors play a limited role in explaining the gender employment gap. We next turn to demand side factors. Adding controls for number of interviews (Row 8), number of job offers (Row 9), and offered wage (Row 10) leaves the gender gap again largely unchanged.[12] Overall, including all these supply- and demand-side variables only explains 10.6% of the raw gender employment gap, leaving a large unexplained gender gap at 24.4 pp. In other words, even after holding constant job preferences, search behavior, and even the number of job offers, women remain significantly less likely to be employed than men. This suggests that the gender gap emerges at an even later stage: job acceptance. We confirm this conjecture in Figure A.11, which shows that, among students who receive a job offer, women are 27.7 pp less likely than men to be employed six months after graduation. Even after controlling for the supply-side factors detailed above, the number of interviews and offers, and the offered wage, women remain 18.8 pp less likely than men to have accepted a job.

Differences in Returns While controlling for student characteristics does little to shrink gender gaps in a pooled regression, it is possible that individual characteristics may differentially predict men or women's future employment. To test for this, we regress employment outcomes at six months post-graduation, separately for men and women, on the same supply-side variables used

12. While these variables do not substantially reduces the gender employment gap, they do increase the adjusted R^2, confirming their relevance to predicting students' labor market outcomes.

as controls in Figure III. Figure IV presents the multivariable results, where each row includes all other variables as controls. Figure A.12 shows the bivariate version, where each row regresses employment on the variable of interest without control.[13] None of the traditional supply-side factors — including GPA, wage and non-wage preferences, baseline employment beliefs, or number of job applications — exhibit statistically different predictive power by gender. For example, keeping other supply-side factors constant, a one-standard-deviation increase in baseline belief about employment probability is associated with a 7.5 pp increase in men's likelihood of working six months later, compared to a 4.2 pp increase for women, a statistically insignificant difference (p-value = 0.297).

III.C The Role of Job Search Timing in Explaining the Gender Employment Gap

In a context where many women never enter the labor force, the decision to work immediately after graduation is pivotal for shaping long-term labor market outcomes. Thus far, we have shown that factors commonly invoked in the literature as key drivers of gender employment gaps — such as different preferences, constraints from household responsibilities, and employer discrimination — have limited explanatory power at the point of labor market entry.

Prompted by this, we delve deeper into our survey data to explore explanations that extend beyond traditional accounts. In doing so, we uncover a critical, but previously overlooked, predictor of women's decision to work: the timing of job search. To quantify timing, we define "applying early" as sending at least one job application before our second survey wave, that is within two months of graduation. We find that men and women are equally likely to apply early, with about two-thirds of both groups doing so. As a result, controlling for early application in Figure III (Row 7) has little effect on the gender employment gap. However, Figure IV reveals that this variable is the only variable that differentially predicts employment between men and women. For women, applying early is associated with, all else equal, a 23.1 pp (133.8%) increase in employment probability six months later, while it has no statistically significant effect on men's employment (difference p-value = 0.023). It is worth highlighting that the coefficient on applying early for women is not only statistically significant but economically meaningful: women who apply early are more than twice as likely to be employed six month post-graduation than those who do not.

This finding suggests that job search timing, rather than traditional demand- or supply-side factors, may play a critical role in determining women's decision to enter the labor market. One potential obstacle to this interpretation is if the observed link between application timing and employment reflects selection on unobservables among women (e.g. more motivated women

13. Means and standard deviations for the independent variables shown in the figure are provided in Table B.2.

apply first), rather than a causal effect of timing itself. Even if the relationship is causal, its interpretation hinges on women's beliefs. If women accurately perceive how timing influences employment outcomes, then differences in application timing likely reflect deliberate trade-offs to maximize expected utility. However, if these beliefs are incorrect, women may fall prey to an "illusion of time" — where they delay job search under the false assumption that job application timing does not matter, unintentionally lowering their employment chances. To distinguish between these possibilities, we implement an experiment that shifts application timing through a financial incentive for early job search.

IV Experimental Evidence on the Timing of Job Search

IV.A Experimental Design

Design We test our hypothesis about the critical role of job search timing through a field experiment. We randomly assign students to treatment and control groups and incentivize early applications among treated students through a modest monetary reward. The reward is conditional on applying to jobs early, rather than working. This ensures that any observed treatment effect on employment cannot be mechanically driven by students who apply solely to claim the financial incentive. A potential concern with this design is that the financial incentive may simply heighten the salience of the relationship between early applications and employment, signaling to treated students that applying, and therefore working, early is socially desirable. However, as explained in Section IV.C (paragraph "The Illusion of Time"), we are able to rule out this interpretation based on our data and results.

The Test Our null hypothesis is that being induced to apply early through the treatment has no impact on subsequent employment. There are two scenarios under which the null holds. First, there is no causal link between application timing and employment. This would imply that the correlation we documented earlier simply reflects unobserved individual heterogeneity that independently affects both timing and employment. Second, there *is* a causal link between timing and employment, but it is fully internalized by students. In this case, students may apply to a few jobs earlier to claim the incentive, but the experiment would not alter the optimal timing of their job search and therefore employment. Therefore, if we reject the null, not only must timing have an effect on employment, but the students driving treatment effects must also hold inaccurate beliefs about that relationship such that, absent treatment, they would apply too late. To directly test for the presence of such misperceptions, we also collect students' beliefs about the causal link between application timing and employment.

Parameters of Interest and Identification Assumptions The experiment allows us to estimate two parameters of interest: the causal effect of the experimental incentive on employment, β_{ITT}, and the causal effect of early applications on employment for compliers, β_{LATE}.[14] The identification of β_{ITT} rests on two assumptions: (i) treatment assignment is orthogonal to individual characteristics correlated with employment, and (ii) the stable unit treatment value assumption (SUTVA). A successful randomization ensures assumption (i), and Table B.3 (Columns 1–4) confirms that the treatment and control groups are balanced on all key baseline characteristics. Violations of SUTVA are unlikely because students from both the treatment and control groups apply to jobs along with graduates from all over the country, making our study sample atomistic in the broader national labor market. In addition, the treatment does not convey any information, explicit or implicit, that suggests early application improves employment outcomes. We later directly confirm that participants in the treatment group did not interpret the incentive as a signal about the benefits of early applications (see Section IV.C paragraph "The Illusion of Time"). As a result, information spillovers to the control group can also be ruled out.

To identify β_{LATE}, we require the additional assumption that treatment affects employment only through its effect on the timing of applications. This "exclusion restriction" is necessary for the treatment to serve as a valid instrument for early applications. This assumption is plausible for two reason. First, the financial reward was deliberately kept small enough to avoid inducing meaningful income effects on labor supply. Second, we also randomly vary the size of the incentive among treated students but find no differential effects. This helps to further rule out income effects, which would be expected to scale with the size of the reward.

Implementation We field the experiment at a public university in Lahore in June 2023. The full timeline of our experimental survey is illustrated in yellow in Figure A.4. The experimental sample consists of 1,947 students scheduled to graduate in mid-July 2023. We randomly assign 50% of the sample to a treatment group and offer them a monetary reward conditional on applying to at least four relevant jobs by August 15th, one month after graduation.[15] A job is considered relevant if it matches the student's skill set. To claim their reward, students must submit a brief online form

14. We note that our experiment does not identify the average causal effect of application timing on employment. To do so, we would need to randomly assign students into different application timings, effectively making some apply later than they would have in the absence of the experiment. Such a design would be both unethical, as it jeopardizes some students' chance of ever finding a job, and irrelevant for informing real-world policies.

15. We chose to require at least four applications, as four was the median number of applications among appliers by the two-month follow-up in the diagnostic sample.

with proof of their applications to the research team through a brief online questionnaire, including screenshots showing the application date and job title.[16]

The incentive amount is PKR 5,000 (~ 18 USD or 89 USD after adjusting for Purchasing Power Parity), equivalent to two days of pay at the median monthly salary in our diagnostic sample at the six-month follow-up. To insure against the possibility of low take-up, we offer a much higher reward of PKR 20,000 to 10% of the sample.[17] In practice, take-up was high across both treatment arms, and effects on applications and employment are similar. Therefore, we pool the two treatment groups in the analysis that follows.

To ensure that students do not perceive treatment assignment as a signal of their labor market prospects, we tell them explicitly that assignment is random. 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." Next, a spinning wheel appears on the tablet with its outcome jointly observed by the student and the enumerator (see Figure A.13 for a visual). If the student is not selected into treatment, they are told: "The lottery has decided that you will skip directly to the last module of the survey."

We conduct three follow-up surveys. The first follow-up occurs in early September 2023, shortly after the deadline to receive the treatment incentive, in order to ensure that we had a "first-stage" effect of the treatment on early job search. The second follow-up occurs in early January 2024 to measure treatment effects on our main outcome of interest: employment. We re-survey students a final time in September 2024, fourteen months after graduation, to measure the persistence of the employment effects.

Alternative Design Before presenting results from our experimental design, we note that we also considered an alternative intervention: an information campaign highlighting the low employment rates of college-educated women and their correlation with application timing. This idea was motivated by a growing body of work that uses information experiments to correct misperceptions about labor market outcomes (Aloud et al. 2020; Jäger et al. 2024; Roussille 2024). For such an intervention to be effective, however, applicants have to hold inaccurate beliefs about aggregate employment rates. This does not hold in our context. As shown in Section II.B, while women overestimate their own employment prospects, they hold much lower, and more accurate, expectations about other women in their cohort. As a result, providing aggregate statistics may fail to induce

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

17. The Purchasing Power Parity conversion uses estimates from the World Bank: https://data.worldbank.org/indicator/PA.NUS.PPP?year=2023

behavioral changes if female respondents do not view these statistics as relevant to themselves. Spillover risks were much higher too. For these reasons, we decided against a purely informational campaign.

IV.B Our Experimental Sample

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 academic major and gender, over-sampling women (65%) as they are the primary focus of the experiment. For major, we stratify the sample 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 from the sample, and a cap of 200 female and 100 male students per major, imposed to ensure broad representation across fields. This cap is binding for a few majors, in which case sub-groups of students are randomly and incrementally invited to participate until the target is reached. Within this sampling frame, each male and female student has a 50% chance of being assigned to treatment. We receive 2,468 responses at baseline. Since our focus is on labor market beliefs and outcomes, we exclude 223 students (9.0%) enrolled in graduate school and another 299 students (12.1%) who have secured a job.[18] After these adjustments, we obtain a final baseline sample of 1,947 students.

Balance and Attrition We test for balance across treatment arms on a wide range of baseline characteristics.[19] Table B.3, Columns 1–4 show that treatment and control groups are balanced at baseline on all key variables, confirming the success of our randomization procedure. Specifically, no significant differences are observed in gender composition, GPA, major distribution, marital or family backgrounds, and key employment-related beliefs. Columns 5–8 and 9–12 of Table B.3 show that this balance is maintained in the six-month and fourteen-month follow-ups.

Table B.4 further investigates whether attrition is systematically correlated with treatment status or baseline characteristics. We then define the six-month sample as respondents who respond to both the baseline and the six month survey; and for the fourteen-month sample, we further restrict

18. The share of students that secured a job before graduation (12.1%) is much lower than in some high-income countries. For instance, in the U.S., 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 in the month preceding graduation can meaningfully shift students' application timeline, as most students have yet to start their job search.

19. For readability, we exclude the two-month follow-up from the attrition and balance tables, as this wave is not used beyond showing descriptives about the shift in application behavior right after the application deadline. The two-month follow-up has a higher response rate than later ones, and balance test results are consistent with those from the six- and fourteen-month surveys.

to respondents who also answer the fourteen-month survey. Attrition is 25.9% and 37.4% in the six- and fourteen-month samples, with sample sizes of 1,442 and 1,218 students, respectively. As shown in Table B.4, Row 2, Columns 2–9, there is no differential attrition by treatment status in either the six- or fourteen-month follow-ups. Nor is attrition systematically driven by baseline characteristics like major, family background, or key employment-related beliefs. One exception is that women are slightly overrepresented among attritors. However, Table B.3 confirms that the share of women remains balanced between treatment and control in both waves, suggesting this pattern is unrelated to treatment status. GPA is the only other variable that consistently differs between attritors and non-attritors in both waves. On average, students who remain in the panel have GPAs about 0.05 points higher than those who attrit. However, this difference is economically negligible (~1.5%) and unlikely to meaningfully affect our results.

Descriptive Statistics Table II presents descriptive statistics for the six-month experimental sample, which includes students who respond to both the baseline and six-month follow-up surveys. The final column reports p-values from a test of equal means between genders. Women make up 64.2% of the sample, with 926 female and 516 male respondents. The average age is 23 for men and 22 for women. As in the diagnostic sample, women's GPAs are slightly higher (~ 5%) than men's on average, and this difference is statistically significant. However, 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 major. Men and women also have comparable backgrounds, as measured by parental education, parental employment, and indicators of family wealth. Marriage and engagement rates are low: only around 4% of both men and women are married at graduation, with a similar share engaged (4.3% of women and 3.1% of men).

External Validity of Diagnostic Findings Appendix C shows that the main diagnostic findings in Section III, derived from private university students, replicate using the control group of the experimental sample. This confirms that our diagnostic insights are relevant to a broader population of college graduates.

Treatment Take-up Take-up, defined as the share of respondents in the treatment group that claim and receive the financial award, is 53.5% for women and 48.5% for men. Figure A.14 examines whether take-up is correlated with students' baseline characteristics. We find that, for both genders, students who take up treatment are more likely to major in engineering or computer science and less likely to major in the humanities. Second, women who are already engaged or married are less likely to take up the treatment. Third, for both genders, compliance is positively correlated with baseline beliefs about one's own employment as well as the employment of same-gender peers. Finally, take-up is not correlated with gender norms, as measured by questions from the World Value Survey, for either gender. We further test for the "relevance" assumption, namely that the financial incentive leads some women to start applying earlier. To do so, we ask respondents, at both the six- and fourteen-month follow-ups, about the date of their first job application. As shown in Table III, Column 1, 57.1% of women in the treatment group have sent at least one job application by August 15th (the deadline for the monetary reward), compared to 31.6% in the control group. Similarly, 54.7% of men in the treatment group have sent at least one early application, compared to 37.0% in the control group.

IV.C Results

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

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

where Y_{it} denotes the outcome of interest for individual i at time t. The coefficient α_1 captures gender differences in outcomes within the control group, quantifying how outcomes for male students differ from those of female students. The coefficient α_2 is the primary parameter of interest; it measures the intent-to-treat effect of the intervention on women assigned to treatment ($T_i = 1$). The coefficient α_3 represents the additional effect of the treatment on men. For interpretational ease, in our results tables we show the treatment effect on men as $\alpha_1 + \alpha_3$ instead of α_3. Additionally, we include X_i, a vector of individual baseline covariates selected via the post-double selection Lasso procedure to improve statistical power.[20] We estimate Equation (1) separately at two time t: six months and fourteen months post-graduation. All standard errors are robust to heteroskedasticity.

Intent-to-Treat: Results Table III shows results from estimating Equation 1. Panel A reports treatment effects for women, while Panel B does so for men. In Panel A, Column 2, we find that treated women are 7.5 pp (22.3%, p-value = 0.015) more likely to be employed six months post-graduation than control women. As shown in Column 4, this employment effect persists in

20. We adapt the post-double-selection approach set forth by Belloni, Chernozhukov, and Hansen (2014) and McKenzie (2012). We show that our results are robust to estimating the model without these controls.

the fourteen-month follow-up, where treatment increases the likelihood of working for women by 6.9 pp (p-value = 0.046).

We further examine effects on the likelihood of working for a positive wage at a firm — as opposed to being self-employed, working in a household enterprise, working for no pay, or being unemployed.[21] This "firm work" outcome is important for two reasons. First, firm work is preferred by the overwhelming majority of women (90.7%) in our baseline sample, over self-employment or working in a family business.[22] Second, in low-income countries, self-employment or informal work is associated with lower labor force attachment and earnings potential. For instance, Breza, Kaur, and Shamdasani (2021) show that much of self-employment in India is in fact "disguised" or "hidden" unemployment due to "labor rationing" when demand is limited.[23] Given these considerations, our intervention is explicitly designed to encourage job applications to private firms rather than business creation or self-employment, making firm employment a natural outcome of interest. In Panel A, Column 3, we find that our treatment increases women's probability of working for a firm six months after graduation by 10.2 pp (40.3%, p-value = 0.001). Column 5 shows this effect persists fourteen months after graduation, at 10.0 pp (p-value = 0.004), relative to a control mean of 41.3%.

The persistence of treatment effects more than a year after the incentive is awarded indicates that the intervention does more than simply accelerating job entry among women who would have entered later anyway. Instead, it leads to a sustained increase in overall employment levels. Moreover, employment is not an absorbing state: women can decide to revert to non-employment at any time. Thus, by revealed preference, the persistence of effects also indicates that women who start working early due to treatment choose to remain employed, signifying long-term labor force attachment.

Turning to Panel B, we detect no treatment effect on men, whether in overall or firm employment. These results are consistent with our correlational findings in Section III.C, which show a positive association between early applications and employment for women, but not for men.[24] Given the

21. See Appendix Section D for details on how the firm work indicator is constructed from the survey questions.

22. Women are asked at baseline: "What type of work would you prefer to do after you graduate?". Options include: Work for a private firm (or government); Work in my family-owned business; Be self-employed; and Be an intern at a firm.

23. Based on extensive data and literature review, *The World Development Report* on Gender (World Bank 2012) finds that women in low-income countries are predominantly employed in low-productivity, low-wage jobs, often home-based and driven more by "necessity" than by "opportunity". It concludes that the over-representation of women in these "jobs" is a primary driver of gender gaps in earnings and productivity. Similarly, Ashraf, Delfino, and Glaeser (2022) document that female entrepreneurs typically earn less and are concentrated in low-return industries. Together, these facts underscore the socioeconomic significance of shifting women into formal employment, especially for reducing gender disparities driven by composition of work.

24. Appendix Table B.5 shows results from estimating Equation (1) without Lasso-selected controls. The treatment

null effect on men, the positive treatment effect on women translates into a ∼35% decrease in the gender employment gap both six and fourteen months after graduation.

A Pivotal Few Months Figure V highlights that the months immediately following graduation play a pivotal role in shaping women's employment outcomes — and that our intervention shifts many women's job search into this critical period. Using self-reported dates of first job applications, we analyze employment outcomes as a function of the month of first application. Panel (a) reveals a sharp decline in employment rates among control group women as the time of first application drifts farther from graduation. For instance, 70.4% of control women who applied in June 2023 are working for a firm by September 2024. This falls to 52.3% for women applying in July 2023, and further to 41.7% for those applying in August 2023.

While these patterns may be partly driven by selection (e.g., more employable women may apply earlier), they suggest that even modest shifts in application timing could significantly improve employment prospects. Panel (b) confirms this using numbers from the treatment group. Our treatment triples the share of women applying before August 2023, from 9.2% in control to 24.4% in treatment. If earlier applications were driven purely by selection, then we would expect "compliers", i.e., early applicants in the treatment group, to have a lower employment rate than their control counterparts. Instead, Panel (a) shows that, conditional on applying early (by July 2023), firm employment rates are similar between treated and control groups. Taken together, these findings — the large shift in application timing, the steep gradient in employment outcomes by application month, and the absence of selection-driven differences — suggest that our intervention improved women's employment by shifting their job search into the critical few months right after graduation.

Dynamics of Female Labor Supply: Early Gains, Lasting Effects While we have shown that early applications raise women's aggregate employment at the six- and fourteen-months follow-ups, it remains to be explored when these effects arise and how they evolve. Figure VI plots treatment effects on firm employment on a monthly basis. Panel (a) shows the effect on having ever worked at a firm by a given date for women, and Panel (b) does so for men.[25] As expected from a successful randomization, there are no differences between the control and treatment groups by May 2023,

effects for women are similar in magnitude as in Table III and statistically significant. At six months, effects on employment and firm employment are significant at the 5% and 1% levels, respectively; at fourteen months, they are statistically significant at the 10% and 5% levels. We again find no effect for men.

25. This variable differs from "working for a firm" at a given date, as it captures whether someone has "ever worked for a firm" by a given date. We cannot capture the first object as it would require collecting the start and end dates of all jobs held by each respondent, which is cognitively challenging and prone to survey fatigue. In contrast, the "ever worked" indicator requires only the start date of the respondent's first job.

just before our intervention date. For women, treatment effects emerge about a month after the intervention, reach marginal significance by the mid-August incentive deadline, climb to about 10 pp by November (five months post-graduation), and plateau at just below 15 pp after March 2024. These effects remain stable through the fourteen-month follow-ups. In contrast, the intervention has no effect on men's employment at any point in time.

Because women's employment gains largely stabilize by six months post-graduation and persist over time, we cautiously interpret our fourteen-month horizon as sufficient to capture the "medium-run" effects of the intervention on women's labor supply — before life events such as marriage or childbirth may reshape work trajectories.[26] Two other pieces of evidence from the six-month survey support the notion that women in our sample intend to keep working in the near future. First, working women report they expect to continue in their *current* job for an average of 3.6 years, with no sizable difference between treatment and control groups. Second, we directly ask working women about their long-term labor supply intentions: "Do you intend to work (for a firm or in your own business) after getting married?". 85.0% of working women answer "Yes". While such self-reports may be biased, they suggest that women who enter the labor market view employment as a lasting commitment, not a temporary detour.

Even if labor supply decisions ultimately change after marriage, early labor market experience remains valuable in its own right. Prior research shows that it can shape women's long-run participation. For instance, Jensen (2012) shows that entering the workforce early increases young Indian women's aspirations for post-marriage careers. Working early also eases re-entry after childbearing, as past co-worker networks play an important role in the job search of mothers (Henke, Schmieder, and Berge 2021).

Selection into Take-up To test the extent of selection into treatment take-up, Table B.6 reports the effects separately for students who were offered the treatment and took it up and those who were offered but did not take it up, each relative to the control group. Panel A reports results for women. We find large and significant effects among those who took up the treatment: their employment rate is 13.6 pp higher (p-value = 0.000) than control six months post-graduation, and 11.6 pp higher (p-value = 0.003) at fourteen months. In contrast, women who were offered but did not take up the treatment have the same employment rates as control, suggesting minimal selection into treatment take-up among women. Panel B tells a different story for men. While effects are also positive (4.1-7.9 pp) among men who took up treatment, they are accompanied by *negative* effects

26. For context, college-educated women in Pakistan marriage at age 25 on average, three to four years after college graduation.

of similar magnitude among non-treated men. This pattern suggests selection into take-up among men: those who chose to engage with the intervention may be more motivated or qualified for employment than those who did not. As a result, the overall intent-to-treat effect for men is close to zero.

Local Average Treatment Effects: Specification 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 in the control group applied early, even without the financial incentive. Therefore, we use a standard instrumental-variable (IV) approach to estimate a local average treatment effect, using lottery assignment (interacted with gender) as an instrument for applying early. Formally, we estimate the following model with two-stage least squares (2SLS):

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

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

where T_i denotes treatment assignment, and $Early_i$ denotes whether the student applied early — defined as submitting their first application before August 15th.[27] In the first stage, the coefficients β_2 and $\beta_2 + \beta_3$ capture the effect of the financial incentive (treatment) on the likelihood of applying early for women and men, respectively. The second stage estimates the causal effect of applying early, as instrumented by treatment assignment (interacted with gender), on labor market outcomes such as employment.

Local Average Treatment Effects: Results In Table IV, we compare descriptive ordinary least squares (OLS) and experimental 2SLS estimates to gauge the relative importance of selection into early applications versus the causal effect of early applications. For women (Panel A), the OLS estimate in Column 1 shows that early applications are associated with a 23.6 pp increase in firm employment six months after graduation. The 2SLS estimate in Column 2 is higher than the OLS, at 38.4 pp. These effects persist at fourteen months (Columns 3 and 4), with a 2SLS estimate of 32.5 pp. For men (Panel B), while OLS (Columns 1 and 3) yields positive coefficients, 2SLS estimates (Columns 2 and 4) are small and statistically insignificant, ranging from -1.0 to 10.3 pp. The OLS and 2SLS coefficients differ for several reasons. OLS would be biased upward if more motivated individuals selected into applying earlier, and biased downward due to measurement

27. Since it targets a specific application date, this definition is more granular than the one in Section III, where applying early was defined as sending an application by the second follow-up. In the experimental surveys, we explicitly ask for the date of first application, allowing us to define applying early based on the August 15th incentive deadline.

error. In contrast, 2SLS isolates the causal effect on compliers — individuals who apply early when offered the incentive but do not otherwise. Overall, these findings imply that early applications have strong and lasting effects on firm employment for female compliers but little effect for male compliers.

Search Timing Impacts Job Acceptance Decisions Having established that the treatment incentivizes early applications and raises female employment, we now investigate where the treatment operates, within the education-to-employment pipeline. One natural hypothesis is that the treatment increases overall search effort, leading to more job offers and ultimately higher employment. To test this channel, Table VI reports treatment effects on two intermediate outcomes: the number of applications and the number of job offers. Treated women apply more, at both six and fourteen months (Columns 1 and 3), but they do not receive more offers than women in the control group (Columns 2 and 4). Therefore, increased search effort is unlikely to explain the employment gains, as it does not translate into better access to job opportunities. Moreover, because both groups receive a similar number of offers, the lower employment rate among control women must stem from a lower job acceptance rate rather than a lack of offers.[28]

Another possibility concerns the composition of jobs offered to (or accepted by) women. Even if the number of offers is similar between treatment and control, treated women may secure more desirable or higher-paying jobs simply by applying earlier. However, as shown in Panel A of Table B.8, women's occupational distribution at fourteen months is nearly identical across both groups. For example, teaching — the most common occupation among women and one plausibly sensitive to seasonal demand — is equally prevalent among treated (23.8%) and control (24.1%) women. Finally, Figure A.15 compares the distributions of current wages (Panel (a)) and offered wages (Panel (b)) between treated and control at the six and fourteen-month follow-ups. These distributions are similar and statistically indistinguishable between both groups. Collectively, these results indicate that the treatment's employment effects are not driven by differences in the quantity or quality of job offers. Instead, the key margin of response is that treated women are more likely to accept the offers they receive.

The Illusion of Time Our treatment has large, positive effects on women's employment. As outlined in Section IV.A, this not only implies a rejection of the null hypothesis that job search

28. Appendix Table B.7 shows results at the extensive margin, i.e., whether a student sends any application or receives any offer. Consistent with intensive-margin results on the numbers of applications and offers, we find that the treatment increases the likelihood of sending at least one application, even at the fourteen-month mark, but has no effect on the likelihood of receiving at least one offer.

timing has no causal effect on women's ability to accept job offers, but it also means women fail to anticipate this effect. In other words, women operate under "the illusion of time": they delay job search under the false assumption that timing does not matter, thereby unintentionally lowering their employment chances.

To confirm this interpretation, we gather direct survey evidence on women's lack of anticipation fo the effect of timing. At baseline, after randomizing respondents into being offered treatment, we ask them (i) when they expect to send their first application, (ii) how many applications they expect to send by August 15th, the incentive deadline, and (iii) what is their perceived likelihood of working six months post-graduation. The last question is worded the same way as in the diagnostic survey (see Section II.B). Table V reports intent-to-treat estimates for these variables. Treatment significantly shifts earlier women's expectations about when they will start applying (Column 1, p-value = 0.000) and increases the expected number of applications by August 15th (Column 2, p-value = 0.067). However, we find no effect on women's perceived likelihood of working six months later (Column 3, p-value = 0.391). Taken together, these results demonstrate that treated women do not anticipate timing to play a key role in determining employment.

These results also rule out that the treatment works by signaling that (early) employment is important or socially desirable.[29] Indeed, if the incentive had altered students' perceptions of work—by implying that working is endorsed or expected—we would expect shifts in stated employment intentions, i.e. treated students should have a higher perceived likelihood of working six months later. Yet we observe no such change.[30]

Taking Stock This section establishes that applying early has a large, positive causal effect on women's employment — and that women do not anticipate this effect. The next section explores why job search timing matters uniquely for women, and why they fail to foresee its consequences.

29. Although the use of a lottery helps mitigate concerns that treatment assignment boosts confidence or reflects favoritism, it does not eliminate the possible information asymmetry between treatment and control groups. Control students go directly to the last module without knowing about the incentive, while we encourage early applications along treated students. Since incentives are typically not offered for actions deemed harmful, the reward itself may be perceived as an implicit endorsement of early job search and labor market participation.

30. Two additional findings help rule out the social desirability explanation. First, the treatment has no impact on men's employment, meaning that any salience or messaging effects would have to operate exclusively on women, which is unlikely. Second, the vast majority of women in both treatment and control groups already report at baseline that they intend to work. This suggests that participants already hold the belief that working is desirable; our intervention is unlikely to alter that mindset.

V The Overlap Between Marriage and Labor Market Timing

Because timing matters uniquely for women, we seek an explanation that is gender-specific. While men and women report similar preferences for work and follow comparable job search strategies, their outside options differ: women marry earlier than men, and marriage may constrains women's labor supply in ways it does not for men. In this section, we provide evidence that this asymmetry helps explain why early applications raise employment for women but not for men.

Preamble: From Campus to Home College graduation marks a major inflection point in the lives of Pakistani women. During college, women spend their days on campus attending classes, participating in co-curricular activities, and interacting regularly with peers and faculty. As Tables I and II highlight, few women are married or engaged during this period. Upon graduation, however, with no prior job to step into and no classes to attend, women suddenly find themselves spending all their time at home. With limited mobility (Field and Vyborny 2022), they are unlikely to interact extensively with anyone beyond close family members. This abrupt shift sets the stage for another transition that begins almost immediately: entry into the marriage market.

The Window of Opportunity In Pakistan, college-educated women typically get married three to four years after graduation. However, entry into the marriage market, which involves receiving and evaluating marriage proposals, starts immediately after graduation. Figure VII illustrates this dynamic. The solid red line shows the cumulative share of women in the control group who have received at least one marriage offer by a given date. While most women do not marry until several years later, as much as one-third have received a marriage offer within just two months of graduating. The figure also overlays the employment share among control women, plotted by the month of first job application. The steepest decline in employment closely coincides with the sharp rise in marriage offers in the initial months after graduation. Applying in September instead of June is associated with a 30.4 pp lower employment rate. Over the same period, the share of women with a marriage offer increases by 29.8 pp. Although correlational, these two trends are too closely synchronised to be dismissed as coincidental.

This pattern suggests that, for women, there exists a narrow window — after graduation but before marriage market activities accelerate — during which entering the labor force is more feasible. A natural question is whether accepting jobs in this window carries marriage market penalties. Although marriage itself is still years away for most women, and therefore cannot be measured in our data, we collect the number of marriage offers and the quality of these offers, proxied by the highest education level among the potential grooms. Columns 1 and 4 of Table B.10 show that women in the treatment group are no less likely to get married or engaged than control women within six or fourteen months post-graduation. Columns 2 and 5 further show that treated women receive the same number of marriage proposals as control women at both follow-ups. Finally, Column 3 shows that the quality of proposals does not differ by treatment status. While we cannot rule out unobservable differences in marriage offers, our evidence suggests that, at least in the narrow window between graduation and the onset of marriage market activities, treated women are not penalized in the marriage market for being employed.

Missing the Window The fact that a small incentive payment moves many women into the window of opportunity indicates that many women ignore the existence of the window. We now present additional evidence connecting this to misperceptions about the timing of the marriage market.

First, we show that women update their expectations about their age of marriage over time. Figure VIII plots women's baseline beliefs about age at marriage (x-axis) against updated beliefs six months post-graduation (y-axis), separately for treatment and control groups. The 45-degree line represents the benchmark of time-invariant beliefs. While the slope is positive (~ 0.6), it lies significantly below 1, suggesting that women who initially expected later marriages systematically update their beliefs downward (earlier). For instance, women who expected at baseline to marry at age 26 revise that estimate down to 25 by the six-month follow-up. In contrast, women who initially expected to marry sooner (e.g., by age 24) have stable expectations. This suggests that women who initially expected later marriages held inaccurate beliefs, which they correct after being exposed to the quick onset of marriage market activities after graduation.

Tying this finding back to our experiment, we find that treatment is more effective precisely for women who, at baseline, expect to marry later.[31] Panel (b) of Figure IX tests for treatment effect heterogeneity based on baseline marriage beliefs. We split our sample into women who initially expect to marry before age 25 (63.3%) and those who expect to marry later (36.7%).[32] We find much stronger treatment effects on firm employment for the women who expects to marry late, at 17.4 pp versus only 5.6 pp for those expecting early marriage (difference p-value = 0.031).[33]

31. Notably, treatment effects are not driven by misperceptions about the labor market. Figure IX, Panel (a) shows that employment effects do not differ by baseline expected wage offers, beliefs about market wages, or beliefs about other women's job prospects.

32. We exclude the small share of women who are already married or engaged at baseline from this analysis as their belief about their future age of marriage is not a well defined object. We take 25 as the age threshold to split our groups as it is the national median.

33. To maximize power, we pool data from the six- and fourteen-month survey waves, include wave fixed effects, and cluster errors at the individual level. Figure A.16, Panel (b) also examines treatment effect heterogeneity on early application behavior using the same baseline marriage beliefs. Here, we find no evidence of differential selection into early application take-up.

What Changes in the Window: Examining Preferences As marriage market activities intensify, women become less likely to accept job offers. One possibility is that preferences change: women lose interest in working as their attention turns to the marriage market. Alternatively, women's willingness to work does not change, but external constraints arise that limit their ability to do so.

To test for changes in preferences, at the six-month survey we ask women directly about their preferences for work: "Do you want to work in the next year?".[34] We find that 87.6% of all women, and 83.4% of unemployed women, answer "yes", with no difference by treatment status. Consistent with this stated desire to work, Table B.9 shows that reservation wages *fall* substantially over time: by 14.5 log points at six months and 7.1 log points at fourteen months, relative to baseline. Again, there is no difference by treatment status. In sum, women's expressed willingness to work remains strong and may even be rising over time.

What Changes in the Window: Examining Constraints The above patterns rule out preference changes as an explanation for falling job acceptance. Instead, they point to the role of external constraints. We provide several pieces of evidence consistent with the influence of one particular constraint: women's families. First, existing literature has shown that timing shapes families' perception of marriage market outcomes. For example, Adams and Andrew (2024) find that families in South Asia believe a daughter's marriage-market prospects deteriorate rapidly once she is out of school. A large and growing literature also emphasizes the role of families in shaping women's labor supply but not men's (Dean and Jayachandran 2019; Bursztyn, González, and Yanagizawa-Drott 2020; Jayachandran 2021; Lowe and McKelway 2024).[35]

Second, we show that treatment effects are concentrated among women who have to involve their parents in their employment decision. In our baseline survey about their family's involvement in their job search: "Whom do you have to consult when deciding to accept a job offer?". We consider parents to be involved if the respondent answers that they have to consult their mother, father, or both.[36] We find that 60.0% of women report they have to consult their parents, vs.

34. We purposefully framed the question in terms of preference rather than expectations to isolate desire for work from external constraints.

35. Family influence is particularly prominent in Pakistan. In a representative sample of urban households, 79% of women report that the head of the family decides, either unilaterally or with them, whether they should work (Junaid et al. 2021). Several other papers have highlighted family constraints on women's labor supply in Pakistan. In an experiment on women in Lahore with similar age, marital, and educational profiles to our sample, Subramanian (2024) finds that making family discussions about job search more salient led to a 60% decrease in applications to jobs with male supervisors. Similarly, Field and Vyborny (2016) document that 40% of non-working women in Pakistan cite lack of permission from their husband or father as the main reason for not working.

36. The full list of options are Friends, Mother, Father, Brother(s), Sister(s), Cousin(s), Husband or fiancé, Rest of

38.8% of men. Figure IX, Panel (b) examines treatment heterogeneity by parental involvement. While treatment effects on early applications are broadly similar (see Figure A.16), effects on firm employment differ sizably by parental involvement. Among women who do not need to consult their parents, the treatment effect on firm employment is modest, at 6.8 pp. In contrast, for women whose parents have a say on their job decisions, the effect rises by nearly threefold, to 16.3 pp (difference p-value = 0.079).

Last, for family involvement to explain our treatment effects, it should come as a surprise to women. In support of this, the left panel of Figure X shows that only 20% of women report that they may struggle to work after graduation due to "family reasons," such as lacking approval from their families or being pressured to prioritize marriage. In contrast, 91% of women recognize that *other* women will face these family-related obstacles. Further, we find no relationship between reporting parental involvement in their job search and expecting family to be a barrier to one's own employment. These observations paint a picture in which women are aware of family as a common barrier to work for the "typical" women, but they underestimate how these barriers may apply to their families and them. This contrast between beliefs about oneself and about others mirrors the gap we find between women's high employment expectations for themselves and low expectations for their peers. Together, these results shed light on a broader behavioral phenomenon among the women in our sample: they are aware of the constraints the "typical" women faces, but believe—mistakenly—that those constraints won't apply to them.

We note that the lack of a marriage market penalty for early employment can be reconciled with growing family resistance to work if there is, in fact, a penalty to starting work *later*. In this case, parents may justifiably grow more concerned over time about the potential impact of work on their daughters' marriage prospects. Another possibility is that there is no marriage penalty at any stage, but parents suffer from confirmation bias: once marriage activities begin, parents whose non-working daughters receive attractive offers interpret these outcomes as evidence that abstaining from work improved their daughters' standing — while parents of working daughters may draw the opposite inference. Our experiment is not equipped to distinguish between these alternatives, as we can only estimate the causal effect of starting work early, not late. Though we cannot distinguish between these explanations, the policy implication is the same. Early job search allows women to secure employment before external constraints—whether social, familial, or perceived—arise, opening a window of opportunity that policy can target.

family, Teachers (or career office, career councilor, university website), Classmates enrolled in my course / seniors, No one, Other.

VI Conclusion

The social norms that govern the division of labor within and outside the household create a systematic link between the marriage market and the labor market. As a result, decisions regarding marriage, fertility, employment, and occupational choice are interdependent. Where these norms are gendered — as they typically are — the degree of interdependence becomes asymmetric: women face a tighter set of constraints, and their choices across the marriage and labor domains are less readily separable than those faced by men. In particular, the relative timing of entry into these domains carries lasting consequences. In our study, we show that women who enter the labor force prior to the start of marriage market activities are significantly more likely to be employed. Even if they stop working after marriage, they will have accumulated labor market experience that may alter their bargaining power at home, and can facilitate future re-entry into the labor market.

The extent to which these constraints bind also depends on whether women recognize the interdependence of choices across domains and whether they can strategically time these choices to preserve individual agency. In our study, college-educated women in Pakistan — a setting where the allocation of labor is strongly gendered — fail to anticipate how soon their marriage market arrives after graduation. This misperception, which we term the "illusion of time," leads women to delay their job search under the mistaken belief that job application timing does not matter, unintentionally lowering their employment chances. We find that these misperceptions can add up to persistent gender employment gaps. Indeed, despite having similar aspirations, preferences, and even more job offers than men, women are about half as likely to be employed six months after graduation. In this context, even a small behavioral nudge can yield sizable effects. Our experiment, which offers a modest financial incentive for applying early, leads to a 34% reduction in the gender employment gap.

Our findings highlight a new area for research and policy intervention. Governments and firms can act to weaken the interdependence that drive gender disparities in the labor market. One promising avenue is to redesign promotion pathways and career ladders so that major advancement opportunities do not coincide with key life stages for women, such as peak fertility years. Decoupling career progression from marriage and fertility cycles can help mitigate the penalty women face when timing overlaps between competing life domains. Another avenue is to raise awareness among women about these critical junctures, targeting their self-belief bias to help them anticipate potential barriers and proactively invest in strategies to navigate the barriers — should they choose to do so.

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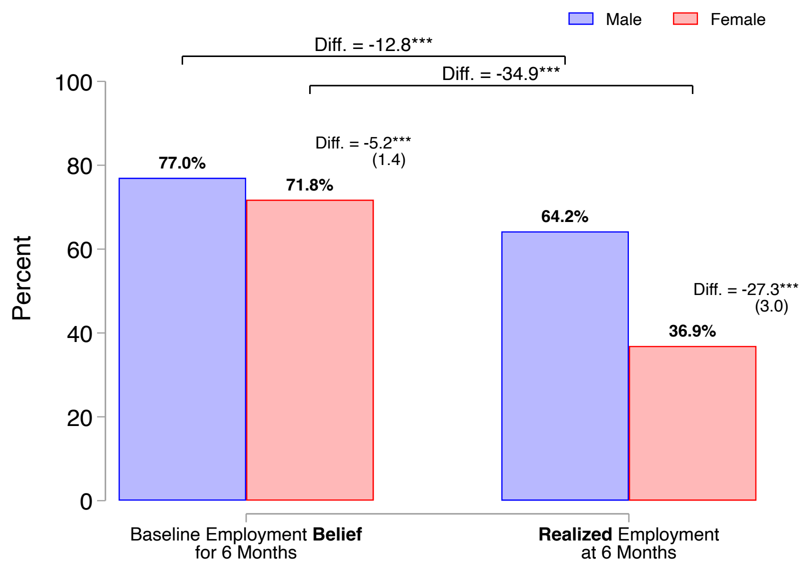
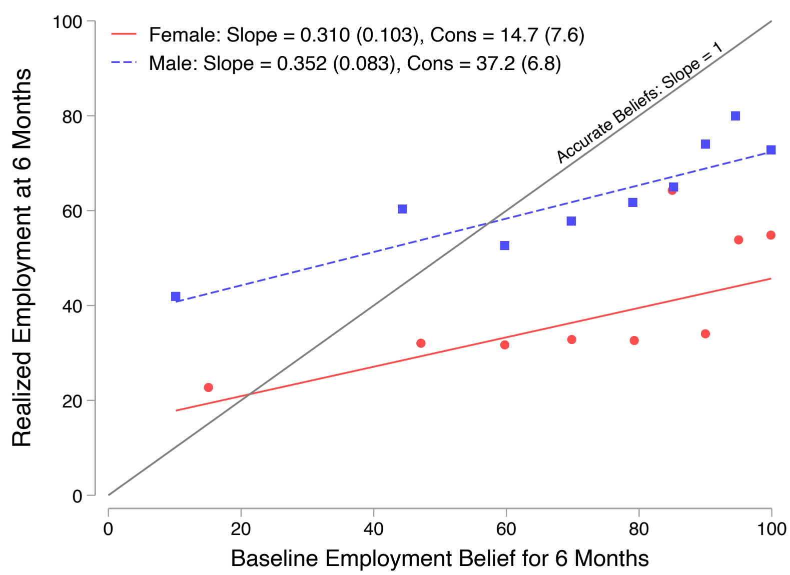
Figures

Figure I: Baseline Employment Beliefs vs. Realized Employment Outcomes



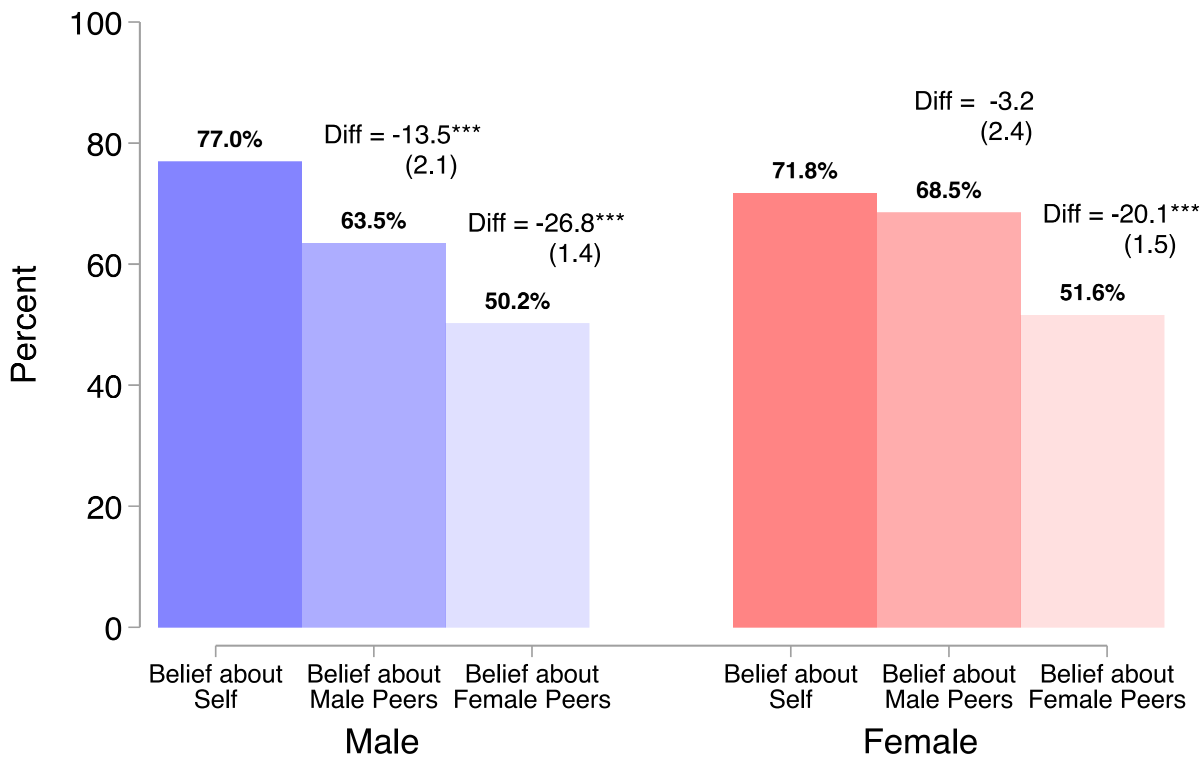
(a) Mean Levels: Expected vs. Realized Employment



(b) Binned Scatter: Expected vs. Realized Employment

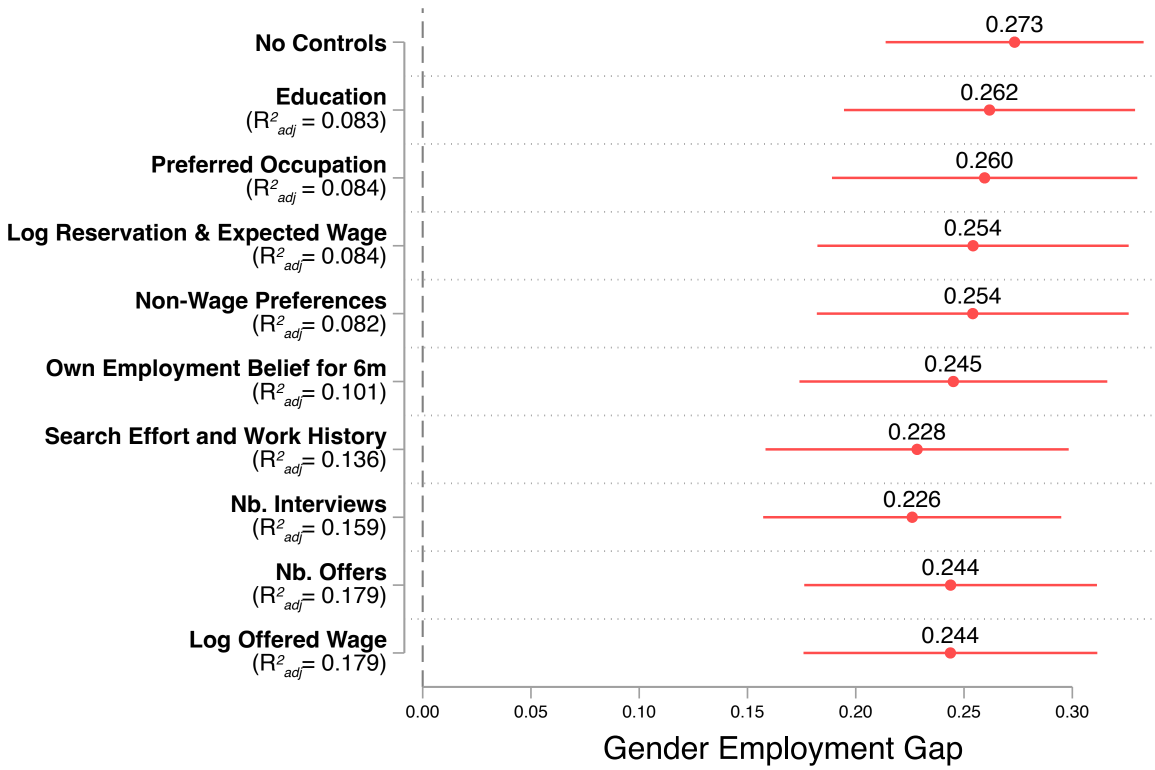
Notes: This figure compares students' baseline beliefs about their future employment prospect with realized employment outcomes. The sample consists of respondents from the diagnostic sample (see Section II.A for details). Panel (a) contrasts students' average baseline belief about their employment likelihood six months post-graduation (left pair of bars) with their realized employment at the six-month mark (right pair of bars), separately for men (blue) and women (red). Gender gaps in responses are shown directly above the female bar. Average within-gender differences between baseline beliefs and realized employment are shown above the horizontal brackets. Panel (b) shows a binned scatter plot of baseline employment beliefs against realized employment, separately for men (blue) and women (red). The solid 45-degree line represents accurate beliefs, points above (below) which indicate underestimation (overestimation) of employment chances. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure II: Employment Beliefs about Self vs. Peers



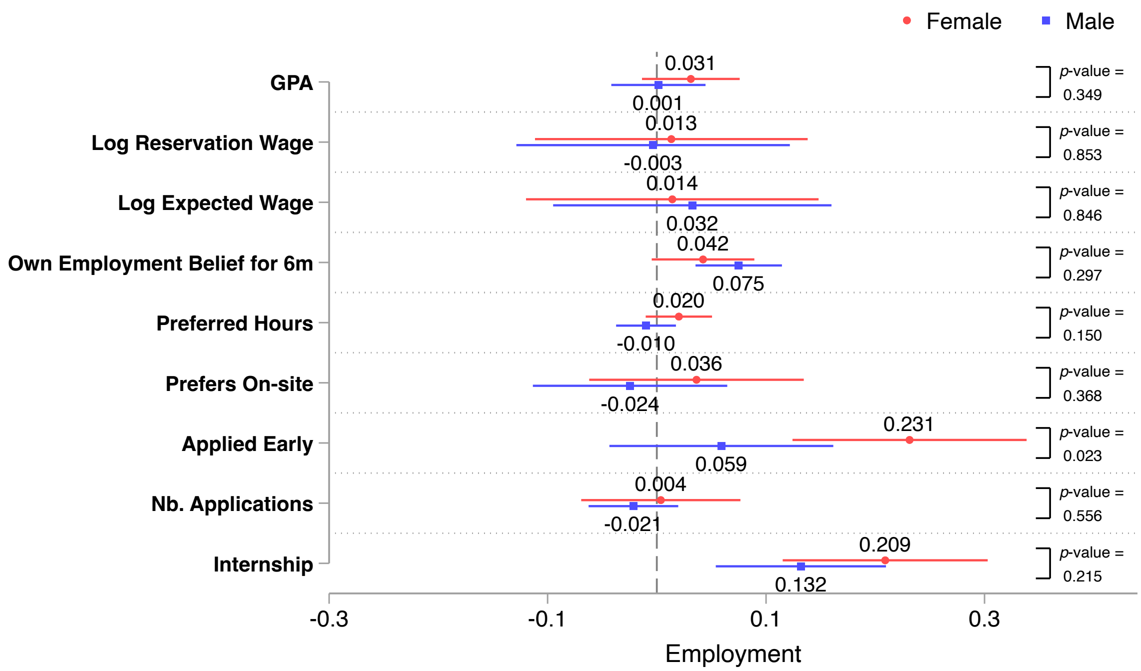
Notes: This figure presents respondents' average baseline beliefs about their own employment prospect six months post-graduation, versus beliefs about their peers' employment prospect. The sample consists of respondents from the diagnostic sample (see Section II.A for details). Male (female) responses are represented by the blue (red) cluster of bars on the left (right). The leftmost bar in each cluster (bars 1 and 4) shows average baseline beliefs about one's own employment likelihood. The middle bar in each cluster (bars 2 and 5) shows beliefs about male peers' employment likelihood. The rightmost bar in each cluster (bars 3 and 6) shows beliefs about female peers' employment likelihood. The average differences between beliefs about oneself and beliefs about male (female) peers are reported above the middle (rightmost) bar in each cluster. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure III: Explaining the Gender Employment Gap



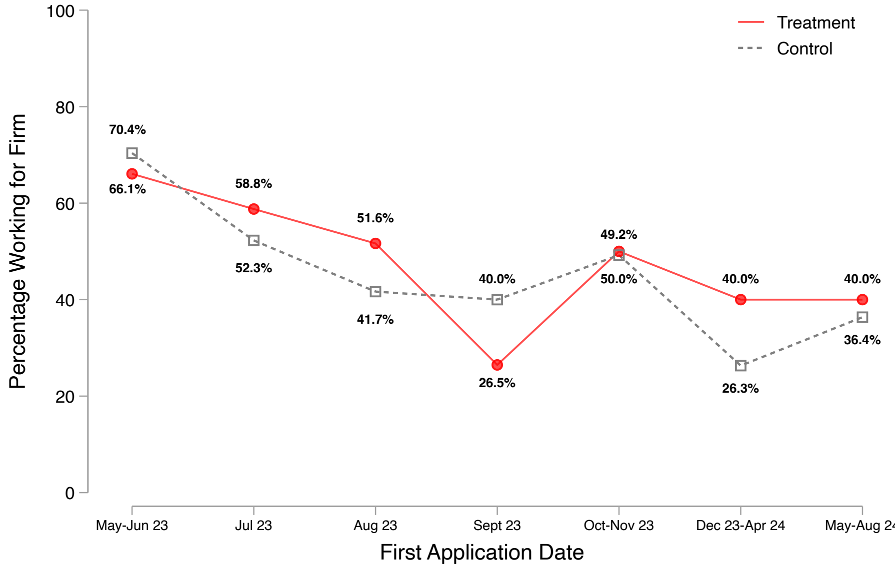
Notes: This figure shows the gender gap in employment six months post-graduation and to what extent it can be explained by observable baseline characteristics. Each row reports the coefficients, 95% confidence intervals, and adjusted R-squared values from a regression of employment on gender and control variables in or above that row. The sample consists of respondents in the diagnostic sample (see Section II.A for details). Education controls include cumulative GPA and major fixed effects. Preferred Occupation controls include fixed effects derived from respondents' text-entry descriptions of the preferred job type at baseline, semantically mapped to Standard Occupational Classification (SOC) codes. Reservation and Expected Wage controls include baseline wage expectations. Non-Wage Preferences controls include baseline preferences regarding onsite vs. remote work and preferred daily work hours. Own Employment Belief for 6 Months control includes the baseline belief about one's own employment likelihood six months later. Search Effort and Work History controls include an indicator for applying early (i.e., having submitted at least one application by the two-month follow-up), the total number of job applications submitted by the six-month follow-up, and an indicator for internship experience. Nb. Interviews (Offers) control includes the number of interviews (offers) received by the six-month follow-up. Log Offered Wage control includes the highest log wage offer a student has received for a job (regardless of whether they have accepted it). To address missing values (e.g., if a student did not receive a job offer), we assign a constant (999) to missing entries and include a binary indicator in the regression. All unbounded continuous variables are winsorized at the 2% level. The mean employment level for men at six-months is 64.2%.

Figure IV: The Determinants of Gender-Specific Labor Supply

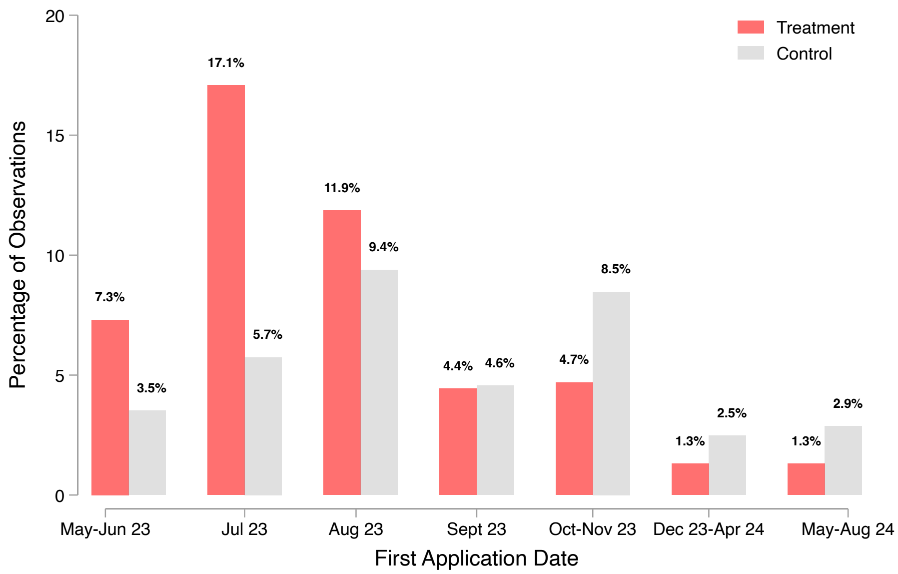


Notes: This figure presents results from regressing employment status six months post-graduation on a set of independent variables, separately for women (red) and men (blue). Each row reports the regression coefficient on the specified variable, with variables in all other rows included as controls. The sample consists of respondents in the diagnostic sample (see Section II.A for details). Independent variables include cumulative GPA (measured in standard deviations), log baseline reservation wage, log baseline expected wage, baseline belief about one's own employment likelihood (transformed onto a 0-1 scale and measured in standard deviations), preferred daily work hours, preference for onsite vs. remote work, an indicator for applying early (submitted at least one application by the two-month follow-up), total number of applications submitted by the six-month follow-up (measured in standard deviations), and an indicator for internship experience. All unbounded continuous variables are winsorized at the 2% level. Horizontal bars show 95% confidence intervals. Vertical brackets report p-values from testing equality of coefficients across gender. Corresponding means and standard deviations for the independent variables shown in the figure are provided in Table B.2. Figure A.12 presents results from bivariate regressions without including other variables as controls.

Figure V: Explaining the Magnitude of our Treatment Effects



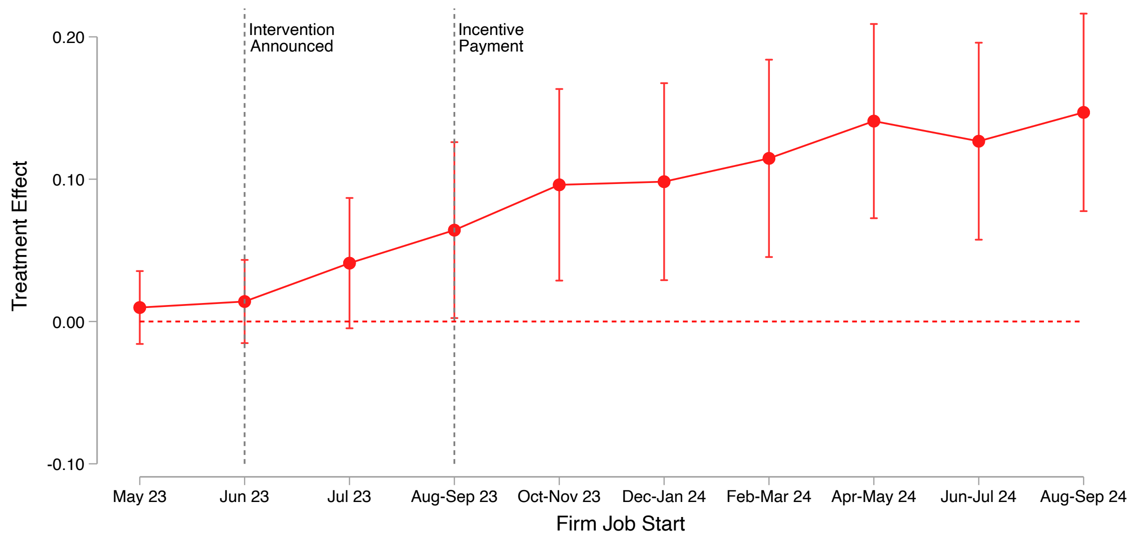
(a) Percent Working for Firm by First Application Date



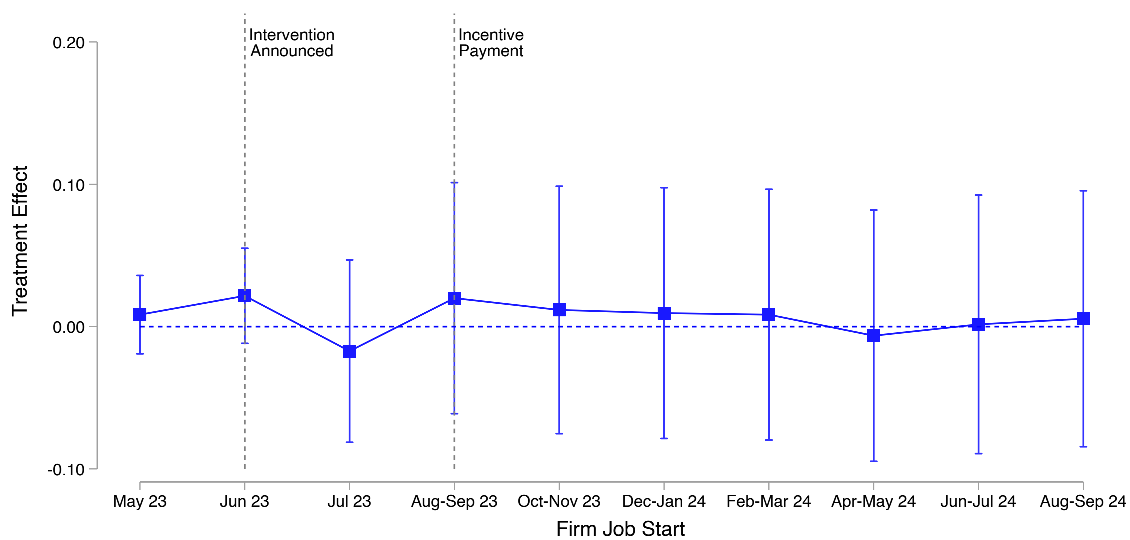
(b) Distribution of First Application Date

Notes: This figure shows the relationship between application timing and employment outcomes, split by treatment status, shedding light on how our treatment effects take place. Panel (a) shows the share of women employed at a firm at the fourteen-month follow-up, by the month of their first job application, separately for treated (solid red) and control (dashed gray) women. For instance, 70.4% of the control women who sent their first application in May or June 2023 are working for a firm in September 2024. Panel (b) shows the distribution of first application dates, separately for treated (red) and control (gray) women. For instance, 3.5% of women in the control group sent their first application in May or June 2023. The sample in Panel (a) contains all female respondents in the fourteen-month experimental sample (see Section IV.A for details). The sample in Panel (b) consists of respondents in the fourteen-month experimental sample who provided the date of at least one job application.

Figure VI: Dynamic Treatment Effects on Firm Employment



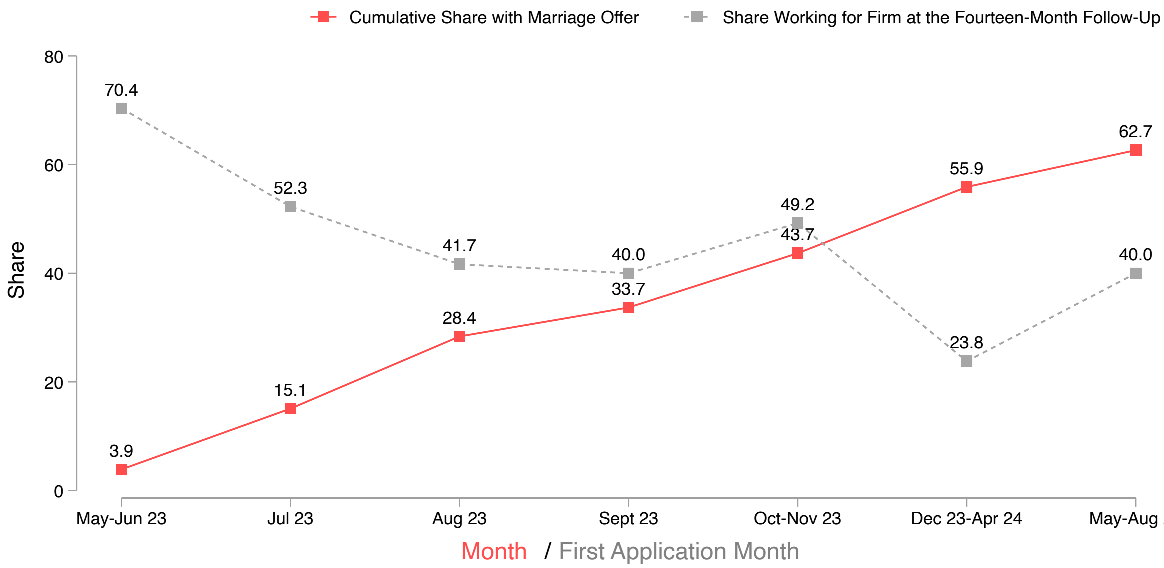
(a) Female: Treatment Effects on Firm Employment



(b) Male: Treatment Effects on Firm Employment

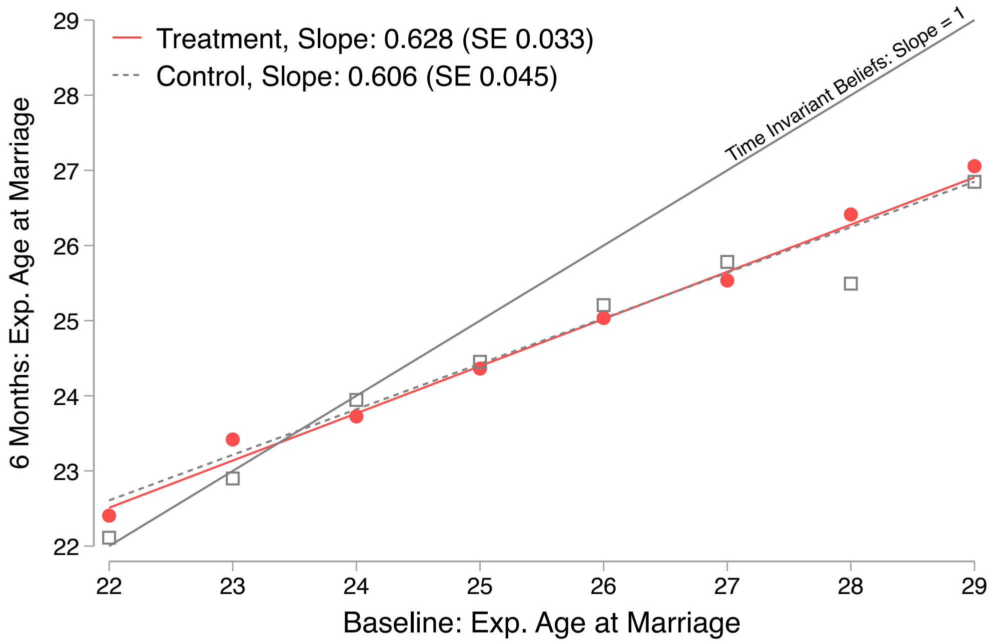
Notes: This figure presents dynamic treatment effects on having ever worked at a firm by a given date post-graduation. The sample consists of respondents in the fourteen-month experimental sample (see Section IV.A for details). Panel (a) shows treatment effects for women, and Panel (b) does so for men. For instance, the rightmost point in Panel (a) displays, for women, the treatment effect on holding a post-graduation job at a firm by September 2024. In both panels, the first dashed vertical line indicates the date the intervention was announced, and the second dashed vertical line indicates the deadline by which treated students could submit proof of early applications for monetary rewards. Both panels include a dashed horizontal line marking zero on the y-axis. Vertical bars show 95% confidence intervals.

Figure VII: The Relationship between the Job Market and the Marriage Market



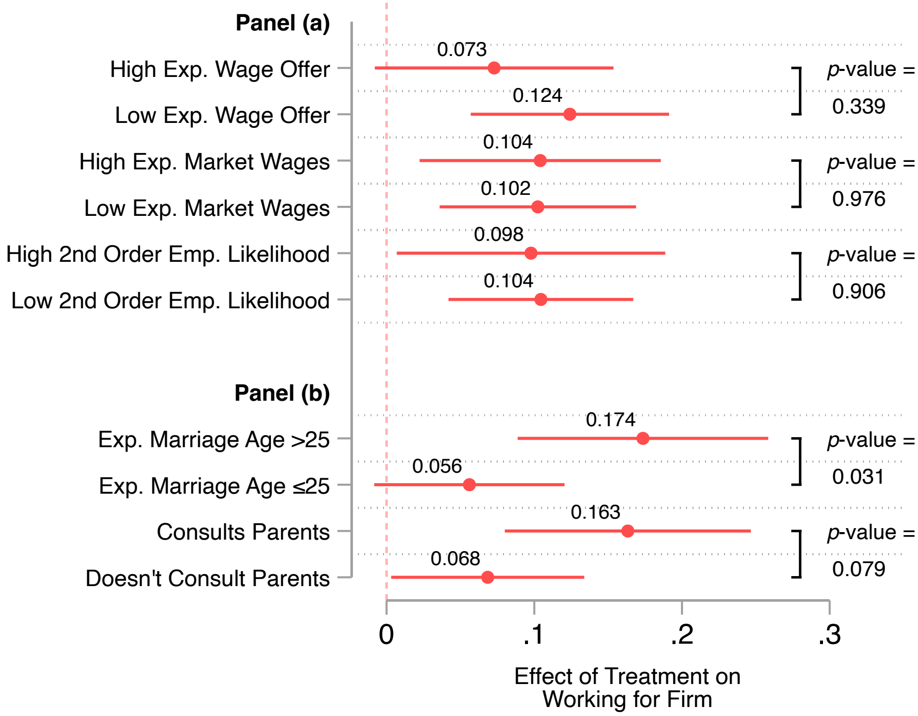
Notes: This figure presents the relationship between women's marriage offers and employment outcomes over time. The sample consists of women in the control group of the fourteen-month experimental sample (see Section IV.A for details), excluding the small share of women who are already married or engaged at baseline for the marriage offer measure. The solid red line shows the cumulative share of women who have received at least one post-graduation marriage offer by each month. For instance, 28.4% of women in our sample have received a marriage offer by August 2023, and 33.7% by September 2023. The dashed gray line shows, as in Figure V Panel (a), the share of women in the control group who are employed at a firm by the fourteen-month mark, as a function of the month of their first job application. For instance, 70.4% of the control women who sent their first application in May or June 2023 are employed at a firm in September 2024.

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



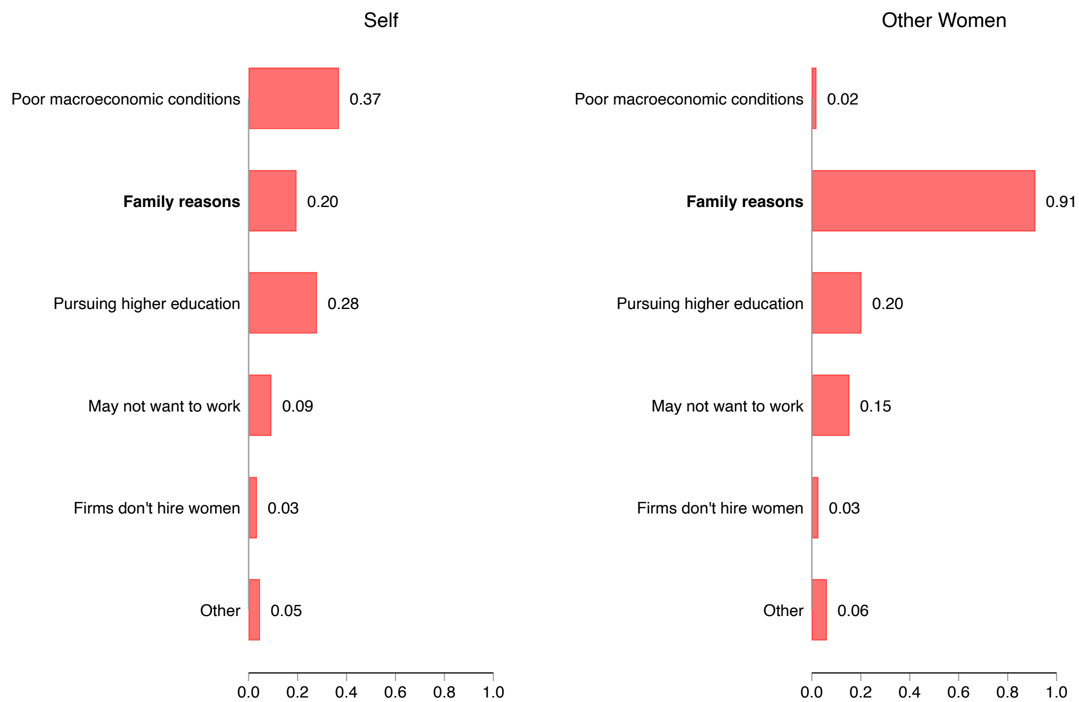
Notes: This figure examines how women's perceived timing of marriage evolves over time. It shows a binscatter plot of women's expected age of marriage at baseline against their updated expectations six months post-graduation, separately for treated (solid red) and control (dashed gray) women. The sample consists of women in the six-month experimental sample (see Section IV.A for details), excluding the small share of women who are already married or engaged at baseline. The solid gray 45-degree line denotes time-invariant beliefs, i.e., the expected age of marriage does not change between baseline and the six-month follow-up. A slope below one suggests that women who initially expected to marry later tend to revise their expectations downward (earlier) over time. Expected age at marriage is winsorized at the 2% level.

Figure IX: Heterogeneous Treatment Effects on Firm Employment



Notes: This figure presents heterogeneous treatment effects on women's likelihood of working for a firm. The analysis pools the six- and fourteen-month experimental samples (see Section IV.A for details). Panel (a) explores heterogeneity based on three baseline labor market beliefs: expected own wage offer, expected market wages, and belief about other women's employment likelihood. Each variable is split into "High" (above the median) and "Low" (below the median). Panel (b) explores heterogeneity based on baseline marital expectations and familial involvement in job search. Specifically, it includes whether respondents expect to marry after age 25 (the national median for college-educated women) and whether they have to consult their parents for job decisions. For each pair of subgroups, the coefficients come from regressing an indicator for working for a firm on treatment interacted with a subgroup indicator, with experimental wave fixed effects. Vertical brackets display p-values from testing equality between complementary subgroups. Standard errors are clustered at the individual level. The dashed red vertical line marks zero on the x-axis, while horizontal bars show 95% confidence intervals.

Figure X: Potential Reasons for Staying Out of Labor Force: Self vs. Peers



Notes: This figure presents women's baseline beliefs about why they and other women in their class may not work in the future. The sample consists of women in the control group of the six-month experimental sample (see Section IV.A 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. 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 reported expecting a non-zero share of their female peers to be unemployed. Respondents provided open-ended answers, which enumerators categorized into predefined categories or coded under "Other" if none applied. Enumerators could select multiple categories for a response. Responses were coded as "Family reasons" if they include statements like "I may not get permission from family to work" or "I am getting married, have a baby, or focus on my family."

Tables

Table I: Descriptive Statistics for the Diagnostic Sample

	All (1)	Male (2)	Female (3)	Diff. (4)	P-value (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
Life Sciences / Pharmacy	12.1	5.1	21.6	-16.6	0.00
Sciences	13.2	5.8	23.2	-17.5	0.00
Humanities / Languages / Education	15.5	13.4	18.5	-5.1	0.03
Social Sciences	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 II.A for details). Column 1 presents statistics for all respondents. Columns 2 and 3 present statistics separately for male and female respondents. Column 4 shows the difference between genders (male minus female), and Column 5 reports the p-value from a test of 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 percentage 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 II: 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
Life Sciences / Pharmacy	12.6	10.1	14.0	-4.0	0.02
Sciences	27.0	29.7	25.6	4.1	0.10
Humanities / Languages / Education	26.3	27.9	25.4	2.5	0.30
Social Sciences	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 IV.A for details). Column 1 presents statistics for all respondents. Columns 2 and 3 present statistics separately for male and female respondents. Column 4 shows the difference between genders (male minus female), and Column 5 reports the p-value from a test of 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 III: Treatment Effects on Employment

	6 Months		14 Months	
	Working	**Working for Firm**	**Working**	**Working for Firm**
	(1)	(2)	(3)	(4)
Panel A: Female				
Offered Treatment and Took Up	0.136***	0.173***	0.116***	0.154***
	(0.037)	(0.036)	(0.039)	(0.040)
Offered but did not Take Up	0.002	0.019	0.005	0.007
	(0.038)	(0.036)	(0.046)	(0.045)
Female Control Mean	0.336	0.253	0.518	0.413
Panel B: Male				
Offered Treatment and Took Up	0.079	0.115**	0.041	0.082
	(0.051)	(0.053)	(0.045)	(0.052)
Offered but did not Take Up	-0.073	-0.069	-0.085	-0.094*
	(0.053)	(0.050)	(0.053)	(0.057)
Male Control Mean	0.551	0.374	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 respondents in the six-month (Columns 1 to 3) and fourteen-month (Columns 4 and 5) experimental samples (see Section IV.A for details). Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment effect on whether a respondent has applied to at least one job by August 15th, measured at the six-month follow-up survey. 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 Columns 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. Control means are reported separately by gender for each outcome. The last row reports the number of observations. Table B.5 shows the results without the LASSO-selected controls. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table IV: OLS and IV Estimates of Early Applications on Firm 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^{***}	0.384^{***}	0.190^{***}	0.325^{***}
	(0.030)	(0.112)	(0.035)	(0.110)
Female, Not Applied Early, Mean	0.188	0.188	0.351	0.351
Panel B: Male				
Applied Early (by Aug. 15th)	0.234^{***}	0.103	0.123^{***}	-0.010
	(0.042)	(0.235)	(0.045)	(0.212)
Male, Not Applied Early, Mean	0.265	0.265	0.479	0.479
Nb. Observations	1,442	1,442	1,218	1,218

Notes: This table presents OLS and 2SLS treatment effects of early job applications (by August 15th) on firm employment. The sample consists of respondents in the six-month and fourteen-month experimental samples (see Section IV.A for details). Panel A shows results for women, and Panel B shows results for men. Column 1 reports the OLS estimates from regressing firm 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 reported separately by gender for each outcome. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table V: Treatment Effects on Labor Market Intentions

	Intended Search Start (Days)	**Intended Nb. Apps by Aug. 15**	**Emp. Likelihood in 6 Mo.**
	(1)	(2)	(3)
Panel A: Female			
Treatment	-20.440***	0.593*	-0.885
	(2.658)	(0.324)	(1.031)
Female Control Mean	50.280	5.586	79.802
Panel B: Male			
Treatment	-12.648***	-0.580	0.743
	(3.632)	(0.559)	(1.271)
Male Control Mean	43.748	7.366	81.618
Nb. Obs.	1,417	1,417	1,442

Notes: This table presents treatment effects on self-reported job search intentions and employment likelihood from the baseline survey. To match the sample in Table III, we keep students who responded both to baseline and the six-month follow-up in the experiment (see Section IV.A for details). Responses were collected after the treatment group was informed about their eligibility for a financial incentive for submitting four early applications. Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment 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 2 reports the treatment effect on the number of job applications the respondent intends to send by August 15th. Column 3 reports the treatment effect on the respondent's baseline belief about their own employment likelihood 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 reported separately by gender for each outcome. The last row reports the number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table VI: Treatment Effects on Applications and Offers

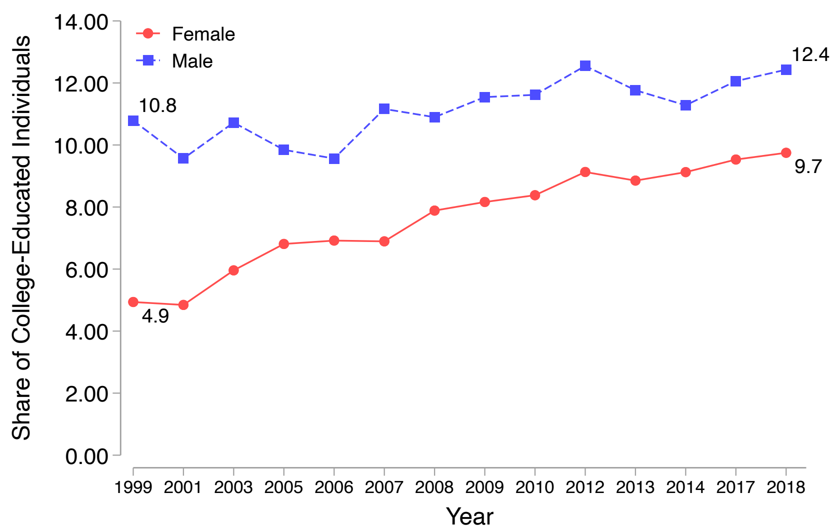
	6 Months		**14 Months**	
	Nb. Apps	**Nb. Offers**	**Nb. Apps**	**Nb. Offers**
	(1)	(2)	(3)	(4)
Panel A: Female				
Treatment	1.445**	0.155	1.710**	-0.000
	(0.736)	(0.163)	(0.713)	(0.097)
Female Control Mean	8.184	2.047	4.726	0.899
Panel B: Male				
Treatment	0.486	0.136	-0.387	-0.012
	(1.050)	(0.202)	(0.969)	(0.120)
Male Control Mean	9.565	1.941	6.516	0.959
Nb. Obs.	1,435	1,435	1,210	1,210

Notes: This table presents the treatment effects on intermediate labor market outcomes. The sample consists of respondents in the six-month experimental sample (see Section IV.A for details). Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment effect on the number of applications sent between graduation and the six-month follow-up. Column 2 reports the treatment effect on the number of job offers received between graduation and the six-month follow-up. Column 3 reports the treatment effect on the number of applications sent in the six months prior to the fourteen-month follow-up. Column 4 reports the treatment effect on the number of job offers received in the six months prior to the fourteen-month follow-up. The number of applications and 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 reported separately by gender for each outcome. The last row reports the number of observations. There are fewer observations in this table relative to Table III because the analysis is limited to cases with non-missing values for the number of applications and offers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

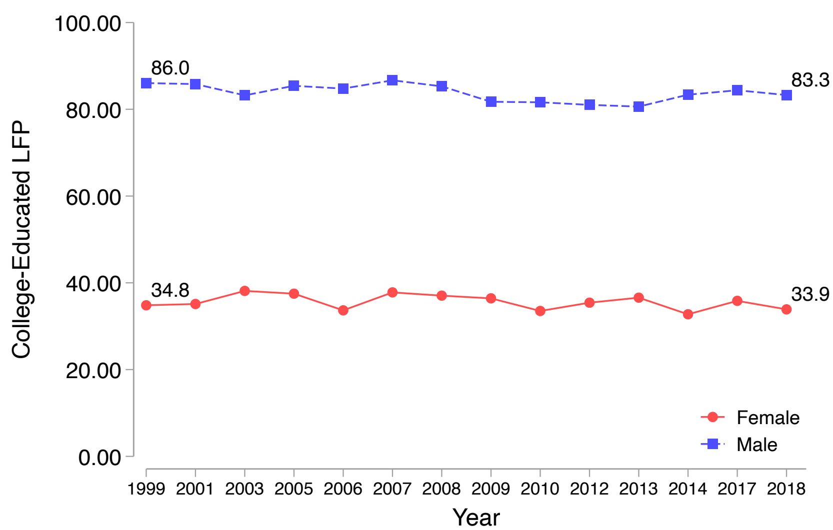
Appendix

A Appendix Figures

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



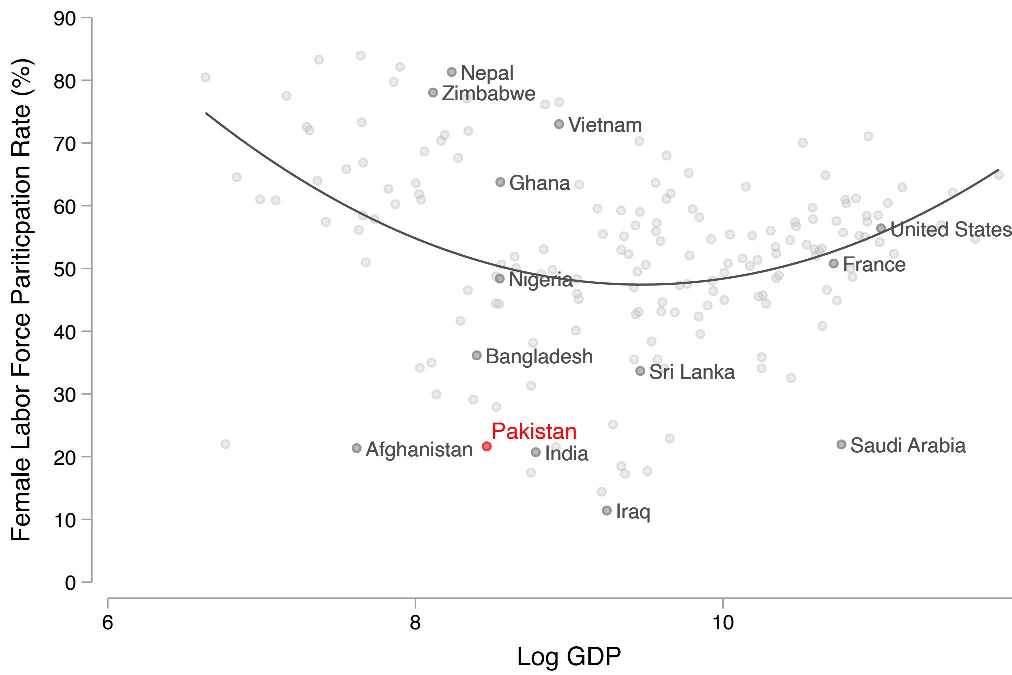
(a) Gender Gaps in College Education



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

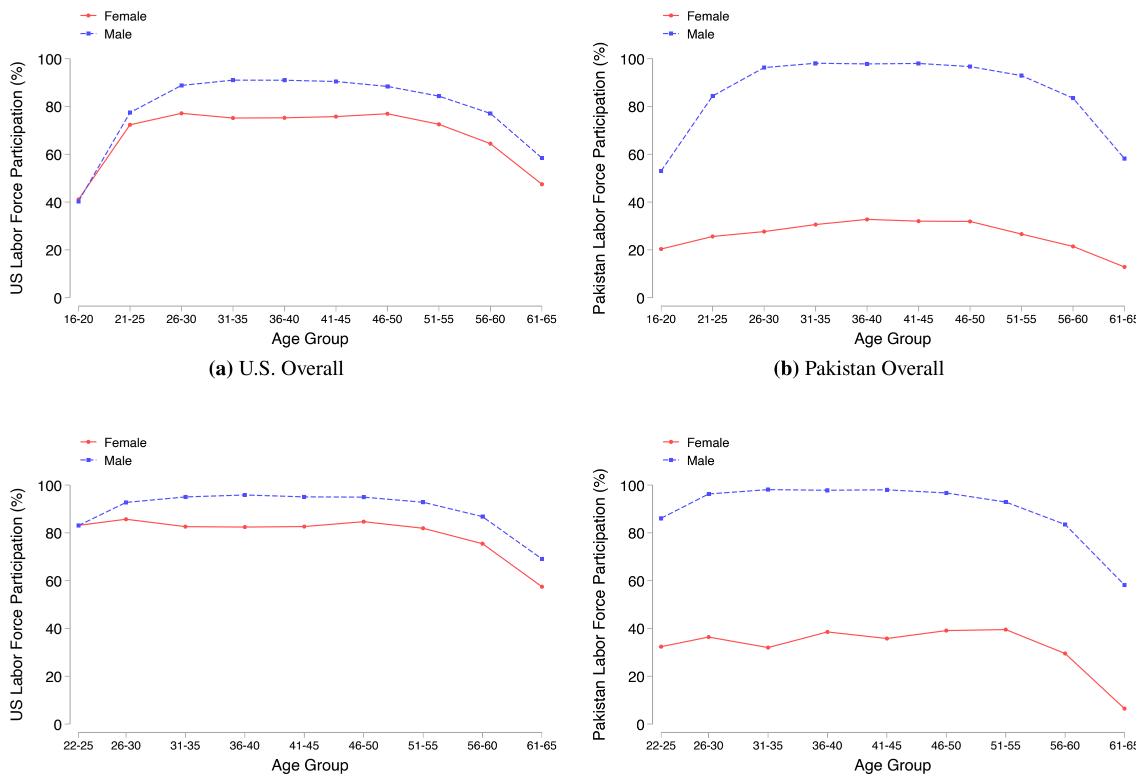
Notes: This figure presents trends in college education and labor force participation in Pakistan between 1999 and 2018, separately for men (dashed blue) and women (solid red). Panel (a) shows the share of individuals aged 22–35 who are college-educated. Panel (b) shows the labor force participation rates for college-educated individuals in the same age group. Data for both panels are 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 countries, with Pakistan highlighted in red. The U-shaped relationship between GDP and female labor force participation is represented by the solid black line. Countries that lie close to 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

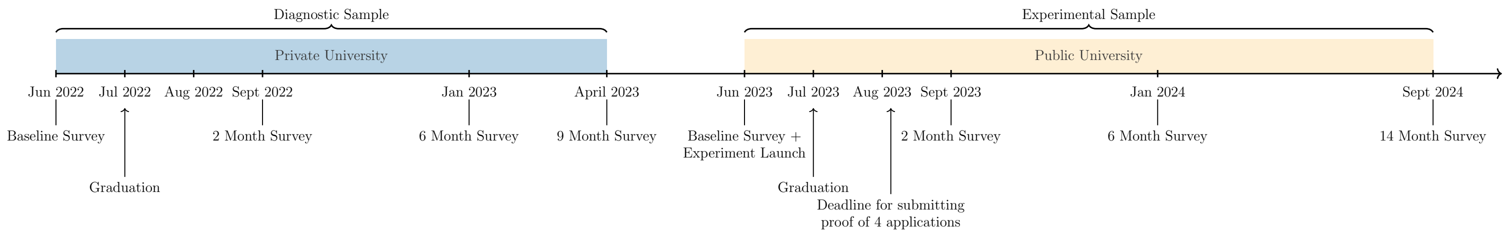
(b) Pakistan Overall

(c) U.S. College Graduates

(d) Pakistan College Graduates

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

Figure A.4: Research Timeline

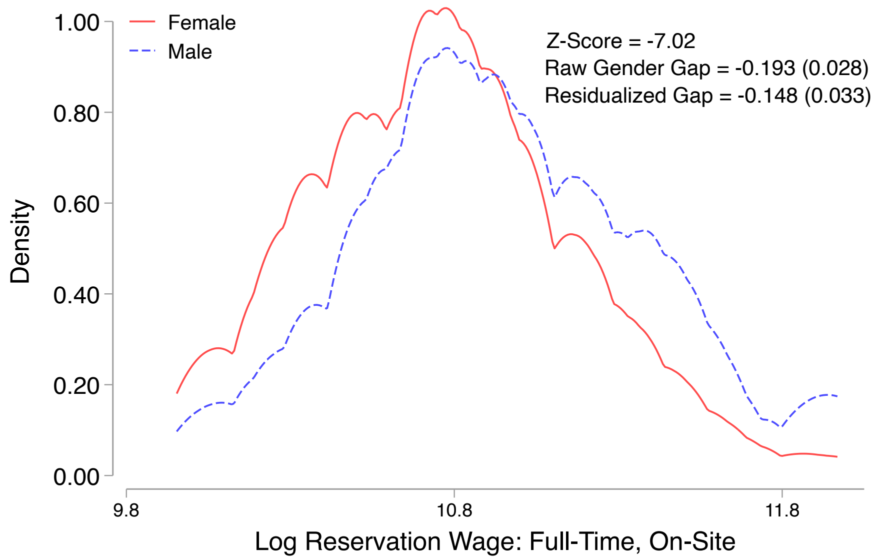


Notes: This figure presents the timing of research surveys relative to students' graduation timeline. The first surveys (represented in blue on the timeline) were conducted with the diagnostic sample described in Section II.A at the private university. The baseline survey was conducted in June 2022, 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 IV.A 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 the 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 four applications for monetary reward was August 15th, 2023. This cohort of students was followed up with two, six, and fourteen months later, in September 2023, January 2024, and September 2024, respectively.

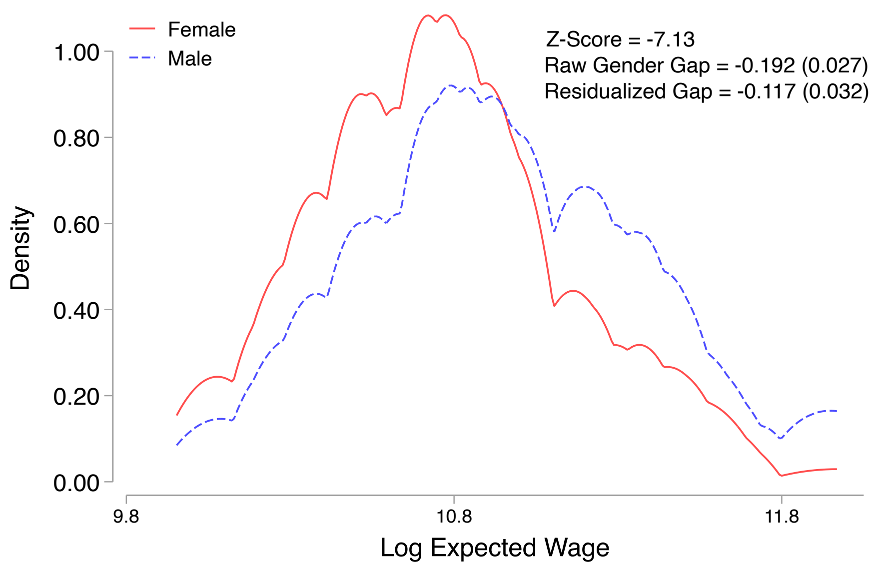
Figure A.5: Survey Incentives

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: Supply-Side Factors I: Reservation Wage and Expected Wage



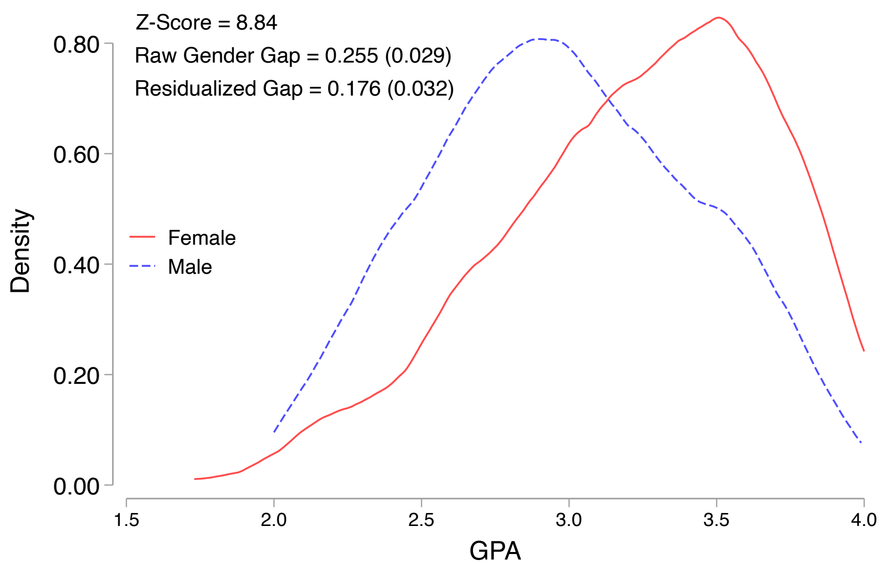
(a) Kernel Density: Log Reservation Wage



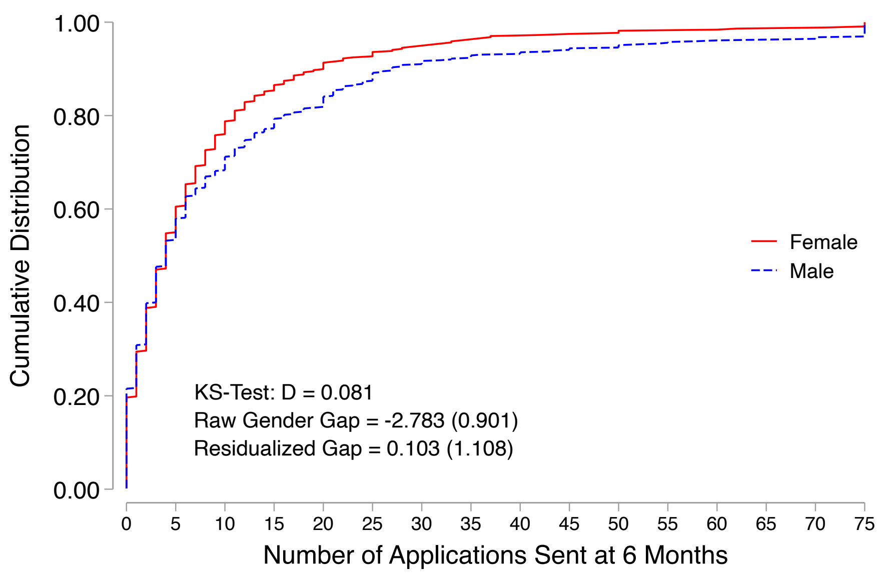
(b) Kernel Density: Log Expected Wage

Notes: This figure presents the distribution of baseline reservation and expected wages, separately for men (dashed blue) and women (solid red). The sample consists of respondents in the diagnostic sample (see Section II.A 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. Both panels show raw and residualized gender gaps, calculated as the female-male difference, and the z-score for the raw difference between women and men. The residualized estimate controls for cumulative GPA, major, and preferred occupation. Reservation and expected wages are winsorized at the 2% level.

Figure A.7: Supply-Side Factors II: GPA and Search Effort



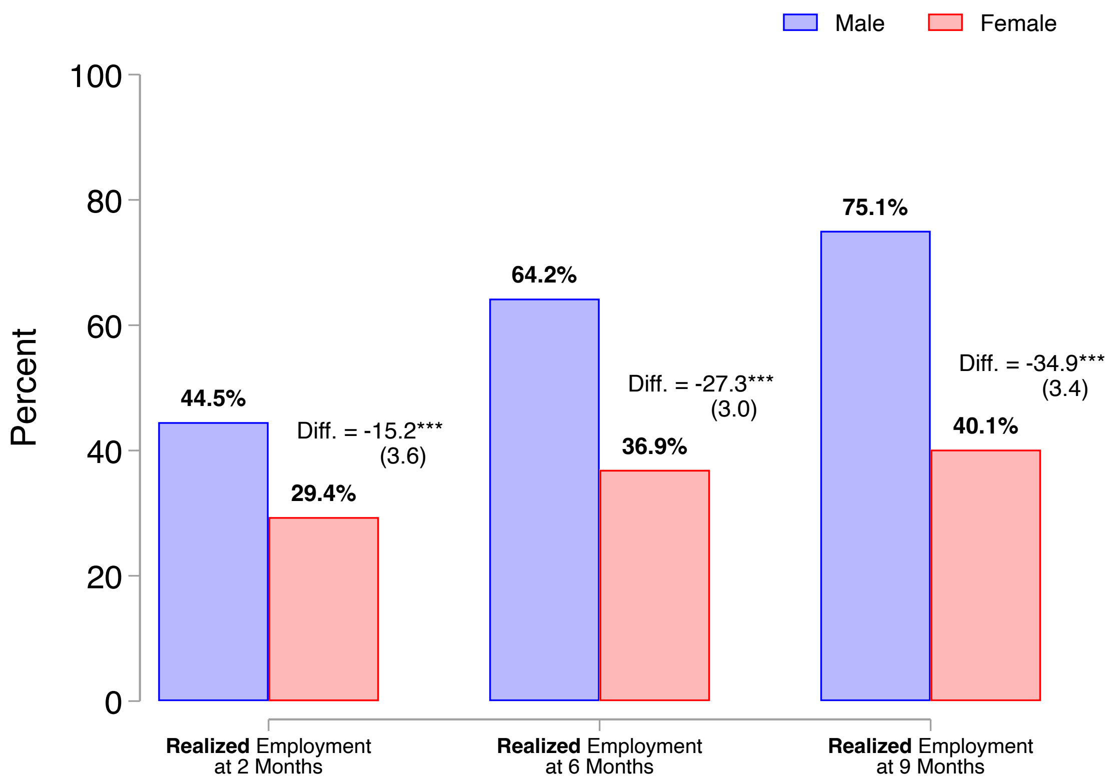
(a) Kernel Density: GPA



(b) CDF: Job Applications at Six Months

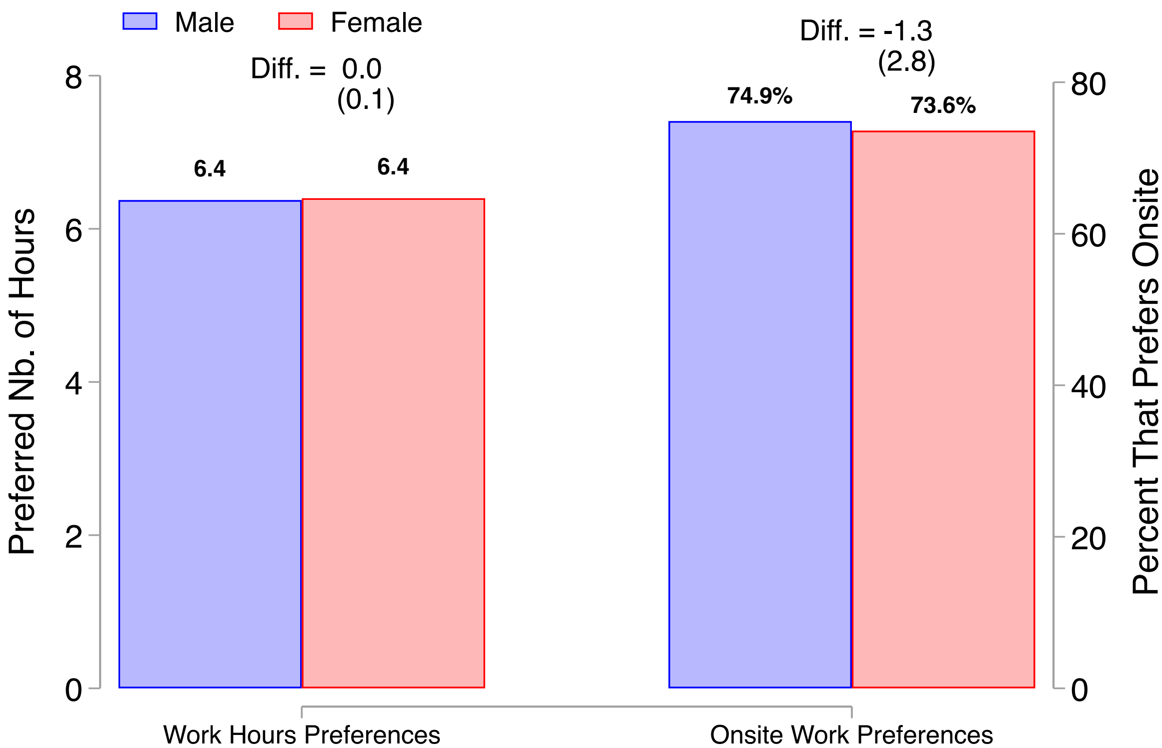
Notes: This figure presents the distribution of baseline GPA and number of job applications sent by the six-month follow-up, separately for men (dashed blue) and women (solid red). The sample consists of respondents in the diagnostic sample (see Section II.A for details). Panel (a) shows the kernel density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

Figure A.8: Employment Rates By Gender Across Survey Waves



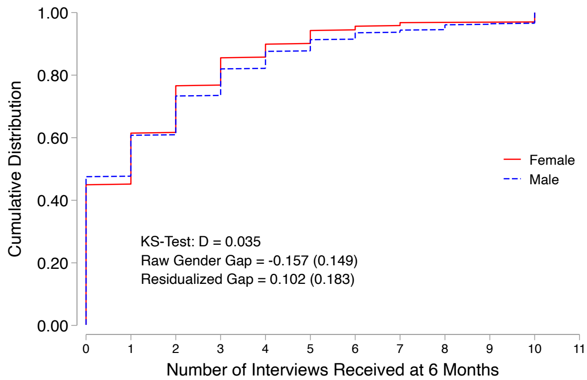
Notes: This figure presents realized employment rates, separately for men (blue) and women (red) and by survey wave. The sample consists of respondents in the diagnostic sample (see Section II.A for details). The left, middle, and right pairs of bars correspond to realized employment at the two, six, and nine-month follow-up surveys, respectively. The difference between male and female employment is shown above the female bar in each pair. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.9: Supply-Side Factors III: Preferred Work Arrangements

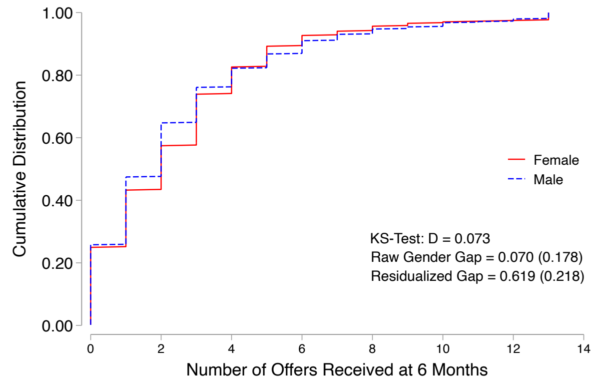


Notes: The figure presents information on baseline preferred work arrangements, separately for men (blue) and women (red). The sample consists of respondents in the diagnostic sample (see Section II.A for details). The left pair of bars shows the average number of preferred daily work hours. The right pair of bars shows the percentage of respondents that prefer to work onsite rather than remotely. The difference between male and female responses is shown above the female bar in each pair. Preferred daily work hour is winsorized at the 2% level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

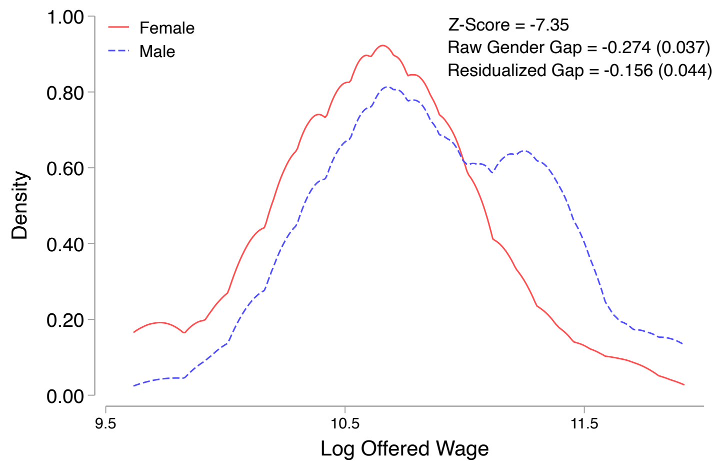
Figure A.10: Demand-Side Factors: Interviews, Offers and Offered Wages



(a) CDF: Job Interviews at Six Months



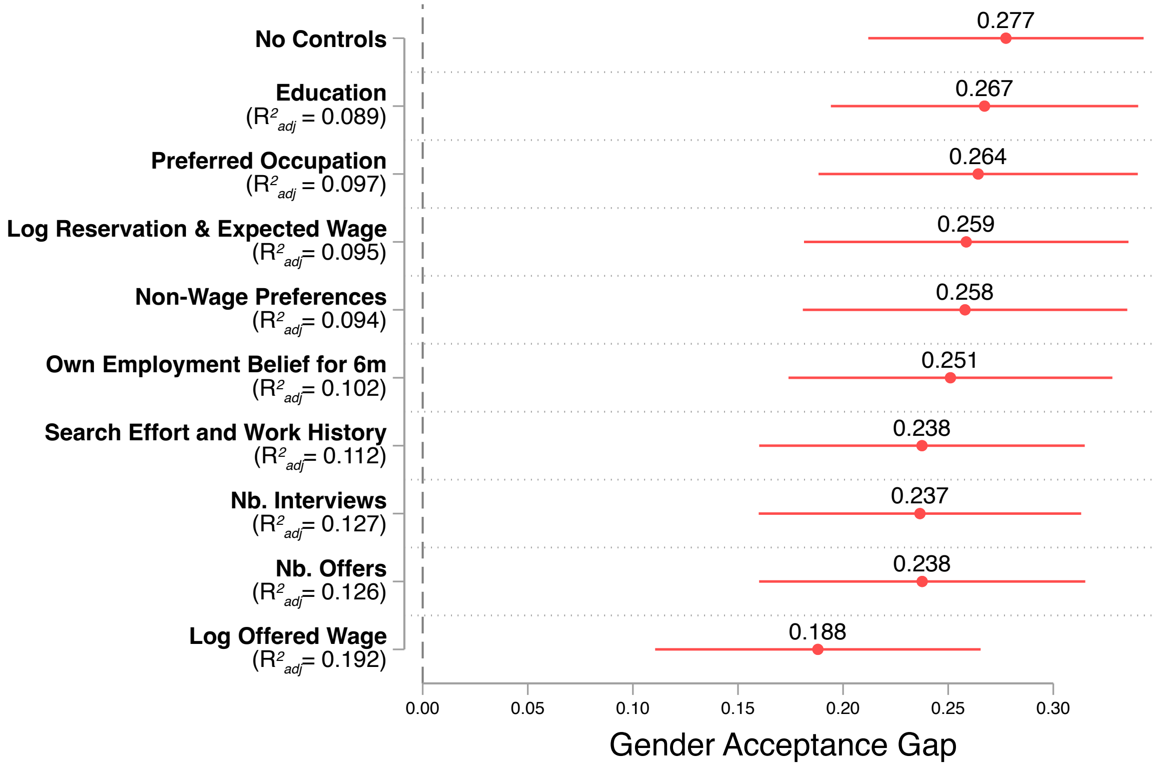
(b) CDF: Job Offers at Six Months



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

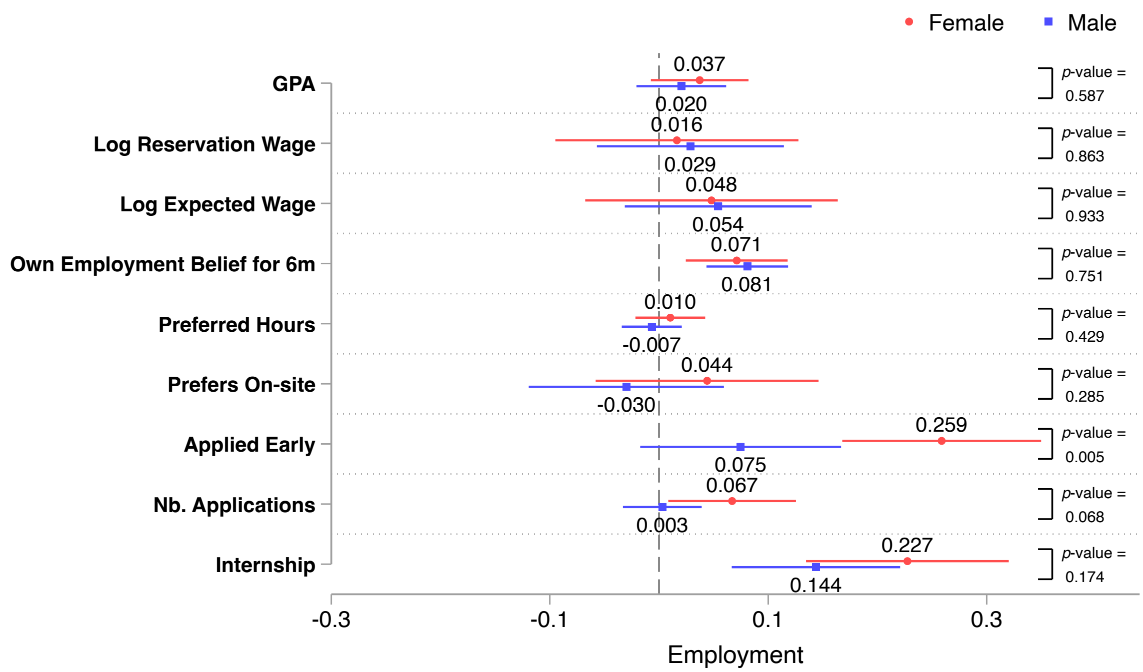
Notes: The figure presents the distribution of job interviews, job offers, and offered wages received by the six-month follow-up, separately for men (dashed blue) and women (solid red). The sample consists of respondents in the diagnostic sample (see Section II.A for details). Panel (a) shows the cumulative 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. Offered wage represents the highest wage offer a student has received for a job (regardless of whether they have accepted it). 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 raw difference in mean log offered wages between women and men. The residualized estimate in Panels (a) and (b) controls for cumulative GPA, major, preferred occupation, preference for onsite vs. remote work, number of preferred daily work hours, internship experience, reservation wage, and expected wage. The residualized estimate in Panel (c) controls for cumulative GPA, major, and preferred occupation. Number of interviews, number of offers, and offered wage are winsorized at the 2% level.

Figure A.11: Explaining the Gender Acceptance Gap Six Months After Graduation



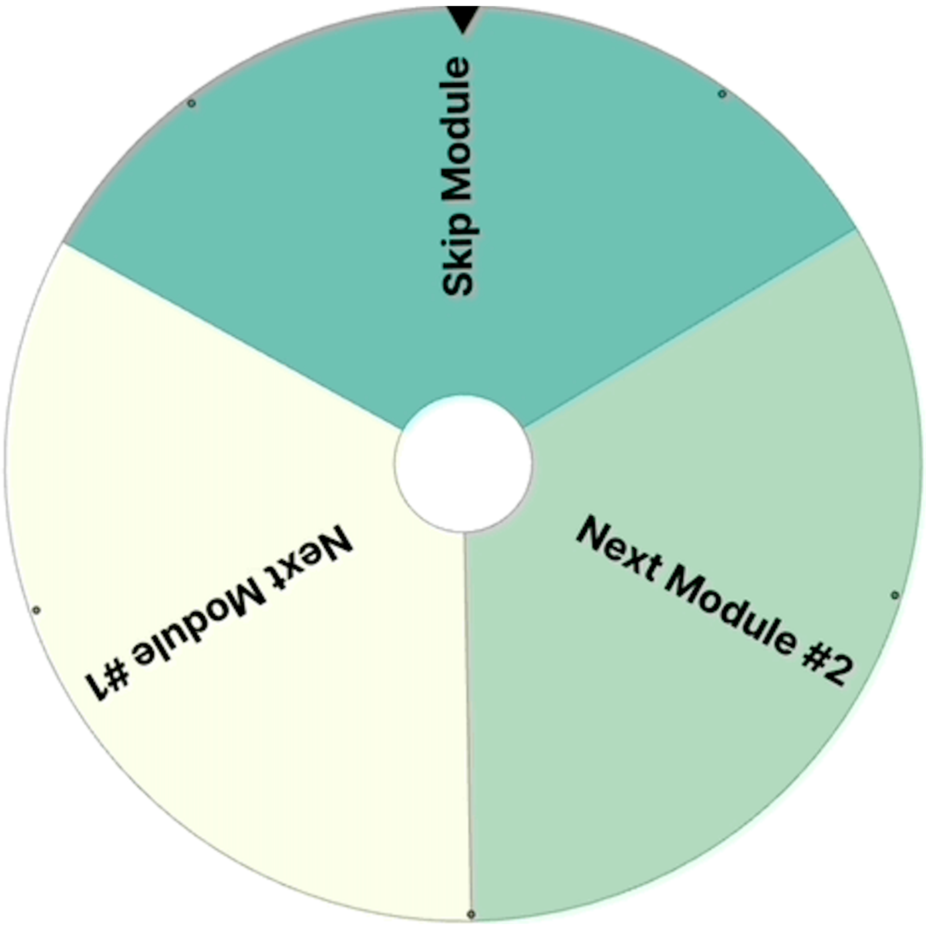
Notes: This figure shows the gender gap in job offer acceptance six months post-graduation and to what extent it can be explained by observable baseline characteristics. Each row reports the coefficients, 95% confidence intervals, and adjusted R-squared values from a regression of employment on gender and control variables in or above that row. The sample consists of respondents in the diagnostic sample (see Section II.A for details). Education controls include cumulative GPA and major fixed effects. Preferred Occupation controls include fixed effects derived from respondents' text-entry descriptions of the preferred job type at baseline, semantically mapped to Standard Occupational Classification (SOC) codes. Reservation and Expected Wage controls include baseline wage expectations. Non-Wage Preferences controls include baseline preferences regarding onsite vs. remote work and preferred daily work hours. Own Employment Belief for 6 Months control includes the baseline belief about one's own employment likelihood six months later. Search Effort and Work History controls include an indicator for applying early (i.e., having submitted at least one application by the two-month follow-up), the total number of job applications submitted by the six-month follow-up, and an indicator for internship experience. Nb. Interviews (Offers) control includes the number of interviews (offers) received by the six-month follow-up. Log Offered Wage control includes the highest log wage offer a student has received for a job (regardless of whether they have accepted it). To address missing values (e.g., if a student did not receive a job offer), we assign a constant (999) to missing entries and include a binary indicator in the regression. All unbounded continuous variables are winsorized at the 2% level. The mean acceptance rate for men is 72.4%.

Figure A.12: Timing Distinctively Predicts Women's Employment (Bivariate Estimates)



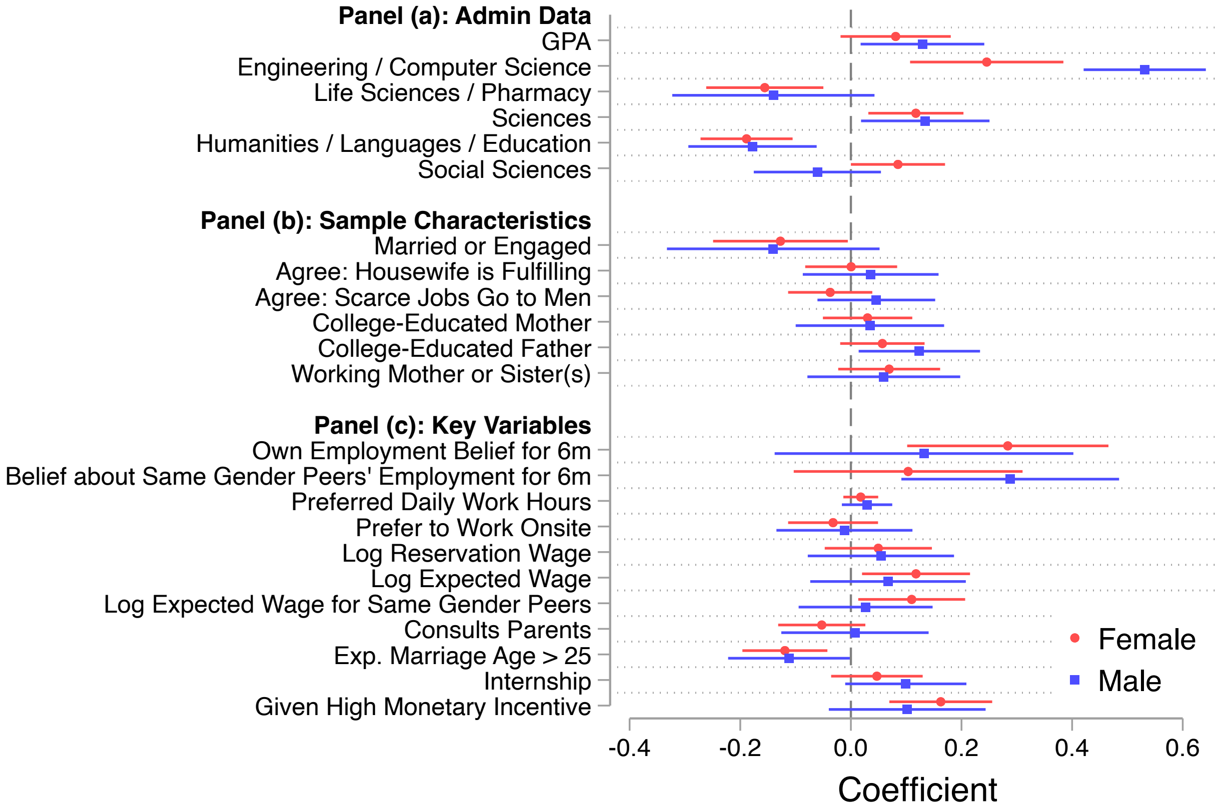
Notes: This figure presents results from regressing employment status six months post-graduation on a set of independent variables, separately for women (red) and men (blue). Each row reports the coefficient from a bivariate regression on the specified variable, without including other variables as controls. The sample consists of respondents in the diagnostic sample (see Section II.A for details). Independent variables include cumulative GPA (measured in standard deviations), log baseline reservation wage, log baseline expected wage, baseline belief about one's own employment likelihood (transformed onto a 0-1 scale and measured in standard deviations), preferred daily work hours, preference for onsite vs. remote work, an indicator for applying early (submitted at least one application by the two-month follow-up), total number of applications submitted by the six-month follow-up (measured in standard deviations), and an indicator for internship experience. All unbounded continuous variables are winsorized at the 2% level. Horizontal bars show 95% confidence intervals. Vertical brackets report p-values from testing equality of coefficients across gender. Corresponding means and standard deviations for the independent variables shown in the figure are provided in Table B.2. Figure IV presents the results of a multivariable regression where all other predictors of employment are included as controls.

Figure A.13: 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 IV.A 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.

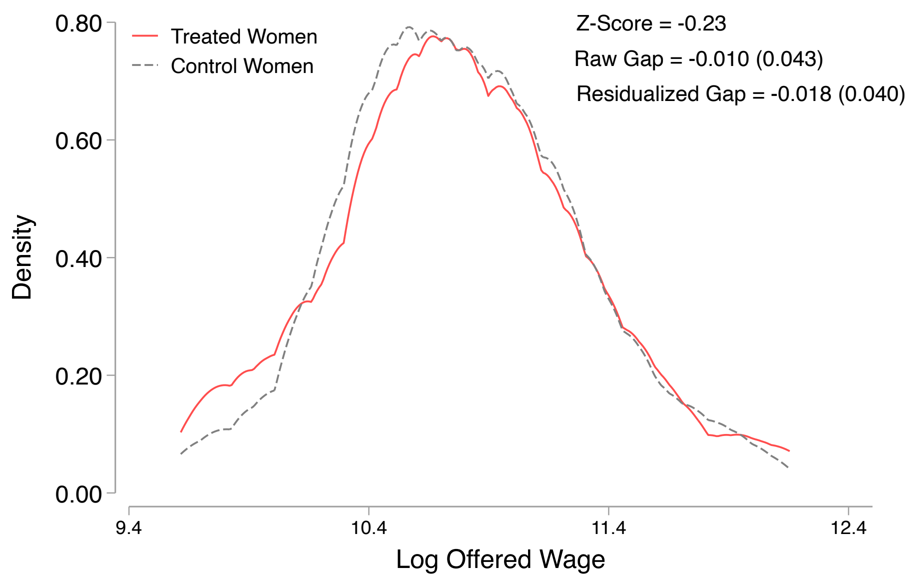
Figure A.14: Characteristics of the Treated



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 for women (red) and men (blue). Each coefficient comes from a bivariate regression of the variable specified on the left on an indicator for having taken up treatment. The sample consists of respondents in the six-month experimental sample (see Section IV.A for details). Panel (a) shows administrative data, such as GPA and college major. Panel (b) shows baseline 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 that may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, wage expectations, and whether the student was offered the higher monetary incentive. All unbounded continuous variables are winsorized at the 2% level. The horizontal bars show 95% confidence intervals.

Figure A.15: Wage Distribution for Treated and Control Women

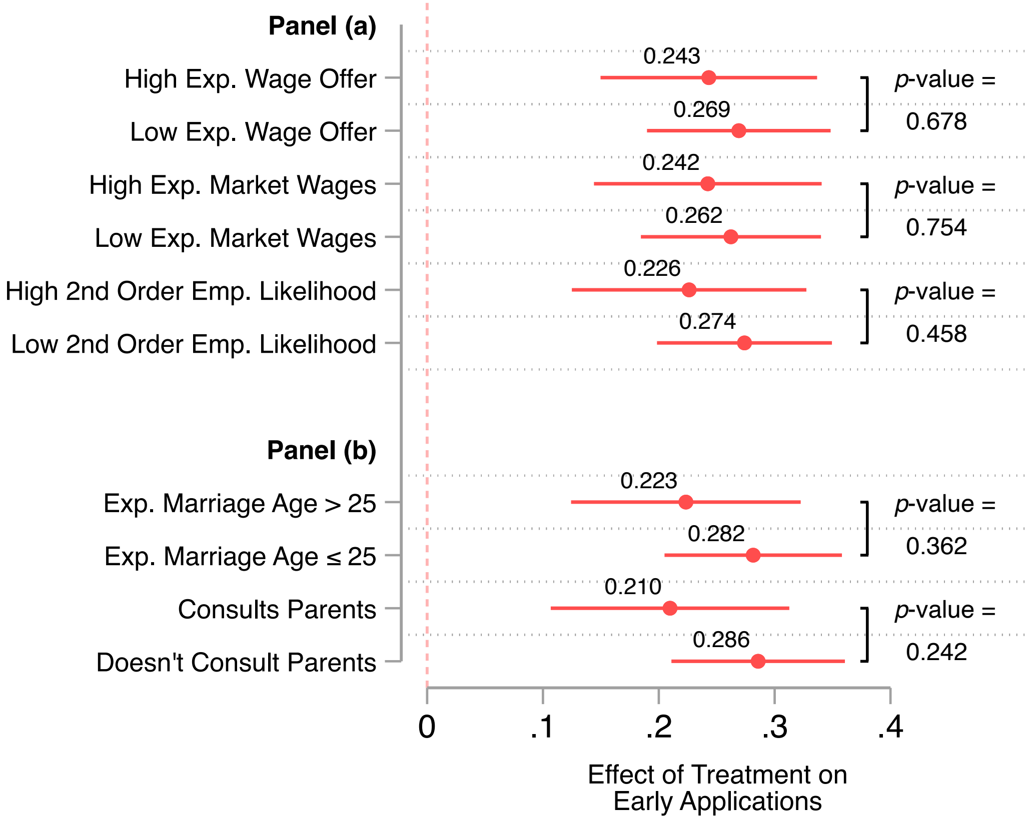
(a) Log Current Wage by Treatment



(b) Log Offered Wage by Treatment

Notes: This figure presents the distribution of current and offered wages for women, separately for treated (red) and control (gray) women. The samples consist of respondents in the pooled six-month and fourteen-month experimental samples (see Section IV.A for details) who provided a current or offered wage, respectively. Panel (a) shows the kernel density of log current wage, and Panel (b) shows the kernel density of log offered wage. Both panels show raw and residualized gaps, calculated as the treatment-control difference, and the z-score for the raw difference between treated women and control women. The residualized estimate controls for cumulative GPA, major, and preferred occupation. Current wage and offered wage are winsorized at the 2% level.

Figure A.16: 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 15th — the deadline for treated students to qualify for the financial reward. The analysis pools the six- and fourteen-month experimental samples (see Section IV.A for details). Panel (a) explores heterogeneity based on three baseline labor market beliefs: expected own wage offer, expected market wages, and belief about peers' employment likelihood. Each variable is split into "High" (above the median) and "Low" (below the median). Panel (b) explores heterogeneity based on baseline marital expectations and familial involvement in job search. Specifically, it includes whether respondents expect to marry after age 25 (the national median for college-educated women) and whether they have to consult their parents for job decisions. For each pair of subgroups, the coefficients come from regressing an indicator for applying early on treatment interacted with a subgroup indicator, with experimental wave fixed effects. Vertical brackets display p-values from testing equality between complementary subgroups. Standard errors are clustered at the individual level. The dashed red vertical line marks zero on the x-axis, while horizontal bars show 95% confidence intervals.

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.	1,493	1,029	464			910	583		
Panel A: Administrative Data									
Female	43.87	42.66	46.55	-3.89	0.16	42.53	45.97	-3.44	0.19
GPA	3.07	3.09	3.04	0.04	0.05	3.07	3.07	-0.00	0.81
Age	22.42	22.47	22.31	0.16	0.01	22.45	22.38	0.07	0.32
Majors:									
Engineering / Computer Science	25.18	26.24	22.84	3.39	0.32	24.40	26.42	-2.02	0.16
Life Sciences / Pharmacy	14.00	12.15	18.10	-5.96	0.01	12.64	16.12	-3.49	0.11
Sciences	13.33	13.22	13.58	-0.36	0.88	15.71	9.61	6.11	0.00
Humanities / Languages / Education	13.40	15.55	8.62	6.93	0.00	11.65	16.12	-4.48	0.02
Social Sciences	34.09	32.85	36.85	-4.01	0.10	35.60	31.73	3.87	0.15
Panel B: Survey Responses (Sample Characteristics)									
Married	4.29	4.28	4.31	-0.03	0.92	3.96	4.80	-0.85	0.51
Engaged	6.90	6.61	7.54	-0.93	0.58	6.37	7.72	-1.35	0.37
College-Educated Mother	41.06	41.01	41.16	-0.15	0.94	39.23	43.91	-4.68	0.07
College-Educated Father	54.19	53.16	56.47	-3.31	0.25	52.75	56.43	-3.68	0.17
Panel C: Survey Responses (Key Variables)									
Own Employment Belief for 6m	74.42	74.77	73.66	1.11	0.46	74.87	73.73	1.14	0.42
Belief about Female Peers' Employment for 6m	50.96	50.81	51.31	-0.50	0.76	50.91	51.04	-0.13	0.97
Preferred Daily Work Hours	6.39	6.39	6.39	-0.01	0.98	6.40	6.37	0.02	0.73
Prefer to Work Onsite	72.49	74.33	68.41	5.92	0.02	74.58	69.22	5.36	0.03
Reservation Wage	54.72	55.40	53.20	2.20	0.21	54.42	55.19	-0.77	0.41
Expected Wage	54.42	55.11	52.88	2.23	0.21	55.05	53.42	1.63	0.37

Notes: This table compares attritors and non-attritors in the diagnostic sample (see Section II.A 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 baseline survey responses about demographic background, such as marital status and parental education. Panel C shows baseline survey responses that may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. Column 1 reports the distribution of characteristics for the baseline 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 corresponding p-values from a test of equality, controlling for gender. Columns 6 through 9 show the same analyses as Columns 2 through 5, respectively, for the nine-month follow-up survey. All unbounded continuous variables are winsorized at the 2% level.

Table B.2: 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	10.71	0.42	10.90	0.46
Log Expected Wage	10.70	0.40	10.90	0.46
Preferred Daily Work Hours	6.40	1.41	6.38	1.42
Prefers On-site	0.74	0.44	0.75	0.43
Own Employment Belief for 6m	0.72	0.22	0.77	0.24
Applied Early	0.73	0.45	0.72	0.45
Nb. Applications	7.86	12.18	10.64	16.70
Internship	0.38	0.49	0.52	0.50

Notes: This table presents the mean and standard deviations for the diagnostic predictors of employment shown in Figure IV and Figure A.12, separately for female and male respondents. The sample consists of respondents in the diagnostic sample (see Section II.A for details). The predictor variables include cumulative GPA, log baseline reservation wage, log baseline expected wage, preferred daily work hours, preference for onsite vs. remote work, baseline belief about one's own employment likelihood (transformed onto a 0-1 scale), an indicator for applying early (submitted at least one application by the two-month follow-up), total number of applications submitted by the six-month follow-up, and an indicator for internship experience. All unbounded continuous variables are winsorized at the 2% level.

Table B.3: Experimental Sample Treatment Balance: Baseline, Six-Month, and Fourteen-Month Follow-Ups

	Baseline				**6m Follow-Up**				**14m Follow-Up**			
	Control	Treatment	Diff.	P-value	Control	Treatment	Diff.	P-value	Control	Treatment	Diff.	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nb. Obs.	939	1,008			688	754			582	636		
Panel A: Administrative Data												
Female	65.18	66.27	-1.09	0.61	63.08	65.25	-2.17	0.39	62.03	63.84	-1.81	0.51
GPA	3.31	3.31	0.00	0.92	3.32	3.33	-0.01	0.88	3.33	3.33	0.00	0.76
Majors:												
Engineering / Computer Science	8.20	6.45	1.75	0.14	7.56	6.63	0.93	0.48	8.08	6.60	1.47	0.32
Life Sciences / Pharmacy	12.67	11.90	0.77	0.58	13.08	12.20	0.88	0.58	13.92	10.85	3.07	0.11
Sciences	25.13	27.28	-2.15	0.27	25.15	28.78	-3.63	0.11	25.77	29.87	-4.10	0.11
Humanities / Languages / Education	28.01	26.09	1.92	0.34	28.49	24.27	4.22	0.07	27.49	23.90	3.59	0.16
Social Sciences	25.99	28.27	-2.29	0.26	25.73	28.12	-2.39	0.31	24.74	28.77	-4.03	0.11
Panel B: Survey Responses (Sample Characteristics)												
Married	4.37	5.36	-0.99	0.31	3.92	4.77	-0.85	0.43	3.95	4.40	-0.45	0.69
Engaged	5.01	3.87	1.14	0.21	4.65	3.18	1.47	0.14	4.30	3.30	0.99	0.36
College-Educated Mother	28.43	28.57	-0.14	1.00	27.62	28.12	-0.50	0.93	26.63	27.99	-1.36	0.66
College-Educated Father	43.98	42.56	1.42	0.50	43.17	42.18	0.99	0.64	41.75	40.57	1.19	0.63
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	80.43	80.26	0.16	0.94
Belief about Female Peers' Employment for 6m	51.23	50.70	0.52	0.54	51.15	50.08	1.07	0.28	51.37	49.91	1.47	0.19
Preferred Daily Work Hours	7.30	7.34	-0.03	0.46	7.29	7.36	-0.07	0.16	7.33	7.38	-0.05	0.37
Prefer to Work Onsite	69.29	67.49	1.80	0.43	69.95	67.81	2.14	0.45	70.14	66.83	3.31	0.26
Reservation Wage	53.48	52.52	0.96	0.42	53.02	52.72	0.30	0.92	52.56	52.57	-0.01	0.91
Expected Wage	62.03	60.54	1.49	0.26	62.47	60.85	1.63	0.33	62.34	61.10	1.24	0.49

Notes: This table compares treatment and control groups in the experiment. The first row reports the number of observations at baseline, in the six-month experimental sample, and the nine-month experimental sample, separately by treatment status (see Section IV.A for details). Panel A shows administrative data such as GPA, age, and college major. Panel B shows baseline survey responses about demographic background, such as marital status and parental education. Panel C shows baseline survey responses that may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. 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 corresponding p-values from a test of equality, 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. All unbounded continuous variables are winsorized at the 2% level.

Table B.4: 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.	1,947	1,442	505			1,218	729		
Percentage Treated	51.77	52.29	50.30	1.99	0.42	52.22	51.03	1.19	0.58
Panel A: Administrative data									
Female	65.74	64.22	70.10	-5.88	0.01	62.97	70.37	-7.40	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	22.71	0.03	0.92	22.71	22.76	-0.05	0.15
Majors:									
Engineering / Computer Science	7.29	7.07	7.92	-0.85	0.54	7.31	7.27	0.04	0.98
Life Sciences / Pharmacy	12.28	12.62	11.29	1.33	0.34	12.32	12.21	0.11	0.78
Sciences	26.25	27.05	23.96	3.09	0.19	27.91	23.46	4.46	0.04
Humanities / Languages / Education	27.02	26.28	29.11	-2.83	0.22	25.62	29.36	-3.74	0.07
Social Sciences	27.17	26.98	27.72	-0.75	0.73	26.85	27.71	-0.86	0.66
Panel B: Survey Responses (Sample Characteristics)									
Married	4.88	4.37	6.34	-1.97	0.11	4.19	6.04	-1.85	0.08
Engaged	4.42	3.88	5.94	-2.06	0.10	3.78	5.49	-1.71	0.12
College-Educated Mother	28.51	27.88	30.30	-2.42	0.48	27.34	30.45	-3.11	0.31
College-Educated Father	43.25	42.65	44.95	-2.30	0.47	41.13	46.78	-5.64	0.03
Panel C: Survey Responses (Key Variables)									
Own Employment Belief for 6m	79.76	80.30	78.20	2.10	0.08	80.34	78.78	1.56	0.18
Belief about Female Peers' Employment for 6m	50.96	50.59	52.00	-1.41	0.23	50.61	51.54	-0.93	0.43
Preferred Daily Work Hours	7.32	7.33	7.29	0.04	0.91	7.36	7.25	0.10	0.24
Prefer to Work Onsite	68.36	68.83	67.01	1.82	0.61	68.40	68.29	0.11	0.78
Reservation Wage	52.98	52.86	53.33	-0.47	0.42	52.56	53.68	-1.12	0.12
Expected Wage	61.26	61.62	60.23	1.40	0.62	61.69	60.54	1.15	0.83

Notes: This table compares attritors and non-attritors in the experiment. The first row reports the number of observations at baseline, in the six-month experimental sample, and the nine-month experimental sample, separately by attrition status (see Section IV.A for details). Panel A shows administrative data such as GPA, age, and college major. Panel B shows baseline survey responses about demographic background, such as marital status and parental education. Panel C shows baseline survey responses that may determine labor force participation, such as employment beliefs about oneself and others, work arrangement preferences, and wage expectations. Column 1 reports the distribution of characteristics for the baseline 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 corresponding p-values from a test of equality, controlling for gender. Columns 6 through 9 show the same analyses as Columns 2 through 5, respectively, for the fourteen-month follow-up survey. All unbounded continuous variables are winsorized at the 2% level.

Table B.5: 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*	0.092**
	(0.032)	(0.030)	(0.036)	(0.036)
Female Control Mean	0.336	0.253	0.518	0.413
Panel B: Male				
Treatment	0.006	0.023	-0.011	0.008
	(0.044)	(0.043)	(0.043)	(0.047)
Male Control Mean	0.551	0.374	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 respondents in the six-month (Columns 1 and 2) and fourteen-month (Columns 3 and 4) experimental samples (see Section IV.A for details). Panel A shows results for women, and Panel B shows results for men. Column 1 reports the treatment effect on employment at six months. Column 2 reports the treatment effect on firm 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 are estimated without controlling for the LASSO-selected variables (i.e., the only independent variables are gender, treatment, and their interaction). Control means are reported separately by gender for each outcome. The last row reports the number of observations. Table III shows the results with the LASSO-selected controls. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Assessing Selection into Treatment Take-up

	6 Months		14 Months	
	Working	**Working for Firm**	**Working**	**Working for Firm**
	(1)	(2)	(3)	(4)
Panel A: Female				
Offered Treatment and Took Up	0.136***	0.173***	0.116***	0.154***
	(0.037)	(0.036)	(0.039)	(0.040)
Offered but did not Take Up	0.002	0.019	0.005	0.007
	(0.038)	(0.036)	(0.046)	(0.045)
Female Control Mean	0.336	0.253	0.518	0.413
Panel B: Male				
Offered Treatment and Took Up	0.079	0.115**	0.041	0.082
	(0.051)	(0.053)	(0.045)	(0.052)
Offered but did not Take Up	-0.073	-0.069	-0.085	-0.094*
	(0.053)	(0.050)	(0.053)	(0.057)
Male Control Mean	0.551	0.374	0.719	0.561
Nb. Obs.	1,442	1,442	1,218	1,218

Notes: This table presents the effects of the treatment assignment on labor market outcomes, separately by whether the student was offered treatment and took it up or was offered treatment but did not take it up. The sample consists of respondents in the six-month (Columns 1 and 2) and fourteen-month (Columns 3 and 4) experimental samples (see Section IV.A for details). Panel A shows results for women, separately for the two groups, and Panel B does so for men. Column 1 reports the treatment effect on employment at six months. Column 2 reports the treatment effect on firm 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 reported separately by gender for each outcome. The last row reports the number of observations. Table III shows the same table with overall treatment effects rather than by take-up status. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: 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	0.083***	0.055*	0.084***	0.040
	(0.024)	(0.030)	(0.020)	(0.029)
Female Control Mean	0.786	0.656	0.877	0.777
Panel B: Male				
Treatment	0.027	0.012	0.021	-0.006
	(0.031)	(0.040)	(0.022)	(0.035)
Male Control Mean	0.842	0.672	0.936	0.840
Nb. Obs.	1,435	1,435	1,210	1,210

Notes: This table presents the treatment effects on job applications and job offers at the extensive margin. The sample consists of respondents in the six-month (Columns 1 and 2) and fourteen-month (Columns 3 and 4) experimental samples (see Section IV.A for details). 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 for at least one job at six months. Column 2 reports the treatment effect on a respondent's likelihood of receiving at least one job offer 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 reported separately by gender for each outcome. The last row reports the number of observations. There are fewer observations in this table relative to Table III because the analysis is limited to cases with non-missing values for the number of applications and offers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Distribution Across Top Three Occupation Groups by Gender and Treatment

	Treatment (1)	**Control** (2)	**Diff** (3)	**P-value** (4)
Panel A: Women				
Teaching and Education	22.05	22.67	-0.62	0.83
I.T. and Telecommunications	10.92	10.50	0.42	0.84
Marketing and Sales	8.95	7.88	1.08	0.57
Panel B: Men				
Teaching and Education	14.67	14.13	0.54	0.88
I.T. and Telecommunications	13.04	10.87	2.17	0.52
Marketing and Sales	7.61	9.24	-1.63	0.57

Notes: This table presents the three most common occupation groups at the fourteen-month follow-up, separately by gender and treatment status. The sample consists of respondents in the fourteen-month experimental sample (see Section IV.A for details) who are employed by the fourteen-month mark. Occupation grouping is based on Standard Occupational Classification (SOC) codes, semantically derived from respondents' text-entry descriptions of their current job title. Panel A shows the top three occupation groups for women, and Panel B shows the top three occupation groups 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 corresponding p-values from a test of equality.

Table B.9: Log Reservation Wages Over Time

	Log Reservation Wage
	(1)
Six Month Response	-0.145***
	(0.027)
Fourteen Month Response	-0.071**
	(0.033)
Treatment	-0.024
	(0.020)
Treatment × Six Month Response	-0.002
	(0.038)
Treatment × Fourteen Month Response	0.007
	(0.044)
Female Control Mean	3.867
Nb. Obs.	2,142

Notes: This table reports time trends and treatment effects of the experimental intervention on log reservation wages among female students. The sample is restricted to women who were observed in the baseline, six-month, and fourteen-month follow-up waves (see Section IV.A for details). Each observation is a person × wave response. The dependent variable is log self-reported reservation wage, constructed using two survey questions tailored to current employment status. For employed respondents, the survey asks how much less than their current salary they would be willing to accept if their current job were to shut down. Their reservation wage is computed as their current salary minus this amount. For unemployed respondents, the survey first asks them to imagine a full-time, on-site job in their field and estimate the wage they would be offered. It then asks how much less than this offer they would be willing to accept. Their reservation wage is calculated as the expected offer minus this stated amount. The specification includes indicators for the six- and fourteen-month follow-up waves, as well as interactions between treatment and wave. The baseline wave serves as the omitted category. Coefficients are estimated using the post-double-selection LASSO procedure. Control means are reported for the female control group in the baseline wave. The final row reports the number of observations used in the estimation. Standard errors are clustered at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Treatment Effects of the Experiment on Marriage Outcomes

	6 Months			14 Months	
	Married or Engaged	**Nb. Marriage Offers**	**Highly Educated Groom**	**Married or Engaged**	**Nb. Marriage Offers**
	(1)	(2)	(3)	(4)	(5)
Treatment	0.011	0.059	0.007	0.024	-0.083
	(0.021)	(0.162)	(0.034)	(0.030)	(0.311)
Female Control Mean	0.098	1.545	0.293	0.175	3.266
Nb. Obs.	806	752	741	697	594

Notes: This table presents the treatment effects on marriage outcomes. The sample consists of women in the six-month (Columns 1 to 3) and fourteen-month (Columns 4 and 5) experimental sample (see Section IV.A for details), excluding those who are already married or engaged at baseline. Column 1 reports the treatment effects on being married or engaged by the six-month follow-up. Column 2 reports the treatment effects on the number of marriage offers received by the six-month follow-up. Column 3 reports the treatment effects on whether the highest education level among all received offers is a Master's degree or higher, which proxies the quality of marriage offers. Columns 4 and 5 report 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. All regressions control for the variables selected following the post-double-selection LASSO procedure. The last two rows report the female control mean and the number of observations. The number of marriage offers is winsorized at the 2% level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 I to III hold when produced using the control group in our experimental sample.[37] 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 I 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: 79.8% of women and 81.6% of men expect to be employed within six months of graduation. The modest gender gap in expectations (1.8 pp) is comparable to the gap in the diagnostic sample (5.2 pp), 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–46.2 pp below their expectations, and 21.5 pp 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 pp below their average baseline expectations and 27.3 pp 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 I 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 (0.52 for women and 0.62 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 estimated, due to a smaller sample size, which results from restricting our analysis to the control group.

Figure C.2 compares the baseline employment beliefs about self and peers in the experimental sam-

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

ple, replicating insights from Figure II. 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 beliefs reported in the diagnostic sample (50.2% by men and 51.6% by women).

Figure C.3 follows Figure III 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 27.3 pp. In the control group of the experimental sample, the employment gap is smaller but still substantially large at 21.5 pp. As in Figure III Rows 2 to 6, gradually adding controls for education (GPA and major), preferred occupation, reservation and expected wage, preferences for work hours and remote work, and baseline beliefs about own employment prospects reduces the employment gap in the control group of the experimental sample only modestly, by 4.9 pp. Adding controls for job search effort and work history (Row 7) further narrows the gap by just 0.9 pp. Finally, gender disparities in employment remain similar even after accounting for demand-side factors (number of interviews, job offers, and offered wages; Rows 8 to 10), with the residual gap at 16.0 pp. Taken together, these controls only reduce the raw gap by 5.5 pp. This is similar to the diagnostic sample, where the gap shrinks from 27.3 pp to 24.4 pp (2.9 pp), 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.

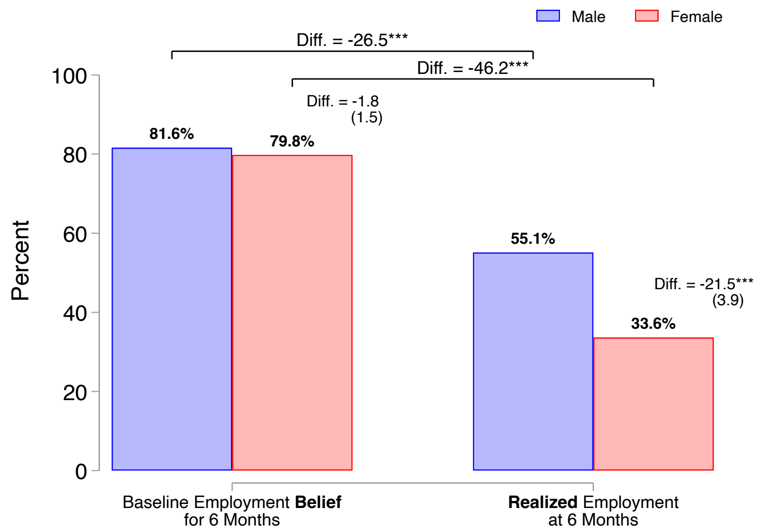
Beyond replication of the patterns already documented at the private university, we collect additional data at the public university in support of the fact that women at the time they graduate from college *want* to work. First, we explicitly ask women at baseline if they want to work on a paid basis within six months of graduation.[38] Of the women surveyed, 97.6% reported that they want to be working six months after graduation. We also ask women who reported less than a 100% likelihood of

38. The exact question was: "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?"

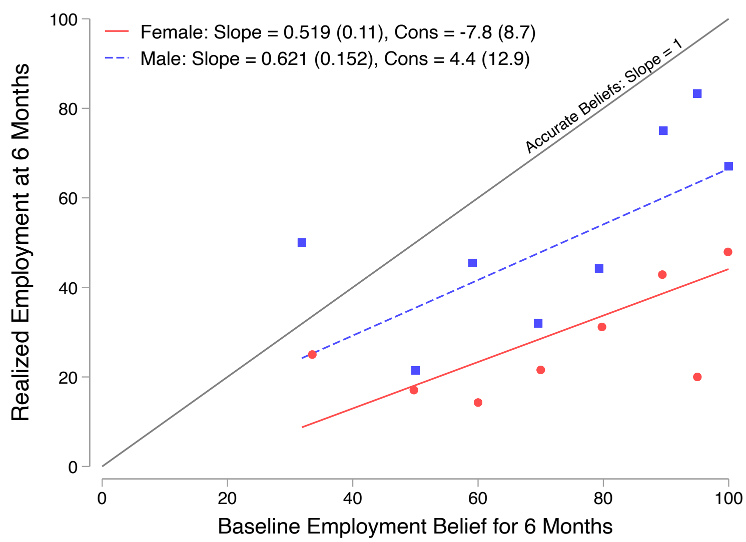
working within six months, why they think they may not work. The first panel of Figure X titled "Self" reports the distribution of their responses. The most prevalent barrier, cited by 37% of women, was poor macroeconomic conditions that may limit job availability. Importantly, only 9% told us that they 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 X 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 II, most families own all of these assets, but there is more variation in car ownership across households. Accordingly, Figure C.4 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 (79.6% and 78.7%). 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.

External Validity Figures

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



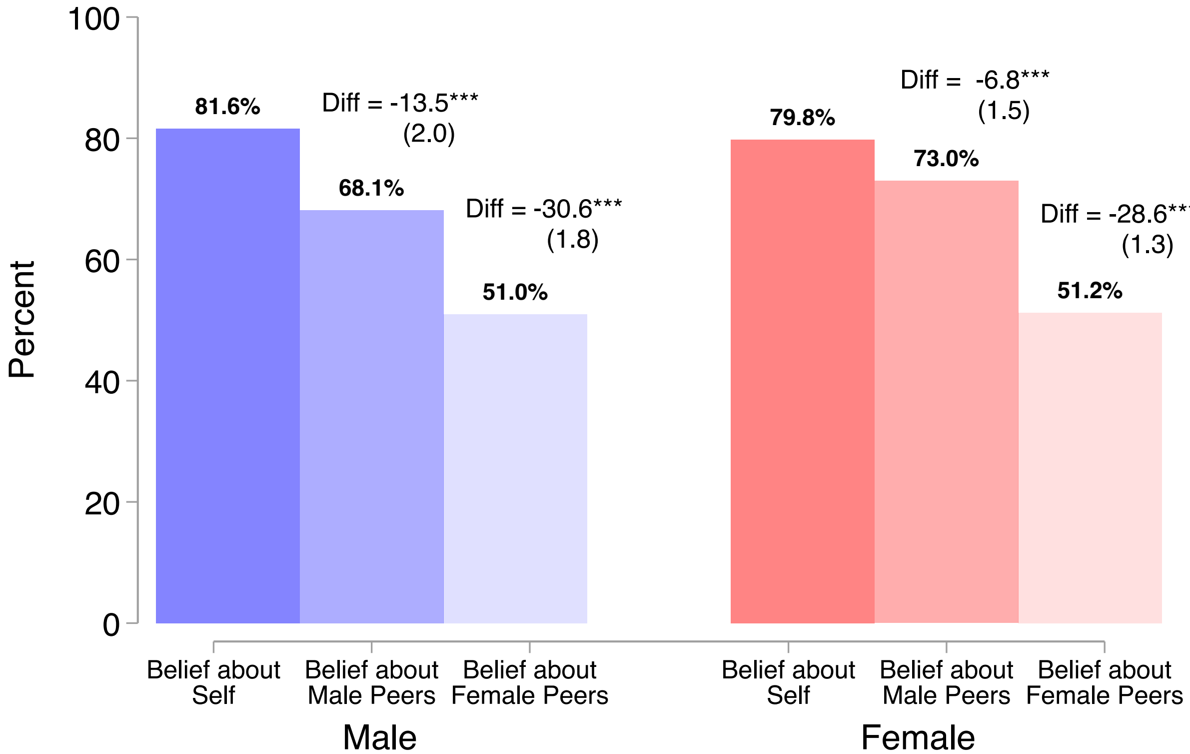
(a) Mean Levels: Expected vs. Realized Employment



(b) Binned Scatter: Expected vs. Realized Employment

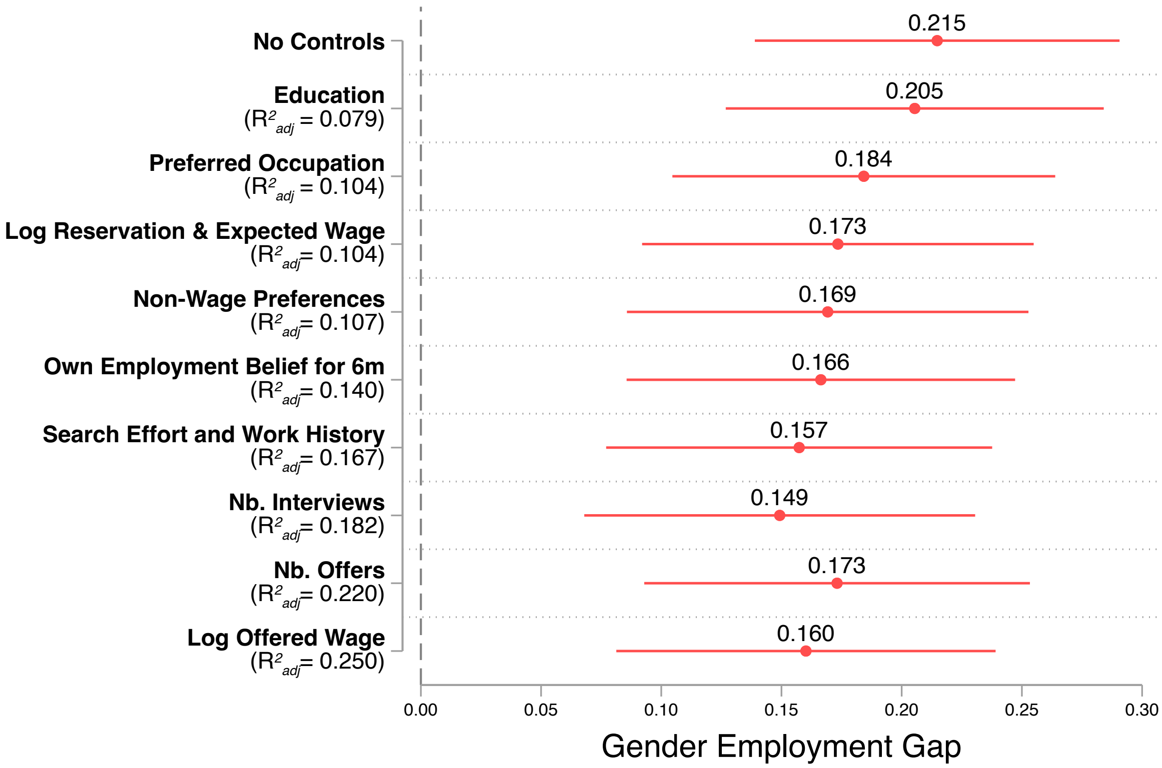
Notes: This figure replicates Figure I using data from the control group of the six-month experimental sample (see Section IV.A for details). Panel (a) contrasts students' average baseline belief about their employment likelihood six months post-graduation (left pair of bars) with their realized employment at the six-month mark (right pair of bars), separately for men (blue) and women (red). Gender gaps in responses are shown directly above the female bar. Average within-gender differences between baseline beliefs and realized employment are shown above the horizontal brackets. Panel (b) shows a binned scatter plot of baseline employment beliefs against realized employment, separately for men (blue) and women (red). The solid 45-degree line represents accurate beliefs, points above (below) which indicate underestimation (overestimation) of employment chances. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.2: Employment Beliefs about Self vs. Peers: Experiment Control Sample



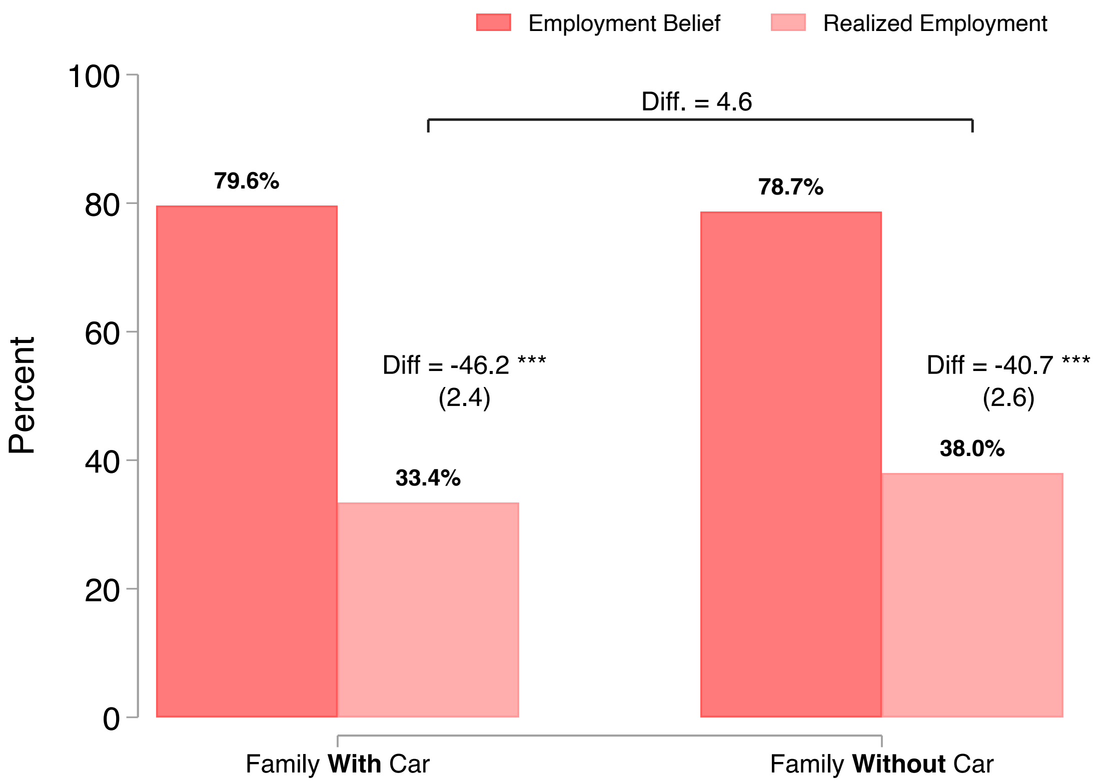
Notes: This figure replicates Figure II using data from the control group of the six-month experimental sample (see Section IV.A for details), contrasting respondents' average baseline beliefs about their own employment prospect six months post-graduation, versus beliefs about their peers' employment prospect. Male (female) responses are represented by the blue (red) cluster of bars on the left (right). The leftmost bar in each cluster (bars 1 and 4) shows average baseline beliefs about one's own employment likelihood. The middle bar in each cluster (bars 2 and 5) shows beliefs about male peers' employment likelihood. The rightmost bar in each cluster (bars 3 and 6) shows beliefs about female peers' employment likelihood. The average differences between beliefs about oneself and beliefs about male (female) peers are reported above the middle (rightmost) bar in each cluster. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.3: Explaining the Gender Employment Gap: Experiment Control Sample



Notes: This figure replicates Figure III using data from the control group of the six-month experimental sample (see Section IV.A for details). Each row reports the coefficients, 95% confidence intervals, and adjusted R-squared values from a regression of employment on gender and control variables in or above that row. Education controls include cumulative GPA and major fixed effects. Preferred Occupation controls include fixed effects derived from respondents' text-entry descriptions of the preferred job type at baseline, semantically mapped to Standard Occupational Classification (SOC) codes. Reservation and Expected Wage controls include baseline wage expectations. Non-Wage Preferences controls include baseline preferences regarding onsite vs. remote work and preferred daily work hours. Own Employment Belief for 6 Months control includes the baseline belief about one's own employment likelihood six months later. Search Effort and Work History controls include an indicator for applying early (i.e., having submitted at least one application by the two-month follow-up), the total number of job applications submitted by the six-month follow-up, and an indicator for internship experience. Nb. Interviews (Offers) control includes the number of interviews (offers) received by the six-month follow-up. Log Offered Wage control includes the highest log wage offer a student has received for a job (regardless of whether they have accepted it). To address missing values (e.g., if a student did not receive a job offer), we assign a constant (999) to missing entries and include a binary indicator in the regression. All unbounded continuous variables are winsorized at the 2% level.

Figure C.4: Employment Beliefs and Realized Outcomes by Wealth



Notes: This figure examines heterogeneity by family 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 IV.A for details). Women whose families own (do not own) a car are represented by the left (right) pair of 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D Variable Construction

This section details the construction of variables requiring modifications from the raw survey data. Unless noted, the construction for diagnostic and experimental samples is identical. Variables appear alphabetically. All continuous variables are winsorized at the 2% level. When the variable has a clear lower bound and data entry errors are not possible (e.g. the number of applications is bounded by 0 and the survey was coded such that negative values could not be logged), we only winsorize at the upper end, not the lower end. Complete question text, response constraints, and conditional logic are detailed in the accompanying survey instrument.

D.I Labor Market Outcomes:

- **Working**: Respondents are directly asked whether they are currently working in a paid capacity. This yes/no response forms the basis of the binary employment indicator used in our analysis.[1] We also consider a respondent to be working if they tell us they are working in a family business.

- **Working for Wage at a Firm:** We create a separate version of the **Working** indicator that captures whether the respondent is doing paid work for a firm. This indicator is coded as zero for respondents who are working but not receiving a wage, as well as those who report working as freelancers, in their own business, or in a family business.

- **Cumulative Number of Job Applications:** In each survey wave after baseline, we ask respondents how many job applications they have submitted since graduation. Additionally, at the six- and fourteen-month follow-ups, we collect information on recent applications, asking about the number of applications sent in the past month (at the six-month follow-up) and in the past six months (at the fourteen-month follow-ups). Because these responses rely on recall, respondents may sometimes report a lower cumulative number of applications in a later wave than they did in an earlier wave. When this occurs, we update the later wave's response to match the previously reported higher value. Similarly, if the reported cumulative applications since graduation in a given wave is lower than the sum of the previously reported cumulative total and the number of applications the respondent says they have submitted

1. The only exception is the baseline survey for the experimental sample. In this survey, we construct the yes/no binary indicator for "working" from a question on the current work status of respondents. Response options include: (1) accepted a paid job or internship; (2) already working in a paid job or internship; (3) starting their own business; (4) already started their own business; (5) agreed to work in a family business; (6) already working in a family business; and (7) none of these. We classify respondents as employed if they select any option from (1) through (6).

recently, we update their cumulative total accordingly.

- **Cumulative Number of Job Offers:** We apply the same correction process to this variable as we do for **Cumulative Number of Job Applications**, meaning if a respondent reports fewer total job offers in a later wave than in an earlier one, we update the later value to match the previously reported higher value. Similarly, if the reported cumulative offers in a given wave are lower than the sum of previously reported number of recent offers, we adjust the cumulative count accordingly. Additionally, if a respondent does not report a value for number of job offers at a given survey wave, but tells us they have sent no job applications and are not working, we impute zero job offer for that survey wave. Conversely, if a respondent is working in a firm, but is either missing a value for job offers or says they have received zero job offers, we impute the value of job offers to equal one.

- **Accepted Job Binary:** At each survey wave, we compare a respondent's **Cumulative Number of Job Offers** with whether or not the respondent is currently **Working**. If a respondent has received at least one job offer and is currently employed, we classify them as having accepted a job offer.

- **Date of First Job Application:** We ask students in the experimental sample at the six- and fourteen-month follow-ups what date they sent their first job application after graduation. If a student only recalls the month, we impute the day to be the 15th of the month, since that is the midpoint. To minimize noise from limited recall, we take their six-month follow-up value for date of earliest application, and only take the fourteen-month value if the six-month value is missing.

- **Applied Early Binary:** In the diagnostic sample, we create this indicator from **Cumulative Number of Job Applications**, considering a respondent to have applied early if they sent at least one application by the two-month follow-up. In the experimental sample, we consider a respondent to have applied early if they sent their first job application by the August 15th deadline to receive the treatment incentive (hence, we construct the variable from **Date of First Job Application:**). Our definition in the experimental sample is more precise (uses a date of application rather than the number of applications at the first follow up) because, in the experimental sample, we added a question on when the respondent sent their first application, which we did not ask in the diagnostic sample. We picked August 15th as the "apply early" because it matched our application deadline for the financial reward.

- **Current Occupation:** During each survey wave, enumerators ask students that are currently working for their job title. After applying standard cleaning procedures to the text responses (e.g., converting to lowercase, removing stop words, etc.), we use the Python package `occupationcoder` (Turrell et al. 2019) to automatically classify titles into two and three-digit Standard Occupational Classification (SOC) sub-major groups as categorized by the United Kingdom's Office for National Statistics (ONS). [2] We perform some manual adjustments to ensure accurate updates to work-related outcomes: if the cleaned job title includes apprenticeship-related keywords (e.g., "trainee"), we recode the SOC job title category as "Apprenticeship"; if the title suggests the respondent is not currently working (e.g., "continuing study"), we recode the SOC job title category to missing; if the title indicates freelance work, we assign the category "Freelancer" .

- **Offered Wage:** We code a respondent's offered wage to be equal to the highest wage offer they have received in any earlier or current survey wave. At wave three, the offered wage is the highest offer reported in survey waves 1-3. At wave four, the offered wage is the highest offer reported in survey waves 1-4.

D.II Labor Market Beliefs and Expectations:

- **Own Employment Beliefs:** On a scale of 0–100, respondents are asked to estimate the likelihood that they will be employed in six months. The only alteration we make to the raw questionnaire response is that, if a respondent is already working at baseline but does not provide a probability of working in six months (1.5% of diagnostic sample respondents), we impute 100 for their answer. No such respondents are present in the experimental sample.

- **Employment Beliefs about Peers**: Respondents are asked to estimate the likelihood that their female and male peers will be employed in six months, stating how many (male/female) classmates out of 10 random (male/female) classmates will be employed in six months. We multiply these responses by 10, so that the scale is the same as questions about one's own employment beliefs.

- **Preferred Occupation:** We ask students at baseline what job title they would be most interested in if they have to work for a firm. After applying standard cleaning procedures to the text responses (e.g., converting to lowercase, removing stop words, etc.), we use the Python package `occupationcoder` (Turrell et al. 2019) to automatically classify titles

2. This is different from the U.S. Standard Occupational Classification (SOC) system.

into two and three-digit Standard Occupational Classification (SOC) sub-major groups as categorized by the United Kingdom's Office for National Statistics (ONS). For example, a student that says they would like to become a forensic scientist will be mapped to SOC three-digit-code 211 (Natural and Social Science Professionals) and two-digit code 21 (Science, research, engineering and technology professionals). We use the two-digit SOC code as a control for preferred occupation in our analysis.

- **Preferred Work Hours:** Respondents in the experimental sample are directly asked how many hours per day they would prefer to work. In the diagnostic sample, this question is not asked. Instead, we ask a binary question about whether they would rather work full or part time. To harmonize this measure across samples, we impute preferred daily work hours in the diagnostic sample based on their stated preference for full-time or part-time work, assigning eight hours for full-time preferences and five hours for part-time.

- **Reservation Wage:** At baseline, respondents report their reservation wage for various work arrangements (full-time onsite, part-time onsite, full-time remote, and part-time remote), along with their expected wage offer for a full-time onsite job for their preferred job title. To create a standardized reservation wage variable that allows for comparisons across respondents, we use their reported full-time onsite reservation wage if available (which is the case for 96.8% of the diagnostic sample and 99.9% of the experimental sample). If this value is missing, we substitute their full-time remote reservation wage. If neither full-time wage is provided but a part-time onsite wage is available, we scale it to a full-time equivalent by multiplying by (40/25), assuming a 25-hour part-time workweek. If all previous values are missing but a part-time remote wage is available, we similarly adjust it to a full-time equivalent by multiplying by (40/25). In later survey waves, we calculate a respondent's reservation wages depending on whether the respondent is working or not. Respondents who are working report their current wage and are asked how much less than their current wage they would accept for their current job. The first minus the second object yields the reservation wage in that wave. Respondents who are not working report their updated expected wage offer for a full-time, onsite job and how much less than the expected offer they would accept for the role. Here as well, the first minus the second object yields the reservation wage in that wave.

- **Reasons Not to Work:** In the experimental sample, we construct two sets of variables capturing reasons for potential non-employment, based on respondents' open-ended answers to survey questions. The first set pertains to women's beliefs about their own future employment: women who report less than 100% likelihood of working in six months are asked why they think there is a chance they may not work. The second set pertains to respondents' beliefs about their peers: women who believe that fewer than 10 out of 10 randomly selected female peers will be employed in six months are asked why they think their classmates may not work. In both cases, respondents provide open-ended responses, which enumerators categorize using a predefined list of answer options. Enumerators are permitted to select multiple options or enter responses under an "Other" category. The mapping of answers to the categories used in Figure X is shown in Table D.1.

D.III Marriage Market Variables:

- **Expected Age of Marriage:** Respondents are asked to estimate the number of months/years until they expect to get married at each survey wave. If the response is given in months, we convert to years by dividing by 12 and add it to their baseline age to calculate their expected age at the time of marriage. In follow-up waves, if a respondent transitions from not being married in a prior wave to being married in the current wave, we assume marriage occurred midway between the two waves and impute marriage age accordingly. For example, if a respondent is newly married at the six-month follow-up after not being married at baseline, we assign their marriage age as baseline age plus 0.25 years (i.e., three months). If marriage occurs between later waves, we assign increments of 0.375, 0.625, or 0.75 years depending on the timing.

- **Marriage Offers Received:** In each survey wave except the fourteen month one, we ask respondents how many marriage proposals they have received since graduating. In the fourteen-month follow-up for the experimental sample, to avoid poor recall, we ask how many proposals they have received in the past six months and add it to their six-month response (acknowledging there is a two months gap in that sum but that is the same for control and treatment). To ensure consistency across survey waves, we apply the same approach used for **Cumulative Number of Job Applications** and **Cumulative Number of Job Offers**: if a respondent reports fewer cumulative marriage proposals in a later wave than in an earlier wave, we update the later response to match the previously reported higher value.

D.IV Other Constructed Variables:

- **Undergraduate Majors:** To summarize respondents' fields of study in our balance tables, we create binary indicators for each major category after mapping the students' majors into generalized categories (see Tables D.2 and D.3 for the majors corresponding to each general category in the diagnostic and experimental sample, respectively).[3]

Variable Construction Tables

Table D.1: Mapping of Responses About Reasons Not to Work to Categories

Raw Response	**Classified Category**
Jobs are scarce due to poor economic conditions	Poor macroeconomic conditions
I may not get permission from family to work	Family reasons
Other women may not get permission from family to work	Family reasons
I am having a baby/getting married/focusing on family	Family reasons
Other women get married and have kids soon after graduation	Family reasons
I want to keep studying	Pursuing higher education
Other women are pursuing further studies	Pursuing higher education
I may not want to work	May not want to work
Other women may not want to work	May not want to work
Firms don't want to hire women / harder for women to find a job	Firms don't hire women
Other	Other

Notes: This table categorizes responses explaining why respondents or their peers may not be working, mapping them into predefined categories. For additional details, see Section D.

3. Majors are obtained from administrative data from the universities.

Table D.2: Diagnostic Sample: Mapping of Majors to General Major Categories

General Major Category	**Corresponding Majors**
Engineering / Computer Science	
	Bachelor of Science in Civil Engineering
	Bachelor of Science in Computer Science
	Bachelor of Science in Electrical Engineering
	Bachelor of Science in Mechanical Engineering
	Bachelor of Science in Software Engineering
Humanities, Languages and Education	
	Bachelor of Science in English
	Bachelor of Science in Media
Life Sciences / Pharmacy	
	Bachelor of Science in Botany
	Bachelor of Science in Food Science and Technology
	Bachelor of Science in Zoology
Sciences	
	Bachelor of Science in Biochemistry
	Bachelor of Science in Biotechnology
	Bachelor of Science in Chemistry
	Bachelor of Science in Mathematics
	Bachelor of Science in Microbiology
	Bachelor of Science in Physics
Social Sciences (inc. Business and Law Degrees)	
	Bachelor of Laws (LLB)
	Bachelor of Business Administration (BBA)
	Bachelor of Science in Accounting and Finance
	Bachelor of Science in Commerce
	Bachelor of Science in Economics
	Bachelor of Science in International Relations
	Bachelor of Science in Psychology

Notes: This table maps the majors offered at the diagnostic university into five general categories: (1) Engineering and Computer Science, (2) Humanities, Languages, and Education, (3) Life Sciences and Pharmacy, (4) Sciences, and (5) Social Sciences (including Business and Law degrees). The general major classification, along with its binary indicators, is used as a control variable throughout our analyses. For further details, see Section D.

Table D.3: Experimental Sample: Mapping of Majors to General Major Categories

General Major Category	Corresponding Majors
Engineering / Computer Science	
	Bachelor of Science in Architecture
	Bachelor of Science in Computer Sciences
	Bachelor of Science in Electrical Engineering
	Bachelor of Science in Information Technology
	Bachelor of Science in Software Engineering
	Bachelor of Science in Technology Education
Humanities, Languages and Education	
	Bachelor of Science in Arabic
	Bachelor of Science in Communication Studies
	Bachelor of Science in English
	Bachelor of Science in English (Applied Linguistics)
	Bachelor of Science in French
	Bachelor of Science in Gender Studies
	Bachelor of Science in Graphic Design
	Bachelor of Science in History
	Bachelor of Science in Islamic Studies
	Bachelor of Science in Kashmiryat
	Bachelor of Science in Painting
	Bachelor of Science in Persian
	Bachelor of Science in Philosophy
	Bachelor of Science in Physical Education
	Bachelor of Science in Punjabi
	Bachelor of Science in Special Education
	Bachelor of Science in Urdu
	Bachelor of Science in Education
Life Sciences / Pharmacy	
	Bachelor of Science in Agriculture
	Bachelor of Science in Agricultural Food Science and Technology
	Bachelor of Science in Botany
	Bachelor of Science in Pharmacy
Sciences	
	Bachelor of Science in Applied Geology
	Bachelor of Science in Chemical Engineering
	Bachelor of Science in Environmental Sciences
	Bachelor of Science in Geography
	Bachelor of Science in Information Management
	Bachelor of Science in Mathematics
	Bachelor of Science in Microbiology and Molecular Genetics
	Bachelor of Science in Molecular Biology
	Bachelor of Science in Physics
	Bachelor of Science in Space Science
	Bachelor of Science in Statistics
Social Sciences (inc. Business and Law Degrees)	
	Bachelor of Science in Applied Psychology
	Bachelor of Science in Business Information Technology
	Bachelor of Science in Commerce
	Bachelor of Science in Criminology
	Bachelor of Science in Economics
	Bachelor of Science in Management
	Bachelor of Science in Political Science
	Bachelor of Science in Sociology

Notes: This table maps the majors offered at the diagnostic university into five general categories: (1) Engineering and Computer Science, (2) Humanities, Languages, and Education, (3) Life Sciences and Pharmacy, (4) Sciences, and (5) Social Sciences (including Business and Law degrees). The general major classification, along with its binary indicators, is used as a control variable throughout our analyses. For further details, see Section D .

E Survey Instrument

Unless noted, all questions in the baseline survey and the six-month survey were asked to both the diagnostic and experimental samples. The fourteen-month survey was fielded only for the experimental sample. In the interest of space, we list here relevant questions for the analysis presented in this paper. We do not provide the instrument for the nine-months survey in the diagnostic sample because it is very similar to the six-months ones and only a small part of the analysis draws on this wave.

Contents

I Enumerator Guidelines

For multiple-select questions aimed at identifying reasons or motivations, enumerators were told not to read out answer choices. Instead, they were asked to listen to the respondent and select the option that best matched the response. If none applied, "Other" could be selected. The answer choices for these questions are marked with boxes in the questionnaire below, while questions requiring only one response use circles.

For wage questions, enumerators were told to reassure respondents that responses would remain confidential and will be used only for research, and to record amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Enumerators also reminded respondents they could skip any question they found uncomfortable, specifically when introducing questions about wages and a respondent's marriage market decisions.

II Baseline Surveys

Consent Script

My name is {Enumerator's Name}.

Your university is collaborating with the London School of Economics (LSE) and the Massachusetts Institute of Technology (MIT) to understand the future plans of the graduating students.

This will allow the university to provide better counseling to our students in the future, and keep in touch with the alumni. Participating in this survey is totally up to you.

Answering these questions will take you approximately 20 minutes. All survey participants will be offered a KFC meal and dessert from Layers.

The information provided by you will remain strictly confidential. Your name will never be published in any report. The published results of the survey will be a compilation of information of hundreds of people.

If any question makes you uncomfortable, you can skip it or stop talking with me at any time. If you have any more questions about this research, you can contact sticerd@lse.ac.uk.

Do you agree to participate in the survey?

- ○ Yes
- ○ No

Basic Information

Q1

How old are you?

Q2

What is your gender?

◯ Male

◯ Female

Q3

What is your marital status?

◯ Never married

◯ Divorced

◯ Separated

◯ Widowed

◯ Married

◯ Engaged

Q4

Are you enrolled in or admitted to a higher education program (e.g., masters, PhD) that you plan to attend right after graduation?

◯ Yes

◯ No

Note: *Respondents in the experimental sample who answered 'Yes' were screened out of the survey.*

Q5

Will you graduate this summer?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample. Respondents who answered 'No' were screened out of the survey.*

Q6

Condition: Asked if Q5 = "Yes"

When will you graduate from your program?

Enumerator: Enter ***month*** *and* ***year*** *of graduation*

Note: *This question was asked only to the experimental sample.*

Q7

Condition: Asked if Q3 != "Never Married" or "Engaged"

Do you have children?

○ Yes

○ No

Q8

Have you already accepted a paid job/internship/business opportunity, or are you currently working in a paid job/business/internship?

○ Accepted a paid job/internship

○ Already working in a paid job/internship

○ Starting own business

○ Already started own business

○ Agreed to work in family business

◯ Already working in family business

◯ None of the above

Note: *This question was asked only to the experimental sample.*

Q9

Condition: Asked if Q8 = "Already working in a paid job/internship" or "Already started own business" or "Already working in family business"

When did you start working?

*Enumerator: Enter **month** and **year***

Note: *This question was asked only to the experimental sample.*

Q10

Condition: Asked if Q8 = "Accepted a paid job/internship" or "Starting own business" or "Agreed to work in family business"

When will you start working?

*Enumerator: Enter **month** and **year***

Note: *This question was asked only to the experimental sample.*

Q11

Condition: Asked if Q8 = "Accepted a paid job/internship" or "Already working in a paid job/internship" or "Already started own business" or "Already working in family business"

Will you continue in the same job/business after you graduate?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample. If the respondent answered "Yes" and Q8 = "Already working in a paid job/internship" or " "Accepted a paid job/internship", they were categorized as ineligible for the experiment (not assigned to either treatment or control).*

Q12

Condition: Asked if Q8 = "None of the above" or [(Q8 = "Accepted a paid job/internship" or "Already working in a paid job/internship" or "Already started own business" or "Already working in family business") and Q11 = "No"]

Do you want to work (e.g., for a firm or in your own/family business) in the next 6 months after you graduate?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q13

Condition: Asked if Q12 = "Yes"

What type of work would you prefer to do after you graduate?

◯ Work as an employee for a firm

◯ Work in my family-owned business

◯ Be self-employed as a freelancer for short-term assignments (e.g., online tasks or content writing through Upwork)

◯ Be self-employed by starting my own business (e.g., starting marketing/public relations consulting firm)

Note: *This question was asked only to the experimental sample.*

Q14

Do you want to be working (e.g., for a firm or in your own/family business) 2 years from now?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Job Title Elicitation

Q15

Condition: Asked if Q12 = "No"

If you <u>had</u> to look for a job after you complete your current degree, which of the following employment options, if any, would you consider?

◯ Work as an employee for a firm

◯ Work in my family-owned business

◯ Be self-employed as a freelancer for short-term assignments (e.g., online tasks or content writing through Upwork)

◯ Be self-employed by starting my own business (e.g., starting marketing/public relations consulting firm)

◯ None of the above

Q16

Condition: Asked if Q15 != "Work as an employee for a firm" and Q12 = "No"

If you <u>had</u> to work for a firm, which job title would you be most interested in among all the possibilities given your current qualifications?

Enumerator: Enter -99 if the respondent insists they are not interested in working for a firm at all.

Q17

Condition: Asked if Q16 = -99 Q12 = "No"

What is the most common job title that matches what people with your current qualifications typically do?

Q18

Condition: Asked if Q12 = "Yes" or [Q12 = "No" and Q15 = "Work as an employee for a firm"]

After you graduate, which job title would you be most interested in among all the possibilities given your current qualifications?

Q19

Imagine a firm wants to hire you in a full-time on-site job for {the job title from Q16, Q17, or Q18}. How much do you think you would be offered in monthly starting salary for the job? Answer the question regardless of whether you will accept the job or choose to work at all.

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Reservation Wage Elicitation

Imagine that you have graduated from your current degree and are offered a job with 4 possible schedules, which corresponds to {the job title from Q16, Q17, or Q18}.

The four possible schedules are:

- Full-time, onsite
- Full-time, remote
- Part-time, onsite
- 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? 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: Enter -99 if they would not accept a given schedule for any amount of money. Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q20A

Full-time job; on-site: 40 hours per week, 9am to 5pm, Monday to Friday.

Q20B

Full-time job; work from home: 40 hours per week, 9am to 5pm, Monday to Friday.

Enumerator: Enter -99 if they would not accept a given schedule for any amount of money. Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q20C

Part-time job; on-site: 25 hours per week, 9am to 2pm, Monday to Friday.

Enumerator: Enter -99 if they would not accept a given schedule for any amount of money. Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q20D

Part-time job; work from home: 25 hours per week, 9am to 2pm, Monday to Friday.

Enumerator: Enter -99 if they would not accept a given schedule for any amount of money. Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Comprehension Check

Q21

Imagine you are offered (0.8 * PKR {first non-missing wage from Q20A, Q20B, Q20C, and Q20D},000) for {corresponding schedule from first non-missing wage from Q20A, Q20B, Q20C, and Q20D} corresponding to {the job title from Q16, Q17, or Q18}.

This is a take-it-or-leave-it offer; the firm does not negotiate salary. Would you accept the job?

◯ Yes

◯ No

Schedule Preferences

Q22

Do you prefer to work full-time or part-time?

◯ Full-time

◯ Part-time

Note: *This question was asked only to the diagnostic sample.*

Q23

How many hours do you prefer to work in a day?

Note: *This question was asked only to the experimental sample.*

Q24

Do you prefer on-site work or working from home?

◯ Work from home

◯ On-site work

Labor Market Beliefs

Q25

Do you agree, disagree or neither agree nor disagree with the following statement: When jobs are scarce, men should have more right to a job than women.

◯ Agree

◯ Disagree

◯ Neither agree nor disagree

Q26

Do you agree, disagree or neither agree nor disagree with the following statements: Being a housewife is just as fulfilling as working for pay.

◯ Agree

◯ Disagree

◯ Neither agree nor disagree

Q27

Out of 10 randomly selected male students in your cohort at your university, how many men do you think will be employed within 6 months after graduating?

Q28

Condition: Asked if Q27 >= 0 and < 10

Out of the remaining {10 - answer from Q27} men, why do you think they are not working?

☐ Some men don't want to work

☐ They are pursuing further studies

☐ Jobs are scarce due to poor economic conditions

☐ Waiting for better opportunities

☐ Going abroad

☐ They are doing unpaid work / internships / apprenticeships

☐ Other reason

Enumerator: Select all of the options that apply to the respondent's answer.

Note: *This question was asked only to the experimental sample.*

Q29

Condition: Asked if Q28 = "Other reason"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q30

Out of 10 randomly selected female students in your cohort at your university, how many women do you think will be employed within 6 months after graduating?

Q31

Condition: Asked if Q30 >= 0 and < 10

Out of the remaining {10 - answer from Q30} women, why do you think they are not working?

- ☐ They get married and have kids soon after graduation
- ☐ Some women don't want to work
- ☐ Their parents/husbands wouldn't give them permission to work
- ☐ Firms don't want to hire women/harder for women to find a job
- ☐ There are few suitable jobs for women
- ☐ Other reason

Enumerator: Select all of the options that apply to the respondent's answer.

Note: *This question was asked only to the experimental sample.*

Q32

Condition: Asked if Q31 = "Other reason"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q33

Think of the typical {respondent's from Q2} student from your university working as a {job title from Q16, Q17, or Q18}. What do you think that student's monthly starting salary for a full-time on-site job (40 hours per week, 9am to 5pm, Monday to Friday) will be?

Note: *This question was asked only to the experimental sample.*

Q34

Think of the typical {opposite to respondent's gender from Q2} student from your university working as a {job title from Q16, Q17, or Q18}. What do you think that student's monthly starting salary for a full-time on-site job (40 hours per week, 9am to 5pm, Monday to Friday) will be?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Note: *This question was asked only to the experimental sample.*

Q35

Whom do you have to consult when deciding to accept a job offer?

- ☐ Friends
- ☐ Mother
- ☐ Father
- ☐ Brother(s)
- ☐ Sister(s)
- ☐ Cousin(s)
- ☐ Husband or fiancé
- ☐ Rest of family
- ☐ Teachers, career office, career councilor, university website
- ☐ Classmates enrolled in my course / seniors
- ☐ No one
- ☐ Other

Enumerator: Select all of the options that apply to the respondent's answer.

Q36

Condition: Asked if Q35 = "Other"

If other, please specify.

Labor Force Participation

Q37

Did you work, intern, or do a business in the past 12 months that you are no longer engaged in now?

◯ No

◯ Yes, worked for a firm

◯ Yes, worked as a freelancer

◯ Other (e.g. family business)

Q38

Condition: Asked if Q37 = "Other (e.g. family business)"

If other, please specify.

Q39

How many jobs have you applied to in the past three months?

Q40

Within the last 7 days, about how many total hours did you spend on job search activities? Please round up to the nearest total number of hours.

Note: *This question was asked only to the experimental sample.*

Q41

How many interviews have you received in the past three months?

Note: *This question was asked only to the experimental sample.*

Q42

How many job offers have you received in the past three months?

Q43

Condition: Asked if Q42 > 0

What monthly salary offer did you receive? If you got several salary offers, what was the highest?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q44

Condition: Asked if Q42 > 1

What is the lowest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Note: *This question was asked only to the experimental sample.*

Marriage Questions

Q45

Condition: Asked if Q3 = "Married"

In what year did you get married?

Q46

Condition: Asked if Q3 != "Married"

In how many years from now do you expect you will get married?

Q47

Condition: Asked if Q7 = "Yes"

How many children do you have?

Q48

Did you or your family ever send any marriage proposals?

- ◯ Yes
- ◯ No

Note: *This question was asked only to the experimental sample.*

Q49

Condition: Asked if Q48 = “Yes"

How many marriage offers have you or your family sent?

Note: This question was asked only to the experimental sample.

Q50

Condition: Asked if Q49 > 0

What was the month and year when you or your family sent the first ever marriage offer?

Note: This question was asked only to the experimental sample.

Q51

Did you ever receive any marriage offers?

- ◯ Yes
- ◯ No

Note: This question was asked only to the experimental sample.

Q52

Condition: Asked if Q51 = “Yes"

How many marriage offers have you received?

Note: *This question was asked only to the experimental sample.*

Q53

Condition: Asked if Q51 = “Yes"

What was the month and year you received your first marriage offer?

Enumerator: Enter ***month*** *and* ***year***

Note: *This question was asked only to the experimental sample.*

Q54

Think of 10 random women in your class. How many women out of 10 would have received a marriage offer within 3 months of graduation?

Note: *This question was asked only to the experimental sample.*

Q55

Think of 10 random women in your class. How many women out of 10 would have received a marriage offer within 6 months of graduation?

Note: *This question was asked only to the experimental sample.*

Roster

Q56

Please provide the following information about yourself:

Personal email address:

Personal mobile phone number:

Q57

Did you or your family own a car or any 4 wheel vehicle during the last year?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q58

Did you or your family own a motorbike during the last year?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q59

Do you have internet access in the household you live in?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q60

Do you own a personal smartphone?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q61

Do you own a personal laptop?

- ◯ Yes
- ◯ No

Note: *This question was asked only to the experimental sample.*

Family

Q62

What is the employment status of your father?

- ◯ Working for pay in a firm
- ◯ Self-employed in own business
- ◯ Out of the labor force
- ◯ Working in housework
- ◯ Retired
- ◯ Parents passed away
- ◯ Studying
- ◯ Other

Note: *This question was asked only to the experimental sample.*

Q63

Condition: Asked if Q62 = "Other"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q64

What is your father's job title? Tell us the job title of their most recent paid job if he is currently unemployed or retired.

Note: *This question was asked only to the experimental sample.*

Q65

What is the highest level of education received by your father?

- ◯ Uneducated
- ◯ Matric / O' levels
- ◯ F.A. / F.Sc. / A' levels
- ◯ Bachelors
- ◯ Masters
- ◯ Doctorate (PhD)

Q66

What is the employment status of your mother?

- ◯ Working for pay in a firm
- ◯ Self-employed in own business
- ◯ Out of the labor force
- ◯ Working in housework

◯ Retired

◯ Parents passed away

◯ Studying

◯ Other

Note: *This question was asked only to the experimental sample.*

Q67

Condition: Asked if Q66= "Other"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q68

What is your mother's job title? Tell us the job title of their most recent paid job if she is currently unemployed or retired.

Note: *This question was asked only to the experimental sample.*

Q69

What is the highest level of education received by your mother?

◯ Uneducated

◯ Matric / O' levels

◯ F.A. / F.Sc. / A' levels

◯ Bachelors

◯ Masters

◯ Doctorate (PhD)

Q70

Condition: Asked if Q2 = "Female" and Q3 = "Engaged"

How old is your fiancé?

Q71

Condition: Asked if Q2 = "Female" and Q3 = "Married"

How old is your husband?

Q72

Condition: Asked if Q2 = "Female" and Q3 = "Engaged"

What is the highest level of education received by your fiancé?

◯ Uneducated

◯ Matric / O' levels

◯ F.A. / F.Sc. / A' levels

◯ Bachelors

◯ Masters

◯ Doctorate (PhD)

Q73

Condition: Asked if Q2 = “Female” and Q3 = “Married"

What is the highest level of education received by your husband?

◯ Uneducated

◯ Matric / O’ levels

◯ F.A. / F.Sc. / A’ levels

◯ Bachelors

◯ Masters

◯ Doctorate (PhD)

Q74

Do you have siblings?

◯ Yes

◯ No

Note: *This question was asked only to the experimental sample.*

Q75

Condition: Asked if Q74 = “Yes"

How many brothers do you have?

Note: *This question was asked only to the experimental sample.*

Q76

Condition: Asked if Q74 = “Yes"

How many sisters do you have?

Note: This question was asked only to the experimental sample.

Q77

Condition: Asked if Q75 > 0

How many older brothers do you have?

Note: This question was asked only to the experimental sample.

Q78

Condition: Asked if Q76 > 0

How many older sisters do you have?

Note: This question was asked only to the experimental sample.

Q79

Condition: Asked if Q78 > 0

What is the employment status of your oldest sister?

- ○ Working for pay in a firm
- ○ Self-employed in own business
- ○ Unemployed

◯ Working in housework

◯ Retired and not looking for jobs

◯ Studying

◯ Other

Note: *This question was asked only to the experimental sample.*

Q80

Condition: Asked if Q79 = "Other"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q81

Which province are you from?

◯ Azad Kashmir

◯ Balochistān

◯ Gilgit-Baltistan

◯ Islāmābād

◯ Khyber Pakhtunkhwa

◯ Punjab

◯ Sindh

Q82

In which province would you prefer to live after graduation?

- ◯ Azad Kashmir
- ◯ Balochistān
- ◯ Gilgit-Baltistan
- ◯ Islāmābād
- ◯ Khyber Pakhtunkhwa
- ◯ Punjab
- ◯ Sindh

Q83

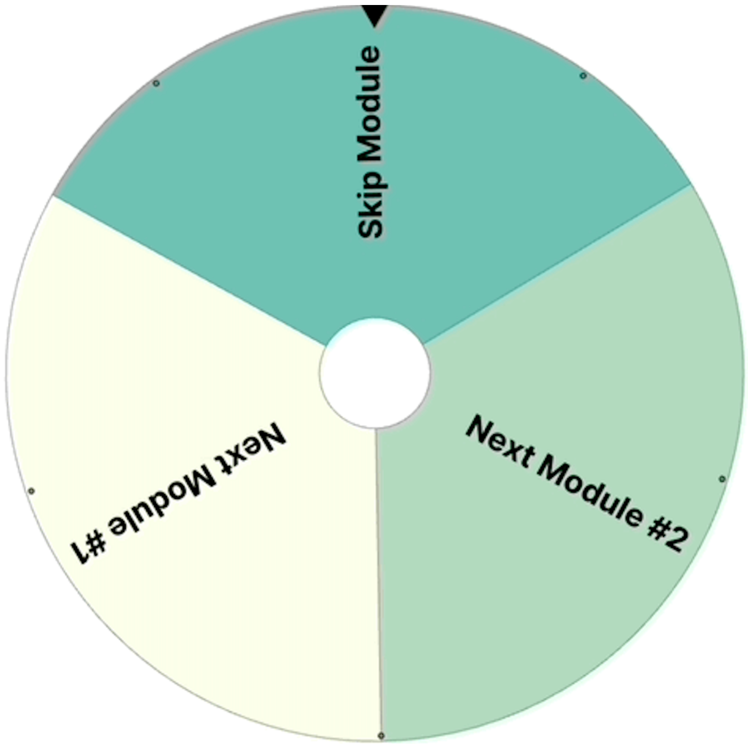
Which city are you from?

Q84

In which city would you prefer to live in after graduation?

Treatment Randomization

You have now reached the last part of the survey which is experimental. At this stage, whether you are shown one of the two experimental modules, or taken straight to the end of the survey will be randomly determined by this wheel.



Enumerator: Turn to respondent. Please touch the screen to spin the wheel.

Note: This module was only shown to the experimental sample.

Q85

Condition: Asked if ***Treatment Randomization*** *= "Next Module #1"*

Our research team is committed to supporting your job search.

You have been randomly selected to receive 20,000 rupees if you apply to at least four jobs relevant to your preferred title, {the job title from Q16, Q17, or Q18}, **and/or your field**, {student's major from pre-loaded administrative data} **and/or skill-set before August 15th**.

The process is simple: We will give you a link to a form. On this form, you will be able to upload a proof of your four applications (e.g., screenshot of the "Application Submitted" page). Only applications to jobs relevant to your preferred title, {the job title from Q16, Q17, or Q18}, and/or your field, {student's major from pre-loaded administrative data} and/or skill-set will be considered valid.

A member of our team may get in touch with you to verify the details of your application and to confirm that you have sent authentic and relevant applications. Only applicants for whom all applications are authentic and relevant will get the **20,000 rupees** via mobile money transfer.

Would you like to participate in this follow-up study?

◯ Yes

◯ No

Q86

Condition: Asked if ***Treatment Randomization*** *= "Next Module #2"*

Our research team is committed to supporting your job search.

You have been randomly selected to receive 5,000 rupees if you apply to at least four jobs relevant to your preferred title, {the job title from Q16, Q17, or Q18}, **and/or your field**, {student's major from pre-loaded administrative data} **and/or skill-set before August 15th**.

The process is simple: we will give you a link to a form. On this form, you will be able to upload a proof of your four applications (e.g., screenshot of the ""application submitted" page). Only applications to jobs relevant to your preferred title preferred title, {the job title from Q16, Q17, or Q18}, and/or your field, {student's major from pre-loaded administrative data} and/or skill-set will be considered valid.

A member of our team may get in touch with you to verify the details of your application and to confirm that you have sent authentic and relevant applications. Only applicants for whom all applications are authentic and relevant will get the **5,000 rupees** via mobile money transfer.

Would you like to participate in this follow-up study?

◯ Yes

◯ No

Note

*Condition: Read out if **Treatment Randomization** = "Skip Module"*

The lottery has decided that you will skip directly to the last module of the survey.

Note

Below is the link to the form where you can upload proof of applications any time before August 15th, as well as submit your money transfer details.

We will check all responses on August 15th, and if you have fulfilled all requirements, we'll initiate the money transfer. We will also email this link to you at the end of the survey.

{QR Code Shown Here}

Work Intentions

Q87

In how many days, weeks, or months from now do you plan to start applying to jobs?

Enumerator: Enter if you recorded the answer in Days, Weeks, or Months.
***Note:** This question was asked only to the experimental sample.*

Q88

How many jobs do you plan to apply for by August 15th?

***Note:** This question was asked only to the experimental sample.*

Q89

On a scale from 0 (very unlikely) to 100 (very likely), how likely is it that you will be working within 6 months of graduating?

Note: *This question was asked at this point in the survey (after treatment assignment) to the experimental sample. In the diagnostic sample, it was asked after Q30.*

Q90

Condition: Asked if Q89 < 100

Why do you think there is a chance you may not work?

- ☐ Poor macroeconomic conditions; jobs are scarce
- ☐ I don't have experience
- ☐ I don't have networks to help get a job
- ☐ Firms don't want to hire women
- ☐ I may not get permission from family to work
- ☐ I may not want to work
- ☐ I want to keep studying
- ☐ Because I am getting married / having a baby / focusing on family
- ☐ Other reason

Note: *This question was asked only to the experimental sample.*

Q91

Condition: Asked if Q90 = "Other"

If other, please specify.

__Note:__ This question was asked only to the experimental sample.

End of Survey

Note

We thank you for your time spent taking this survey. Your response has been recorded.

Enumerator Entries

Q92

Enumerator: Please enter your final comments here.

III Two-Month Follow-Up Survey

Current Employment and Job Search Status

Q1

How many jobs have you applied to since graduation?

Q2

How many job offers have you received since graduation?

Q3

Are you currently working in a paid capacity (e.g., for a firm, in your own business or for your family business) or have you recently accepted a paid job offer?

◯ Yes

◯ No

Q4

Condition: Asked if Q3 = "Yes"

Are you working for your own business, or for a family business, or for a private firm?

◯ Working for own business

◯ Working for a family business

◯ Working for a private firm

Q5

Condition: Asked if Q3 = "Yes"

What is your current monthly salary?

Q6

Condition: Asked if Q2 > 0

What is the highest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q7

Condition: Asked if Q2 > 1

What is the lowest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q8

Condition: Asked if Q4 = "Working for own business" or "Working for a family business" or "Working for a private firm"

What is your job title?

Labor Market Beliefs and Preferences

Q9

Condition: Asked if Q4 = "Working for own business" or "Working for a family business" or "Working for a private firm"

If the work you are doing suddenly shut down and you had to apply for a new job, would you agree to work for less than {wage from Q5},000?

- ◯ Yes
- ◯ No

Q10

Condition: Asked if Q9 = "Yes"

As a {job title from Q8}}, how much less than {wage from Q5},000 will you accept?

Q11

Condition: Asked if Q3 = "No" and Q1 = 0

If you had to apply for a job, which job title would you be interested in, among all the possibilities given your current qualifications?

Q12

Condition: Asked if Q3 = "No" and Q1 > 0

Which job title are you interested in, among all the possibilities given your current qualifications?

Q13

Imagine a firm wants to hire you in a full-time on-site job as a {job title from Q11 or Q12}.

How much do you think you would be offered in monthly starting salary for the job?

Answer this question regardless of whether you will accept the job or choose to work at all.

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q14

Condition: Asked if Q3 = "No"

As a {job title from Q11 or Q12}, would you be willing to work for less than {expected salary from Q13},000?

- ◯ Yes
- ◯ No

Q15

Condition: Asked if Q14 = Yes

As a {job title from Q11 or Q12}, how much less than {expected salary from Q13} would you accept?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Marriage Questions

Q16

What is your marital status?

◯ Never married

◯ Divorced

◯ Separated

◯ Widowed

◯ Married

◯ Engaged

Q17

Condition: Asked if [Marital Status from Baseline != "Married" or != "Engaged"] or [(Marital Status from Baseline = "Married" and Q16 != "Married") or (Marital Status from Baseline = "Engaged" and Q16 != "Engaged" or != "Married")].

How many marriage offers have you received since graduating?

[ ]

Q18

Think about a graduate from your university, in the same field and cohort. Imagine she is a non-working woman. In your opinion, how many marriage offers would she get within a year of graduation?

[ ]

Note: *This question was asked only to the experimental sample.*

Q19

Condition: Asked if Q18 > 0

Of these Q18 offers, how many are from high-income men? Consider high-income to mean they are making more than PKR 150K monthly.

Note: This question was asked only to the experimental sample.

Q20

Condition: Asked if Q18 > 0

Of these Q18 offers, how many are from men that are highly-educated men? Consider highly-educated to mean they have a Master's Degree or above.

Note: This question was asked only to the experimental sample.

Q21

Think about a graduate from your university, in the same field and cohort. Imagine she is a working woman. In your opinion how many marriage offers would she get within a year of graduation?

Note: This question was asked only to the experimental sample.

Q22

Condition: Asked if Q21 > 0

Of these Q21 offers, how many are from high-income men? Consider high-income to mean they are making more than PKR 150K monthly.

Note: *This question was asked only to the experimental sample.*

Q23

Condition: Asked if Q21 > 0

Of these Q21 offers, how many are from men that are highly-educated men? Consider highly-educated to mean they have a Master's Degree or above.

Note: *This question was asked only to the experimental sample.*

Q24

Condition: Asked if Gender from Baseline = "Female" and Marital Status from the 2-month Survey != "Married"

For you personally, will you receive more marriage offers if you are...

- ◯ A working woman
- ◯ A non-working woman
- ◯ No difference

Note: *This question was asked only to the experimental sample.*

Q25

Condition: Asked if Gender from Baseline = "Female" and Marital Status from the 2-month Survey != "Married"

For you personally, will it be easier to find a good husband if you are/become...

◯ A working woman

◯ A non-working woman

◯ No difference

Note: *This question was asked only to the experimental sample.*

Q26

Condition: Asked if Gender from Baseline = "Female" and Marital Status from the 2-month Survey != "Married"

For you personally, would you prefer a husband that...

◯ Wants you to work

◯ Doesn't mind you working

◯ Does not want you to work

Note: *This question was asked only to the experimental sample.*

Q27

Condition: Asked if Gender from Baseline = "Male" and Marital Status from the 2-month Survey != "Married"

For you personally, are you more likely to make a marriage offer to...

◯ A working woman

◯ A non-working woman

◯ No difference

Note: *This question was asked only to the experimental sample.*

Q28

Condition: Asked if Gender from Baseline = "Male" and Marital Status from the 2-month Survey

!= “Married"

Which of the following statements is most true for you personally...

- ◯ I would want my wife to work
- ◯ I do not mind if they work
- ◯ I would rather they do not work

Note: *This question was asked only to the experimental sample.*

End of Survey

Note

We thank you for your time spent taking this survey. Your response has been recorded.

IV Six-Month Follow-Up Survey

Consent Form

My name is {Enumerator's Name}.

I am calling from the research team that surveyed you in June and September at your university for a study led by the London School of Economics (LSE), the Massachusetts Institute of Technology (MIT) and your university.

We want to ask you some follow up questions that will take 5 to 10 minutes. These questions are to understand how your post-graduate life has changed in the last few months. Your answers will allow us to provide better counseling to future students, and keep in touch with the alumni. Participating in this survey is totally up to you.

The information provided by you will remain strictly confidential. Your name will never be published in any report. It will not be possible to link your responses to you in any publication. The published results of the survey will be a compilation of information from hundreds of people. If any question makes you uncomfortable, you can skip it or stop talking with me at any time.

Do you agree to participate in the survey?

◯ Yes

◯ No

Current Employment and Job Search Status

Q1

Are you currently working in a paid capacity (e.g., for a firm, in your own business or for your family business) or have you recently accepted a paid job offer?

◯ Yes

◯ No

Q2

Condition: Asked if Q1 = "Yes"

For your main source of earning, are you working for your own business, or for a family business, or for a private firm in paid capacity?

- ◯ Working for own business
- ◯ Working for a family business
- ◯ Working for a private firm

Q3

Are you currently working in an unpaid capacity?

- ◯ Doing an internship/apprenticeship
- ◯ Working in family business without pay
- ◯ No unpaid work
- ◯ Other

Q4

Condition: Q3 = "Other"

If other, please specify.

Q5

How many jobs have you applied to since graduation?

Q6

How many jobs have you applied to in the last month?

Q7

When did you send your first job application since we surveyed you at your university in June?

*Enumerator: Enter **day** and **month**.*

Note: *This question was asked only to the experimental sample.*

Q8

How many jobs did you interview for since graduation?

Q9

How many job offers have you received since graduation?

Q10

Condition: Asked if Q9 > 0

How many job offers have you received in the last month?

Q11

When did you receive your first job offer since we surveyed you at your university in June?

*Enumerator: Enter **day** and **month**.*

Note: *This question was asked only to the experimental sample.*

Q12

Condition: Asked if Q1 = "No"

Within the last 7 days, about how many total hours did you spend on job search activities? Please round up to the nearest total number of hours.

Note: *This question was asked only to the experimental sample.*

Q13

Condition: Asked if Q9 > 0

What is the highest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q14

Condition: Asked if Q9 > 1

What is the lowest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = “10”).

Q15

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

When did you start working?

*Enumerator: Enter **month** and **year***

Q16

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

What is your job title?

Q17

Condition: Asked if Q2 = “Working for a private firm"

What is the name of the firm you work for?

Q18

Condition: Asked if Q2 = “Working for own business" or “Working for a family business"

What type of business are you currently working in (e.g., real estate, clothing brand, marketing firm)?

Q19

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

Do you work full time or part time?

○ Full-Time

○ Part-Time

Q20

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

How many days do you work in a given week?

Q21

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

On average, how many days do you work from home in a given week?

Q22

Condition: Asked if Q2 = “Working for own business" or “Working for a family business" or “Working for a private firm"

What is your current monthly salary?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q23

Condition: Asked if Q20 != Q21

How many minutes does it take you to commute from home to work?

Note: *This question was asked only to the experimental sample.*

Q24

Condition: Asked if Q20 != Q21

How much does it cost you to commute to work per month?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Note: *This question was asked only to the experimental sample.*

Labor Market Beliefs and Preferences

Q25

Condition: Asked if Q2 = "Working for own business" or "Working for a family business" or "Working for a private firm"

If the work you are doing suddenly shut down and you had to apply for a new job, would you agree to work for less than {wage from Q22},000?

- ◯ Yes
- ◯ No

Q26

Condition: Asked if Q25 = "Yes"

As a {job title from Q16}}, how much less than {wage from Q22},000 will you accept?

☐

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q27

Condition: Asked if Q1 = "No"

How many jobs do you plan to apply to in the next 3 months?

☐

Note: *This question was asked only to the experimental sample.*

Q28

Do you want to work in the next year?

- ◯ Yes
- ◯ No

Note: *This question was asked only to the experimental sample.*

Q29

Condition: Asked if Gender from Baseline = "Female" and {Marital Status from the 2-month Survey} != "Married"

Do you intend to work after getting married?

◯ Yes

◯ No

Note: *{Marital Status from the 2-month Survey} references the respondent's reported marital status at the two-month follow-up survey.*

Q30

Condition: Asked if Q1 = "Yes"

For how many months or years do you think you will continue to work in this job?

Enumerator: Enter if you recorded the answer in months or years.

Note: *This question was asked only to the experimental sample.*

Q31

Condition: Asked if Q1 = "No" and Q5 = 0

If you had to apply for a job, which job title would you be interested in, among all the possibilities given your current qualifications?

Q32

Condition: Asked if Q1 = "No" and Q5 > 0

Which job title are you interested in, among all the possibilities given your current qualifications?

Q33

Imagine a firm wants to hire you in a full-time on-site job as a {job title from Q31 or Q32}.

How much do you think you would be offered in monthly starting salary for the job?

Answer this question regardless of whether you will accept the job or choose to work at all.

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q34

Condition: Asked if Q1 = "No"

As a {job title from Q31 or Q32}, would you be willing to work for less than {expected salary from Q33},000?

- ◯ Yes
- ◯ No

Q35

Condition: Asked if Q34 = Yes

As a {job title from Q31 or Q32}, how much less than {expected salary from Q33} would you accept?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q36

On a scale from 0 (very unlikely) to 100 (very likely), how likely is it that you will be working within 3 months?

Q37

Condition: Asked if Q36 < 100.

Why do you think there is a chance you may not work?

- ☐ Poor macroeconomic conditions; jobs are scarce
- ☐ I don't have experience
- ☐ I don't have networks to help get a job
- ☐ Firms don't want to hire women
- ☐ I may not get permission from family to work
- ☐ I may not want to work
- ☐ I want to keep studying
- ☐ Because I am getting married / having a baby / focusing on family
- ☐ Other reason

Q38

Condition: Asked if Q37 = "Other"

If other, please specify.

Marriage Questions

Q39

What is your marital status?

- ◯ Never married
- ◯ Divorced
- ◯ Separated
- ◯ Widowed
- ◯ Married
- ◯ Engaged

Q40

Condition: Asked if Q39 = “Engaged"

When did you get engaged?

*Enumerator: Enter **day** and **month**.*

Q41

Condition: Asked if Q39 = “Engaged"

What is the highest level of education received by your fiancé?

- ◯ Uneducated
- ◯ Matric / O’ levels
- ◯ F.A. / F.Sc. / A’ levels
- ◯ Bachelors
- ◯ Masters

◯ Doctorate (PhD)

Q42

Condition: Asked if Q39 = "Engaged"

What is the monthly income of your fiance?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Note: *This question was asked only to the diagnostic sample.*

Q43

Condition: Asked if Q39 != "Engaged" or "Married"

How many marriage offers have you received since graduating?

Q44

Condition: Asked if Q43 >= 0

When did you receive your first marriage offer after graduating?

◯ June

◯ July

◯ August

◯ September

◯ October

◯ November

◯ December

◯ January

◯ February

Note: *This question was asked only to the diagnostic sample.*

Q45

Condition: Asked if Q43 >= 0

When did you receive your first marriage offer after graduating?

*Enumerator: Enter **day**, **month**, and **year**.*

Note: *This question was asked only to the experimental sample.*

Q46

Condition: Asked if Gender from Baseline = "Female" and Q43 > 0 and Q39 != "Married"

Out of the marriage offers you have received, what is the number of men who are ok with you working?

Note: *This question was asked only to the experimental sample.*

Q47

Condition: Asked if Marriage Offers from the 2-month Survey > 0 or Q43 > 0 and Q39 != "Married"

On a scale of 0 (very unlikely) to 100 (very likely) how likely are you and your family to accept one of the marriage offers you have already received?

Note: *This question was asked only to the experimental sample.*

Q48

Condition: Asked if Q39 != “Engaged" or “Married"

How many marriage proposals have you or your family sent since graduating?

Q49

Condition: Q39 != “Engaged" or “Married" and Q48 > 0

When did you send your first marriage offer after graduating?

- ◯ June
- ◯ July
- ◯ August
- ◯ September
- ◯ October
- ◯ November
- ◯ December
- ◯ January
- ◯ February

Note: *This question was asked only to the diagnostic sample.*

Q50

Condition: Q39 != "Engaged" or "Married" and Q48 > 0

When did you send your first marriage offer after graduating?

Enumerator: Enter ***month*** *and* ***year****.*

Note: *This question was asked only to the experimental sample.*

Q51

Condition: Q39 != "Married"

In how many months or years from now do you expect you will get married?

Enumerator: Enter if you recorded the answer in ***months*** *or* ***years****.*

Q52

Condition: Asked if Q39 = "Married"

How long ago did you get married?

Enumerator: Enter if you recorded the answer in ***months*** *or* ***years****.*

Q53

Condition: Q39 = "Married"

What is the highest level of education received by your husband / wife?

○ Uneducated

◯ Matric / O' levels

◯ F.A. / F.Sc. / A' levels

◯ Bachelors

◯ Masters

◯ Doctorate (PhD)

Q54

Condition: Asked if Q2 = "Female" and Q43 > 0

What is the highest level of education amongst all the marriage offers you have received?

◯ Uneducated

◯ Matric / O' levels

◯ F.A. / F.Sc. / A' levels

◯ Bachelors

◯ Masters

◯ Doctorate (PhD)

Note: *This question was asked only to the experimental sample.*

Q55

Condition: Asked if Q39 = "Married"

What is the monthly income of your husband / wife?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Note: *This question was asked only to the diagnostic sample.*

Beliefs About Classmates

Q56

Out of 10 randomly selected male students in your cohort at your university, how many men do you think are employed right now?

Q57

Out of the remaining {10 - answer from Q56} men, why do you think they are not working?

- ☐ Some men don't want to work
- ☐ They are pursuing further studies
- ☐ Jobs are scarce due to poor economic conditions
- ☐ Waiting for better opportunities
- ☐ Going abroad
- ☐ They are doing unpaid work / internship / apprenticeship
- ☐ Other reason

Enumerator: Select all of the options that apply to the respondent's answer.

Note: *This question was asked only to the experimental sample.*

Q58

Condition: Asked if Q57 = "Other reason"

If other, please specify.

Note: *This question was asked only to the experimental sample.*

Q59

Out of 10 randomly selected female students in your cohort at your university, how many men do you think are employed right now?

Q60

Condition: Asked if Q59 >= 0 and < 10

Out of the remaining {10 - answer from Q59} women, why do you think they are not working?

- ☐ They get married and have kids soon after graduation
- ☐ Some women don't want to work
- ☐ Their parents/husbands wouldn't give them permission to work
- ☐ Firms don't want to hire women/harder for women to find a job
- ☐ There are few suitable jobs for women
- ☐ Other reason

Enumerator: Select all of the options that apply to the respondent's answer.

Q61

Condition: Asked if Q60 = "Other reason"

If other, please specify.

End of Survey

Note

We thank you for your time spent taking this survey. Your response has been recorded.

V Fourteen-Month Follow-Up Survey

Note: *This questionnaire was asked only to the experimental sample. The diagnostic sample was asked a similar questionnaire during a nine-month follow-up survey.*

Consent Form

My name is {Enumerator's Name}.

I am calling from the research team that surveyed you at your university last summer, and over the phone in September and January for a study led by the London School of Economics (LSE), and the Massachusetts Institute of Technology (MIT).

We wanted to ask you some additional questions about your post-graduate life. It will take 10 minutes and to thank you for your time, we will give you a PKR 1,000 Food Panda voucher or a mobile credit if you don't use Food Panda.

Participating in this survey is totally up to you. The information provided by you will remain strictly confidential. If any question makes you uncomfortable, you can skip it or stop talking with me at any time.

Do you agree to participate in the survey?

◯ Yes

◯ No

Current Employment and Job Search Status

Q1

Since graduating, have you ever worked in a paid capacity (e.g., for a firm, in your own business or for your family business)? Or have you accepted a paid job offer recently?

◯ Yes

◯ No

Q2

Condition: Asked if Q1 = “Yes"

Are you currently working in a paid capacity (e.g., for a firm, in your own business or for your family business) or have you recently accepted a paid job offer?

◯ Yes

◯ No

Q3

Condition: Asked if Q2 = “Yes"

Are you working for your own business, or for a family business, or for a private firm?

◯ Working for own business

◯ Working for a family business

◯ Working for a private firm

Q4

Are you currently working in an unpaid capacity?

◯ Doing an internship/apprenticeship

◯ Working in family business without pay

◯ No unpaid work

Q5

Condition: Asked if Q2 = “Yes"

When did you start your current (paid) job?

Q6

Condition: Asked if Q1 = "Yes"

What was the start date of your first job since graduation?

Enumerator: Enter their graduation date (2023-07-30) if they had started working before graduation and are still doing that job.

Q7

How many jobs have you applied to since graduation?

Q8

Condition: Asked if Q7 > 0

How many jobs have you applied to in the last six months?

Q9

Condition: Asked if Q7 > 0 and Q8 > 0

How many jobs have you applied to in the last month?

Q10

Condition: Asked if Q8 > 0 and Number of Job Applications Sent by 6-Month Survey = 0

When did you send your first job application after graduation?

Q11

How many job offers have you received since graduation?

Q12

How many job offers have you received in the last six months?

Q13

Condition: Asked if Q12 > 0

When did you receive your first job offer after graduation?

Q14

How many jobs did you interview for in the last six months?

Q15

Condition: Asked if Q12 > 0 or Q11 > 0

What is the highest monthly salary you have been offered?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Currently Employed

Q16

Condition: Asked if Q2 = "Yes"

What is your job title?

Q17

Condition: Asked if Q2 = "Yes"

Is this a full-time job or a part-time job?

- ◯ Full-time
- ◯ Part-time

Q18

Condition: Asked if Q2 = "Yes"

What is your current monthly salary?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Q19

Condition: Asked if Q2 = "Yes"

As a {job title from Q16}, would you be willing to work for less than {current wage from Q18},000?

◯ Yes

◯ No

Q20

Condition: Asked if Q19 = "Yes"

As a {job title from Q16}, how much less than {current wage from Q18},000? would you be willing to work for?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = "10").

Labor Market Beliefs and Preferences

Q21

Condition: Asked if Q2 = "No" and Q11 = 0 or Q8 = 0

If you had to apply for a job, which job title would you be interested in, among all the possibilities given your current qualifications?

Q22

Condition: Asked if Q2 = "No" and Q11 >= 0 or Q8 >= 0

Which job title are you interested in, among all the possibilities given your current qualifications?

Q23

On a scale from 0 (very unlikely) to 100 (very likely), how likely is it that you will be working within 6 months?

Q24

Condition: Asked if Q23 < 100

Why do you think there is a chance you may not work?

- ☐ Poor macroeconomic conditions; jobs are scarce
- ☐ I don't have experience
- ☐ I don't have networks to help get a job
- ☐ Firms don't want to hire women
- ☐ I may not get permission from family to work
- ☐ I may not want to work
- ☐ I want to keep studying
- ☐ Because I am getting married / having a baby / focusing on family
- ☐ Other reason

Q25

Condition: Asked if Q24 = "Other"

If other, please specify.

Q26

Condition: Asked if Q1 = “No" or Q2 = “No"

Imagine a firm wants to hire you in a full-time on-site job for {the job title from Q21 or Q22}.

How much do you think you would be offered in monthly starting salary for the job?

Answer the question regardless of whether you will accept the job or choose to work at all.

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = “10”).

Q27

As a {job title from Q21 or Q22}, would you be willing to work for less than {expected salary from Q26},000?

- ◯ Yes
- ◯ No

Q28

Condition: Asked if Q27 = “Yes"

As a {job title from Q21 or Q22}, how much less than {expected salary from Q26},000? would you accept?

Enumerator: Please remember to enter amounts in thousands of PKR (e.g., 10,000 PKR = “10”).

Marriage Questions

Q29

What is your marital status?

- ◯ Never married
- ◯ Divorced
- ◯ Separated
- ◯ Widowed
- ◯ Married
- ◯ Engaged

Q30

Condition: Asked if Q29 = "Engaged" and Marital Status from the 6-Month Survey ! = "Engaged"

When did you get engaged?

[ ]

Q31

Condition: Asked if [Marital Status from the 6-Month Survey ! = "Engaged" or "Married" and Q29 ! = "Engaged" or "Married"] or [Marital Status from the 6-Month Survey = "Engaged" and Q29 ! = "Engaged" or "Married"] or [Marital Status from the 6-Month Survey = "Married" and Q29 ! = "Married"]

How many marriage offers have you received in the last 6 months?

[ ]

Q32

Condition: Asked if Gender from Baseline = "Female" and [Marriage Offers from the 6-Month

Survey > 0 or Q31 > 0] and Q29 != “Engaged" or “Married"

On a scale of 0 (very unlikely) to 100 (very likely) how likely are you and your family to accept one of the marriage offers you have already received?

Q33

Asked if Marriage Offers from the 6-Month Survey = 0 and Q31 > 0

When did you receive your first marriage offer since we surveyed you at your university in June?

Q34

Condition: Asked if [Marital Status from the 6-Month Survey ! = “Engaged" or “Married"] or [Marital Status from the 6-Month Survey = “Married" and Q29 ! = “Married"] or [Marital Status from the 6-Month Survey = “Engaged" and Q29 ! = “Engaged" or “Married"]

How many marriage proposals have you or your family sent in the last 6 months?

Q35

Condition: Asked if Q29 = “Married" and [Marital Status from the 6-Month Survey ! = “Married"

When did you get married?

Q36

Condition: Asked if Gender from Baseline = “Female" and Q29 != “Married" or “Engaged"

On a scale of 0 (very unlikely) to 100 (very likely), how likely do you think it is that you will find a husband and in-laws who would allow you to work after getting married?

Q37

Condition: Asked if Gender from Baseline = “Female" and Q29 = “Married" or “Engaged" and Q1 = “No" or (Q1 = “Yes" and Q2 = “No")

On a scale of 0 (very unlikely) to 100 (very likely), how likely do you think it is that your husband would let you work?

Q38

Condition: Asked if Gender from Baseline = “Female"

Think of your 5 closest female friends. First, tell us from among the 5 how many are employed / working?

Q39

Condition: Asked if Q38 < 5

Of the remaining friends who are not working, how many are currently looking for work?

End of Survey

Q40

How would you like to receive your reward payment?

- ◯ Foodpanda voucher
- ◯ Mobile credit

Note

We thank you for your time spent taking this survey. Your response has been recorded.