

# Essays in Empirical Development Economics

by

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Dissertation submitted in partial fulfillment of the  
requirements for the degree of Doctor of Philosophy  
in Public Policy  
in the Graduate School of  
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ABSTRACT

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# Abstract

Social norms can play an important role in economic decision-making. Individuals face costs if they deviate from cultural norms in their families or communities, and firms seek to preserve reputation in order to bolster their position in their market. In this dissertation, I explore the role of cultural norms and reputation in individual, household, and firm decision-making in developing countries. The first chapter is comprised of information and priming experiments on a job search platform in urban Pakistan identifying the role of social norms and workplace attributes on educated women's job search and occupational choice. The second chapter studies the relationship between gold price in year of birth and household decision-making at adulthood using nationally representative data in India. The third chapter combines a lab-in-field generosity game with field-based measures of healthcare provider effort to document that a sizable proportion of healthcare providers in this setting in rural India exert clinical effort with patients in ways consistent with maintaining reputation in their communities.

# Dedication

For my parents Renuka and Subra, who have taught me to dream big and have unwaveringly supported me in achieving those dreams.

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Most of all, I thank my family for everything: my mother and father, Renuka and Subra, and my brother, Avinash.

# Introduction

Cultural norms and reputation can play a significant role in many types of economic decisions. In this dissertation, I explore the role of social norms and the importance of reputation on women's job search, household decisions about fertility, health, and education, and healthcare providers' effort with patients in developing country settings.

The first chapter focuses on women's labor supply. Across the world, there have been improvements in women's educational attainment which have not been fully reflected in women's labor market outcomes. Countries in the Middle East, North Africa, and South Asia have some of the lowest rates of female labor force participation in the world. I conduct an experiment in Pakistan, which is geographically and culturally representative of many of these regions, to study the role of information about workplace attributes on women's job search and occupational choice. I find that there is a discrepancy between what attributes influence young women to apply for jobs and what attributes they believe their parents care most about, which can explain in part low rates of job search among women in this setting. These results indicate that policymakers seeking to increase women's engagement with the labor market should consider deeply the social pressures that women face which might be constraining their choices. Even within the framework of strong social norms about women's and men's interactions in public spaces, the results show that access to information relevant to social constraints increases women's job search, which is a first step to increasing employment.

The second chapter focuses on the role of gold price on household decision-making in India. Gold is culturally important in India, serving as a coveted medium of jewelry/ornamentation but also a highly liquid investment. Customarily in Indian weddings, the bride's family pays for the wedding expenses, a significant portion of which is gold jewelry that is gifted to the bride by her natal family to function in part as a private financial safeguard for her future. This custom imposes pressure on families to invest

in gold for their daughters' weddings. In this chapter, I first document the relationship between global gold price in the year of birth and sibling composition, and that these relationships differ for girls and boys. I then document the long-run relationship between global gold price in year of birth and household decision-making at adulthood, finding negative relationships particularly for health and use of contraception. These results highlight that cultural norms which impact resource allocation should be taken into account when considering broader development policies.

The third chapter focuses on private-sector healthcare providers in rural India. Field-based survey and observational data in this coauthored chapter show that healthcare providers who exhibit high levels of publicly observable signals of generosity exert more effort with their patients when they know that they are being observed, but do not behave differently from their counterparts when they do not know that they are being observed. This result suggests that some healthcare providers are motivated to maintain a reputation as being generous within their community. The effort to maintain that reputation can influence their effort in care, and thus could be used as a policy lever in encouraging high-quality healthcare provision.

# Chapter 1

## Workplace Attributes and Women's Labor Supply Decisions: Evidence from a Randomized Experiment

### 1.1 Introduction

The global ratio of female to male enrollment in secondary education has nearly reached one; in tertiary education, this ratio has surpassed one (UNESCO, 2019a,b). However, women are less likely than men to participate in the labor force, spend more hours than men on unpaid work, and earn less than men around the world (Addati et al., 2016). Furthermore, occupational segregation by gender is a factor in many labor markets (Menon and Rodgers, 2017). Thus, while women's educational attainment has improved globally in the last two decades, this has not been reflected equally in women's labor market outcomes. This empirical fact is concerning as it could reflect inefficient allocation of human capital in the economy, having longer-run implications for economic growth and gender equity.<sup>1</sup>

Educated women might not see returns on the labor market for a few reasons. On the demand side, hiring discrimination can favor men (Altonji and Blank, 1999; Goldin and Rouse, 2000).<sup>2</sup> Women might prefer flexible working hours which are not available at all workplaces (International Labour Office, 2010; World Bank, 2012; Mas and Pallais, 2017). In this paper, I focus on supply-side constraints in developing countries stemming from social stigma against women working outside the home. Taking these social norms as given, I conduct an information experiment and related priming ex-

---

<sup>1</sup>This study is registered in the AEA RCT Registry with the unique identifying number is: "AEARCTR-0004639". The Duke University Institutional Review Board reviewed and approved this study.

<sup>2</sup>In Pakistan, firms routinely specify whether they seek to hire men, women, or are open to any gender.

periment with educated female jobseekers on a formal job search platform to identify whether information can change women's job search behavior. My results show that receiving information about gender of the supervisor on a job posting nearly doubles the job application rate, that active jobseekers are significantly more likely to apply to jobs with female supervisors than male supervisors, and that being primed to think about family job search advice decreases the application rate.

This study is set in Lahore, Pakistan, where women's educational attainment has grown but female labor force participation remains low (Field and Vyborny, 2016; Pakistan Bureau of Statistics, 2018). Women's labor force participation rose from 14% to 25% between 1990 and 2014 (Field and Vyborny, 2016). However, four times as many men as women in urban parts of Punjab province (where Lahore is located) worked for pay in the last month (Pakistan Bureau of Statistics, 2017). Women in Pakistan and other developing country settings can face two types of costs from working outside the home, stemming from social norms.

The first cost is on the extensive margin: stigma attached to working anywhere outside the home. About 75% of women in urban areas of Punjab province report that other household members made the decision about whether they can work outside the home, and that the women themselves had no say (Pakistan Bureau of Statistics, 2017). Across Pakistan, a quarter of women who are not currently working report that the reason they are not working is because their husband or father has not given them permission (Pakistan Bureau of Statistics, 2017). These types of norms, or a belief that others subscribe to such norms, are also found in other countries (World Bank, 2012; Field et al., 2016; Bursztyn et al., 2018).

The second cost is on the intensive margin: women can face additional stigma from the workplace attributes at a job. In this paper, I focus on two workplace attributes: gender of employees at the firm and gender of the supervisor at the job. Social norms in Pakistan advocate gender segregation in public spaces. Other mechanisms by which

gender composition or gender of the supervisor can impose costs on women's work are supported by studies conducted in both developing and developed countries. Women might be discouraged from male-dominated workplaces due to fears of marital dissolution (McKinnish, 2007; Svarer, 2007). Gender of coworkers and supervisors can play a role due to concerns about safety when working in a male-dominated environment, which has been shown to be psychologically costly (Fitzgerald, 1993; Wu, 2017). In the US, women have been shown to prefer jobs with paycales that rely less on competition, independent of gendered workplace attributes (Flory et al., 2014). Other job characteristics such as salary, flexible working hours, and how well a job conforms to one's gender identity, also factor into women's labor supply decisions (Fitzgerald, 1993; Akerlof and Kranton, 2000; Mas and Pallais, 2017). Insofar as gender-related workplace attributes are correlated within occupation, the impacts of a preference for working with same-gender employees or for a same-gender supervisor can contribute to occupational segregation by gender (England, 2000; Levanon et al., 2009; World Bank, 2012).

Particularly when most job search is informal as is the case in Pakistan, women do not have enough exposure to other women working outside the home to form an accurate view of labor market conditions, which in turn could keep them from seeking employment. Individuals' beliefs about salaries and long-run outcomes from educational choices have been documented to impact decisions governing education, employment, and occupation even if those beliefs are inaccurate (Jensen, 2012; Stinebrickner and Stinebrickner, 2014; Wiswall and Zafar, 2015; Zafar, 2013; Delavande and Zafar, 2019). Female jobseekers in my setting overestimate occupation-wise salary and underestimate the prevalence of men and male supervisors in occupations in which they are interested. Women seem to know that they face the extensive margin cost of working anywhere outside the home, but do not have accurate information about the labor market to sort into workplaces which might reduce their intensive margin

costs. In such an environment where social norms about women's role in public spaces are strong, I hypothesize that beliefs about workplace attributes related to these norms can significantly impact labor supply. Low incidence of women's labor force participation and employment can then be indicative of a low-information and low-employment equilibrium. The challenge is how to shift away from such an equilibrium with low information and low women's employment to one with better-informed jobseekers and higher women's employment. The hypothesized mechanism is that more information about jobs allows women to sort into firms which reduce their intensive margin costs to working outside the home, which can in turn bring more women into the workforce overall.

Taken together, the literature has shown that jobseekers do not have perfect information about labor markets, and that workers have preferences over workplace attributes such as salary and flexible working hours, which can impact employment decisions. Furthermore, family preferences can play a role in women's labor supply decisions, particularly where there is social stigma about women working outside the home.

There are two important gaps in this literature which this paper addresses: the causal impact of information about gender composition and gender of the supervisor on women's job search and beliefs about the labor market, and the causal impact of family involvement in job search on women's job applications in a setting where social norms oppose women working outside the home. Due to the experimental design, I am able to observe jobseekers making real application decisions in response to actual jobs in the labor market.

I experimentally manipulate the information environment on a formal job search platform, to study how access to accurate information about the labor market impacts educated women's application decisions. In a cross-randomization, I conduct a primary experiment to study the role of family involvement in job search on women's job

application decisions. I measure jobseekers' prior and posterior beliefs about gender-related workplace attributes in preferred occupations and measure endline rankings of preferred occupations, to estimate belief updating and the role of beliefs about gender-related workplace attributes on occupational choice. Job search among educated women in this context is very low, consistent with supply-side constraints negatively impacting women's transition from education to the labor market. Thus, the main outcome of interest is job application decisions. Increasing job search itself is of first order importance to improving downstream outcomes such as employment, wages, and firm-jobseeker match quality.

In the framework of costs which I have laid out, women face an extensive margin cost to working outside the home stemming from their family's adherence to social norms. The experimental evidence supports this; priming jobseekers about family job search advice significantly decreases the overall job application rate. The rest of the results focus on the intensive margin costs which depend on workplace attributes.

In this framework, if women have a preference over the gender of their coworkers, in line with social norms about gender segregation, receiving information about gender composition of the firm should significantly increase job application rates, as it allows women to sort into the firms that they prefer. Furthermore, women should be significantly more likely to apply to jobs that are at workplaces with mostly or all female employees compared to workplaces with mostly or all male employees, holding all else constant. The experimental results do not show that information about gender composition has a significant impact on job application rate, and women do not significantly prefer workplaces with mostly women compared to mostly men. However, those who are primed to think about family job search advice before making their application decisions are more likely to apply to a job if they learn the gender composition of the firm, than otherwise. This is consistent with families having strong preferences about the gender composition of a firm, even if jobseekers themselves do not.

Analogously, if women have a preference over having a female or male supervisor, receiving information about gender of the supervisor should significantly increase the application rates. Furthermore, if women prefer female supervisors, they should be more likely to apply to jobs with a female supervisor than those with a male supervisor, holding all else constant. The experimental results support both of these hypotheses. Receiving information about gender of the supervisor increases the job application rate; active jobseekers in particular are significantly more likely to apply to jobs with a female supervisor than a male supervisor, holding other observable job characteristics fixed. The mechanism does not seem to be family preferences, as women who were primed about family job search advice are not significantly more likely to apply to jobs which they learn have a female supervisor. Finally, in line with lack of information about gender of the supervisor itself being the mechanism, receiving information about gender of the supervisor through the platform significantly updated jobseekers' beliefs about the distribution of the probability of having a male supervisor by occupation, compared to their prior beliefs.

Descriptive rank-ordered logit analysis suggests that women prefer occupations that they believe will have more women in the workplace. Women also prefer occupations which they believe are less likely to hire women - which is consistent with a belief that occupations that will easily hire women are less prestigious (Goldin, 2014).

Taken together, these results show that access to information about workplace attributes, particularly gender of the supervisor, can have a large positive impact on women's job applications in an environment where women's employment and labor force participation rates are very low. While this experiment was a targeted change to the information environment in a formal job search setting, the results have broader implications for the policy environment. Web-based and phone-based job search platforms are becoming increasingly common in developing country settings to match increasing mobile phone usage. This type of technology greatly reduces costs for firms

and platforms to publicize more information about jobs which could in turn improve the information environment and increase women's employment.

With such low women's employment rates, and in many cases, a lack of role models or support within their own families, women must rely on external information to inform their job search and career decisions. Improving the information environment could thus have immediate impacts on women's employment decisions but also larger positive impacts of creating more role models for other women to learn from. This could yield a positive multiplier effect which increases women's employment in a setting where women's human capital gains are already growing.

In the rest of this paper, I describe the labor market platform and experimental design in Sections 1.2 and 1.3. I then describe the data in Section 1.4. Next, I outline the empirical strategy and experimental results in Sections 1.5 and 1.6. In Section 1.7, I describe and estimate a model of how beliefs about workplace attributes inform stated occupational choice. I provide robustness checks for the experimental results in Section 1.8 and conclude in Section 1.9.

## 1.2 Context

My experiment is conducted on a job search platform called Job Asaan, in Lahore, Pakistan.<sup>3</sup> This platform, supported by a state government agency, seeks to match female jobseekers who hold at least a high school diploma to open job postings at firms throughout Lahore for which they meet basic qualifications. There is no monetary cost to jobseekers or firms for using the service.

---

<sup>3</sup>This job search platform was created by Erica Field, Rob Garlick, and Kate Vyborny of the Duke University Department of Economics.

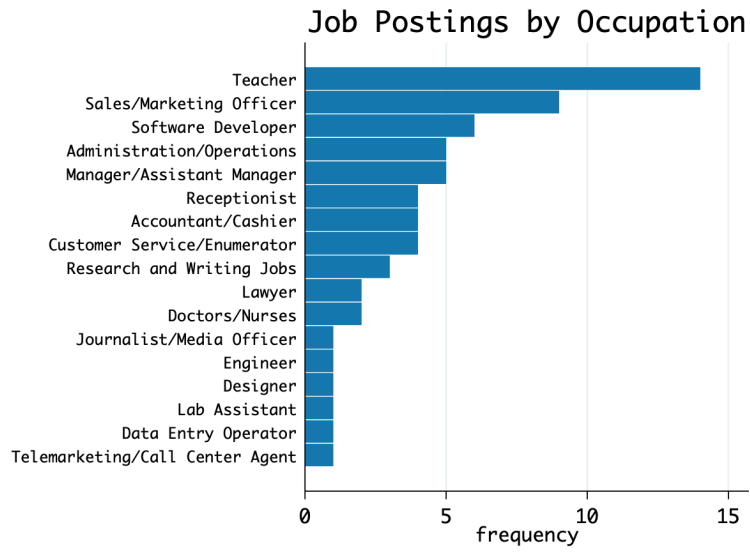
### 1.2.1 Firms & Ad Listings

The Lahore metropolitan area was subdivided into administrative zones, and a stratified random sample of firms was drawn. The field team contacted firms, described the Job Asaan service, and offered firms the opportunity to enroll in the service at no cost. If firms were interested in listing positions, the ad listing survey collected information regarding the basic educational and experience qualifications necessary to be eligible for the position, wage, the gender composition of the firm, the gender of the supervisor for the open position, and how flexible the hours were for the open position. Jobs were posted on a rolling basis.

In addition to the set of jobs listed through the random sampling procedure, jobs were also listed through targeted approaches to firms in neighborhoods or industries (such as finance, education, high-end retail, and healthcare), which were likely to have open positions for women with a high school diploma or higher education. The combined process yielded a total of 64 jobs that Job Asaan jobseekers matched to over the course of the experiment.<sup>4</sup>

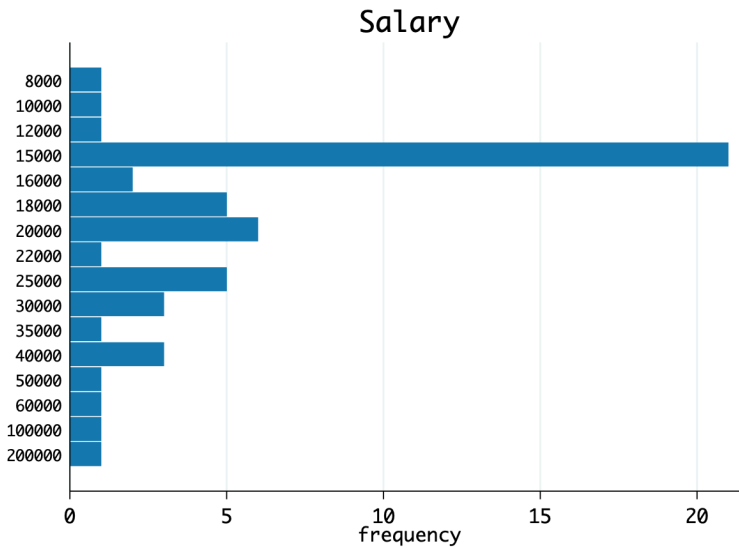
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<sup>4</sup>The targeted approach to seeking job postings for Job Asaan started out slow and took a couple of weeks to gain traction. This is reflected in Figure 4.9 in the appendix to this chapter (Chapter 6) which shows a slow upward trend in the number of jobs from round 1 onwards, but a steep increase for round 5.



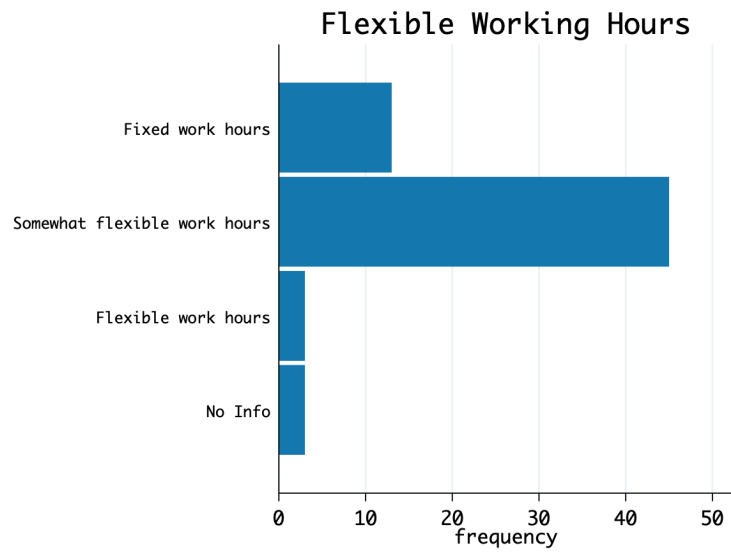
**Figure 1.1: Occupations**

*Notes:* Distribution across job postings in the experiment.



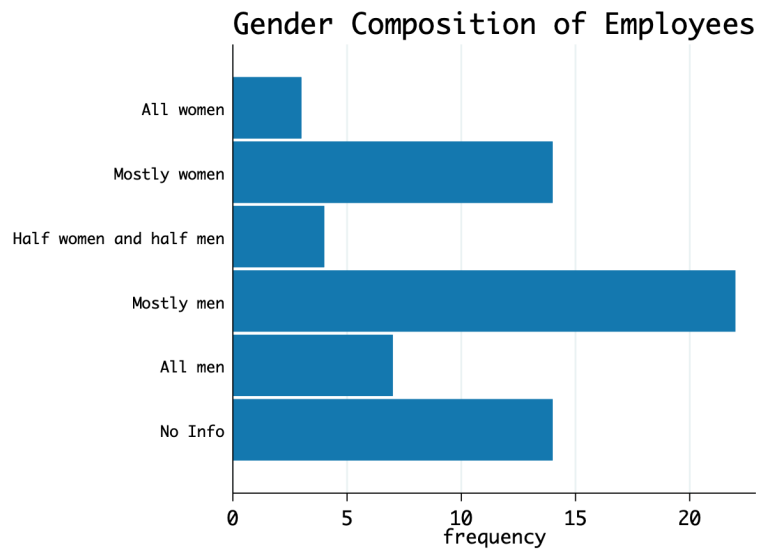
**Figure 1.2: Salary**

*Notes:* Distribution across job postings in the experiment.



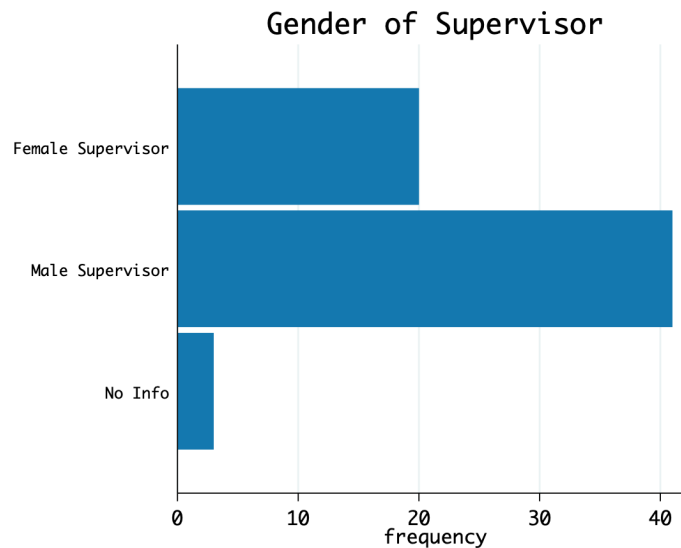
**Figure 1.3: Work Hours**

*Notes:* Distribution across job postings in the experiment.



**Figure 1.4: Gender Composition**

*Notes:* Distribution across job postings in the experiment.



**Figure 1.5:** Gender of Supervisor

*Notes:* Distribution across job postings in the experiment.

Figures 1.1 through 1.3 provide distributions of characteristics of these jobs.<sup>5</sup> Many of these job postings were in teaching or sales, though there are seventeen occupations represented overall. Of the 64 jobs to which women in Job Asaan matched, by definition all are willing to accept applications from women. The median salary is 18,000 PKR/month (about \$180).<sup>6</sup> Fifty-eight percent of these positions have majority male employees, and 67% of the jobs have a male supervisor (among the firms that provided this information). Of the total job postings solicited during the timeframe of the experiment (not restricting to positions that Job Asaan jobseekers were eligible for), 80% are willing to accept applications from women, and the median salary is 15,000

<sup>5</sup>In addition to Job Asaan, these jobs were posted on Job Talash, the name of the broader job search platform that the research team has created in Lahore, Pakistan. Job Talash includes male and female jobseekers of all educational backgrounds, thus firms that seek to hire only men also received job postings through that service.

<sup>6</sup>Job Asaan does not match women to any positions that pay less than the minimum wage. The minimum wage in Lahore is 15,000 PKR/month (about \$150). The three job postings which offer a lower salary than the minimum wage are internships.

PKR/month (about \$150, and the minimum wage in Lahore). Seventy-four percent of these firms have majority male employees, and 77% of the jobs have a male supervisor (among the firms that provided this information).

## 1.2.2 Jobseekers

Jobseekers enrolled onto Job Asaan in one of two ways. First, the state government agency conducted a media campaign in July 2018, inviting women with a high school diploma or higher levels of education to sign up for the Job Asaan service. This media campaign covered television, radio, social media, etc, and directed interested jobseekers to a website where they could fill out the Job Asaan sign-up form, which also serves as the baseline survey instrument<sup>7</sup>. Second, Job Asaan conducted outreach events at colleges and universities in Lahore. Here, women who were in their final year of high school or final year of college were invited by their college or university to attend a Job Asaan-sponsored CV training workshop. Job Asaan staff would lead the students in filling out the sign-up form.<sup>8,9</sup> Both forms of signup yielded a total of 4,081 jobseekers on the Job Asaan platform as of March 2019, when my experiment began. Of these, 2,244 had only completed the initial brief signup form, thus Job Asaan did not have CV information to forward to employers. For the remaining 1,837, Job Asaan had CV information to forward to employers. The job matching process is described in more

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<sup>7</sup>If jobseekers needed guidance in filling out the survey information, they were provided with a helpline which they could call, monitored by Job Asaan staff

<sup>8</sup>Since the form is lengthy, it was effectively divided into 2 parts. The initial form had just a few short questions to determine whether the individual was eligible for the service, which was determined by highest education level, gender, being a resident of Lahore, and being over the age of 18 or providing parental permission if aged 17. If the jobseeker passed this initial criteria, they were given the link to the full signup form.

<sup>9</sup>In a small number of cases, Job Asaan used hard copy versions of the form at these events owing to technology limitations. Then, staff entered the information onto the webform after the event. At some colleges, the allocated time for the event was too short to guide students through the full form. In these cases, the team had the students fill out the initial signup form at the event, and staff called them back to complete the full signup form over the phone.

detail below. While 4,081 total individuals signed up for Job Asaan, only 998 were actively searching on the platform at the time that my experiment began.<sup>10</sup>

A description of these jobseekers is found in Table 4.1<sup>11</sup>. The jobseekers are on average 22 years old; 74% are currently enrolled in education. On average, they have less than one year of work experience. Eighty-nine percent have a bachelor's degree or higher; only 9% are currently married. Nine percent of the jobseekers have applied to jobs through Job Asaan prior to the start of my experiment. Jobseekers remain enrolled on the platform until they ask to be removed.

### 1.2.3 Matching

The Job Asaan platform works by matching job-seekers with open positions for which they meet the base qualifications. First, Job Asaan enrolls firms with open job postings on a rolling basis. Approximately every week, jobseekers are matched to these job postings based on whether they have the appropriate level of education and years of experience that the firm seeks for the job, whether the firm is willing to receive applications from women, and whether the job posting is for an occupation that the jobseeker expressed interest in being matched with at baseline<sup>12</sup>. Jobseekers who meet these matching criteria receive a batch of text messages (SMS's) with the jobs they have matched to in the given matching round. The SMS with the information about job postings for the given match round includes the Job Asaan phone number, and the date by which they must call to apply. All jobseekers can call Job Asaan to apply to

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<sup>10</sup>These 998 individuals are defined as having either initiated calls to apply for jobs, or as having picked up the phone when Job Asaan directly called them about job matches.

<sup>11</sup>Table 4.1 includes summary statistics for the full set of 4081 jobseekers and the 998 active jobseekers, showing that the samples are similar on many observable characteristics.

<sup>12</sup>In practice in Lahore, firms often advertise whether they are looking for male or female applicants. Job Asaan asks firms whether they are willing to accept applications from female applicants, male applicants, or any gender and matches jobseekers to job postings that seek female applicants or seek applicants from any gender.

any job postings that they received in the last week. Of the 4,081 jobseekers in the experiment, 1,837 had completely filled out CVs with Job Asaan prior to the start of the experiment. This subsample of 1,837 jobseekers is called the Priming Experiment Sample, and they received a call from Job Asaan each week asking if they were interested in applying to any of the job matches that they had received that week.<sup>13</sup> Each job match SMS notes the jobseeker's name to indicate that the match is specifically for her, and includes the following information about the job posting: job title, firm name, minimum salary, location of the firm within Lahore, whether the position has flexible working hours, and a statement clarifying that the position is open to applications from women. The SMS also specifies the date by which the individual should apply for the position and the Job Asaan helpline number that she can call to apply for the job.

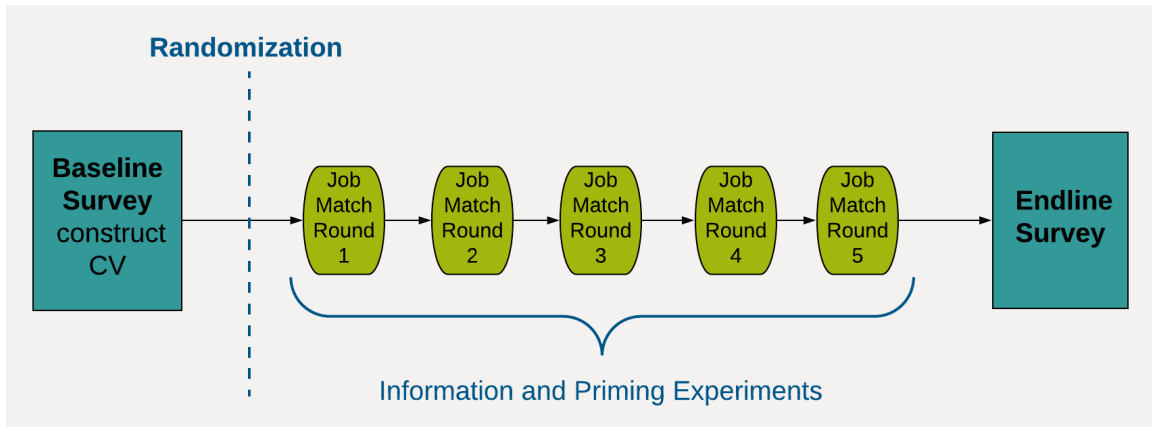
### 1.3 Experimental Design

There are two parts to the experimental design. The first is the information experiment; the second is the priming experiment. Both experiments were cross-randomized and conducted simultaneously on the Job Asaan platform, over a period of five matching rounds. Figure 1.6 depicts the timeline of events. All randomizations were stratified on education level, whether the jobseeker had previously received calls from Job Asaan to apply for jobs (versus being in the group that was assigned to call Job Asaan to apply for jobs), whether the jobseeker had previously applied to any jobs, whether the jobseeker had completed the full signup instrument, whether the jobseeker had completed CV information, the number of matches that the jobseeker had received thus far on the platform, and whether the jobseeker indicated at baseline that she could access the Job

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<sup>13</sup>The 2244 individuals who did not complete the full signup form with the CV information still received the SMS's with the jobs to which they matched, but they did not receive a call from Job Asaan asking them to which jobs in that batch they wanted to apply. Individuals in either category can always call Job Asaan directly to apply for jobs.

Asaan office (as a rough indicator of mobility)<sup>14, 15, 16</sup> The experiment was conducted over five consecutive matching rounds in March and April 2019, each approximately a week apart.<sup>17</sup>



**Figure 1.6:** Timeline of Experiment

### 1.3.1 Information Experiment

There are two cross-randomized information treatments: A random selection of 50% of job-seekers received information about the gender composition (employees) of the firm. A cross-randomized 50% of job-seekers received information about the gender of the direct supervisor for the job. The randomization is at the individual level, meaning

<sup>14</sup>Education level was defined as highest education achieved, or exact institution if more than 20 individuals were currently enrolled at that institution (indicating that the sign-up was from a college outreach event)

<sup>15</sup>The exact number of individuals in each treatment arm is depicted in Figure 4.1 in the appendix to this chapter (Chapter 6).

<sup>16</sup>Table 4.2 in the appendix to this chapter (Chapter 6) has the main balance table, split into the relevant subsamples used for analysis. Table 4.3 in the appendix to this chapter (Chapter 6) performs joint tests for orthogonality of balance variables on each treatment separately. Years of experience is imbalanced for the information about gender composition treatment. This is controlled for in all experimental analysis.

<sup>17</sup>The match dates were March 13, March 24, April 2, April 10, and April 22, 2019.

that each individual received the same categories of information about each job match. However, the actual information they received differed by position/firm.

Gender composition of the firm was presented as five categories:

- All women employees
- Mostly women employees
- Half women and half men employees
- Mostly men employees
- All men employees

If the firm did not disclose the gender composition, then the jobseeker received a message “We do not have gender of the employees at this firm.” This was the case for 14 out of 64 job postings, accounting for 16% of all matches. Twenty-nine job postings were at firms with mostly or all male employees, accounting for 36% of matches. Seventeen job postings were at firms with mostly or all female employees, accounting for 41% of matches. Four job postings were at firms that reported exactly half male and half female employees; these job postings accounted for 7% of matches.

Gender of the supervisor was presented as two categories:<sup>18</sup>

- Female supervisor
- Male supervisor

If the firm did not disclose the gender of the supervisor, then the jobseeker received a message “We do not have gender of the supervisor at this position.” This applied to three out of 64 job postings, amounting to less than three percent of all matches. Female supervisors accounted for 20 out of 64 job postings, but comprised 55% of all matches. This reflects the fact that teaching positions are disproportionately likely to

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<sup>18</sup>The ad listing survey allowed for transgender supervisors, but this option was not used by any firm in the data.

have female supervisors and are an occupation in which jobseekers overwhelmingly indicated interest and thus received matches.

Through Job Asaan, all job postings included the job title (which signals the occupation), location of the job within the city (addressing mobility constraints), and the salary (addressing information that the jobseeker might infer about wages through the gender composition). In addition, over the course of this experiment, all jobseekers received information about whether the position allows flexible working hours to address that women could have a preference for flexible working hours and a statement that “Company accepting female applicants.” to address the fact that jobseekers might interpret gender composition or gender of the supervisor as a signal of whether the firm is actually willing to consider applications from women. The structure of the SMS is denoted in Figure 1.7. All information presented to jobseekers is completely factual.<sup>19</sup> The variation in workplace attributes comes from true variation as reported by firms in Lahore.

Job AD for <u>Jobseeker Name</u> <u>Job Title</u> <u>Firm Name</u> Salary: <u>Salary</u> <u>Neighborhood in Lahore</u> Company accepting female applicants. <u>FIXED/SOMEWHAT FLEXIBLE/FLEXIBLE</u> work hours. Apply before: <u>Date until which applications are accepted.</u> Apply by calling Job Asaan’s helpline Call XXXX-XXXXXX
--

**Figure 1.7:** SMS Structure - Control Group

<sup>19</sup>If a jobseeker in a control group asked for information that she was not randomly selected to receive, she was told that Job Asaan could not disclose that information.

### **1.3.2 Priming Experiment**

The priming experiment is cross-randomized against the information experiment. The Priming Experiment Sample (described earlier) received calls from Job Asaan with each set of matches asking if the jobseeker wanted to apply to any of their matches. This experiment manipulated the salience of family job search advice before the jobseeker made application decisions, but was not designed to impact the content of family job search advice.

Fifty percent of jobseekers in the Priming Experiment Sample were randomly selected to receive a prime at the beginning of the phone call, before they heard the list of jobs to which they were matched and before they were asked whether they wanted to apply to any of these jobs. Specifically, they were asked “We are also interested in understanding how women make decisions about their jobs. Have you discussed your job search with your family in the last week?” The possible responses are “Yes”, “No”, or “I do not wish to answer”. This question was designed to prime the jobseeker about her family’s job search advice before she decided whether to apply to the job matches that she received that round.

## **1.4 Data**

### **1.4.1 Baseline**

The Job Asaan signup instrument also served as the baseline survey for this study. The first portion of the form collected detailed information about educational background and work experience, and was used by Job Asaan to make the jobseeker’s CV to send

to firms as the job application.<sup>20 21</sup> First, the jobseeker ranked her top three most preferred occupations at baseline. Then, she provided beliefs over the following parameters for a typical job in that occupation: mean salary, minimum, mean, and maximum percentage of men at the job, minimum, mean, and maximum expectation that the supervisor would be male, and the probability that the job would hire a woman.<sup>22</sup>

## 1.4.2 Outcomes

### Application Decisions

The main experimental outcome is whether the jobseeker chose to apply to each given job with which she was matched; measured through the administrative Job Asaan data. For the Priming Experiment Sample, Job Asaan has administrative data for each individual in each round in which she received matches. On these calls, Job Asaan asked the jobseeker if she was interested in applying for the given job, and if yes, whether she would attend the job interview if invited. Only if she responded yes to this latter

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<sup>20</sup>This CV information included their educational history (the institutions at which they studied, the subjects they took, their grades, and any noteworthy projects that they completed) and any employment history (names of previous employers, length of employment at each previous job, and job responsibilities). The CV portion of the form also collected the rest of the information necessary to facilitate matching, including the list of occupations in which they are interested, and contact information. The remainder of the baseline questionnaire asked questions about their self-perception of their skills, demographic background, and questions about prevalence of and attitudes towards women working outside the home, amongst their family and friends. Respondents had the option to complete the form in either English or Urdu. The majority of respondents chose to complete the form in English.

<sup>21</sup>There are two cases where the jobseeker would have CV information, but not the rest of the baseline questionnaire. The first is if they signed up on the webform early in summer 2018 during the pilot phase when only the CV portion of the form was live. The second is if they signed up as part of a college outreach event with hard copy forms, and only completed the CV portion of the form and not the survey portion of the form.

<sup>22</sup>The exact question wording is included in the appendix to this chapter (Chapter 6) and draws from the literature in measuring subjective expectations (Manski, 2004; Hurd, 2009; Bruin and Fischhoff, 2017; Delavande and Zafar, 2019; Dominitz and Manski, 2017, 2011; Attanasio, 2009; Delavande, 2008; Delavande et al., 2009; Dominitz and Manski, 2007, 1997).

question did Job Asaan forward her CV to the firm as a job application.<sup>23</sup> For the remaining jobseekers, Job Asaan has administrative data on calls they made to apply to job matches that they received in a given round.<sup>24</sup>

## **Endline**

The endline survey was conducted by phone within two months of the completion of the experiment (between five and eleven months after baseline depending on when the jobseeker signed up). First, jobseekers who provided their rankings and priors about occupations they were most interested in at baseline, were asked to re-rank their interest in those same three occupations, and asked about their updated beliefs about the same parameters for these occupations: mean salary, minimum, mean, and maximum percentage of men at the job, minimum, mean, and maximum probability that the supervisor would be male, and the probability that the job would hire a woman. Then, all jobseekers were asked to rank their top three overall occupations, to capture if their preferred occupations changed over the course of their time searching through Job Asaan. If there were new occupations that they were now interested in, which they were not previously interested in, they were asked their beliefs about those occupations. Finally, they were asked if they have worked anywhere since they enrolled onto the service. The endline survey was not incentivized, and had a response rate of 23%. As indicated in the last column of the balance table, there was no differential attrition by treatment.

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<sup>23</sup>The responses to the question about job interest and whether they would attend the job interview are highly correlated, with only a handful of cases where an individual indicated interest in the job but said that they would not attend an interview.

<sup>24</sup>For the 2,244 jobseekers who did not complete a CV with Job Asaan and were required to call in to apply for jobs, I interpret the job interest question as their decision to apply for the job. If they did indicate interest in a job, Job Asaan asked them to complete their CV information and reminds them that Job Asaan cannot apply for jobs on their behalf without a CV to forward to the firm.

## 1.5 Empirical Strategy

### 1.5.1 Application Decisions

The primary outcome of interest for the information and priming experiments, is whether the jobseeker chose to apply to a given job. The decision to apply to each job is treated as independent, within jobseeker. This is because jobseekers are encouraged to apply to all jobs they are interested in; applying for a given job does not preclude them from applying to others.<sup>25</sup>

#### Information Experiment

The outcome of interest  $Y_{ijk}$  in this set of analysis is whether jobseeker  $i$  chose to apply to job  $j$ , which she matched to in match round  $k$ . The first specification addresses the treatment on treated impact of receiving information about the given workplace attribute.

$$Y_{ijk} = \alpha_0 + \alpha_1 T_i A_j + \alpha_2 T_i + \alpha_3 A_j + \Gamma W_{ijk} + \varepsilon_{ijk} \quad (1.1)$$

Here,  $T_i$  is the treatment indicator that the jobseeker was randomly selected to receive information about the attribute.  $A_j$  denotes whether Job Asaan had information about the workplace attribute to share with the jobseeker.<sup>26</sup> If the firm did not provide the gender composition or the gender of the supervisor, this variable takes a value of zero, and the jobseeker received a message that Job Asaan did not have this information to share with them.<sup>27</sup> In addition,  $W_{ijk}$  is a vector of covariates. This includes job-level covariates which every jobseeker receives information about, regardless of treatment

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<sup>25</sup>The appendix to this chapter (Chapter 6) presents descriptives on matching and application behavior.

<sup>26</sup>In the case of information about gender composition, this omitted category also includes the case that the job has exactly half/half female and male employees.

<sup>27</sup>For gender composition, the exact message that the treatment group received was "We do not have gender of the employees at this firm". For gender of supervisor, the exact message that the treatment group received was "We do not have gender of the supervisor at this position".

arm.<sup>28</sup> This vector also includes an indicator for whether the jobseeker was in the Priming Experiment subsample, the number of jobs which they matched to in that round, and the treatment indicator for the other information treatment.<sup>29</sup> Finally, the vector includes the individual's completed education and years of work experience, which determine the matches that the jobseeker receives. The parameter of interest is  $\alpha_1$ , which denotes the impact of the jobseeker receiving information about the given workplace attribute. This parameter taking a positive value indicates that the jobseeker is more likely to apply to a job when she receives information about that workplace attribute.

In the next specification, I am interested in the impact of receiving information about a female- vs male- dominant workplace.

$$Y_{ijk} = \beta_0 + \beta_1 F_j T_i + \beta_2 U_j T_i + \beta_3 F_j + \beta_4 U_j + \beta_5 T_i + \Gamma W_{ijk} + \varepsilon_{ijk} \quad (1.2)$$

Here,  $F_j$  denotes a female-dominant workplace attribute (ie. majority/all female employees or female supervisor), while  $U_j$  denotes that Job Asaan does not have information about the given workplace attribute. The omitted category is then that the workplace is male-dominant (i.e. majority/all male employees or male supervisor). The parameter of interest is  $\beta_1$ , which denotes the impact of receiving information about a female dominant workplace attribute compared to a male dominant workplace attribute.<sup>30</sup> If this parameter is positive, then this indicates that the jobseeker is more

<sup>28</sup>These include natural log salary, flexible working hours, fixed effects for occupation, and fixed effects for location of the job. In the event that salary or working hours information is missing, these variables take on values of zero, and indicator variables for missing information are included.

<sup>29</sup>Jobseekers receive calls to apply to jobs only if they completed a CV. Otherwise, they still receive the SMS, but have to call Job Asaan to apply for jobs, and at that point are asked to complete the CV so that Job Asaan can apply on their behalf. The covariate for number of matches addresses the salience of each individual job posting. The appendix to this chapter (Chapter 6) includes analysis of job application rates as a function of lagged match rates in previous rounds. Only the number of matches in the current round has a significant impact on the application rate, indicating that salience of individual job postings rather than learning about labor market conditions through number of matches is what is driving the application decisions.

<sup>30</sup>In the case of gender composition, there is another category: firms that report that they have exactly

likely to apply to a job with a female-dominant workplace attribute than a male dominant workplace attribute, holding all else equal. Standard errors are clustered on the individual (the level of the treatment) and randomization strata are included as fixed effects in all specifications.

Both specifications are repeated for the full sample of jobseekers (4081 individuals) and the set of jobseekers who were active on the platform prior to randomization for this experiment (998 individuals). The information was likely more salient for active jobseekers since they had already been engaged with the platform through both SMS and phone calls; however the sample size for these regressions is smaller since not all those who signed up for the platform actively searched for jobs.<sup>31</sup>

### Priming Experiment

I estimate the causal impact of priming with the following equation. Again,  $Y_{ijk}$  denotes whether jobseeker  $i$  chose to apply to job  $j$ , which she matched to in match round  $k$ .

$$Y_{ijk} = \gamma_0 + \gamma_1 P_i + \Gamma W_{ijk} + \varepsilon_{ijk} \quad (1.4)$$

$P_i$  indicates whether jobseeker  $i$  was randomly selected to receive priming about family involvement in job search.<sup>32</sup> I again repeat the analysis separately for all job-

50% male and 50% female employees. In this case, the specification is as follows:

$$Y_{ijk} = \beta_0 + \beta_1 F_j T_i + \beta_2 U_j T_i + \beta_3 F_j + \beta_4 U_j + \beta_5 T_i + \beta_6 H_j T_j + \beta_7 H_j + \Gamma W_{ijk} + \varepsilon_{ijk} \quad (1.3)$$

. Here,  $H_j$  denotes a workplace with exactly 50% male and 50% female employees. The interpretation of  $\beta_1$  the same as the case for gender of the supervisor.

<sup>31</sup>Figure 4.2 in the appendix to this chapter (Chapter 6) depicts that across occupations, active jobseekers apply to a larger proportion of their matches than the full sample.

<sup>32</sup>Note that  $W_j$  is identical to that in Specification 1.2, except it does not include the indicator for whether the jobseeker received calls from Job Asaan to apply for jobs. This is because the sample for this regression is only those who filled out a CV through Job Asaan. They received a call each round asking to which jobs they were interested in applying; the prime was given at the beginning of this call. The vector also includes treatment indicators for each of the information treatments; this is possible since the priming experiment sample is a subsample of the information experiment sample.

seekers and those who were active on the platform prior to randomization.  $\gamma_1$  being negative would indicate that priming about family job search involvement decreases the application rate of educated female jobseekers. This is consistent with a family stigma cost.

## 1.5.2 Belief Updating

As jobseekers received matches through Job Asaan, they gained information about the types of jobs that are available in the labor market in Lahore. In this section, I explore three ways to estimate whether the information they received during the experiment impacted jobseekers' beliefs about occupations at endline, holding fixed their beliefs about the same occupations at baseline.

Here, the unit of observation is at the level of individual, occupation, and job attribute. The main specification is as follows:

$$E_{ilm} = \beta_0 + \beta_1 T_{ilm} + \beta_2 B_{ilm} + \Gamma X_i + \mu_m + \varepsilon_{ilm} \quad (1.5)$$

where  $i$  denotes individual,  $l$  denotes attribute (such as percentage male employees or probability of male supervisor) and  $m$  denotes the occupation for which beliefs are recorded. To address that matches are based on educational level and experience, these are controlled for in the vector  $X_i$ . The different measures of the endline belief (described below) are regressed on a measure of treatment and the prior belief constructed in a parallel manner to the endline belief for that specification. The specification includes occupation fixed effects ( $\mu_m$ ) and standard errors are clustered at the individual level. The coefficient of interest is  $\beta_1$  which indicates the impact of treatment on endline beliefs (denoted  $E_{ilm}$ ), holding constant baseline beliefs ( $B_{ilm}$  which are constructed analogously to  $E_{ilm}$ ).

There are three measures of  $E_{ilm}$  which I employ in this analysis. First, is the mea-

sured endline, as described previously: expected percent men, expected probability of a male supervisor, expected salary, and expected probability of a woman being hired for the job. In addition to the expectations, for the percent of employees at a job who are male and the probability of the job having a male supervisor, I assume a triangular distribution for the beliefs, and use this to construct the standard deviation of the individual's belief.<sup>33</sup>  $B_{ilm}$  is the parallel measure from the baseline survey for each endline belief.

In order to capture accuracy of beliefs, I construct two sets of measures, which are relative to measures calculated from job postings on Job Asaan. The first is the absolute value of the deviation of the jobseeker's belief from the true measure of the parameter using job postings on Job Asaan, denoted  $\gamma_{ilm}$ . Here,  $\alpha_{ilm}$  is individual  $i$ 's belief at endline about attribute  $l$  for occupation  $m$ ;  $\hat{\theta}_{lm}$  denotes the expected value of the attribute  $l$  in occupation  $m$ , as measured using all ads posted during through the service.

$$\gamma_{ilm} = |\alpha_{ilm} - \hat{\theta}_{lm}| \quad (1.6)$$

The final measure of endline belief accuracy is a pseudo-zscore constructed for each of the expected value beliefs (but not for the standard deviations), denoted by  $\zeta_{ilm}$ . This is identical to the previous measure, except that it is divided by the standard deviation of the attribute  $l$  in occupation  $m$ , as measured through the firm survey.

$$\zeta_{ilm} = \left| \frac{\alpha_{ilm} - \hat{\theta}_{lm}}{\hat{\sigma}_{lm}} \right| \quad (1.7)$$

In both cases, I construct a parallel measure using the priors measure instead of endline belief in the calculation to capture baseline accuracy to use for  $B_{ilm}$  in equation

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<sup>33</sup>In cases of clear violation of the triangular distribution, the standard deviation is not calculated, and the observations are omitted from analysis.

## 1.5.

Conditional on expressing interest in an occupation, education, and experience (the variables used for matching), the matches that the jobseeker receives is determined by the distribution of firms that are hiring, not by the individual's beliefs. Thus, I use the number of matches (by occupation) as exogenous variation in explaining the jobseeker's beliefs about the probability of a woman being hired for a job posting in the given occupation. Second, I interact the treatment indicator for receiving information about gender of the supervisor with this measure of number of matches (by occupation) as a source of exogenous variation in explaining the jobseeker's beliefs about the distribution of the probability of having a male supervisor. Third, I interact the treatment indicator for receiving information about gender composition with this measure of number of matches (by occupation), and use this as a source of exogenous variation in explaining the jobseeker's beliefs about the distribution of male employees. Fourth, the priming experiment about family involvement in job search is interacted with this measure of number of matches (by occupation), and used as exogenous variation in explaining the jobseeker's beliefs about salary.

## 1.6 Experimental Results

### 1.6.1 Application Decisions

#### Information Experiment

Table 1.1 denotes the results of Specification 1.1 for gender composition in Panel A and gender of the supervisor in Panel B. The results in Panel A show that for the full sample and the active jobseekers, receiving information about gender composition does not have a large or statistically significant impact on the decision to apply for a job. However, in Panel B, it is evident that receiving information about gender of the supervisor

nearly doubles the application rate for the full sample and for active jobseekers. The first row in Panel B shows the impact of being selected to receive information about gender of the supervisor and that the jobseeker actually received the information (in that Job Asaan had the information from the firm to share with the jobseeker). The second row has a negative and significant coefficient; this is picking up that individuals in the treatment group became used to receiving information about gender of the supervisor. When it was not provided because the firm did not provide the information to Job Asaan, they were less likely to apply than their control group counterparts who were not used to receiving this information at all.<sup>34</sup>

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<sup>34</sup>Table 4.7 in the appendix to this chapter (Chapter 6) denotes the Intent to Treat results. Here, the specification is simply

$$Y_{ijk} = \delta_0 + \delta_1 T_i + \Gamma W_{ijk} + \varepsilon_{ijk} \quad (1.8)$$

. The results show essentially null results, including for gender of the supervisor. This is because of the countervailing effects of jobs where Job Asaan does and does not have information to give to the jobseeker on the jobseeker's application decisions.

**Table 1.1: Information Experiment: Main Results**

Panel A: Information Experiment: Gender Composition		
VARIABLES	(1) Applied for job	(2) Applied for job
Treat Info X Have Info Gender Comp	0.00654 (0.00719)	0.0142 (0.0131)
Treat Info Gender Comp	-0.00370 (0.00688)	-0.0134 (0.0131)
Have Info Gender Comp	0.0280* (0.0163)	0.0297 (0.0251)
Observations	20,650	8,110
Sample	All	Active
Number of Jobseekers	3661	958
Panel B: Information Experiment: Gender of the Supervisor		
VARIABLES	(1) Applied for job	(2) Applied for job
Treat Info X Have Info Gender Sup	0.0463** (0.0220)	0.0652* (0.0369)
Treat Info Gender Sup	-0.0473** (0.0220)	-0.0671* (0.0371)
Have Info Gender Sup	-0.0347 (0.0470)	0.00412 (0.0674)
Observations	20,650	8,110
Sample	All	Active
Number of Jobseekers	3661	958

*Notes:* Includes job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also includes covariates for the number of matches in that round of matching, indicator for receiving calls from Job Asaan to apply for jobs (i.e. complete CV), treatment indicator for opposite information treatment, and strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 1.2 provides the results of Specification 1.2, which denotes the impact of information about a female versus male dominant workplace attribute. For ease of interpretation,  $\beta_1$  and  $\beta_5$  are reported in the table, which denote respectively the impact of information about a female versus male dominant workplace attribute, and the impact of information about a male dominant workplace attribute, holding fixed that Job

Asaan has information about that workplace attribute. In Panel A, it is evident that the probability of applying for the job upon learning that the job has majority or all female employees is greater than for majority or all male employees, but that these differences are very small and not statistically significant. In Panel B, for gender of the supervisor, the difference is much larger and statistically significant for active jobseekers (Panel B column (2)). This indicates that active jobseekers are more likely to apply to job with a female supervisor than a male supervisor. Importantly, due to the specification, these results show that active female jobseekers are more likely to apply to a job with a female supervisor than a male supervisor, holding constant occupation, whether the job has flexible working hours, where in the city the job is located, and salary.

**Table 1.2:** Information Experiment: Gender of Workplace Attribute

Panel A: Information Experiment: Gender Composition		
VARIABLES	(1) Applied for job	(2) Applied for job
Receiving Info About Mostly/All Female VS Mostly/All Male Emp	0.00677 (0.00572)	0.000993 (0.00971)
Receiving Info About Mostly/All Male Emp	0.000503 (0.00504)	0.00103 (0.00861)
Observations	20,650	8,110
Sample	All	Active
Number of Jobseekers	3661	958
Panel B: Information Experiment: Gender of the Supervisor		
VARIABLES	(1) Applied for job	(2) Applied for job
Receiving Info About Female VS Male Sup	0.00598 (0.00531)	0.0206** (0.00900)
Receiving Info About Male Sup	-0.00447 (0.00512)	-0.0123 (0.00923)
Observations	20,650	8,110
Sample	All	Active
Number of Jobseekers	3661	958

*Notes:* Includes job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also includes covariates for the number of matches in that round of matching, indicator for receiving calls from Job Asaan to apply for jobs (i.e. complete CV), treatment indicator for opposite information treatment, and strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Across specifications, the results show that receiving any information increases the application rate, supporting a model where a low-information environment contributes to low female labor force participation and employment.<sup>35</sup> To test specific mechanisms, I conduct heterogeneity analysis for Specification 1.1, which looks at the impact of receiving information (regardless of whether it is of a female- or male- dominant workplace attribute).<sup>36</sup> Tables 1.3 and 1.4 display the results of this analysis. Panel A in each table has results for the full sample, and Panel B has results for those active before the randomization.

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<sup>35</sup>Table 4.4 in the appendix to this chapter (Chapter 6) contains analysis of the distribution of matches that the jobseeker received, by information treatment status, controlling for education and years of experience. Overall, the matches are balanced, with an exception that active jobseekers in the gender of supervisor treatment matched to a lower percentage of matches with flexible working hours, and that jobseekers in the gender of supervisor treatment in general matched to slightly fewer occupations overall. Match-level indicators for occupation and flexible working hours are included in all specifications in this section.

<sup>36</sup>In the heterogeneity specification, the heterogeneity variable is interacted with each of the covariates which are also all included as levels, as is the heterogeneity variable.

**Table 1.3: Information Experiment: Gender Composition - Heterogeneity**

Panel A: All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Less Accurate Beliefs about Labor Market	Correct Priors about Gender Comp	Currently Enrolled	Employed Start of Exp	Received Info - Female Sup	Flex Hours	Above Min Wage
Treat Info X Info Exists Gender Comp X Heterogeneity Var	0.00595 (0.0389)	0.00563 (0.0152)	0.0123 (0.0226)	0.0298 (0.0583)	0.0120 (0.0151)	-0.0177 (0.0185)	0.00330 (0.0169)
Treat Info Gender Comp X Heterogeneity Var	0.0122 (0.0376)		0.00167 (0.0224)	-0.0482 (0.0543)	-0.000229 (0.0139)	0.0216 (0.0179)	0.00573 (0.0152)
Have Info Gender Comp X Heterogeneity Var	-0.0124 (0.0272)	-0.304 (0.309)	-0.000776 (0.0142)	0.0193 (0.0386)	-0.00876 (0.0119)	0.0202 (0.0439)	-0.0157 (0.0301)
Observations	4,608	3,891	11,058	4,205	20,650	20,650	15,388
Number of Jobseekers	1038	904	1413	746	3661	3661	3599
Panel B: Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Less Accurate Beliefs about Labor Market	Correct Priors about Gender Comp	Currently Enrolled	Employed Start of Exp	Received Info - Female Sup	Flex Hours	Above Min Wage
Treat Info X Info Exists Gender Comp X Heterogeneity Var	0.0270 (0.0597)	0.0227 (0.0264)	0.0207 (0.0349)	0.0398 (0.0937)	0.0344 (0.0287)	-0.0362 (0.0302)	-0.00670 (0.0294)
Treat Info Gender Comp X Heterogeneity Var	-0.0497 (0.0592)		0.00438 (0.0367)	-0.0599 (0.0871)	-0.0180 (0.0251)	0.0324 (0.0291)	0.0289 (0.0261)
Have Info Gender Comp X Heterogeneity Var	-0.0226 (0.0458)	-0.549 (0.497)	-0.000869 (0.0211)	0.00399 (0.0693)	-0.0236 (0.0203)	0.0655 (0.0708)	0.0203 (0.0533)
Observations	1,943	1,614	5,242	1,788	8,110	8,110	6,443
Number of Jobseekers	393	340	539	203	958	958	939

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*Notes:* Regression estimates include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. All regressions include a covariate of the number of matches that the jobseeker received in that round of matching, treatment indicator for opposite information treatment, and indicator for receiving calls from Job Asaan to apply for jobs. Strata fixed effects are included. Correct priors can only be defined for jobs where Job Asaan has information about the workplace attribute, hence the collinearity in Column (2). SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment.

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table 1.4: Information Experiment: Gender of Supervisor - Heterogeneity**

Panel A: All Jobseekers							
VARIABLES	(1) Less Accurate Beliefs about Labor Market	(2) Correct Priors about Gender of Sup	(3) Currently Enrolled	(4) Employed Start of Exp	(5) Received Info - Maj/All Female Emp	(6) Flex hours	(7) Above Min Wage
Treat Info X Have Info Gender Sup X Heterogeneity Var	0.180 (0.159)	-0.000563 (0.0145)	-0.109 (0.0662)	0.00778 (0.164)	0.000732 (0.00633)	-0.0509* (0.0269)	0.0579** (0.0237)
Treat Info Gender Sup X Heterogeneity Var	-0.150 (0.159)		0.0933 (0.0658)	-0.0169 (0.163)		0.0489* (0.0264)	-0.0532** (0.0238)
Have Info Gender Sup X Heterogeneity Var	-0.140 (0.113)	-0.0426 (0.291)	0.0537 (0.0530)	0.104 (0.124)	-0.344 (0.314)	1.009*** (0.0522)	0.0412** (0.0164)
Observations	4,608	3,873	11,058	4,205	20,650	20,206	15,388
Number of Jobseekers	1038	915	1413	746	3661	3612	3599

Panel B: Active Jobseekers							
VARIABLES	(1) Less Accurate Beliefs about Labor Market	(2) Correct Priors about Gender of Sup	(3) Currently Enrolled	(4) Employed Start of Exp	(5) Received Info - Maj/All Female Emp	(6) Flex Hours	(7) Above Min Wage
Treat Info X Have Info Gender Sup X Heterogeneity Var	0.0549 (0.135)	0.0100 (0.0222)	0.0466 (0.0998)	0.390 (0.252)	-0.00375 (0.0130)	-0.0584 (0.0460)	0.00437 (0.0123)
Treat Info Gender Sup X Heterogeneity Var	-0.0450 (0.135)		-0.0925 (0.0994)	-0.279 (0.260)		0.0502 (0.0450)	
Have Info Gender Sup X Heterogeneity Var	0.0249 (0.0723)	-0.634 (0.471)	-0.0508 (0.0804)	-0.0984 (0.220)	-0.440 (0.481)	0.271 (0.286)	0.0419 (0.0273)
Observations	1,943	1,653	5,242	1,788	8,110	8,110	6,443
Number of Jobseekers	393	346	539	203	958	958	939

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Notes: Regression estimates include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. All regressions include a covariate of the number of matches that the jobseeker received in that round of matching, treatment indicator for opposite information treatment, and indicator for receiving calls from Job Asaan to apply for jobs. Strata fixed effects are included. Correct priors can only be defined for jobs where Job Asaan has information about the workplace attribute, hence the collinearity in Column (2). All job postings where Job Asaan does not have information about gender of the supervisor have majority/all male employees, hence the collinearity in Column (5). All job postings that active jobseekers in the information treatment group matched to that did not have information about gender of the supervisor had salary above minimum wage, hence the collinearity in Column (7). SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The first mechanism explored is whether those who have less accurate overall beliefs about the labor market respond differently to receiving information about a gender-related workplace attribute.<sup>37</sup> The results show positive coefficients in both tables for those who have less accurate beliefs (having the priors accuracy measure being above the median in the sample, indicating that beliefs are a greater deviation from the truth), indicating that those with less accurate beliefs are more likely to apply when their information level improves, compared to those who already have a more accurate understanding of the labor market. However, these results are not statistically significant. Active jobseekers whose priors were correct about gender composition are more likely to apply when they receive information that conforms with their prior than those whose prior was incorrect; while the magnitude is large relative to the control mean, this impact is not statistically significant. The magnitudes are much smaller for the analogous analysis for gender of the supervisor. Those who are currently enrolled or who are employed when the experiment began, both measures indicating that the jobseeker is not currently unemployed, are more likely in most specifications than their counterparts to apply to a job if they learn information about gender of coworkers or supervisor, but these effects are not significant.

In the final set of heterogeneity analysis, I look at related job characteristics. Jobseekers are more likely to apply to a job when they learn that it has a female supervisor

<sup>37</sup>To measure accuracy, I use the priors data collected at baseline, and construct the following measure based on a pseudo-z-score. This is the sum by individual of baseline equivalents ( $\omega_{ilm}$ ) of the  $\zeta_{ilm}$  measures constructed for the learning analysis.

$$\eta_i \equiv \sum_{m \in M} \eta_{ilm} = \left| \sum_{m \in M} \sum_{l \in L} \frac{\omega_{ilm} - \hat{\theta}_{lm}}{\hat{\sigma}_{lm}} \right| \quad (1.9)$$

Here, L denotes the four expected value parameters that are captured in the baseline survey: expected salary, expected percent of male employees at a firm, expected probability of hiring a woman. These are captured for each of three occupations which the respondent ranked as most desirable at baseline, denoted here by M. The expected value and standard deviation for the truth are defined using the firm survey data. For heterogeneity, this  $\eta_i$  variable is divided into those who have below and above median knowledge of the labor market. This analysis can only be conducted on the sample which provided prior beliefs in the baseline survey.

and receive information about the gender composition of the firm than if they do not learn that it has a female supervisor, however this effect is not statistically significant. The opposite relationship: whether the jobseeker is more likely to apply to a job when she learns that it has majority or all female employees versus not receiving that information, has magnitudes very close to zero and again insignificant. Jobseekers are *less* likely to apply to a job when they learn that it has flexible working hours or and more likely to apply to a salary above minimum wage, compared to other jobs when they learn the gender composition; again these impacts are not statistically significant. Jobseekers are significantly less likely to apply to a job that has flexible working hours than one without flexible working hours, when they learn the gender of the supervisor. This is consistent with the jobseeker interpreting that a job that has the information to provide about gender of the supervisor is particularly organized, and that flexible working hours indicate that the supervisor will mandate that the jobseeker must be flexible enough to work whenever demanded. Finally, jobseekers who receive information about gender of the supervisor are more likely to apply to jobs that are above minimum wage, which could be an indicator of a more coordinated firm overall: one that knows who the supervisor will be, and pays well, could indicate a position with growth opportunities.

## Priming Experiment

**Table 1.5:** Priming Experiment

VARIABLES	(1) Applied for job	(2) Applied for job
Treat: Prime	-0.0119** (0.00571)	-0.0184* (0.0103)
Observations	12,503	5,877
Sample	All	Active
Number of Jobseekers	1664	620

*Notes:* Includes job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also includes covariate of the number of matches in that round of matching and treatment indicators for information treatments. Sample is all matches who completed a CV (and thus received calls from Job Asaan to apply for jobs). Strata fixed effects are included. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. SE are clustered on individual, and reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

The overall results to the priming experiment are displayed in Table 1.5. In both the full sample and the sample of jobseekers active before randomization, the results show that being primed to think about family involvement in job search decreases the application rate by about 25%. This causal estimate is consistent with descriptive survey evidence that women in Pakistan report that their families are a constraint in their labor supply decisions.<sup>38</sup>

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<sup>38</sup>Table 4.5 displays the distribution of matches that those in the priming treatment group received compared to those in the priming control group. These distributions are balanced, except that even controlling for number of occupations in which the jobseeker indicated interest, education, and experience, active jobseekers in the treatment group received fewer matches on average than active jobseekers in the control group. This is addressed in the specifications by controlling for the number of matches in each matching round.

**Table 1.6: Priming Experiment - Heterogeneity**

Panel A: All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Less Accurate Beliefs about Labor Market	Employed Start of Exp	Received Info - Female Sup	Received Info - Gender Sup	Received Info - Maj/All Female Emp	Received Info - Gender Comp	Prior Work Exp
Treat: Prime X Heterogeneity Var	-0.0169 (0.0176)	0.188*** (0.0712)	-0.000105 (0.0104)	-0.000514 (0.0126)	0.000313 (0.0122)	0.0216* (0.0113)	-0.0274** (0.0125)
Observations	4,517	2,260	12,503	12,503	12,503	12,503	12,503
Number of Jobseekers	1018	288	1664	1664	1664	1664	1664

Panel B: Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Less Accurate Beliefs about Labor Market	Employed Start of Exp	Received Info - Female Sup	Received Info - Gender Sup	Received Info - Maj/All Female Emp	Received Info - Gender Comp	Prior Work Exp
Treat: Prime X Heterogeneity Var	-0.0373 (0.0310)	0.400*** (0.112)	0.0220 (0.0159)	0.0213 (0.0211)	0.0410** (0.0184)	0.0564*** (0.0191)	-0.0613*** (0.0232)
Observations	1,892	1,263	5,877	5,877	5,877	5,877	5,877
Number of Jobseekers	384	122	620	620	620	620	620

*Notes:* Regression estimates include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. All regressions include a covariate of the number of matches that the jobseeker received in that round of matching, and treatment indicators for information treatments. Sample is all matches for all jobseekers who completed a CV (and thus received calls from Job Asaan to apply for jobs). Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. SE are clustered on individual, and reported in parentheses. Strata fixed effects are included. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

To test specific mechanisms, I conduct heterogeneity analysis, based on Specification 1.4; results are reported in Table 1.6.<sup>39</sup> Those with less accurate beliefs about the labor market are less likely than their counterparts to apply when primed about family involvement in job search, but this is not statistically significant. Those who were employed before the experiment began are more likely to apply to jobs when primed about family involvement in job search (column (2)), but those who have any prior work experience are less likely than their counterparts to apply when primed (column (5)). This is consistent with those who have ever worked outside the home before having had bad experiences either on-the-job, or in convincing their families that they should work outside the home. Jobseekers who are primed to think about family job search advice are also more likely to apply to jobs when they have information about gender composition of the workplace, indicating that families have advice about the type of workplace that the jobseeker should choose. Information about gender composition allows women to sort along the preferences of their families, even if they themselves do not have strong preferences over gender composition. The revealed preference for workplaces with majority/all female employees is consistent with families adhering to social norms surrounding social segregation of men and women.

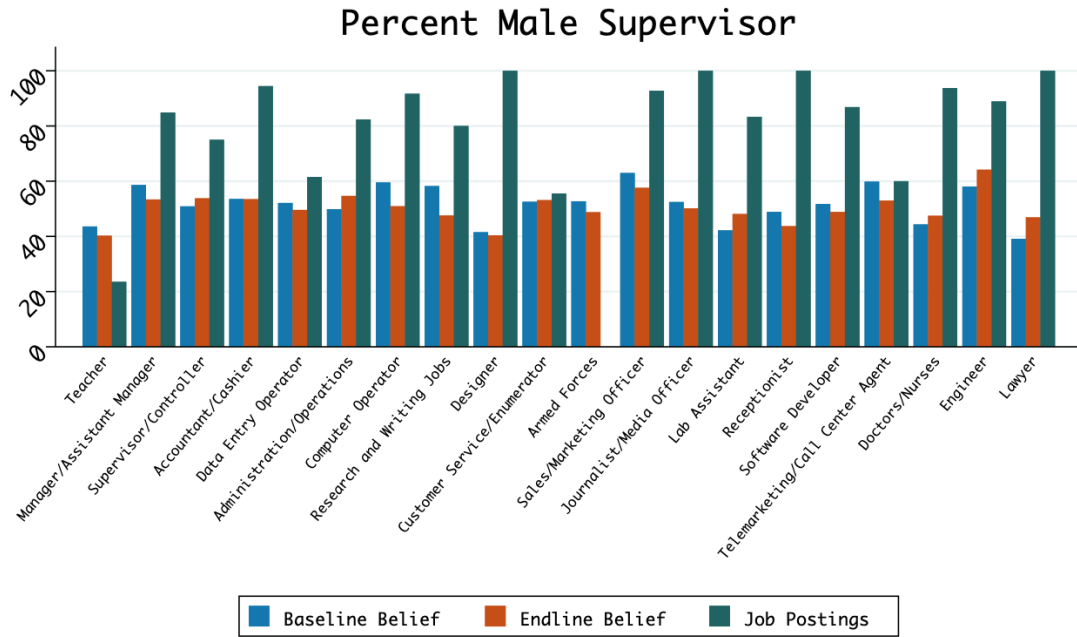
### 1.6.2 Belief Updating

Before turning to the regression results, Figures 1.8 through 1.11 indicate the simple averages of the baseline beliefs (blue bars) and endline beliefs (orange bars) against the relevant averages from the postings on Job Asaan (green bars). Except for teaching positions and slightly for call center positions, jobseekers vastly underestimate the proportion of men working in their desired occupations. However, between baseline and endline, the average belief in the sample approaches the true value among job

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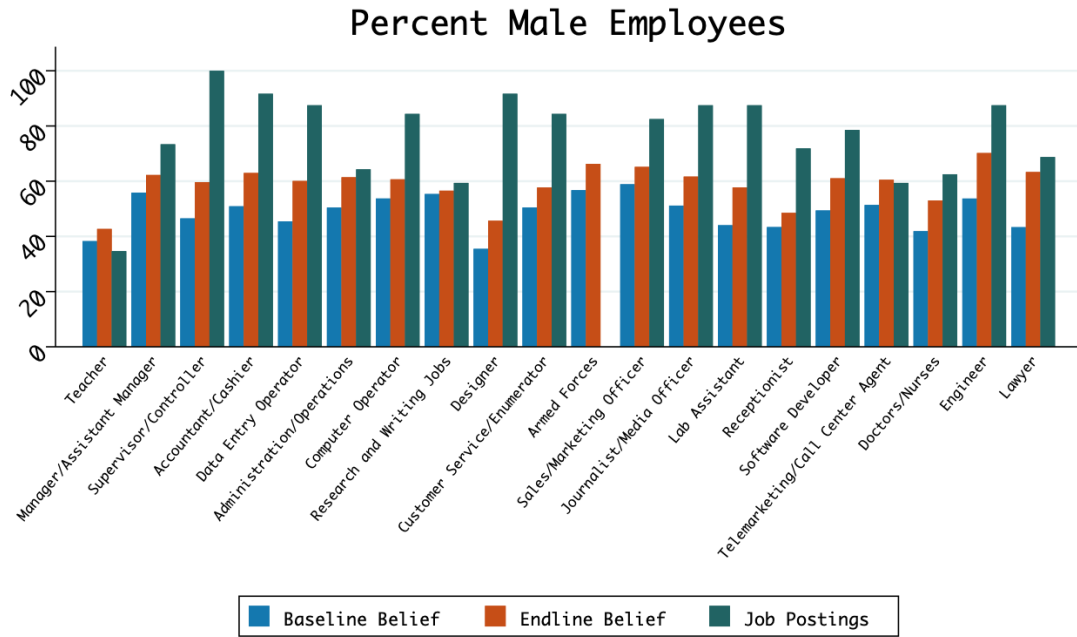
<sup>39</sup>The heterogeneity variable is interacted with each of the variables in Specification 1.4, which are also all included as levels, as is the heterogeneity variable.

postings. This pattern is similar for the proportion of positions with a male supervisor, except that at both baseline and endline the average belief of having a male supervisor in a teaching position is much higher than the actual average probability. In the job postings, most schools which are willing to hire female teachers are schools with female supervisors for those teachers. What is different here, is that endline beliefs about the probability of having a male supervisor are actually less accurate than baseline beliefs for many occupations. Combined with the results on application behavior, it is possible that gender of the immediate supervisor is a particularly salient attribute about which jobseekers might be overcorrecting their beliefs. Consistent with data in other settings, jobseekers overestimate salary in most occupations. The final graph in this series shows that between baseline and endline, jobseekers decrease their estimate of how likely it is that a firm will hire a woman. While the gray bars for this graph are fairly large, they depict the proportion of job postings in that occupation which are willing to accept applications from women, rather than depicting the proportion that eventually hire women, thus serving as an upper bound.



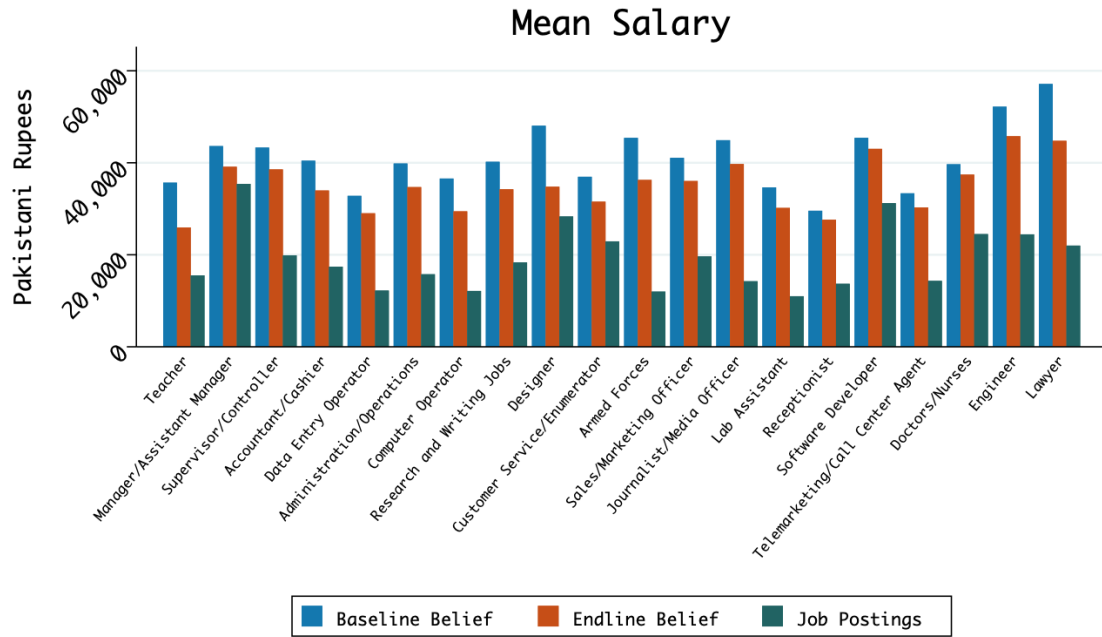
**Figure 1.8:** Beliefs about Gender of Supervisor

*Notes:* Blue bars indicate average prior beliefs (measured at baseline) and orange bars indicate average endline beliefs. Green bars indicate averages from job postings on Job Asaan. No bar indicates that there were no job postings in that occupation which provided the information to be aggregated.



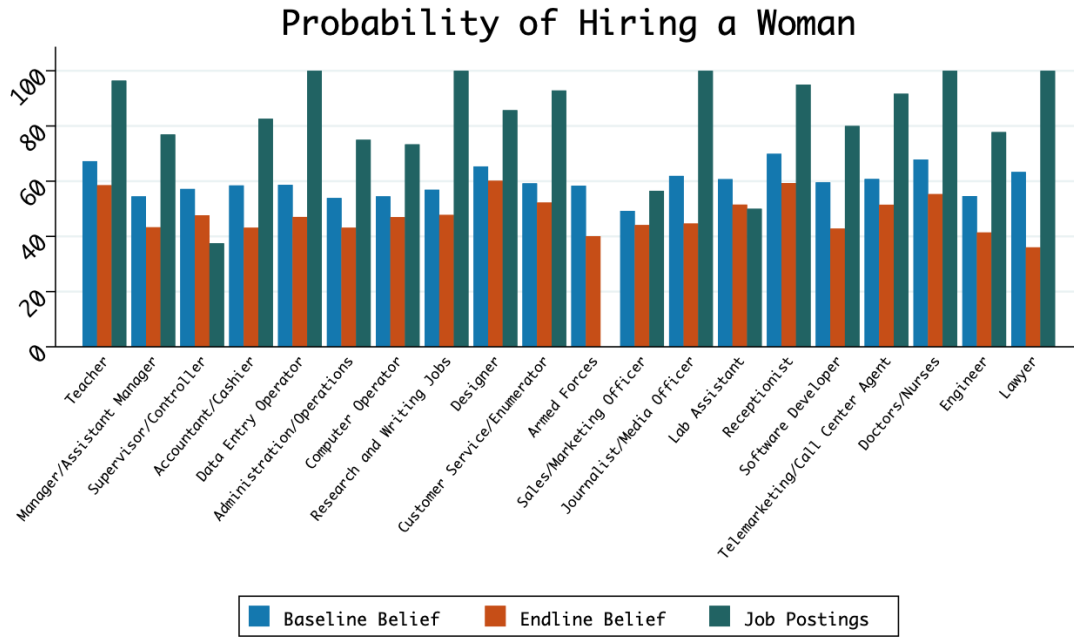
**Figure 1.9:** Beliefs about Gender Composition

*Notes:* Blue bars indicate average prior beliefs (measured at baseline) and orange bars indicate average endline beliefs. Green bars indicate averages from job postings on Job Asaan. No bar indicates that there were no job postings in that occupation which provided the information to be aggregated.



**Figure 1.10: Beliefs about Salary**

*Notes:* Blue bars indicate average prior beliefs (measured at baseline) and orange bars indicate average endline beliefs. Green bars indicate averages from job postings on Job Asaan. No bar indicates that there were no job postings in that occupation which provided the information to be aggregated.



**Figure 1.11:** Beliefs about Probability of Hiring a Woman

*Notes:* Blue bars indicate average prior beliefs (measured at baseline) and orange bars indicate average endline beliefs. Green bars indicate averages from job postings on Job Asaan; this is the proportion of jobs posted on the platform that are willing to accept application from women - an upper bound on the proportion that would actually hire women. No bar indicates that there were no job postings in that occupation which provided the information to be aggregated.

The results in the following tables show whether and how jobseekers updated their beliefs about supervisor gender, gender composition, salary, and probability that a woman would be hired, by occupation. In Tables 1.7 and 1.8, Columns (1) and (2) present results for Specification 1.5 for the mean and standard deviation respectively, Columns (3) and (4) present results for Specification 1.6 for the mean and standard deviation respectively, and Column (5) presents results for Specification 1.7 for the mean. Table 1.7 presents results for updating beliefs about supervisor gender. Across specifications, the information treatment does not significantly shift the endline belief of the

probability of having a male supervisor. However, the exception is that the standard deviation of the belief about the probability of having a male supervisor in the given occupation is significantly higher by about 0.3 percentage points (in terms of probability of having a male supervisor) by each additional match received for individuals who receive information about gender of the supervisor, as seen in Column (2). Furthermore, the results in Column (4) show that this led to a decrease in the absolute value of the difference between the belief and the distribution of male supervisors across matches on the platform, indicating that the information treatment brought the endline belief closer to the “truth” of the distribution of jobs on the platform. Furthermore, this latter result in particular persists even when p-values are adjusted for multiple inferences.

**Table 1.7:** Belief Updating about Supervisor Gender

VARIABLES	(1) Mean: Endline Belief	(2) SD: Endline Belief	(3) Mean: Absolute Value of Difference	(4) SD: Absolute Value of Difference	(5) Mean: Pseudo Z-score
Num Matches (by occ)	0.496	0.319**	-0.253	-0.337**	-0.00748
X Treat Info Supervisor Gender	(0.663)	(0.151)	(0.378)	(0.150)	(0.0101)
	[0.6]	[0.12]	[0.67]	[0.09]	[0.67]
Prior	0.131**	0.115***	0.111	0.131***	0.106
	(0.0638)	(0.0339)	(0.0683)	(0.0340)	(0.0866)
Observations	766	361	746	348	684
Control Mean	50.01	6.841	31.92	29.02	0.838

*Notes:* The unit of observation is at the level of individual and occupation. Sample is all such occupation/individuals where priors and endline beliefs are both completed. "Prior" refers to the belief at baseline constructed analogously to the specific outcome endline measure. Fixed effects at occupation level; standard errors clustered on individual. Standard errors reported in parentheses. Westfall-Young mult. inf. adj. p-values in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1, referring to unadjusted p-values.

Table 1.8 presents results for belief updating about the percentage of male employees that the jobseeker expects in a given occupation. Here, the information treatment did not significantly update jobseekers’ beliefs in any specification.

**Table 1.8: Belief Updating about Gender Composition**

VARIABLES	(1) Mean: Endline Belief	(2) SD: Endline Belief	(3) Mean: Absolute Value of Difference	(4) SD: Absolute Value of Difference	(5) Mean: Pseudo Z-score
Num Matches (by occ)	0.219	-0.0645	-0.169	0.0702	-0.00528
X Treat Info Gender of Coworkers	(0.405)	(0.146)	(0.299)	(0.143)	(0.0110)
	[0.92]	[0.92]	[0.92]	[0.92]	[0.92]
Prior	0.164***	0.0952***	0.136***	0.0400	0.153*
	(0.0420)	(0.0364)	(0.0501)	(0.0381)	(0.0786)
Observations	781	353	758	343	698
Control Mean	55.20	7.360	20.31	18.46	1.107

*Notes:* The unit of observation is at the level of individual and occupation. Sample is all such occupation/individuals where priors and endline beliefs are both completed. "Prior" refers to the belief at baseline constructed analogously to the specific outcome endline measure. Fixed effects at occupation level; standard errors clustered on individual. Standard errors reported in parentheses. Westfall-Young mult. inf. adj. p-values in square brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ , referring to unadjusted p-values.

Tables 1.9 and 1.10 present results about belief updating about salary and the probability that a woman would be hired, by occupation. The priming experiment and matches receiving through the platform do not significantly shift jobseekers' beliefs about either parameter.

**Table 1.9: Belief Updating about Salary**

VARIABLES	(1) Endline Belief	(2) Absolute Value of Difference	(3) Pseudo Z-score
Num Matches (by occ)	-47.08	-103.4	0.00146
X Treat Prime	(166.8)	(151.2)	(0.0120)
	[0.9]	[0.62]	[0.9]
Prior	0.236***	0.248***	0.207***
	(0.0626)	(0.0434)	(0.0662)
Observations	747	747	718
Control Mean	31435	13483	1.811

*Notes:* The unit of observation is at the level of individual and occupation. Sample is all such occupation/individuals where priors and endline beliefs are both completed. "Prior" refers to the belief at baseline constructed analogously to the specific outcome endline measure. Fixed effects at occupation level; standard errors clustered on individual. Standard errors reported in parentheses. Westfall-Young mult. inf. adj. p-values in square brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ , referring to unadjusted p-values.

**Table 1.10: Belief Updating about Probability of Hiring a Woman**

VARIABLES	(1) Endline Belief	(2) Absolute Value of Difference	(3) Pseudo Z-score
Num Matches (by occ)	0.317	-0.254	-0.0128
	(0.430)	(0.426)	(0.0202)
	[057]	[0.57]	[0.57]
Prior	0.0714*	0.100**	0.105
	(0.0387)	(0.0416)	(0.0671)
Observations	803	803	687
Control Mean	46.97	38.32	1.184

*Notes:* The unit of observation is at the level of individual and occupation. Sample is all such occupation/individuals where priors and endline beliefs are both completed. "Prior" refers to the belief at baseline constructed analogously to the specific outcome endline measure. Fixed effects at occupation level; standard errors clustered on individual. Standard errors reported in parentheses. Westfall-Young mult. inf. adj. p-values in square brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ , referring to unadjusted p-values.

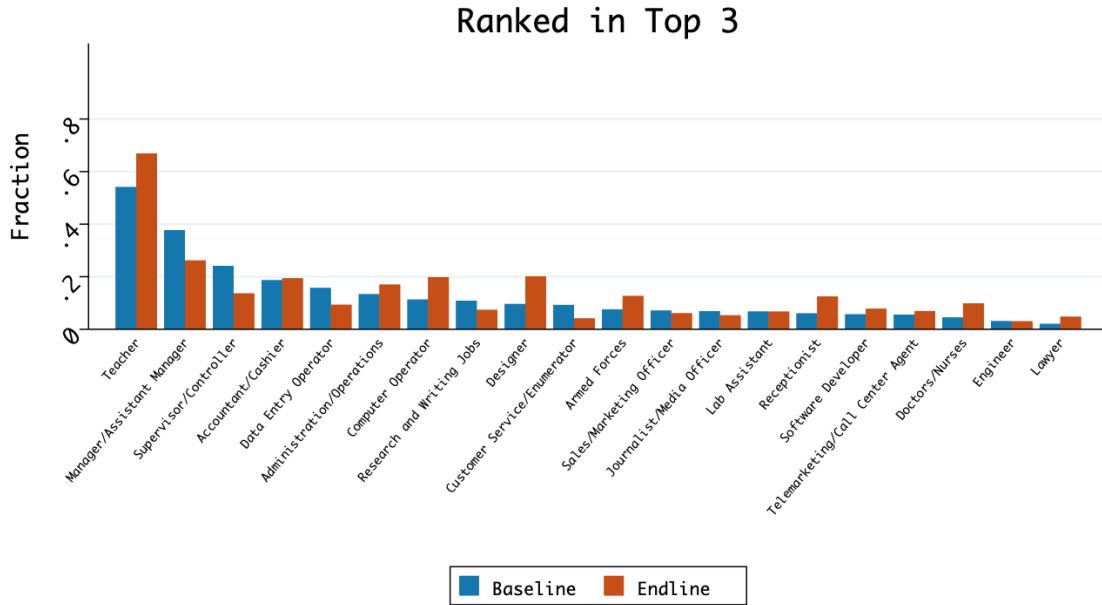
Overall, the sample sizes for these analyses are low, as the sample is restricted to

jobseekers who completed both the full baseline and full endline surveys. The results show that indicators for receiving additional information at the job-level or priming themselves did not shift jobseekers' beliefs about occupations substantially from their baseline prior for most parameters.<sup>40</sup> The notable exception is that across specifications, the treatment led jobseekers to update their beliefs accurately about the variance (standard deviation) of the probability of having a male supervisor, by occupation.

## 1.7 Occupational Choice

Just as workplace attributes impact job application decisions, they can also impact occupational choice. In this section, I explore the role of beliefs about workplace attributes on women's stated preference ranking over occupations, as a measure of occupational choice. Figure 1.12 depicts which occupations jobseekers are most interested in being matched with at baseline and at endline.

<sup>40</sup>At the end of each matching call, the respondent was asked her belief about expectation of men within the occupation (rounds 1-3) or expectation of probability of having a male supervisor (rounds 4-5) for every occupation with which she matched in that round. Table 4.8 in the appendix to this chapter (Chapter 6) estimates a simple specification of regressing this belief on treatment indicators, including occupation fixed effects. The responses only includes respondents who completed a phone call to apply for a job, and thus the sample size is comparatively low. There are small differences between information treatment and control groups, but none are statistically significant.



**Figure 1.12:** Occupational Rankings

*Notes:* Blue bars indicate baseline and orange bars indicate endline. Each bar denotes the percentage of respondents that ranked the given occupation as within their top three most preferred occupations.

At baseline, about 55% of jobseekers ranking 'teacher' in their top three most preferred occupations, which is consistent with teaching being a very culturally accepted profession for women. About 25% of jobseekers ranking 'manager/assistant manager' in their top three most preferred occupations, showing that while the majority of respondents are just beginning their careers, their stated occupational preferences are ambitious. The overall distribution is fairly similar at endline.

The first set of analysis tests whether the information or priming treatment directly had an impact on endline rankings. The first outcome is whether the individual changed their set of rankings from baseline to endline within occupation, controlling for education and experience (the matching criteria), among jobseekers who completed both the baseline and endline questionnaires. The second and third outcomes are respectively

whether the respondent ranked "Manager/Assistant Manager" and "Teacher" as their most preferred outcome at endline. These are the two occupations which jobseekers were most interested in at baseline.

The specifications for the information experiment and priming experiments are both straightforward. In the information experiment specification,  $S_i$  denotes being randomly selected to be in the treatment group to receive information about gender of supervisor, and  $C_i$  denotes being randomly selected to be in the treatment group to receive information about gender composition.

$$Y_{im} = \gamma_0 + \gamma_1 S_i + \gamma_2 C_i + \gamma_3 S_i C_i + \Gamma W_i + \varepsilon_i \quad (1.10)$$

In the priming experiment specification,  $P_i$  denotes being randomly selected to be in the treatment group to receive priming about family job search advice.

$$Y_{im} = \rho_0 + \rho_1 P_i + \Gamma W_i + \varepsilon_i \quad (1.11)$$

Beliefs about workplace attributes can drive individuals' rankings over occupations. To study this relationship, I specify a simple utility function (Zafar, 2013; Attanasio and Kaufmann, 2014). In the following,  $i$  indexes the individual and  $m$  indexes the occupations. Utility is assumed to depend on the jobseeker's beliefs about four parameters of the occupation: the salary, the probability that an open job posting in that occupation would hire a woman, the percentage of employees in a typical job in that occupation that would be women, and the probability that the job would have a female supervisor.<sup>41</sup>

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<sup>41</sup>In the endline and baseline surveys, I ask the jobseeker to report the percentage of employees she believes would be men and the probability of having a male supervisor for each of her most preferred occupations. To maintain consistency across directions of beliefs, I subtract those values from 100 to get the percentage of female employees and the probability of a female supervisor

The utility gained for jobseeker  $i$  from occupation  $m$  is thus:

$$U_{im} = \sum_{l \in L} \beta_l E_{ilm} + \beta_5 \rho_{im} + \varepsilon_{im} \quad (1.12)$$

In this specification,  $L$  denotes the set of four parameters of the occupation: the salary, the probability that an open job posting in that occupation would hire a woman, the percentage of employees in a typical job in that occupation that would be women, and the probability that the job would have a female supervisor;  $E_{ilm}$  denotes individual  $i$ 's endline expected value about parameter  $l$  for occupation  $m$ . In addition, the utility function includes the number of matches that the jobseeker received for that occupation which had flexible working hours,  $\rho_{im}$ . This is not a parameter on which endline beliefs were collected, however it is likely to be an important workplace attribute which can impact women's occupational choice. I also estimate a version of this utility function which includes endline standard deviation belief about the percentage of employees in a typical job in that occupation that would be women, and the endline standard deviation belief about the probability that the job would have a female supervisor.

The jobseeker is assumed to rank preferred occupation by maximizing utility. Using the endline data on rankings and beliefs, I estimate the utility function in Specification 1.12 as a rank ordered logit regression, assuming that the stochastic term  $\varepsilon_{im}$  follows an extreme value distribution (Beggs et al., 1981). This estimation of the values of each  $\beta$  represents the importance of that belief parameter on occupational choice. However, the belief at endline is endogenous: the jobseeker could learn about the occupations that she indicated interest in at baseline, through her job search. Thus, I require a set of instruments which are correlated with her endline beliefs but otherwise exogenous. Since the final specification is a nonlinear model, I cannot estimate the equation as a standard two-stage least squares estimation. Rather, I implement a control function approach to address this endogeneity (Petrin and Train, 2009; Wooldridge, 2014; Hotz

et al., 2018b). The details and results from this estimation are presented in appendix to this chapter (Chapter 6).

### 1.7.1 Occupational Choice: Results

Table 1.11 contains the analysis for whether the information or priming treatments impacted whether individuals changed their ranking of preferred occupations between baseline and endline, and whether it changed whether they ranked being a manager or teacher as their top preference. The results show that neither treatment directly impacted stated occupational rankings.

**Table 1.11: Occupational Rankings**

Panel A: Information Experiment				
VARIABLES	(1) Changed Ranking	(2) Rank 1: Sales/Marketing Officer	(3) Rank 1: Manager/ Assistant Manager	(4) Rank 1: Teacher
Treatment: Information about Gender of Supervisor	0.00108 (0.0194)	0.00302 (0.0106)	-0.0111 (0.0277)	-0.00368 (0.0604)
Treatment: Information about Gender Composition	-0.0162 (0.0157)	0.00223 (0.0103)	-0.00525 (0.0273)	0.0452 (0.0572)
Treatment: Both Information Treatments	-0.0250 (0.0295)	0.00304 (0.0186)	0.00535 (0.0389)	-0.0133 (0.0849)
Observations	4,180	924	924	924
R-squared	0.088	0.332	0.534	0.312
Control Mean	0.137	0.0500	0.0500	0.0500
Panel B: Priming Experiment				
VARIABLES	(1) Changed Ranking	(2) Rank 1: Sales/Marketing Officer	(3) Rank 1: Manager/ Assistant Manager	(4) Rank 1: Teacher
Treatment: Prime	-0.0175 (0.0150)	-0.0379 (0.0279)	-0.0132 (0.0549)	0.0177 (0.0979)
Observations	3,780	355	355	355
R-squared	0.093	0.601	0.754	0.655
Control Mean	0.137	0.0500	0.0500	0.0500

*Notes:* Unit of observation is occupation and individual. Standard errors clustered on individual. Controls include education and years of experience. Fixed effects for occupation and randomization strata. First column depicts impact of information on whether the individual changed their top three rankings, among respondents who completed both baseline and endline rankings. Column (2) and (3) restrict the sample to one observation for each individual who completed endline rankings. The outcomes are whether the individual ranked "Manager/Assistant Manager" or "Teacher" as most preferred, respectively. These are the two most preferred occupations from baseline. Standard errors reported in parentheses.\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 1.12 displays the results of the occupational choice analysis. In the empirical

results, I report an expanded rank-ordered logit which includes the standard error belief parameters as explanatory variables without addressing endogeneity of beliefs and the basic rank-ordered logit (as described in the previous section) without addressing endogeneity. The results accounting for endogeneity are presented in appendix to this chapter (Chapter 6), though they should be interpreted with caution since the first stages are underpowered.

**Table 1.12:** Occupational Choice

VARIABLES	(1) RO Logit	(2) RO Logit
Endline Belief: Mean Salary	-0.0262*** (0.00610)	-0.0288*** (0.00580)
Endline Belief: Mean Percent Female	0.0105*** (0.00293)	0.00918*** (0.00240)
Endline Belief: SD Percent Female	0.0151 (0.0133)	
Endline Belief: Mean Prob Female Supervisor	0.00856*** (0.00309)	0.00361 (0.00249)
Endline Belief: SD Prob Female Supervisor	0.0389*** (0.0151)	
Endline Belief: Mean Prob Hire Woman	-0.0132*** (0.00287)	-0.0131*** (0.00261)
Total Number of Matches w Any Flex Hours	0.114*** (0.0331)	0.110*** (0.0308)
Observations	2,267	2,421

*Notes:* Standard errors clustered on individual. Both sets of estimates are rank-ordered logit. Outcome variable is ranking of top three most preferred occupations. The endline belief for mean salary is in units of 1000 PKR (about 10 USD). The endline beliefs for mean percent female, SD percent female, mean probability of female supervisor, SD of probability of female supervisor, and mean probability of hiring a woman are all in percentage point units. Standard errors reported in parentheses.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

In the first column, the results show that beliefs that an occupation has a higher

percentage of female employees, higher probability of a female supervisor, higher standard deviation (spread) of having a female supervisor, and more matches with flexible working hours are all associated with higher rank. However, a higher expected salary and higher expected probability that a woman would be hired are associated with a lower rank. This is consistent with female jobseekers preferring a female-dominant workplace. A low expected probability of hiring a woman could be an indicator that the occupation is interpreted as high-prestige, and thus is ranked higher. Finally, higher expected salary is associated with lower ranking. This result is consistent with the fact that about 90% of jobseekers in this sample are not married, and that for those who completed this survey question at baseline, 80% of those not married expect to be married within five years. They are aware that they are expected to be on the marriage market, and likely know that a high salary will not garner returns on the marriage market (Bertrand et al., 2015; Murray-Close and Heggeness, 2019).

The second column presents analogous results but without the standard deviation measures included. The patterns are consistent with the results in the first column. An exception is that when the standard deviations of beliefs about having a female supervisor or the percent of female employees are not included in the specification, a higher mean expected probability of having a female supervisor is not significantly associated with occupational rank.

These descriptive results are mostly consistent with women preferring occupations that they believe will have more women and that are of higher prestige, but not necessarily ranking occupations based on the expected probability of having a female supervisor. The magnitude of the results is consistent with a similar increase in utility from having an additional match in that occupation with flexible working hours and a one percentage point higher expectation of percentage of women in a typical firm hiring for that occupation. A higher expected salary by two thousand PKR is associated with about as much of a decrease in utility as a one percentage point increase in the

expected probability that a woman would be hired for that occupation.

## 1.8 Robustness Checks

For robustness of the application decision regressions, I estimate additional specifications. The main information experiment robustness results are in Tables 1.13 and 1.14. The information experiment robustness results looking at differences in application rates for female- dominant or male- dominant jobs are reported in Tables 1.15 and 1.16. I first estimate a simplified model identical to Specification 1.1 (or analogously Specification 1.2 and 1.3), but without the vector of covariates  $W_{ijk}$ . The second specification includes job-level fixed effects instead of job-level covariates. The interpretation of the main coefficients then becomes the difference in application rate for individuals who did and did not receive information about gender-related workplace attributes, for the same job posting. Since job-level fixed effects are included, job characteristics are now omitted from the vector of covariates  $W_{ik}$ . The third specification includes match round level fixed effects, instead of controlling for the number of matches received in the given round. The interpretation is then comparison across jobs within the same match round. The main results for the information experiment are consistent in magnitude and significance to these robustness checks. The fourth specification restricts the sample for the main specification to those in the Priming Experiment sample; results are consistent.

**Table 1.13: Robustness: Information Experiment: Main Results: Gender Composition**

Panel A: All Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Treat Info X Have Info Gender Comp	0.00483 (0.00727)	0.00562 (0.00717)	0.00557 (0.00718)	0.0122 (0.0107)	-0.00441 (0.0334)
Treat Info Gender Comp	-0.00172 (0.00693)	-0.00258 (0.00682)	-0.00248 (0.00683)	-0.00879 (0.0101)	-0.0111 (0.0349)
Have Info Gender Comp	0.00188 (0.00471)		0.00566 (0.0195)	0.0428* (0.0230)	-0.00902 (0.0496)
Observations	20,650	20,650	20,650	12,503	711
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	3661	3661	3661	1664	410
Panel B: Active Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Treat Info X Have Info Gender Comp	0.0119 (0.0132)	0.0128 (0.0130)	0.0131 (0.0131)	0.0184 (0.0175)	0.0453 (0.0426)
Treat Info Gender Comp	-0.0104 (0.0131)	-0.0112 (0.0129)	-0.0114 (0.0129)	-0.0185 (0.0176)	-0.0508 (0.0501)
Have Info Gender Comp	-0.00156 (0.00846)		0.0179 (0.0307)	0.0524 (0.0341)	-0.0272 (0.0269)
Observations	8,110	8,110	8,110	5,877	387
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	958	958	958	620	184

*Notes:* First column: No control variables. Fourth column (only completed calls): Regressions include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also include covariates for the number of matches in that round of matching, opposite information treatment indicator, and indicator for receiving calls from Job Asaan to apply for jobs. All regressions include strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.05.

**Table 1.14:** Robustness: Information Experiment: Main Results: Gender of Supervisor

Panel A: All Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Treat Info X Have Info Gender Sup	0.0438** (0.0223)	0.0464** (0.0219)	0.0451** (0.0220)	0.0524* (0.0289)	0.0189 (0.0163)
Treat Info Gender Sup	-0.0446** (0.0223)	-0.0470** (0.0220)	-0.0457** (0.0220)	-0.0532* (0.0290)	0.0153 (0.0124)
Have Info Gender Sup	-0.0667*** (0.0181)		-0.0661 (0.0561)	-0.0406 (0.0657)	0.0679 (0.0566)
Observations	20,650	20,650	20,650	12,503	711
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	3661	3661	3661	1664	410
Panel B: Active Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Treat Info X Have Info Gender Sup	0.0635* (0.0374)	0.0638* (0.0370)	0.0630* (0.0370)	0.0895* (0.0475)	0.0110 (0.0138)
Treat Info Gender Sup	-0.0629* (0.0377)	-0.0631* (0.0373)	-0.0623* (0.0373)	-0.0926* (0.0481)	0.0135 (0.0144)
Have Info Gender Sup	-0.0867*** (0.0310)		-0.0182 (0.0813)	0.0154 (0.0910)	0.0324 (0.0372)
Observations	8,110	8,110	8,110	5,877	387
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	958	958	958	620	184

*Notes:* First column: No control variables. Fourth column (only completed calls): Regressions include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also include covariates for the number of matches in that round of matching and indicator for receiving calls from Job Asaan to apply for jobs. All regressions include strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.05.

**Table 1.15:** Robustness: Information Experiment: Gender of Workplace Attribute - Gender Composition

Panel A: All Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Receiving Info About Mostly/All Female VS Mostly/All Male Emp	0.00604 (0.00573)	0.00645 (0.00572)	0.00646 (0.00572)	0.00743 (0.00935)	0.00581 (0.0398)
Receiving Info About Mostly/All Male Emp	0.00115 (0.00508)	0.000841 (0.00507)	0.000880 (0.00506)	0.00208 (0.00755)	-0.0234 (0.0206)
Observations	20,650	20,650	20,650	12,503	711
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	3661	3661	3661	1664	410
Panel B: Active Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Receiving Info About Mostly/All Female VS Mostly/All Male Emp	0.000879 (0.00968)	0.00120 (0.00962)	0.00156 (0.00963)	-0.000537 (0.0136)	0.0102 (0.0126)
Receiving Info About Mostly/All Male Emp	0.00166 (0.00858)	0.00167 (0.00851)	0.00160 (0.00852)	0.000525 (0.0118)	-0.00798 (0.0105)
Observations	8,110	8,110	8,110	5,877	387
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	958	958	958	620	184

*Notes:* First column: No control variables. Fourth column (only completed calls): Regressions include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also include covariates for the number of matches in that round of matching, opposite information treatment indicator, and indicator for receiving calls from Job Asaan to apply for jobs. All regressions include strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.05. Test row displays p-value for test that coefficient on Treat Info x Female is same as coefficient on Treat Info x Male.

**Table 1.16:** Robustness: Information Experiment: Gender of Workplace Attribute - Gender of Supervisor

Panel A: All Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Receiving Info About Female VS Male Sup	0.00551 (0.00543)	0.00539 (0.00539)	0.00549 (0.00539)	0.00571 (0.00826)	-0.00460 (0.0308)
Receiving Info About Male Sup	-0.00402 (0.00524)	-0.00374 (0.00521)	-0.00383 (0.00523)	-0.00387 (0.00797)	0.0357* (0.0184)
Observations	20,650	20,650	20,650	12,503	711
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	Yes	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	3661	3661	3661	1664	410
Panel B: Active Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied to job
Receiving Info About Female VS Male Sup	0.0188** (0.00919)	0.0199** (0.00912)	0.0198** (0.00914)	0.0249** (0.0124)	-0.00769 (0.0126)
Receiving Info About Male Sup	-0.00852 (0.00951)	-0.00932 (0.00945)	-0.00929 (0.00948)	-0.0152 (0.0134)	0.0273 (0.0260)
Observations	8,110	8,110	8,110	5,877	387
Job FE	No	Yes	No	No	No
Match FE	No	No Job Covars	Yes	Yes	No
Job Covars	No		Yes	Yes	Yes
Number of Jobseekers	958	958	958	620	184

No

*Notes:* First column: No control variables. Fourth column (only completed calls): Regressions include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also include covariates for the number of matches in that round of matching, opposite information treatment indicator, and indicator for receiving calls from Job Asaan to apply for jobs. All regressions include strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.05. Test row displays p-value for test that coefficient on Treat Info x Female is same as coefficient on Treat Info x Male .

Throughout the experiment, while jobseekers were supposed to either call Job Asaan to apply for jobs or pick up the calls from Job Asaan to say that they were not interested or in which jobs they were interested, in practice, jobseekers only called to apply for jobs, and largely picked up Job Asaan’s calls only when they wanted to apply for jobs. Thus, not picking up the call and not calling Job Asaan are categorized as not applying for the job. The final specification replicates the main specification for all jobseekers,

but treats nonresponse to the call or no call as missing. As expected, given the selection into the call, there are no significant differences in application behavior across treatments in either the main information specification or the specification looking at differences in application rates for female- vs male- dominant workplace attributes.

The robustness checks for application decisions on the priming experiment in Table 1.17 are similar. The first specification omits all covariates, and simply regresses the application decision on the treatment indicator for being randomly selected to receive priming. The second specification includes job fixed effects. Due to the job fixed effects, the coefficient of interest  $\beta_1$  now denotes the difference in application behavior between those who received the prime and those who did not, for the same job posting. The results from both of these specifications are very similar in magnitude and significance to the main results. The third set of results replicates the main specification but treats nonresponse to the call, or no call, as missing. Again, the sample size is very small, and there is no significant difference in application behavior across those who received priming and those who did not.

**Table 1.17: Robustness: Priming Experiment**

Panel A: All Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied to job	(5) Applied for job
Treat: Prime	-0.0126** (0.00578)	-0.0119** (0.00571)	-0.0122** (0.00577)	0.000460 (0.00123)	
Received Prime					-0.123** (0.0618)
Observations	12,503	12,503	12,503	623	12,503
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	No	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	1664	1664	1664	338	1664
Panel B: Active Jobseekers					
VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied to job	(5) Applied for job
Treat: Prime	-0.0186* (0.0105)	-0.0183* (0.0103)	-0.0182* (0.0105)		
Received Prime					-0.176* (0.104)
Observations	5,877	5,877	5,877	362	5,877
Job FE	No	Yes	No	No	No
Match FE	No	No	Yes	No	No
Job Covars	No	No	Yes	Yes	Yes
Number of Jobseekers	620	620	620	165	620

*Notes:* First column: No control variables. Fourth column (only completed calls): Regressions include job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also includes covariate of the number of matches in that round of matching, indicator for receiving calls from Job Asaan to apply for jobs, and information treatment indicators. Fourth column is IV specification. All regressions include strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.05. Test row displays p-value for test that coefficient on Treat Info x Female is same as coefficient on Treat Info x Male. F-test for first stage in Panel A (col 4) is 154.30. F-test for first stage in Panel B (col 4) is 65.04. Column (3) of Panel B is fully collinear and cannot be estimated.

Finally, I conduct a two-stage least squares estimation to address that the main specifications all capture an intent-to-treat, since not all jobseekers pick up the phone call from Job Asaan. I create a variable which indicates that the respondent picked up the phone call and received the priming question from Job Asaan. I instrument for this

using the randomly assigned priming treatment. All covariates from Specification 1.4 are included in the first and second stage. The magnitude of this treatment on treated effect is about ten times larger than the intent to treat (main specification).

## 1.9 Conclusion

Women's education levels have risen in Pakistan and in many other developing countries. However, women's labor supply remains low in terms of participation, hours of paid labor (compared to men), and wages. Conducting an experiment on a labor search platform catering to educated female jobseekers in urban Pakistan, I show that the information environment matters for women's job search, and that women face two types of costs. First, women face an initial threshold cost to working anywhere outside the home. Through experimental results, I show that priming about family job search involvement significantly decreases job application rates, consistent with social norms discouraging from women working outside the home.

Second, women face costs and benefits accruing from specific workplace attributes. Educated female jobseekers are far more likely to apply to jobs when they receive information about the gender of the supervisor at that job. Women who are actively searching for work are more likely to apply to a jobs with a female supervisor compared to a male supervisor, holding other job characteristics fixed. However, in a somewhat surprising result given social norms prescribing segregation of men and women in public spaces, educated female jobseekers do not exhibit a significant preference for a workplace with more or fewer female employees.

At baseline, descriptive survey evidence shows that the information environment surrounding workplace attributes in the labor market is poor. Educated women overestimate salary but underestimate the proportion of men working at typical firms and the probability of having a male supervisor, within occupation. Consistent with the

information regarding gender of the supervisor having a significant impact on the application rate, this treatment also significantly improved jobseekers' accuracy of beliefs about the distribution of the probability of having a male supervisor across occupations, beyond their baseline priors. No other belief parameters were significantly shifted by the experiments beyond the baseline priors. Finally, the descriptive analysis of occupational choice is consistent with women preferring occupations where they believe there will be more women in the workplace.

The results show that improving the information environment greatly improves women's job application rates by allowing women to sort into applying to firms that fit with their preferences over gender of the supervisor. Information about gender composition of the firm did not have as large a magnitude (or statistically significant) impact on job applications, which could be an encouraging sign that social norms about social segregation of men and women are now less relevant for highly educated women in urban Pakistan, though they seem to matter to families. Given that female labor force participation is particularly low in Pakistan, and hasn't risen much in recent decades, this result suggests that such an information intervention might have stronger impacts in settings with less stringent norms about women's work outside the home.

These results are encouraging and suggest that a low-cost information intervention providing accurate information about gender of the supervisor can increase educated women's job application rates on a formal job search platform. This can be an important step in translating women's educational achievements to the labor market. Most job search in Pakistan and other developing country settings is informal, stemming from word-of-mouth recommendations and connections with family and friends. The setting of this study is on a formal job search platform, which is accessible to highly educated women who have access to a phone, and thus the results should be extrapolated to job search among lower socioeconomic status women with caution. However, for this same reason, the results highlight that even for these highly educated women who are

searching for jobs through a formal platform, family job search advice can be a deterrent to their search, or can impact the profile of jobs to which women apply. Promoting women to supervisory roles can be one pathway to increasing the number of women actively searching for work, and to hopefully reach a tipping point where there are enough women in the workplace to improve the information environment surrounding women in the labor force and weaken family pressures against women working.

## Chapter 2

# Gold Prices, Sibling Composition, and Long-Run Household Decision-Making

### 2.1 Introduction

India is one of the world's largest consumers of gold. In 2016, 87% of households in a national survey owned gold; about half of the households overall had purchased gold in the last five years (Jain, 2017). Individual holdings of gold in India serve two purposes: jewelry/ornamentation and highly liquid savings; these are not mutually exclusive (Simha, 1979; Vaidyanathan, 1999). Happy occasions such as festivals, rites of passage such as weddings, and ornamentation with religious significance are all associated with gold purchases across India (Grewe, 2016).

In Indian weddings, the bride's family customarily pays for the wedding expenses. Furthermore, Indian brides traditionally wear gold jewelry, gifted by their natal family. This gold serves as a symbol of social status but also a personal financial safeguard for her within her marriage (Grewe, 2016). Thus, families have to plan for this significant expense and associated gold expenditures from the time of her birth. Conversely, families do not need to plan for wedding expenses nor significant gold expenditures for sons.

Post-independence in 1947, the government of India sought to dampen the population's enthusiasm for gold, concerned that gold purchases were offsetting other more lucrative investments that households could be making, and that the large quantity of gold imports necessary to meet the domestic demand would negatively impact the macroeconomy. Thus, the federal government instated policies to discourage households from purchasing gold, including prohibition of gold imports, price-fixing, and

halting domestic production (Reddy, 2002). In 1979 at a conference of research and industry groups focused on gold, the Bombay Bullion Association attempted to reason with the Indian government to relax import and other constraints on gold, by arguing that "[g]old is not a luxury, it is not even an article of consumption. It is multipurpose, indestructible asset, and a necessity. Not a daily necessity but a life-time necessity, like life insurance. It is in universal demand, by all sections of the people, who prize gold as the most dependable form of saving." (Simha, 1979). Consistent with this idea of a universal demand, a black market for gold flourished in India. In 1979, the Finance Minister argued that this black market was responsible for the wedge between international and domestic gold prices that arose during this time period (Simha, 1979). After the repeal of the Gold Control Act in 1992, India remains a major consumer of gold in world markets (Vaidyanathan, 1999).

The majority of India's gold consumption is satisfied by imports rather than domestic production or mining (Kannan and Dhal, 2008). In the post-liberalization period, global gold prices respond to timing of specific Indian (and Chinese) festivals where gold purchases and gift-giving are common practice (Schmidbauer and Rösch, 2018). However, in the period before liberalization in 1992, there was a large wedge between the international gold price and the domestic gold price in India driven by domestic gold policy. Under this political and economic regime, the international gold price in the pre-1992 period was plausibly exogenous to household decision-making.

Given the gender differences in expected wedding and gold expenses, among second-order and higher parity births, high global gold price in the month of birth leads to female-biased fetal and neonatal mortality (Bhalotra et al., 2020). Due to broader cultural son preference, births within households follow a male-biased stopping rule in India (Clark, 2000; Jayachandran, 2015). Families prefer to have at least one son, resulting in more siblings on average for daughters than sons, and families are more likely to stop having children after having at least one son. This fertility pattern could be

impacted by global gold prices, since after the gender of each birth is revealed, households must update how many and what gender composition of children they can afford to have in the future, given expectations of requisite gold expenditures by gender.

In this chapter, I use variation in international gold price to document the relationship between gold price during the year of birth and sibling composition. I then document long-run household decision-making outcomes in relation to global gold price in the year of birth. I focus on the pre-1992 period, and use global gold price rather than domestic gold price, so that the variation in gold price is plausibly exogenous.

I find that a higher gold price in the year of birth is associated with fewer siblings for girls. Holding fixed the number of siblings, a higher gold price in the year of birth is associated with fewer brothers for both boys and girls, fewer sisters for girls, and more younger sisters for boys. Furthermore, being born in a year with a higher global gold price is associated with a lower probability of being the youngest child overall for girls, but I do not find a significant relationship with the probability of being the youngest for boys. These patterns are consistent with parents being concerned about having to pay for daughters' wedding expenses, but not having that concern for sons. Sons are likely expected to work to support their sisters' wedding expenses.

Sibling composition and birth order can have broader impacts on human capital accumulation, including breastfeeding duration and height (Jayachandran and Kuziemko, 2011; Jayachandran and Pande, 2017). In societies with imperfect markets and son preference, as in India, children have to compete more with brothers than sisters for household resources (Garg and Morduch, 1998). This competition within the natal household can have impacts on broader health status, child labor, mortality, and marital patterns (Pande, 2003; Edmonds, 2006; Rosenblum, 2012; Vogl, 2013). Thus, in this paper, I also study the empirical relationship between the global gold price in the year of birth and individual outcomes, and between the global gold price in the wife's year of birth and household outcomes.

The long-run results show that women and men who are born in years with a higher mean global gold price are less likely to have sorted into marriage, are less likely to have completed a secondary school education, and have lower weight and BMI. Women are more likely to be anemic. Among couples, the global mean gold price in the wife's birth year is not significantly related with the degree of hypergamy, though there are some negative relationships with husband's and wife's health and health behaviors. Husbands of women born in years with a higher global gold price are slightly less likely to have worked in the last twelve months. Most notably, women born in years with a higher mean global gold price are less likely to report ever having had an abortion or using contraception. There are no significant relationships with whether they or their husbands condone the husband beating the wife.

These long-run patterns could be a result of changes in sibling composition, but could also be impacted by shifts in sex ratios as a result of female-biased fetal and neonatal mortality or overall shifts in household resource allocation as a response to changing gold prices (Bhalotra et al., 2020). I am not fully able to separate these mechanisms using available data.

In the remainder of the paper, I discuss methodology and results. In Section 2.2, I document the data sources that I use in the analysis, and in Section 2.3, I discuss the empirical strategy. In Section 2.4, I review results related to sibling composition and in Section 2.5, I discuss long-run patterns. Section 2.6 concludes.

## **2.2 Data**

The global gold price data is from the World Gold Council, which records international gold prices at the weekly level from 1978 through the present. Prices are recorded for troy oz of gold. To document the wedge between international and domestic (India) gold prices, I use data aggregated by the Reserve Bank of India; these prices are for 10

grams of gold.

As discussed in more detail in the next section, the analysis focuses on gold prices between 1980 and 1991. For sibling composition analysis, I use the National Family Health Survey of India (NFHS) 2 and 3, fielded respectively in 1998-1999 and 2005-2006.<sup>1</sup> I use the birth records data, which are a detailed record of birth histories for eligible women between the ages of 15 and 49 during the fielding of the survey. I restrict analysis to births that survived at least one month, since my outcome of interest is the composition of siblings that individuals grew up with.

For long-run impacts, I use individual and household data from the 2015-2016 NFHS (Wave 4). I focus on the sample of adults, both single and married, who were born in 1979 and onwards, i.e. the time period when I also have data on gold prices. I use data on individuals between the ages of 15 and 49 surveyed as part of the household survey, and separately data from the couples dataset. In effect, this refers to individuals aged 24-36 during NFHS 4. For the analysis on couples, I use the birth year of the female partner as the reference year. In effect, this refers to couples where the wife was aged 24-36 during NFHS 4.

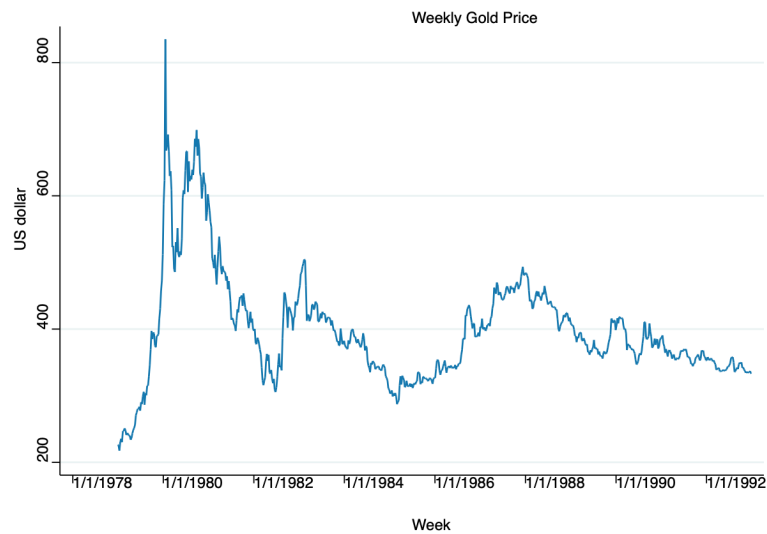
The data for additional covariates come from a variety of sources. Rainfall data at the state and month level comes from the Ministry of Earth Sciences of India. I aggregate this monthly data to the state and year level for analysis. Oil price data comes from the West Texas Intermediate (WTI) spot crude oil price historical data from the Federal Reserve Bank of St. Louis aggregated to the annual level. I obtain historical GDP and population data for India from the World Bank, which I use to calculate GDP per capita per year. Finally, I obtain CPI data to deflate all prices from the Federal Reserve Bank of St. Louis. I benchmark all prices to 2015 levels in USD.

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<sup>1</sup>This is the Indian implementation of the Demographic and Health Surveys.

## 2.3 Empirical Strategy

As seen in Figure 2.1, nominal gold prices climbed significantly in the late 1970s, and hit a peak in the first two weeks of 1980. The overall level of global gold prices declined more steadily through through the early 1980s. For this reason, the analysis is focused on birth cohorts born in 1980 and onwards.<sup>2</sup>



**Figure 2.1:** Gold Price Over Time

India has historically been a major consumer of gold. However, India's gold consumption is satisfied by imports rather than domestic production, making it a price-taker in the global market (Kannan and Dhal, 2008). Furthermore, between independence in 1947 and 1992, the Indian government imposed a set of policies to regulate gold in the country which included strict limits on imports, holdings, and domestic prices (Reddy, 2002). While these policies might have been intended to discourage households from being dependent on gold, in practice this led to a flourishing black market for gold (Vaidyanathan, 1999). These policies also resulted in a significant wedge between domestic and international gold prices, which can be seen in Figure

<sup>2</sup>There are no outliers in the mean global gold price in this period.

2.2, with the red line marking 1992 when the ban on gold imports (imposed in 1968 under the Gold Control Act) was lifted (Vaidyanathan, 1999). The green line in the image denotes the domestic gold price, the orange line depicts the international gold price, and the blue line depicts the spread between the domestic and international gold prices.



Source: Reserve Bank of India; per 10g gold; USD 2015

**Figure 2.2:** International vs Domestic Gold Prices

While India has always been and continues to be a price-taker for gold in the international market, in the period prior to 1992, the international price was lower than the domestic price of gold. However, the domestic gold price in India did respond in part to the global gold price and thus I am using international gold price data for analysis.

Given these two major events related to gold price globally and domestically in India, I am focusing the analysis to the period between 1980 and 1991. This restricts the analysis period to after the sharp increase in global gold prices but before India liberalized economic policy related to gold. The goal of this analysis is to study the relationship between global gold price in the year of birth and household decision-making. Most of the analysis is focused on couples in 2015-2016, where the household

has already been formed.<sup>3</sup> I benchmark year of birth to the year that the wife was born, and thus outcomes related to sorting, etc use a comparison of the husband's characteristics relative to the wife's.

In order to study the relationship between global gold price in the year of birth with sibling composition, I use the specification below.

$$y_{ist} = \alpha_0 + \alpha_1 G_t + \alpha_2 F_i + \alpha_3 G_t \times F_i + \Omega \Lambda + \eta t + \gamma_s + \varepsilon_{ist} \quad (2.1)$$

Here,  $y_{ist}$  refers to the outcome of interest for an individual  $i$  born in year  $t$  in state  $s$ . Here,  $G_t$  denotes the mean global gold price in year  $t$ , and  $F_i$  refers to a birth that is female. The coefficients of interest are  $\alpha_1$  which denotes the impact of global gold price in year of birth on a male child's sibling composition and  $\alpha_1 + \alpha_3$  which denotes the impact of global gold price in year of birth on a female child's sibling composition.

$\Lambda$  denotes the primary set of covariates for the regression. This includes the mean oil price in year  $t$  since oil prices could also play a role in household decision-making through macroeconomic fluctuations. To capture trends in purchasing power,  $\Lambda$  includes GDP per capita for India at the annual level. To capture trends by state and time, including in purchasing power,  $\Lambda$  includes average rainfall at the state ( $s$ ) and year ( $t$ ) of birth level. To capture regional differences in social norms and policies which could impact household decision-making, the specification includes state fixed effects ( $\gamma_s$ ). In the sibling composition analysis  $\Lambda$  also includes the mother's age, and in the case of all outcome variables related to sibling composition barring the outcome looking at number of siblings, number of siblings is included as a covariate. Finally, the specification includes a linear time trend ( $t$ ) to address other policy shifts or changes over time across the country. All prices are in USD, and deflated to 2015 levels using

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<sup>3</sup>Going forward, I refer to "couples" as "marriages" or "households", and for ease of exposition, I use the term "wife" for female partner and "husband" for male partner. Same-sex partnerships and unmarried partnerships are infrequent in the data.

the US CPI. Standard errors for all analyses are clustered on the sampling unit for the NFHS 4 (the source of outcome variables) and the group-interaction of sampling unit and birth year.<sup>4</sup>

In order to study the relationship between gold price in the year of birth with long-run household decision-making, I use the specification below.

$$y_{ist} = \alpha_0 + \alpha_1 G_t + \Omega \Lambda + \eta t + \gamma_s + \varepsilon_{ist} \quad (2.2)$$

This specification is identical to the first specification with two changes. First,  $\Lambda$  no longer controls for mother's age or number of siblings since this is not available in the long-run data. Second, for regressions studying couples, the year of birth is benchmarked to the wife's year of birth.

## 2.4 Results: Sibling Composition

The first set of results explores how sibling composition changes as a result of the global gold price in the child's year of birth. The last set of rows in each of the tables, labeled "Female" denote the value of  $\alpha_1 + \alpha_3$  from Specification 2.1.

Table 2.1 explores how the number of siblings changes as a function of the global gold price in the birth year. A higher global gold price in the year of birth is associated with significantly fewer siblings for girls, but not for boys. Holding fixed the number of siblings, there is a negative association between the gold price in the year of birth with the number of sisters for girls, and number of brothers for both boys and girls. There is a positive association between gold price in year of birth and number of younger sisters for boys, but no significant relationship for girls.

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<sup>4</sup>Complete two-way clustering on sampling and birth year is not possible due to there being too few years in the data, and thus too few clusters to cluster by year.

**Table 2.1: Number of Siblings**

VARIABLES	(1) Num Siblings	(2) Sisters	(3) Brothers	(4) Num Younger Brothers	(5) Num Younger Sisters
Mean gold price	-0.000134 (0.000268)	0.000288 (0.000203)	-0.000419** (0.000185)	0.000161 (0.000159)	0.000399** (0.000173)
Female	0.441*** (0.0726)	0.269*** (0.0548)	0.173*** (0.0514)	0.251*** (0.0415)	0.226*** (0.0453)
Mean gold price X female	-0.000591 (0.000376)	-0.000698** (0.000282)	0.000104 (0.000265)	-0.000327 (0.000216)	-0.000418* (0.000233)
Observations	207,473	207,473	207,473	207,473	207,473
Mean	3.473	1.724	1.749	1.009	0.939
Female	-0.000725***	-0.000410*	-0.000315*	-0.000166	-1.87e-05
P-Val	0.00915	0.0602	0.0944	0.282	0.919

*Note:* Controls for mother's age, mean oil price in year of birth, GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. Columns (2) through (5) including number of siblings as covariate. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Individuals born between 1980 through 1991. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 2.2 shows the probability of being the youngest child or youngest of gender (i.e. youngest boy or youngest girl). This captures whether the parents chose to keep having children after having a girl or boy. For boys, the global gold price in the year of birth is not significantly associated with the likelihood of being the youngest child or youngest boy in the family. However, for girls, a higher gold price in the year of birth is associated with a lower likelihood of being the youngest child overall.

**Table 2.2: Likelihood of Being Youngest**

VARIABLES	(1) Youngest	(2) Youngest of gender
Mean gold price	-6.02e-05 (6.30e-05)	7.46e-05 (7.49e-05)
Female	-0.0288* (0.0151)	0.0309* (0.0183)
Mean gold price X female	-0.000170** (7.99e-05)	-0.000169* (9.78e-05)
Observations	207,473	207,473
Mean	0.242	0.433
Female	-0.000230***	-9.41e-05
P-Val	0.000241	0.229

*Note:* Controls for mother’s age, mean oil price in year of birth, GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Individuals born between 1980 through 1991. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

To summarize, a higher gold price in the year of birth is associated with fewer siblings for girls. Holding fixed the number of siblings, a higher gold price in the year of birth is associated with fewer brothers for both boys and girls, and fewer sisters for girls. Holding fixed the number of siblings, a higher gold price in the year of birth is significantly associated with more younger sisters for boys. Furthermore, being born in a year with a higher global gold price is associated with a lower probability of being the youngest child overall for girls, but no significant relationship with the probability of being youngest for boys. However, these magnitudes are all quite small.

The signs of the effects have ambiguous predictions for long-run impacts of global gold prices. Girls might benefit in terms of health from being born in years with higher global gold prices. Having fewer brothers to compete with could lead to better health (Garg and Morduch, 1998). However, having fewer brothers could also mean less income overall for the natal household, thus tightening the budget constraint for the household (Rosenblum, 2012). Having fewer younger siblings could mean that daugh-

ters can work less than their counterparts born in years with lower gold prices who might have more younger siblings (Edmonds, 2006). Furthermore, if global gold price changes the position of the daughter among all daughters in the family, this could influence the relative age at which the daughter gets married, which in turn could influence educational investments in childhood and eventual spouse quality (Vogl, 2013).

Similarly, the theoretical long-run impacts of global gold prices for boys are also ambiguous. Boys born in years with higher global gold prices might benefit in terms of health from having fewer brothers to compete with, similarly to girls (Garg and Morduch, 1998). However, a higher global gold price in the year of birth is associated with more younger sisters for boys, which likely means higher wedding expenses overall for his natal household that he must be able to financially support.

The long-run theoretical implications are further complicated by the fact that the global gold price in the year of birth directly impacts the sex composition of births (Bhalotra et al., 2020) and could more broadly impact resource allocation within the household since gold purchases are a fundamental part of the Indian economy and culture. In the next section, I turn to long-run empirical results. Sibling composition is one mechanism through which global gold prices could have long-run impacts on individuals' household formation and economic decision-making. However, I cannot fully rule out that other mechanisms may play a role with existing data.

## **2.5 Results: Long Run Impacts**

The first set of results pools all individuals in the NFHS 2015-2016, who were born between 1980 and 1991, regardless of marital status. When all individuals are pooled in Table 2.3, the results are similar across genders. Both women and men who were born in years with a higher mean global gold price are less likely to be married by 2015. If the gold price increases by 10 USD, there is a 0.77 percentage decrease in the

likelihood of being married by 2015 for women, and a 2.71 percentage decrease in the likelihood of being married for men. For both genders, being born in a year with higher mean global gold price leads to a lower weight in adulthood and a lower BMI. Given that that weights and BMI are low on average in India, this should be interpreted as a negative impact. There is a negative relationship between gold price in year of birth and likelihood of completing secondary education for both men and women.

**Table 2.3: Individuals**

Panel A: Women								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ever married	Separated or Divorced	Secondary Educ or Higher	Weight in KG	Height in CM	Smoker	BMI	Anemic
Mean gold price	-0.000591*** (2.86e-05)	1.29e-05 (1.56e-05)	-0.000113* (6.34e-05)	-0.00963*** (0.00157)	-0.000880 (0.000804)	8.17e-06 (6.41e-06)	-0.00385*** (0.000634)	0.000134* (7.05e-05)
Observations	280,024	280,024	280,024	261,772	261,701	265,435	261,417	260,600
Mean	0.771	0.0106	0.604	50.54	151.9	0.00168	21.85	0.531
Panel B: Men								
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ever married	Separated or Divorced	Secondary Educ or Higher	Weight in KG	Height in CM	Smoker	BMI	Anemic
Mean gold price	-0.00164*** (4.58e-05)	8.71e-06 (1.27e-05)	-0.000127** (5.47e-05)	-0.0145*** (0.00379)	-0.00488* (0.00260)	-3.11e-05 (0.000145)	-0.00432*** (0.00137)	0.000100 (0.000105)
Observations	271,508	271,508	271,508	38,171	38,156	39,172	38,132	38,018
Mean	0.605	0.00645	0.756	58.54	163.6	0.121	21.82	0.108

*Note:* Controls for mean oil price in year of birth, GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Individuals aged 24-36 in 2015. Birth Years 1980 through 1991. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The remaining results focus on women and their husbands, with the benchmark year being the year that the wife was born. Thus, the results are for women who eventually marry, and the attributes of their husbands.

The first set of results are presented in Table 2.4. Global gold price in the wife's year of birth is not significantly related with age differences, height differences, or differences in educational attainment between wives and husbands. These are variables that indicate sorting into marriage or relative hypergamy. Furthermore, there are no impacts on the weight difference between spouses or the likelihood that the wife earns

more than the husband. These are measures of comparative consumption and labor within the marriage.

**Table 2.4:** Couple: Marriage Sorting and Overall Labor/Consumption

VARIABLES	(1) Man-Woman Age Diff	(2) Man-Woman Height Diff	(3) Man-Woman Years Educ Diff	(4) Man-Woman Weight Diff	(5) Woman earns more than Man
Mean gold price	-0.00119 (0.00144) [0.93]	-0.000789 (0.00347) [0.993]	-0.000902 (0.00154) [0.967]	-0.000454 (0.00520) [0.993]	1.30e-05 (9.50e-05) [0.993]
Observations	30,858	30,046	30,858	30,061	30,858
Mean	4.944	11.56	1.426	8.578	0.0508

*Note:* Controls for mean oil price and GDP per capita in the wife’s year of birth, linear time trend, average rainfall at the state and wife’s year of birth, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Wife’s birth years 1980 through 1991. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 2.5 presents results related to health and health behaviors. For women, there is a negative relationship between gold price in the year of birth and the likelihood of smoking, but a positive relationship with the likelihood of being anemic. For their husbands, there is a positive relationship between gold price in the wife’s year of birth and the likelihood of smoking. For both men and women, there is a negative relationship between gold price in the wife’s year of birth and weight, which extends to BMI for husbands. Overall, along most significant indicators, a higher global gold price in the wife’s year of birth is associated with worse health outcomes and behavior for both wives and their husbands. The only result which survives multiple inference adjustment is that a greater gold price in the year of birth is associated with a higher probability of being anemic for married women.

**Table 2.5: Couples: Health Measures**

Panel A: Women					
VARIABLES	(1) Weight in KG	(2) Height in CM	(3) BMI	(4) Smoker	(5) Anemic
Mean gold price	-0.00912** (0.00445) [0.146]	-0.00279 (0.00222) [0.225]	-0.00280 (0.00177) [0.206]	-1.32e-05* (7.15e-06) [0.205]	0.000489** (0.000192) [0.081]
Observations	30,548	30,547	30,522	30,858	30,389
Mean	52.33	152	22.59	0.00164	0.538
Panel B: Men					
VARIABLES	(1) Weight in KG	(2) Height in CM	(3) BMI	(4) Smoker	(5) Anemic
Mean gold price	-0.00931** (0.00459) [0.222]	-0.00428 (0.00311) [0.292]	-0.00267* (0.00157) [0.292]	0.000315* (0.000174) [0.222]	-3.21e-05 (0.000120) [0.77]
Observations	30,179	30,167	30,149	30,858	30,067
Mean	60.88	163.6	22.70	0.134	0.112

*Note:* Controls for mean oil price and GDP per capita in the wife's year of birth, linear time trend, average rainfall at the state and wife's year of birth, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Wife's birth years 1980 through 1991. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 2.5 presents results related to education and employment. There is a negative relationship between the gold price in the wife's year of birth and the likelihood that her husband has worked in the last twelve months; however this result does not survive multiple inference adjustment. There are no significant relationships between the global gold price in the wife's year of birth and the probability of having completed secondary school or literacy for either wives or their husbands.

**Table 2.6:** Couple: Education and Labor

Panel A: Women			
VARIABLES	(1) Secondary Educ or Higher	(2) Literate	(3) Worked in last 12 months
Mean gold price	0.000104 (0.000158) [0.879]	2.84e-05 (0.000180) [0.909]	-6.86e-05 (0.000180) [0.909]
Observations	30,858	30,858	30,858
Mean	0.179	0.578	0.322
Panel B: Men			
VARIABLES	(1) Secondary Educ or Higher	(2) Literate	(3) Worked in last 12 months
Mean gold price	-5.31e-05 (0.000193) [0.938]	-1.78e-05 (0.000162) [0.938]	-9.22e-05* (4.99e-05) [0.19]
Observations	30,858	30,858	30,857
Mean	0.235	0.717	0.976

*Note:* Controls for mean oil price and GDP per capita in the wife's year of birth, linear time trend, average rainfall at the state and wife's year of birth, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Wife's birth years 1980 through 1991. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 2.7 denotes results explicitly related to household decision-making. The first two columns show that women born in a year with a 10 USD higher global mean gold price are 2.24 percent less likely to have ever had an abortion and are 1.21 percent less likely to use contraception, suggesting either lower control over their own fertility or a preference for higher fertility. However, there are no significant relationships between the global gold price in the wife's year of birth and whether she reports decision-making power over other household decisions. Both results related to fertility survive multiple inference adjustment.

**Table 2.7: Couple: Women: Decisions**

VARIABLES	(1) Ever had abortion	(2) Does not use contraception	(3) Own health care	(4) Large household purchases	(5) Decides visits to relatives	(6) Spend money husband earns
Mean gold price	-0.000368** (0.000146) [0.041]	0.000499*** (0.000178) [0.026]	4.28e-05 (0.000175) [0.982]	-0.000282 (0.000175) [0.268]	-1.23e-05 (0.000160) [0.982]	3.91e-05 (0.000181) [0.982]
Observations	30,858	30,858	30,858	30,858	30,858	30,858
Mean	0.164	0.412	0.745	0.737	0.749	0.697

*Note:* Controls for mean oil price and GDP per capita in the wife's year of birth, linear time trend, average rainfall at the state and wife's year of birth, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Wife's birth years 1980 through 1991. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The final set of results focusing on married couples show no significant relationship between the global gold price in the wife's year of birth and either spouse's acceptability of the husband beating the wife for various reasons.

**Table 2.8: Couple: Beating**

Panel A: Women					
VARIABLES	(1) Goes out without telling husband	(2) Neglects the children	(3) Argues with husband	(4) Refuses sex	(5) Doesn't cook properly
Mean gold price	-8.54e-05 (0.000175) [0.952]	2.04e-05 (0.000188) [0.952]	0.000134 (0.000185) [0.901]	7.55e-05 (0.000161) [0.952]	5.09e-05 (0.000176) [0.952]
Observations	30,712	30,711	30,669	30,609	30,729
Mean	0.272	0.337	0.304	0.142	0.197
Panel B: Men					
VARIABLES	(1) Goes out without telling husband	(2) Neglects the children	(3) Argues with husband	(4) Refuses sex	(5) Doesn't cook properly
Mean gold price	-0.000193 (0.000136) [0.53]	-0.000164 (0.000159) [0.621]	-0.000203 (0.000151) [0.535]	-8.21e-05 (0.000101) [0.656]	-8.82e-05 (0.000112) [0.656]
Observations	30,715	30,715	30,661	30,661	30,744
Mean	0.152	0.194	0.196	0.0819	0.0973

*Note:* Controls for mean oil price and GDP per capita in the wife's year of birth, linear time trend, average rainfall at the state and wife's year of birth, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Wife's birth years 1980 through 1991. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

These results show that women and men who are born in years with a higher mean global gold price are less likely to have sorted into marriage by 2015 (though the youngest individuals would be 24 given the time period, which is well within expected marriage age in India), and have lower weight and BMI. Among couples, the global mean gold price in the wife's birth year is not significantly related with the degree of hypergamy. There is some evidence of a negative relationship between global gold price in the wife's year of birth and health outcomes for both wives and their husbands. There are no significant relationships between global gold price in the wife's year of birth and the wife's or the husband's education, though there is a negative relationship with the likelihood that the husband worked in the last twelve months. Most notably, women born in years with a higher mean global gold price are less likely to have ever had an abortion or use contraception. After adjusting for multiple inferences in the analysis related to couples, the most notable long-run results are these related to fertility behavior.

Since the relative differences in age, education, and height (an indicator of early childhood human capital investments) are not significantly related to the global gold price in the wife's birth year, the patterns in household decision-making do not seem to be driven by initial sorting on the marriage market on these metrics.

## **2.6 Conclusion**

Gold has played an important cultural role and source of investment for Indian households for centuries. In this paper, I first document the relationship between global gold price in the year of birth and sibling composition. I find a negative relationship between the global gold price in year of birth and the number of siblings overall for girls, but not for boys. Holding fixed the number of siblings, I find a negative relationship between the global gold price in year of birth and the number of brothers for both boys and girls,

sisters for girls, and a positive relationship with the number of younger sisters for boys. I also find that the global gold price in the year of birth is negatively associated with the probability of being the youngest child overall for girls.

Given the broader literature on the role of sibling composition and birth order on health, labor, mortality, and marriage patterns, I also document long-run empirical relationships between gold price in year of birth and household decision-making. When these cohorts are adults, I find a negative relationship between global gold price in year of birth and likelihood of being married and overall health indicators. Among those married, after multiple inference adjustment, I find a negative relationship between the global gold price in year of wife's birth and likelihood that she has ever had an abortion or that she uses contraception. This could either denote less decision-making power over fertility or a desire for a larger family size.

Other mechanisms to explain the long-run results include direct sex ratio differences in cohorts due to disproportionate female fetal and neonatal mortality, and broader household resource allocation due to fluctuations in the gold price. I cannot fully separate these mechanisms with the available data.

Taken together, these results suggest that gold prices could have significant and long-lasting impacts on households. Given the cultural norms surrounding gold purchases in India, the impacts of global gold prices are further-reaching than a direct impact on the amount of gold that households might choose to purchase. More broadly, these results suggest that the price of commodities which hold cultural significance could have broader economic impacts than a simple demand elasticity might suggest.

# Chapter 3

## What you get is what you (can) see: Publicly Observable Signals of Generosity and Effort of Healthcare Providers

### 3.1 Introduction

A growing literature on the economics of health and development documents evidence of the low quality of healthcare received by households in developing countries (National Academies of Sciences and Medicine, 2018; Das et al., 2008).<sup>1</sup> Low quality of care continues to be a major contributor to the global burden of disease either indirectly, when patients do not recover from treatable illnesses in a timely manner due to inappropriate or inadequate care, or directly when poor quality care leads to worse health (such as medical errors and iatrogenic deaths) (National Academies of Sciences and Medicine, 2018; Das et al., 2018).<sup>2</sup>

One problem with quality of health care, especially in rural developing country settings, is that clinical aspects of quality can be unobservable or unknown to patients at the time of care due to information asymmetry problems (Arrow, 1963; Das and Hammer, 2014). Patients might be able to infer quality ex-post based on their recovery from ill health after receiving care, but such learning is difficult in primary care settings

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<sup>1</sup>When submitted for publication, this article will be coauthored with Manoj Mohanan. The data for this project was collected as part of another study by Manoj Mohanan, who also contributed to framing the paper. Nivedhitha Subramanian framed the research question, designed the empirical strategy, conducted the analysis, and drafted the paper.

<sup>2</sup>Quality of care is an especially daunting challenge in settings like Bihar, India, where this study was conducted. Bihar is one the poorest states in India, with health and development indicators that are among the lowest in the country. According to India's latest NFHS survey data in 2015-16, the under-five mortality rate in the state was 58 per 1000 live births (IIPS, 2017). Healthcare practitioners in the state have been shown to have low levels of knowledge about how to treat common medical concerns and also perform inadequately when diagnosing and treating patients (Mohanan et al., 2015).

where many illnesses (such as viral infections) might be self limiting or if other health behaviors are equally important determinants of recovery in addition to appropriate pharmacological treatment. Under such settings, providers might have fewer incentives to exert effort to provide care that is clinically appropriate but not observable to the patient and instead divert effort to tasks that are observable to the patient. Indeed, even in developed country settings, patients are less likely to sue providers who have better bedside manners (Tamblyn et al., 2007) and they also report higher satisfaction when prescribed antibiotics that are not strictly necessary (Martinez et al., 2018).

Providers' performance is driven by a number of factors. Evidence from studies that introduce peer observers to induce Hawthorne effects find that the quality of care delivered improves when providers know they are being observed (Leonard and Masatu, 2006, 2010a,b). Similarly, studies of performance incentives find that adequately high powered incentives can induce providers to deliver higher quality care and improve health outcomes (Miller and Babiarz, 2014). Furthermore, providers might be driven by reputational concerns even when there are no direct financial returns to quality improvement (Kolstad, 2013). The wide range of factors driving provider behavior also makes it challenging to study this behavior and to develop interventions to deliver higher quality of care, especially in rural areas of the developing world.

In this paper, we study the behavior of rural healthcare providers and the quality of care provided by them using a unique combination of datasets from rural Bihar in India. We analyze data on providers' clinical effort both when they are aware that they are being observed and also when they are unaware of being monitored (during audit visits by standardized patients), combined with data from a lab-in-field experiment that induced publicly observable signals of generosity. Our analysis suggests that providers who signal higher generosity in publicly observable experimental settings also exert higher clinical effort with patients when they know that they are being monitored, but they exert similar amounts of effort with unannounced standardized patients. Thus

providers in settings such as ours (rural areas with informal sector providers delivering primary care) could be motivated by reputational concerns that drive the patterns of care reported in the literature such as overprescription of unnecessary drugs. It is important to consider this motivation when designing policies to improve quality of healthcare provision in developing country settings. Furthermore, similar to the empirical results on Hawthorne effects in studies of provider quality, our results suggest that relying on methods that are observable to the provider could yield upwardly biased estimates especially among providers who are most concerned about reputation.

## 3.2 Context

The question of how to motivate high quality of care is particularly important in developing country settings, as households in such settings face generally low quality of healthcare. Households in India have access to many healthcare options within reasonable distances of their homes (Das et al., 2008), and healthcare makes up a significant proportion of the regular household budget in these settings (Banerjee et al., 2004). However, households mostly have access to *low quality* healthcare, across the socioeconomic spectrum (Das and Mohpal, 2016). Very few healthcare providers serving rural and low-income populations in India are actually qualified to provide medical care. In our sample of private healthcare providers in rural Bihar, only about 4% of providers had an MBBS, which is comparable to other rural contexts in northern India (Das et al., 2016).<sup>3</sup> Furthermore, there are high rates of absenteeism - providers often are not physically in their facility at the times when the facility is supposedly open (Banerjee et al., 2004; Chaudhury et al., 2006).

When providers are accessible, the interactions between providers and patients are brief. In our sample, when providers do not know that they are being observed, interac-

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<sup>3</sup>MBBS: Bachelor of Medicine, Bachelor of Surgery; this is the formal medical degree in India.

tions between the provider and the patient are less than 2 minutes. This is comparable to estimates for other parts of India (Das et al., 2008). During such brief exchanges, healthcare providers rarely ask the correct questions to be able to accurately diagnose conditions (Das et al., 2008). Given such oversights, providers are unsurprisingly unable to accurately diagnose conditions very common in the area (Das and Hammer, 2004b). Thus, treatment is often incorrect: overprescription of IVs, injections, and antibiotics is commonplace in such settings (Banerjee et al., 2004; Das and Hammer, 2004a; Mohanan et al., 2015).

An important component of quality of care is whether healthcare providers exert the optimal level of effort with patients. However, in many healthcare systems, doctors don't have the correct incentives to do so (Miller and Babiarz, 2014). Even when providers know correct procedures, there is evidence (including in the setting studied in this paper (Mohanan et al., 2015)) that providers do not follow these procedures with their patients, exhibiting a "know-do" gap (Das et al., 2015).

A growing literature seeks to understand how to incentivize healthcare providers to provide optimal quality of care (Miller and Babiarz, 2014). This literature has studied both the importance of agency over one's own work and financial incentives, finding mixed results. In developed country contexts, there is empirical evidence that doctors overprescribe treatments, procedures, and brand-name drugs when it is profitable for them, but also that providing physician report cards was found to better incentivize improvement in care than financial incentives (Feldstein, 1973; McGuire, 2000; Johnson, 2014; Johnson and Rehavi, 2016; Crea et al., 2019; Kolstad, 2013). In a developing country context, empirical evidence in India suggests that there is a quality premium in prices - private providers who provide palliative treatments, *unnecessary* treatments, and have higher qualifications are able to charge patients higher prices (Das et al., 2016). Furthermore, the same study finds that the same providers exert more effort with patients in their private clinics than their public health facilities. Providers' ef-

fort improves with monitoring in Tanzania (Leonard and Masatu, 2006). A subset of providers in this setting are “professional” in that they consistently maintain high levels of communication with patients; these providers are just as likely to work in centralized or decentralized sectors (i.e. public versus private) - facing very different incentives for providing high quality of care (Leonard and Masatu, 2010a).

Provision of healthcare can include a pro-social component, and there is evidence that pro-social motivation is required to ensure that healthcare providers exert the optimal level of care (Brock et al., 2015). Lagarde and Blaauw (2014) report evidence of pro-socially motivated nurses who demonstrate higher generosity to patients in dictator games are more likely to choose rural jobs.

This paper seeks to understand the motivations of healthcare providers by exploring the relationship between healthcare provider generosity and quality of and effort in healthcare provision. To answer this question, we use a unique dataset of healthcare providers in rural Bihar, India. We use a lab-in-field experimental game to elicit a measure of generosity - defined here as the amount of money that the healthcare provider chooses to donate to a locally active NGO in the game.<sup>4</sup> The results from the generosity game are combined with measures of healthcare provider effort, and treatment/diagnosis accuracy. We provide evidence that reputationally motivated healthcare providers in rural Bihar, India are likely to improve performance when monitored. They value being held in high regard by their patients and their community, and this desire to be held in high esteem is correlated with the exertion of more effort with patients.

Crucially, we are able to measure healthcare provider effort and quality when providers do and do not know that they are being observed. If healthcare providers in this setting are motivated at least in part by reputation, then we should see that those who donate outside amounts to the local NGO should exert significantly more effort with

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<sup>4</sup>This generosity could be related to altruism, intrinsic motivation, or other forms of pro-social motivation, but we do not seek to identify those separate effects (Andreoni, 1990; Ariely et al., 2009).

patients than their peers when they *know* that they are being observed, but not necessarily so when they *do not know* that they are being observed. We do find that those providers who exhibit high levels of generosity to a health-related NGO in the area also exhibit high levels of effort when they know that they are being observed. However, when these providers do not know that they are being observed, measures of provider generosity are largely uncorrelated with provider effort.

### 3.3 Data

Our analysis relies on four sources of data that were collected in 2014-2015 as part of a study of private healthcare providers and social franchising models of healthcare delivery in rural Bihar, India.<sup>5</sup> We rely on (a) surveys of providers that include information on provider characteristics, demographics, qualifications and infrastructure, as well as knowledge of providers as reported on case vignette interviews; (b) direct observation studies where enumerators observed providers for an entire business day and recorded data on care provided; (c) data from standardized patients, where highly trained enumerators present standardized cases in audit study visits to measure provider performance; and (d) data from a generosity lab-in-field game where providers could make donations to a local charity.

The sample of providers in our study is representative of providers in rural areas of Bihar, where few providers have formal medical degrees and most are informal sector providers. In our sample, as shown in Table 1, about 4% of providers have an MBBS degree, and about 13% have a BAMS degree.<sup>6</sup> Almost all (94%) of providers practice

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<sup>5</sup>The Bihar Evaluation of Social Franchising and Telemedicine project, funded by the Bill and Melinda Gates Foundation, studied provider quality and the effect of introduction of telemedicine and social franchising based business models to deliver care in rural areas of Bihar. Mohanan et al. (2016a).

<sup>6</sup>MBBS is the basic formal medical degree for training in allopathic (western) medicine in India; it stands for Bachelor of Medicine, Bachelor of Surgery, and is equivalent to the MD in the US. BAMS (Bachelors of Ayurveda, Medicine, and Surgery) is a degree awarded after training in Ayurveda - the

allopathy (Western medicine) even if they have no formal training.<sup>7</sup> These providers, almost all of whom are in private practice, reported that they had 17 years of experience and see 14 patients per day on average, ranging from one patient to 63 patients across providers. The providers charge on average 75 Indian Rupees (INR) as a consulting fee, earning an average of 525 INR per day.<sup>8</sup>

The sample of providers in our analysis comes from the telemedicine evaluation study in Bihar that was designed to estimate the quality of care that households in the study area receive when they utilize healthcare for common conditions. As such, rather than sampling providers randomly within the universe of providers in the study area, the study enrolled providers who were reported to be the most commonly visited providers by a large representative set of households in the study cluster. These clusters are distinct from administrative boundaries such as villages, blocks, or districts. Given the objective of the original study to evaluate the impact of telemedicine and social franchising business models, the study cluster areas were defined as a central village which had access to high speed internet connectivity and was located on or near major road networks, with surrounding villages that were sufficiently geographically close. Study clusters typically covered a population of about 10,000 households. Within each of these clusters, a random sample of 64 households were asked to list all healthcare providers that they visited in the last six months. The five most frequently named providers in each cluster were then selected for follow-up data collection. Our final data from 80 study clusters where the project collected data on provider performance includes information on 377 providers.<sup>9</sup>

The provider quality surveys were conducted between June and December 2014.

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Indian system of medicine.

<sup>7</sup>Alternatives to western medicine include Ayurveda and homeopathy.

<sup>8</sup>These averages come from the provider observation data, rather than providers' self-reports.

<sup>9</sup>For further information on study clusters and sampling of providers (Mohan et al., 2015, 2016a,b)

The providers were first approached for survey interviews, where information regarding their age, educational background, experience, and facilities, were collected. At this point, they also consented to receiving follow-up visits from enumerators to conduct vignettes, provider observations, in addition to visits from standardized patients, as described below.

By combining data from provider observation visits with data from unannounced standardized patient visits, we are able to assess measures of performance and provider effort where the providers *do* and *do not know* that they are being observed. For provider observation, enumerators observed the providers' practice on an unscheduled visit - recording the patient caseload, demographics of patients, and also observing the provider-patient interactions to ascertain the amount of time spent with patients, types of questions asked, examinations conducted, and types of treatment provided or prescribed. This measurement method yields the type and level of effort that providers exert when they are aware that they are being observed. Second, the research team conducted an audit study using unannounced standardized patients (SP), presenting specific tailored cases of a father whose child is presenting symptoms of diarrhea or pneumonia, to measure quality of treatment when the provider does not know they are being observed.<sup>10</sup> The SP methodology elicits what the providers actually do, when they *do not know* that they are being observed. Importantly, by standardizing and controlling the cases that the providers see in the SP methodology, the researcher is able to measure whether the provider accurately diagnosed and treated the patient.

One constraint with the SP method is that SPs can only be deployed in clinic locations with a sufficiently large patient volume such that new patients (SPs) would not be conspicuous by their presence and the provider might suspect that they are part of

<sup>10</sup>In rural Bihar, it is not uncommon for a parent, typically a father since women traditionally stay within the home due to cultural norms, to seek care on behalf of a child who is unwell at home. The SP case of a parent of an unwell child has been developed and implemented successfully in a number of previous studies and settings in Bihar and elsewhere (Das et al., 2015; Mohanan et al., 2015; Sylvia et al., 2015).

the research team. As a result, the sample size for SP based measures of provider effort is lower than for the provider observation data. Within the set of providers where the SP methodology could be carried out, providers were randomly selected to receive either the diarrhea case or the pneumonia case. This sample is similar to the full sample across the main descriptive variables<sup>11</sup>.

In a separate visit which was conducted in June 2015 (a year after the provider surveys), enumerators conducted a generosity game with the providers.<sup>12</sup> The generosity lab-in-field game was played in the consulting room of the health care provider's facility - most providers' facilities were basic with either just one room that had no privacy or even in settings where the clinic had a separate examination room, the surveys and interviews were conducted in the main consulting area that is public. While the game was intended to be private, in practice, the game was often observed by patients or local passers-by. The lab-in-field game was originally intended to be played as a private game where provider donations are unobservable. However, like most surveys in rural India, the arrival of enumerators bearing a survey instrument invariably attracted onlookers and members of the community. Consequently, social norms of survey interviews being conducted publicly resulted in the generosity game being implemented with community members observing the process.

The game was structured in the following way: The enumerator introduced the game after completion of an in-person survey about adoption of the telemedicine / franchising model when it was promoted in their area during the preceding years. As compensation for their time for responding to the survey, providers were given 100 INR

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<sup>11</sup>See Appendix 6

<sup>12</sup>The follow up visits were conducted as part of data collection for the evaluation of the social franchising program. The generosity game were conducted as part of an effort to collect information on factors that could explain providers' decision to adopt the telemedicine franchise model. The game was developed and implemented by Manoj Mohanan, Marcos Vera Hernandez and Pau Olivella as part of the telemedicine evaluation project.

in denominations of 10 INR, before beginning the game.<sup>13</sup> This amount is under 20% of what an average provider would earn in a day's work. The enumerator then offered the providers an opportunity to make a charitable donation to Smile Train - an NGO very active in the region<sup>14</sup>. Smile Train serves children born with cleft lip to provide free reconstructive surgery. Since the NGO is active locally, the providers were already very aware of this organization and the work that it does. A key reason for choosing Smile Train as the beneficiary in this generosity game was that a charity providing free surgical care to children born with cleft lip would be particularly salient to healthcare providers. The enumerator then reminded the provider of the 100 INR given to them and gave the provider an envelope that they could place any cash (or none) if they wish to donate to Smile Train. Although enumerators were trained to specify that the amount they wish to donate is private information and they should place any amount (or none) privately and return a sealed envelope to the enumerator, in practice most providers made the donation publicly often declaring the amount of money donated to the enumerators. The enumerator then collected the envelope and the donated amounts of money were then transferred to Smile Train. The summary statistics for this measure are included in Table 3.1. The mean amount donated to Smile Train is 105 INR - meaning that the average provider in the sample donated almost the entire amount that they received as compensation for survey participation, approximately 20% of daily income, to Smile Train.

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<sup>13</sup>100 INR was about \$1.57 in 2015, when the game was conducted.

<sup>14</sup><https://www.smiletrainindia.org/>

**Table 3.1: Summary Statistics**

	Full Sample					
	N	mean	sd	min	p50	max
Age	377	42.966	10.653	22	42	74
Years of experience	377	17.239	10.066	0	16	45
MBBS (%)	377	.04	.196	0	0	1
BAMS (%)	377	.127	.334	0	0	1
Has other degree (%)	377	.088	.283	0	0	1
Practices allopathic medicine	377	.944	.23	0	1	1
Practices ayurveda, homeopathy, or unani (AYU)	377	.255	.436	0	0	1
Work hours	377	61.228	19.084	10	63	98
Number of patients	377	14.523	9.973	1	12	63.333
Works in a gov facility	377	.005	.073	0	0	1
Sells medicine	377	.629	.484	0	1	1
Infrastructure index	377	-.053	1.321	-1.246	-.38	16.264
Consulting fee	377	63.92	43.003	0	50	256
Donation to Smile Train	377	105.082	91.632	0	100	600
Donation over 100 INR	377	.244	.43	0	0	1

Notes: All rows provide summary statistics for the providers and their facility which we observe in this study. In order, the rows are age, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, an infrastructure index, the amount of donation to Smile Train in the experimental game, and whether that donation was above 100 INR. The infrastructure index is predicted from a principal components analysis of the following facility features: whether or not the facility has electricity, whether the facility has a power backup, the number of consulting rooms, the number of beds for day observation, whether the facility has a laboratory to provide tests, whether the facility can conduct X-rays, and whether the facility has a computer system. Barring the variables on donation to Smile Train, all variables were measured in September and October 2014. The variables on donation to Smile Train were measured in June 2015.

### 3.4 Empirical Strategy

The objective of our analysis is to explore the relationship between healthcare provider generosity as measured in the lab-in-field generosity game and providers' effort in healthcare, specifically to test whether providers who donate more in the publicly observable generosity game setting exerted different levels of care when they were aware of being observed compared to when they were unaware of being observed. We first

explore patterns in donations made by providers in the generosity game, and then correlate observed donations to measures of provider performance. We rely on an OLS model in our main analyses. In the provider observation data (measuring effort, when providers know that they are being observed), we observe multiple provider-patient interactions for each provider. Thus, this model takes the provider-patient interaction as the unit of observation. Equation 3.1 is used for a set of outcome variables measured at the provider-patient interaction level: including length of visit in minutes, whether a physical examination was conducted, whether immediate treatment was given, etc.

$$y_{ijd} = \beta_0 + \beta_1\gamma_{id} + \beta_2\zeta_{id} + \Gamma X_{id} + \Lambda K_{ijd} + \delta_d + \varepsilon_{ijd} \quad (3.1)$$

Here,  $j$  refers to the particular patient for provider  $i$ , while  $d$  denotes district. The variable  $\gamma_{id}$  refers to the provider's result from the generosity game - this indicator variable is equal to 1 if the provider donated strictly greater than 100 INR to Smile Train. We use 100 INR as the cutoff as it indicates that the provider donated money out of pocket, rather than just from the compensation they received for participating in the survey. The  $X_{id}$  refers to a vector of covariates capturing provider characteristics: age, age squared, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, and an infrastructure index. Summary statistics for all covariates are presented in Table 3.1. We also include a vector of covariates  $K_{ijd}$  denoting the age and gender of the patient  $j$ . The regression includes a district fixed effect ( $\delta_d$ ) to account for any differences in healthcare markets across districts. Finally, this model includes a control for the number of patients that

the provider saw on the observation day, denoted  $\zeta_{id}$ . Standard errors are clustered at the provider level, to account for within-provider correlation in treatment of individual patients.

The standardized patient data (measuring effort, when providers do not know that they are being observed), is defined at the provider level. Thus, we take the provider as the unit of observation for these regressions. Equation 3.2 is used for a set of outcome variables measuring diagnosis and treatment effort and accuracy, for either the SP diarrhea or SP pneumonia case to which the provider was randomly assigned.

$$y_{ikd} = \beta_0 + \beta_1\gamma_{id} + \beta_2\eta_{ikd} + \Gamma X_{id} + \delta_d + \omega_k + \varepsilon_{ikd} \quad (3.2)$$

Here,  $i$  denotes the provider,  $d$  denotes the district, and  $k$  denotes the enumerator who posed as the SP. The diarrhea and pneumonia cases are pooled into the same regression, and we include a control variable ( $\eta_{ikd}$ ) indicating whether the outcome is measured from the diarrhea case. This model includes a SP fixed effect ( $\omega_k$ ) for each of the enumerators who trained and posed as patients, to account for any differences in how specific individuals presented the cases. All standard errors in this model are bootstrapped, to account for small sample size.

Finally, we include an OLS model of the relationship between the price of the visit (in INR), and characteristics of the provider and the visit, run at the provider-patient visit level. These regressions are run on two samples: the provider observation sample (where the provider knows that they are being observed) and the standardized patient sample (where the provider does not know that they are being observed). The specification is as follows:

$$\rho_{ijd} = \omega_0 + \Gamma X_{id} + \Lambda W_{ijd} + \delta_d + \varepsilon_{ijd} \quad (3.3)$$

Here,  $i$  refers to the provider,  $j$  refers to the provider-patient interaction, and  $d$  refers to district. The outcome of interest is total charge to the patient, in INR.  $X_{id}$  is a vector of provider/facility level characteristics. In both samples, this includes whether the provider has an MBBS, provider's age, and whether the facility is open at night.  $W_{ijd}$  is a vector of provider-patient interaction level characteristics. In the provider observation sample, this includes the length of the visit in minutes, whether an injection was given, whether an IV was given, whether written documents were provided, whether instructions were given, whether a physical examination was conducted, whether the provider gave treatment during the visit, the number of medicines dispensed, and whether the patient was a child and/or female. In the SP data, this vector includes the length of the visit in minutes, the number of medicines dispensed, whether any treatment was provided during the visit, whether any explanation was given, and whether the treatment was correct. In both samples, fixed effects for the district are included, and standard errors are bootstrapped. In the standardized patient sample, SP fixed effects are also included.

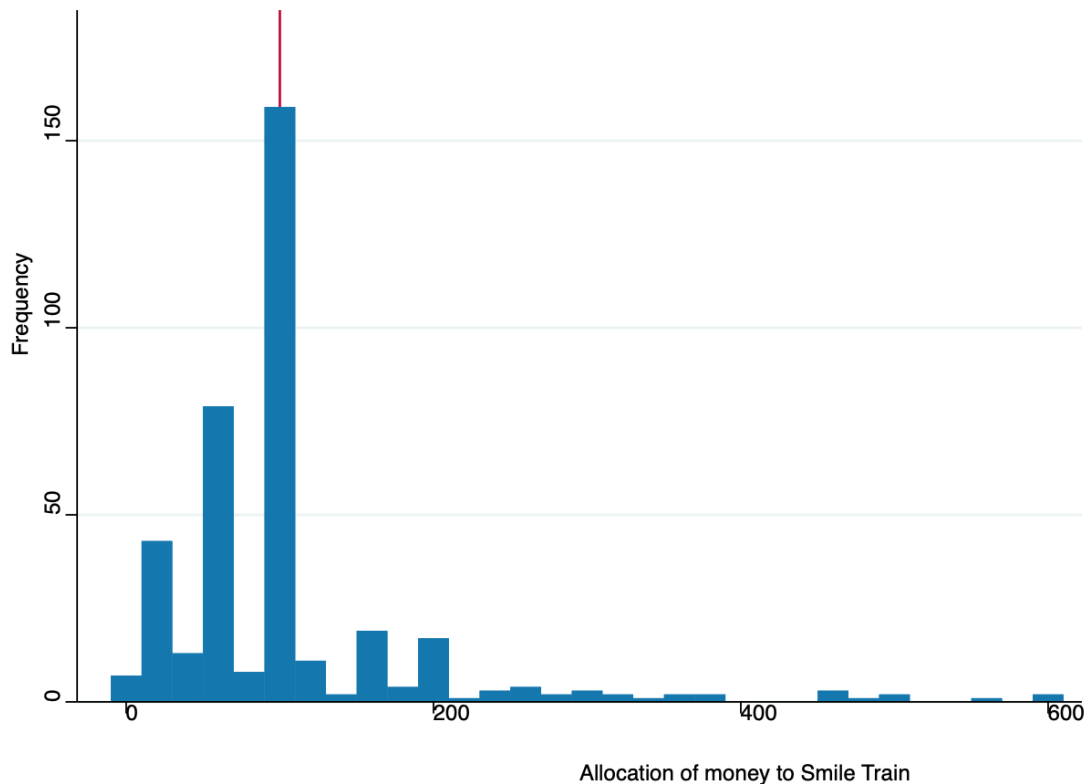
### 3.5 Results

Figure 3.1 shows the distribution of providers' donations to Smile Train in the generosity game. As described earlier, the providers were given 100 INR in cash as compensation for their time to participate in the provider survey about telemedicine adoption prior to introducing the generosity game, and asked how much they would like to donate to Smile Train in the generosity game itself. The histogram shows that the bulk of responses were right at or above 100 INR. In fact, the median response was 100 INR and 24% of providers gave strictly more than 100 INR to Smile Train, meaning that they gave additional money out of pocket. The largest donation was 600 INR - which is more than the average provider earns in a single day. The large relative sizes of

these contributions raise the question of whether these donations are purely altruistic or whether these donations responded to other factors. Although the generosity game was designed to be implemented with undisclosed amounts of donation, in practice there were several onlookers who watched the surveys and games being implemented. The potential for biased responses due to social desirability and bystander effects has long been a concern in survey research on sensitive topics (Krumpal, 2013; Nederhof, 1984). Notes from the field suggest that providers were behaving in this way to demonstrate their generosity to bystanders. Smile Train is very active in the area and providers were familiar with the NGO and its work. All providers could have readily donated money to Smile Train at any other point in time without being prompted by the enumerator. However, Smile Train reported to us that they have not received donations from rural healthcare providers in Bihar.<sup>15</sup> Thus, the donations made in this generosity game were likely driven at least in part due to posturing, rather than purely by altruism, to help bolster reputation as a caring provider.

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<sup>15</sup>The director of communications and business development for Smile Train India confirmed to us via personal communication that no healthcare providers from rural Bihar have donated to their organization, barring the donation made as part of the experiment.



**Figure 3.1:** Histogram of Donations to Smile Train

*Notes:* Vertical line indicates 100 INR.

We construct an indicator variable  $\gamma_{id}$  - for whether the provider gave a donation strictly above 100 INR - as the key explanatory variable of interest for our analysis. A donation of 100 INR in a rural setting like Bihar is a noticeably high level of generosity. We start by analyzing data from provider observation, where providers are aware that they were being observed - a self-declared enumerator arrived on an unscheduled visit on a randomly selected day to observe all of the provider’s interactions with patients. The outcomes in Table 3.2 are at the patient-provider interaction level, with each column showing results from regressions that estimate providers’ effort as a function of the generosity measure, patient volume, a vector of covariates that include provider

and patient characteristics as well as district fixed effects.

**Table 3.2: Provider Observation Regressions**

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Physical examination	Written documents	Gave instructions	Immediate treatment	Minutes	Number of medicines	Number of history questions
donation_over100	0.00592 (0.0323)	0.0733* (0.0413)	0.0109 (0.0396)	0.0271 (0.0359)	0.559 (0.352)	0.188** (0.0919)	0.231* (0.122)
patients	0.00230 (0.00464)	-0.000505 (0.00354)	0.00248 (0.00313)	-0.000758 (0.00505)	-0.0964* (0.0545)	-0.00244 (0.00974)	-0.00809 (0.0143)
Observations	2,673	2,673	2,673	2,673	2,673	2,673	2,673
R <sup>2</sup>	0.128	0.336	0.059	0.129	0.047	0.071	0.080
Mean	.566	.337	.68	.288	7.648	3.582	3.011

Notes: Estimates obtained through OLS. Robust standard errors, clustered at the provider level, are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, and the following covariates: age, age squared, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, and an infrastructure index. All dependent variables are measured through provider observations conducted between August and October of 2014. The dependent variables in order presented in the table are whether a physical examination was conducted, whether the provider gave the patient written documents, whether the provider gave the patient instructions for care at home, whether the provider treated the patient immediately at the visit, the duration of the visit in minutes, the number of medicines prescribed to the patient, and the number of questions the provider asked the patient about medical history. The duration of the visit includes time that the patient might have been waiting to see the provider.

The results show that providers who donated out of pocket were statistically significantly more likely to provide written documents, ask more questions about history and prescribe more medicines. The coefficients in these regressions suggest that providers donating money out of pocket (in excess of the 100 INR they were given at the beginning of the game) were about 20% more likely to give written documents to patients, ask about 8% more history questions and prescribe about 5% more medicines, relative to the mean levels in the sample. Providers who donated out of pocket also spent about 0.56 minutes more with each patient - this estimate is nearly significant at the 10% level (p-value of 0.11). The coefficients on other measures - conducting physical exams, giving instructions on treatment, and providing treatment immediately are all positive, but are not statistically significant at conventional levels. Asking more history questions, providing written documentation, and prescribing more medications could be interpreted as exerting more effort, but these are also conspicuous types of effort that are easily observable to the enumerator in provider observation settings. As a result, it is difficult to disentangle better care from providers trying to exert effort on visible measures even if they are not necessarily productive - similar to the multi-tasking concern in contract theory. Without knowing the true condition of each of the patients, we cannot infer whether the treatment provided was the correct one, or whether provider effort was diverted to visible inputs that do not necessarily improve clinical quality of care.

The standardized patients (SP) method enables us to address both of these concerns. The cases are predefined with carefully scripted presentation of symptoms so the underlying illness and its appropriate treatment is known to researchers. Furthermore, the SPs are rigorously trained to be indistinguishable from normal patients in the area to ensure that providers are unaware that their actions are being observed by study enumerators (Das et al., 2012). For our analysis of data from SP visits, we pool the diarrhea and pneumonia cases together to focus first on correct diagnosis and

treatment in Table 3.3.<sup>16</sup> Panel A presents results for diagnosis: including whether the correct diagnosis was given, whether the provider asked to see the child, and the number of history, cause, severity, and essential questions that were asked. Panel B presents results for treatment: whether the correct treatment was given, whether oral rehydration salts were prescribed, whether counseling was given about food, and whether any explanation was given for the treatment. None of the specifications for either diagnosis or treatment are significant, and all are low in magnitude.<sup>17</sup> Panel C presents overall measures of provider performance. The Global Assessment Scale is an indicator of whether the SP felt that the provider gave him good medical care. On this purely subjective measure, providers who donated out of pocket outperformed their peers. Taken together, we see that when providers do not know that they are being observed, there are no large differences in effort between providers who do and do not donate out of pocket (more than the 100 INR originally given to them). The one exception is the subjective measurement - where SP enumerators felt that they received better overall care from the providers who donated out of pocket, relative to those who did not. This is particularly striking given that the SP data were collected nearly a year prior to the generosity game, suggesting potential differences in personalities or behavior of providers who donate more that are not picked up in measures of clinical care but correlate with providers making publicly observable donations.

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<sup>16</sup>The correct treatment for diarrhea was to only give ORS, while the correct treatment for pneumonia was antibiotics. We see in the sample that not a single provider gave the correct treatment for diarrhea (all overtreated). A higher rate correctly treated pneumonia, but this likely reflects a high rate of false positives due to the overprescription of antibiotics common in this context. We also ran the same regressions on separate samples for diarrhea cases and pneumonia cases (dropping the indicator for being a diarrhea case), and do not find significant results. Qualitatively the results are similar to the pooled results, although with half of the sample size.

<sup>17</sup>Results are robust to whether or not we classify referring the patient to a different provider as correct treatment. This is due in part to a very low rate of referrals in the SP cases.

**Table 3.3: Standardized Patient Regressions**

Panel A: Diagnosis						
VARIABLES	(1) Correct diag	(2) Asked to see child	(3) Num history Qs	(4) Num cause Qs	(5) Num severity Qs	(6) Num essential Qs
Donation over 100 INR	0.0181 (0.0338)	-0.0111 (0.0677)	0.103 (0.236)	-0.0287 (0.138)	0.0540 (0.0875)	0.0253 (0.147)
Diarrhea	-0.0455 (0.0630)	-0.243 (0.149)	-0.640 (0.515)	0.0307 (0.214)	0.554*** (0.191)	0.585 (0.425)
Observations	318	318	318	318	318	318
R <sup>2</sup>	0.152	0.214	0.270	0.225	0.220	0.185
Mean	.069	.261	3.16	1.305	.248	1.553
Panel B: Treatment						
VARIABLES	(1) Correct treat	(2) ORS	(3) Counselling about food	(4) Explanation		
Donation over 100 INR	0.0465 (0.0374)	0.0534 (0.0754)	0.0169 (0.0233)	0.00939 (0.0305)		
Diarrhea	-0.150*** (0.0548)		0.0709 (0.0513)	-0.0673* (0.0357)		
Observations	318	160	316	318		
R <sup>2</sup>	0.226	0.148	0.127	0.270		
Mean	.079	.138	.022	.940		
Panel C: Overall						
VARIABLES	(1) Global Assessment Scale	(2) Minutes				
Donation over 100 INR	0.0710** (0.0358)	0.0220 (0.0983)				
Diarrhea	-0.222*** (0.0837)	0.236 (0.204)				
Observations	316	318				
R <sup>2</sup>	0.234	0.291				
Mean	1.874	1.754				

Notes: Estimates obtained through OLS. Bootstrapped standard errors are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, standardized patient fixed effects, and the following covariates: age, age squared, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, and an infrastructure index. All dependent variables are measured through standardized patient visits to the providers between July through September of 2014. The dependent variables in order presented in Panel A are whether the provider gave the correct diagnosis, whether the provider asked to see the child, the number of questions that the provider asked regarding the child's medical history, the number of questions that the provider asked related to the cause of the illness, the number of questions that the provider asked regarding the severity of symptoms, and the number of questions that the provider asked that would be essential for diagnosis. The dependent variables in order presented in Panel B are whether the provider gave the correct treatment, whether the provider prescribed oral rehydration salts, whether the provider gave counseling about food, and whether the provider gave an explanation of the treatment. The dependent variables in order presented in Panel C are the global assessment scale: whether the standardized patient felt subjectively that the provider created an environment for a good patient-provider interaction, appeared knowledgeable, addressed the patient's worries seriously, explained the illness, and explained the treatment plan, and the duration of the visit in minutes.

Our final set of key results in Tables 3.4 and 3.5 investigate the presence of a qual-

ity premium in prices, both when providers know and do not know that they are being observed. We are unable to separate out whether the determinants of price are supply or demand driven. Instead, we examine if there are systematic characteristics of providers, clinics, and visits that are correlated significantly with prices charged. Using data from provider observation (Table 3.4), we see that providers with an MBBS are able to charge about 75% higher prices, and providers are able to charge about 25% higher for each additional medication that they dispense. However, providing written documentation to patients is associated with about 30% less in total charges, likely because these providers did not give medicines. The results also indicate that providers charge about 50% more if they give the patient an IV. At lower magnitudes, providing verbal instructions, spending an additional minute with the patient, and having a facility that is open at night are also significantly correlated with a higher total charge to the patient. Furthermore, referring the patient to another provider is associated with a 20% reduction in price.<sup>18</sup> Our findings are similar to what was reported in Das et al. (2016) and Wagner et al. (2019); there is a quality premium in prices in such settings, and that this quality premium is more pronounced with easily visible or observable measures of effort. Column 2 includes the indicator for donating more than 100 INR to Smile Train; this dampens the magnitude of the correlation with having an MBBS, and the negative correlation between price and the patient being a child is now negative, but other magnitudes and significances are largely unchanged. The coefficient on donating over 100 INR itself is not significant. While a large donation to Smile Train is correlated with more effort on average in the provider observation dataset, where providers were aware that they were being observed, they do not charge higher prices to patients.

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<sup>18</sup>Donating out of pocket did not have a significant relationship with the incidence of referrals in the provider observations data

**Table 3.4: Price Regressions - Provider Observations**

VARIABLES	(1) Price (INR)	(2) Price (INR)
Donation over 100 INR		2.165 (3.498)
Provider has mbbs	56.53*** (6.397)	44.55*** (7.419)
Age of provider	0.0590 (0.117)	0.122 (0.121)
Duration of visit in minutes	1.985*** (0.410)	2.098*** (0.459)
Injection given	4.731 (5.106)	5.512 (5.401)
IV given	38.40* (19.93)	39.96* (20.80)
Written documents	-20.79*** (3.392)	-22.89*** (3.727)
Instructions given	8.902*** (2.830)	8.514*** (2.980)
Physical examination	8.582*** (3.080)	8.353** (3.273)
Immediate treatment	6.341 (4.112)	7.850* (4.361)
Number of medicines	20.12*** (1.676)	20.53*** (1.780)
Referred to another provider	-14.78* (7.749)	-14.50* (8.385)
Facility open at night	7.154** (2.983)	9.693*** (3.170)
Public facility	-0.376 (20.74)	16.70 (29.47)
Patient is child	-4.606 (3.007)	-7.078** (3.216)
Patient is female	3.806 (3.264)	4.066 (3.482)
Constant	-17.27* (9.632)	-22.68** (10.01)
Observations	2,905	2,673
R <sup>2</sup>	0.212	0.214
Mean	73.334	73.334

Notes: Estimates obtained through OLS. Robust standard errors are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects. The dependent variable, total price charged to the patient in INR, was measured through provider observations conducted between August and October of 2014.

**Table 3.5: Price Regressions - Standardized Patients**

VARIABLES	(1) Price (INR)	(2) Price (INR)
Donation over 100 INR		-5.590 (5.902)
Provider has mbbs	28.49 (22.61)	11.23 (14.10)
Age of provider	-0.118 (0.239)	-0.0378 (0.298)
Duration of visit in minutes	8.015*** (2.138)	8.460*** (3.177)
Number of medicines dispensed	-5.743 (8.676)	0.388 (9.751)
Explanation given	67.26*** (11.74)	59.69*** (10.62)
Referred to another provider	-29.84*** (11.14)	-36.32*** (10.73)
Facility open at night	-9.789 (6.351)	-9.048 (5.955)
Correct treatment	-4.573 (8.603)	-5.160 (8.993)
Constant	5.786 (13.40)	5.799 (17.04)
Observations	379	345
$R^2$	0.249	0.246
Mean	67.977	67.977

Notes: Estimates obtained through OLS. Bootstrapped standard errors are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects and controls for whether the provider is a public provider. The dependent variable, the total price charged to the patient, is measured through standardized patient visits to the providers between July through September of 2014.

Our analysis of data from standardized patient visits, again pooling the diarrhea and pneumonia cases, shows similar results as seen earlier with provider observations. Table 3.3 shows that exerting more effort with the standardized patient (as measured by length of the visit and whether provider gives an explanation of the diagnosis/treatment) is correlated with higher total charges, as is care provided in a public facility. The coefficients for MBBS are imprecisely estimated. This is likely due to the small number of MBBS providers in the SP sample. Including an indicator for donating out of pocket in the regression (in column 2) further reduces the positive correlation between having an MBBS degree and prices charged, suggesting that the MBBS providers also donated larger amounts of money. The facility staying open at night is also correlated with slightly lower fees, almost equal in magnitude to the effect of one additional minute of visit time. Taken together, this evidence on the relationship between care provided and prices charged from standardized patient visits suggests that the premium for quality of health care in these rural primary care settings is driven by effort that is easily observable to the patient.

### **3.6 Conclusion**

This paper uses novel data on healthcare quality, provider effort, and a lab-in-field game that induced publicly observable signals of generosity to shed light on what motivates the behavior of healthcare providers in a developing country context. We use data on providers' clinical effort, diagnosis and treatment when they are unaware of being monitored during audit visits by standardized patients, as well as data collected by enumerators sitting in providers' offices to directly monitor them. Our results show that providers who make out of pocket donations in a publicly observable generosity game setting exert more effort than their peers when they know that they are being observed, but do not perform significantly differently from their peers when they do

not know that they are being observed.<sup>19</sup> We also document a quality premium in prices in this setting - providers with an MBBS are able to charge drastically higher prices, and providers are able to charge higher prices for effort that is observable to patients - both when providers know and do not know that they are being observed. However, neither correct treatment of patients (from SP data) nor large donations to Smile Train, are significantly correlated with higher prices paid by patients.

Understanding the links between motivations for healthcare providers and actual patient outcomes, is important for policies that aim to improve quality of care. Our findings suggest that reputational concerns are significant for healthcare providers in these settings, and given an opportunity to publicly demonstrate higher level of patient care, they could be motivated to improve the care they deliver. These findings also suggest supporting efforts such as quality rating and accreditation that provide patients with signals of quality and performance of healthcare providers. Furthermore, the difference in providers' performance between when they are aware of being observed and when they are not, also underscores how information asymmetry in such settings contributes to lower effort than what providers could possibly exert.

Our study also draws attention to potential problems with data on provider behavior that is collected in field settings, where bystander effects can be substantial in influencing responses. Previous research has documented the presence of Hawthorne effects when providers are observed by enumerators (Leonard and Masatu, 2006), and how such effects dissipate over a short period of time. Our findings on suggestive evidence that providers modify behavior when they are aware of being observed by potential patients point to the need for further research on this explored aspect of factors that might influence quality of care.

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<sup>19</sup>We also completed similar analysis for data from provider vignettes, which measure providers' knowledge during survey interviews where enumerators ask providers what care they would provide for specific clinical cases. We do not find differences between providers who do or do not donate out of pocket on these knowledge measures. Results are included in the Appendix.

# Chapter 4

## Appendix to Chapter 1

### 4.1 Descriptive Statistics and Balance

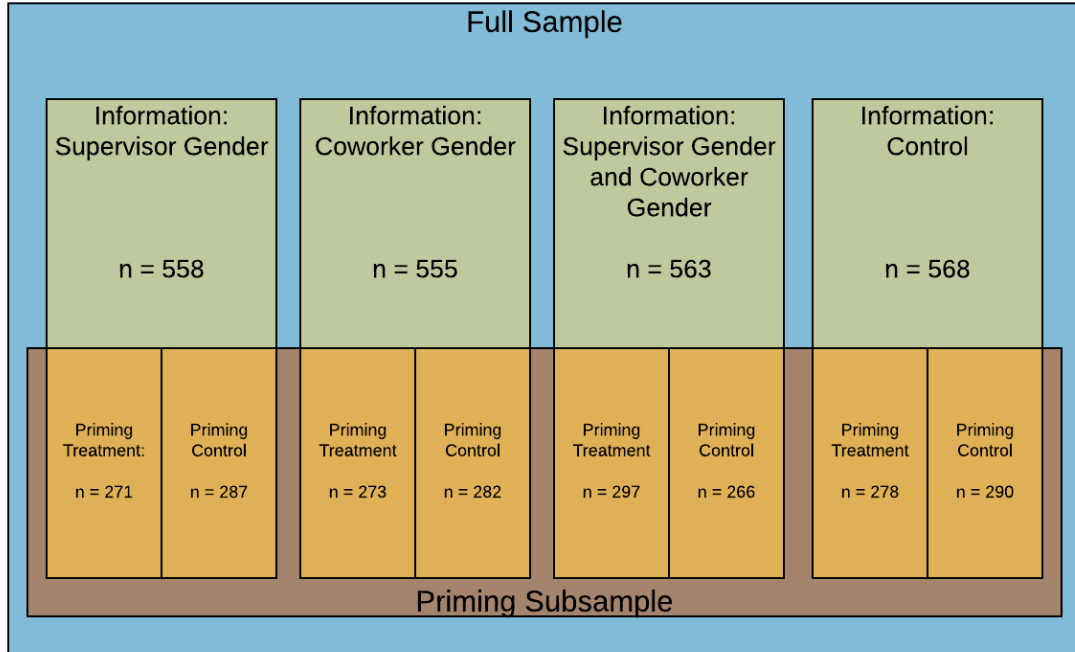
The tables below provide descriptive statistics on observable characteristics at baseline for all jobseekers, those actively using the platform before the experiment began, and those who completed the endline survey.

**Table 4.1: Summary Statistics**

Panel A: All Jobseekers						
Variable	Mean	Std. Dev.	Min.	Max.	N	
Age in years	21.714	3.861	17	59	3719	
Currently enrolled	0.762	0.426	0	1	1695	
Years of experience	0.632	1.664	0	25	4081	
At least bachelors	0.888	0.315	0	1	4027	
married	0.092	0.289	0	1	1691	
Number of Interested Occupations	3.543	2.78	0	20	4081	
Applied to any jobs on Job Asaan prior to experiment	0.086	0.28	0	1	4081	
Number of matches through Job Asaan prior to experiment	0.938	0.775	0	2	4081	
Panel B: Active Jobseekers						
Variable	Mean	Std. Dev.	Min.	Max.	N	
Age in years	22.921	4.894	17	59	856	
Currently enrolled	0.675	0.469	0	1	579	
Years of experience	1.112	2.172	0	25	998	
At least bachelors	0.914	0.281	0	1	983	
married	0.116	0.32	0	1	605	
Number of Interested Occupations	4.828	3.391	1	20	998	
Applied to any jobs on Job Asaan prior to experiment	0.352	0.478	0	1	998	
Number of matches through Job Asaan prior to experiment	1.511	0.546	0	2	998	
Panel C: Individuals who Completed Endline						
Variable	Mean	Std. Dev.	Min.	Max.	N	
Age in years	21.629	3.915	17	55	863	
Currently enrolled	0.797	0.403	0	1	364	
Years of experience	0.649	1.714	0	25	947	
At least bachelors	0.885	0.319	0	1	932	
married	0.077	0.267	0	1	375	
Number of Interested Occupations	3.421	2.776	0	20	947	
Applied to any jobs on Job Asaan prior to experiment	0.098	0.298	0	1	947	
Number of matches through Job Asaan prior to experiment	0.833	0.762	0	2	947	

*Notes:* Calculations on baseline variables.

This diagram provides a breakdown of the number of jobseekers in each cell created by the randomization structure.



**Figure 4.1:** Randomization Structure

The following tables indicate that the treatment and control groups in are similar on observables. The notable exception is years of experience, which is controlled for in analysis.

**Table 4.2: Balance**

Panel A: Information Experiment, All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Age in years	Years of experience	At least bachelors	Number of Interested Occupations	Applied to any jobs on Job Asaan prior to experiment	Number of matches through Job Asaan prior to experiment	Has endline data
Treatment: Information about Gender Composition	0.0797 (0.158)	0.190*** (0.0698)	0.00252 (0.00564)	-0.0371 (0.0809)	0.00106 (0.00202)	0.00228 (0.00202)	0.00955 (0.0200)
Treatment: Information about Gender of Supervisor	0.0577 (0.157)	0.0717 (0.0695)	-0.00136 (0.00561)	-0.0433 (0.0805)	0.000324 (0.00201)	0.000474 (0.00201)	-0.0193 (0.0199)
Treatment: Both Information Treatments	-0.0555 (0.230)	-0.0867 (0.102)	-0.00459 (0.00823)	0.0465 (0.118)	-0.00239 (0.00295)	-0.00266 (0.00295)	0.0206 (0.0292)
Constant	21.59*** (0.109)	0.523*** (0.0479)	0.889*** (0.00387)	1.990*** (0.0555)	0.0854*** (0.00139)	0.938*** (0.00139)	0.232*** (0.0137)
Observations	3,732	4,081	4,027	4,081	4,081	4,081	4,081
R-squared	0.464	0.335	0.880	0.733	0.980	0.997	0.150
Panel B: Priming Experiment, All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Age in years	Years of experience	At least bachelors	Number of Interested Occupations	Applied to any jobs on Job Asaan prior to experiment	Number of matches through Job Asaan prior to experiment	Has endline data
Treatment: Prime	-0.276 (0.231)	-0.162 (0.102)	0.00873 (0.00893)	-0.101 (0.134)	-0.00203 (0.00353)	-0.00203 (0.00353)	-0.000397 (0.0205)
Constant	23.12*** (0.157)	1.034*** (0.0694)	0.899*** (0.00611)	4.330*** (0.0915)	0.192*** (0.00242)	1.219*** (0.00242)	0.209*** (0.0140)
Observations	1,492	1,837	1,808	1,837	1,837	1,837	1,837
R-squared	0.537	0.355	0.751	0.518	0.978	0.995	0.301
Panel C: Information Experiment, Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Age in years	Years of experience	At least bachelors	Number of Interested Occupations	Applied to any jobs on Job Asaan prior to experiment	Number of matches through Job Asaan prior to experiment	Has endline data
Treatment: Information about Gender Composition	0.379 (0.407)	0.243 (0.202)	0.00210 (0.0130)	-0.341 (0.233)	-0.00995 (0.00658)	-0.00150 (0.00742)	0.0403 (0.0457)
Treatment: Information about Gender of Supervisor	0.143 (0.400)	-0.0110 (0.199)	-0.00491 (0.0129)	-0.210 (0.230)	-0.00535 (0.00649)	-0.00239 (0.00732)	0.0472 (0.0451)
Treatment: Both Information Treatments	-0.270 (0.600)	-0.197 (0.300)	0.00492 (0.0194)	0.243 (0.347)	0.0145 (0.00979)	-0.00611 (0.0110)	-0.0726 (0.0679)
Constant	22.73*** (0.267)	1.049*** (0.132)	0.914*** (0.00853)	3.561*** (0.152)	0.356*** (0.00430)	1.515*** (0.00485)	0.217*** (0.0298)
Observations	856	998	983	998	998	998	998
R-squared	0.657	0.478	0.869	0.762	0.989	0.989	0.313
Panel D: Priming Experiment, Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Age in years	Years of experience	At least bachelors	Number of Interested Occupations	Applied to any jobs on Job Asaan prior to experiment	Number of matches through Job Asaan prior to experiment	Has endline data
Treatment: Prime	-0.137 (0.443)	-0.280 (0.208)	0.00194 (0.0144)	0.266 (0.260)	0.00207 (0.00766)	-0.00276 (0.00863)	0.0207 (0.0384)
Constant	24.13*** (0.287)	1.466*** (0.137)	0.935*** (0.00955)	5.014*** (0.171)	0.548*** (0.00505)	1.625*** (0.00569)	0.219*** (0.0253)
Observations	496	638	627	638	638	638	638
R-squared	0.698	0.502	0.754	0.601	0.983	0.982	0.414

*Notes:* Calculations on baseline variables and indicator for having participated in endline survey. I reject in Column (2) of Panel A, owing to imbalance in years of experience across the gender composition information treatment. This variable is controlled for in analysis. All regressions include strata FE.

**Table 4.3: Balance: Joint Tests**

Panel A: All Jobseekers				
	(1)	(2)	(3)	(4)
	Info Gender Composition	Info Gender of Supervisor	All Info	Prime
F-stat	2.489	.306	1.274	1.265
p-value	.029	.909	.272	.277
Panel B: Active Jobseekers				
	(1)	(2)	(3)	(4)
	Info Gender Composition	Info Gender of Supervisor	All Info	Prime
F-stat	1.259	.947	1.409	.985
p-value	.28	.45	.219	.428

*Notes:* Tests of joint orthogonality of balance variables on each treatment indicator separately. Balance variables: age (in years), years of experience, has at least bachelor's degree, applied to any jobs on Job Asaan prior to experiment, and Number of matches on Job Asaan prior to experiment. Sample size for Columns (1)-(3), Panel A: 3732. Sample size for Columns (1)-(3), Panel B: 856. Sample size for Column (4), Panel A: 1837. Sample size for Column (4), Panel B: 496. We reject in Column (1) of Panel A, owing to imbalance in years of experience across the gender composition information treatment. This variable is controlled for in analysis. All regressions include Strata FE.

**Table 4.4: Distribution of Matches by Information Treatment**

Panel A: Information Experiment: Gender Composition, All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PKR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Information about Gender Composition	0.408 (0.272)	0.00515 (0.00998)	0.00151 (0.00845)	-0.178 (0.163)	0.00180 (0.00588)	-0.0449 (0.0365)	
Constant	3.659*** (1.092)	0.674*** (0.0483)	0.749*** (0.0409)	6.060*** (0.791)	0.602*** (0.0285)	-0.0250 (0.146)	
Observations	4,081	3,661	3,661	3,661	3,661	4,081	
R-squared	0.704	0.504	0.463	0.460	0.341	0.693	
Panel B: Information Experiment: Gender of Supervisor, All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PKR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Information about Gender of Supervisor	-0.113 (0.272)	0.00286 (0.00995)	0.00180 (0.00842)	-0.0320 (0.163)	0.000951 (0.00586)	-0.0205 (0.0364)	
Constant	3.913*** (1.095)	0.675*** (0.0484)	0.749*** (0.0409)	6.004*** (0.792)	0.603*** (0.0285)	-0.0347 (0.147)	
Observations	4,081	3,661	3,661	3,661	3,661	4,081	
R-squared	0.704	0.504	0.463	0.460	0.341	0.693	
Panel C: Information Experiment: Gender Composition, Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PKR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Information about Gender Composition	-0.590 (0.699)	0.0174 (0.0206)	0.0200 (0.0185)	-0.480 (0.379)	-0.00660 (0.0133)	-0.192* (0.103)	
Constant	3.528 (2.943)	0.469*** (0.0918)	0.519*** (0.0825)	10.04*** (1.686)	0.552*** (0.0591)	0.550 (0.435)	
Observations	998	958	958	958	958	998	
R-squared	0.754	0.423	0.449	0.418	0.399	0.734	
Panel D: Information Experiment: Gender of Supervisor, Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PKR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Information about Gender of Supervisor	-0.725 (0.697)	0.00755 (0.0205)	0.0250 (0.0184)	-0.436 (0.377)	-0.0229* (0.0132)	-0.000129 (0.103)	
Constant	3.672 (2.951)	0.472*** (0.0921)	0.514*** (0.0827)	10.08*** (1.692)	0.562*** (0.0591)	0.464 (0.437)	
Observations	998	958	958	958	958	998	
R-squared	0.754	0.422	0.449	0.418	0.401	0.733	

Notes: Control variables include number of occupations in which the jobseeker indicated interest, education, and years of experience. FE for randomization strata. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

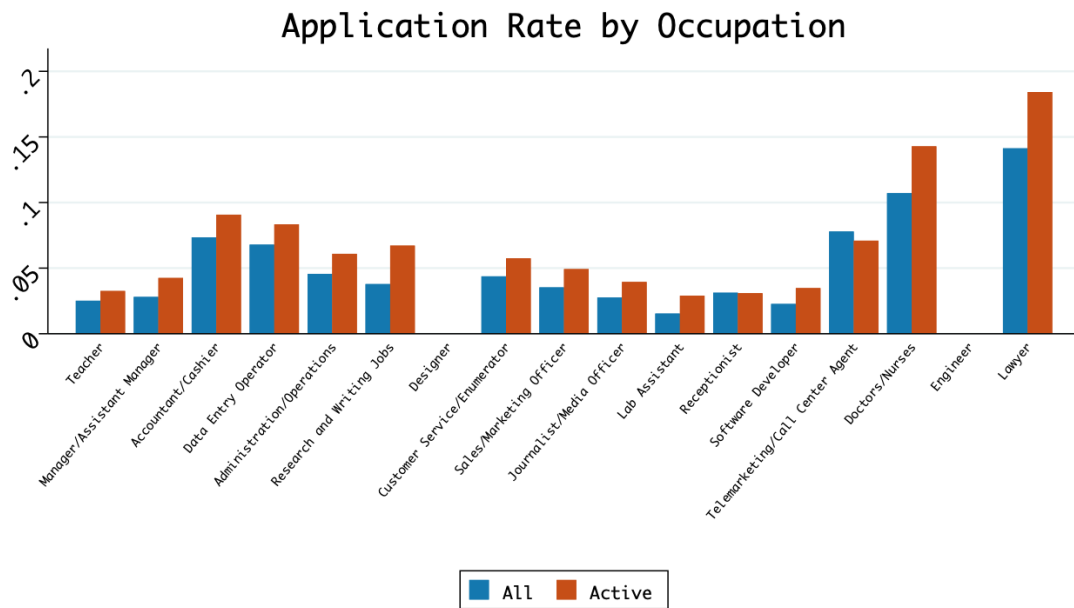
**Table 4.5: Distribution of Matches by Prime Treatment**

Panel A: Priming Experiment: All Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PRR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Prime	-0.482 (0.542)	-0.00563 (0.0151)	0.00800 (0.0140)	0.391 (0.267)	-0.00108 (0.00960)	0.0174 (0.0591)	
Constant	3.284** (1.646)	0.606*** (0.0588)	0.683*** (0.0544)	6.644*** (1.037)	0.640*** (0.0373)	-0.763*** (0.180)	
Observations	1,837	1,664	1,664	1,664	1,664	1,837	
R-squared	0.698	0.500	0.471	0.492	0.429	0.803	
Panel D: Priming Experiment: Active Jobseekers							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	
	Total Matches During Experiment	Pct of Matches with Mostly/All Female Employees	Pct of Matches with Female Supervisor	Mean Salary (in 1000 PRR) across Matches	Pct of Matches with Flexible Working Hours	Unique Occupations Matched to During Experiment	
Treatment: Prime	-2.538** (1.047)	0.0290 (0.0233)	0.0210 (0.0227)	0.0743 (0.470)	0.00545 (0.0163)	-0.134 (0.126)	
Constant	2.733 (3.723)	0.475*** (0.0892)	0.556*** (0.0868)	8.953*** (1.795)	0.557*** (0.0622)	-0.375 (0.450)	
Observations	638	620	620	620	620	638	
R-squared	0.752	0.517	0.529	0.493	0.517	0.825	

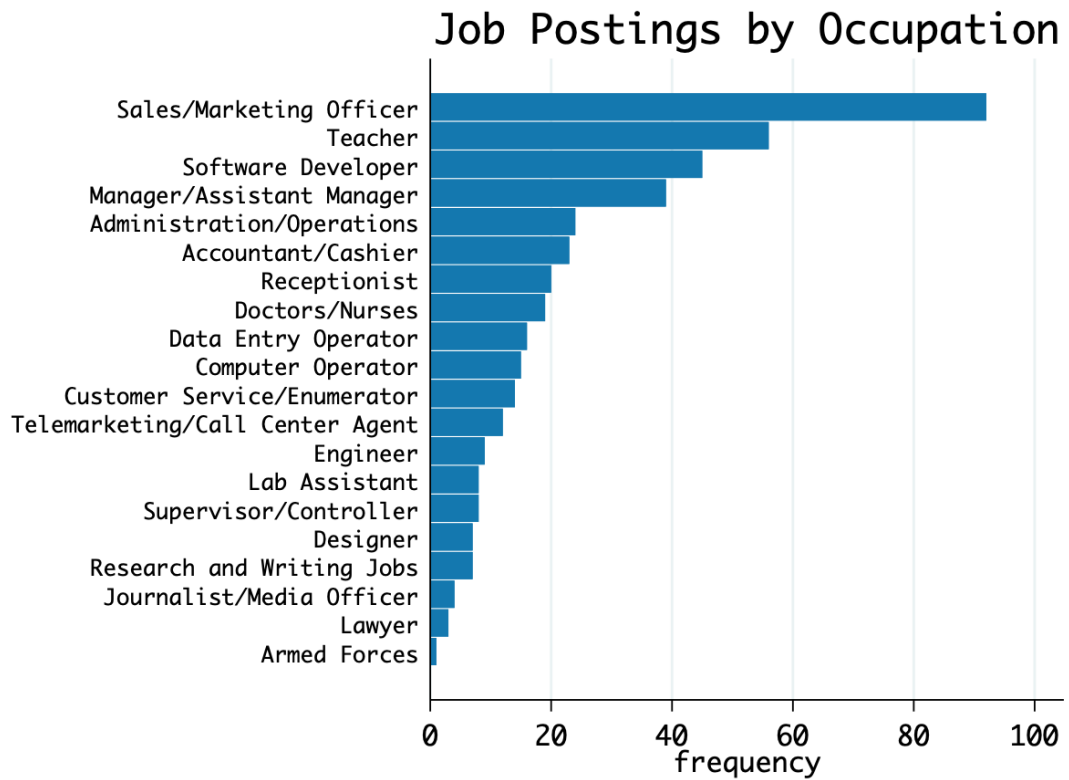
*Notes:* Control variables include number of occupations in which the jobseeker indicated interest, education, and years of experience. FE for randomization strata. Active jobseekers in the priming treatment received more matches on average than those in the control group, but this is controlled for in the application decision analysis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## 4.2 Matches and Job Postings

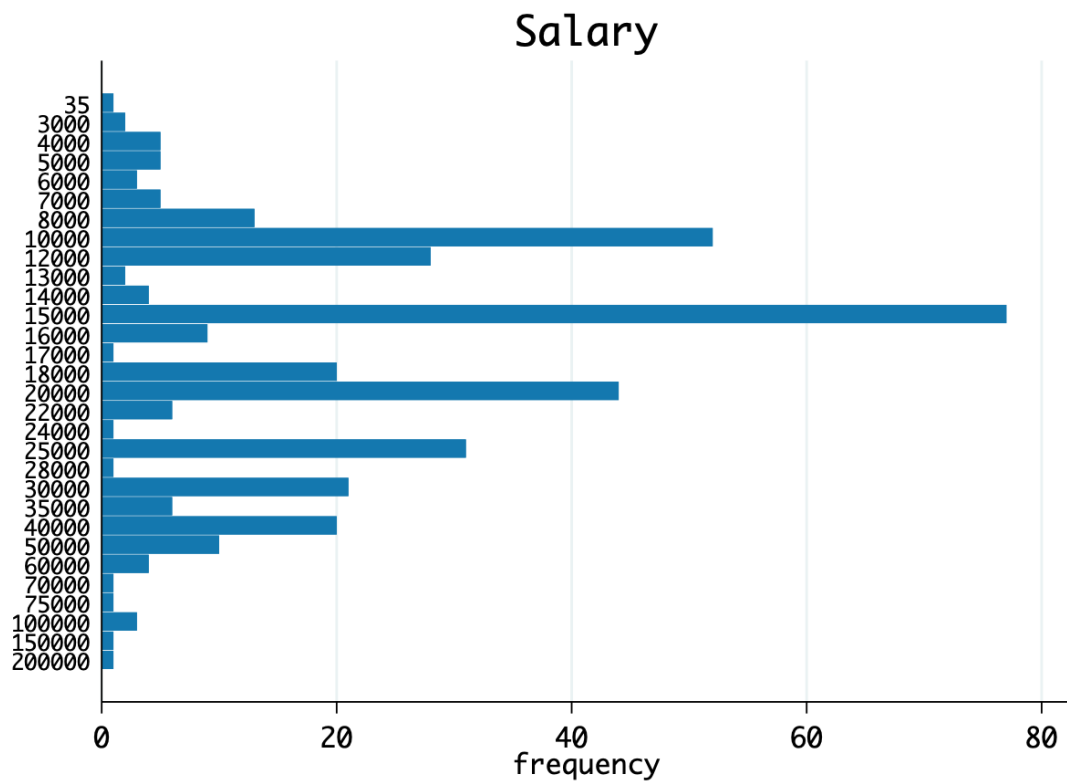
These graphs and tables provide more description about the job postings and matches on the platform.



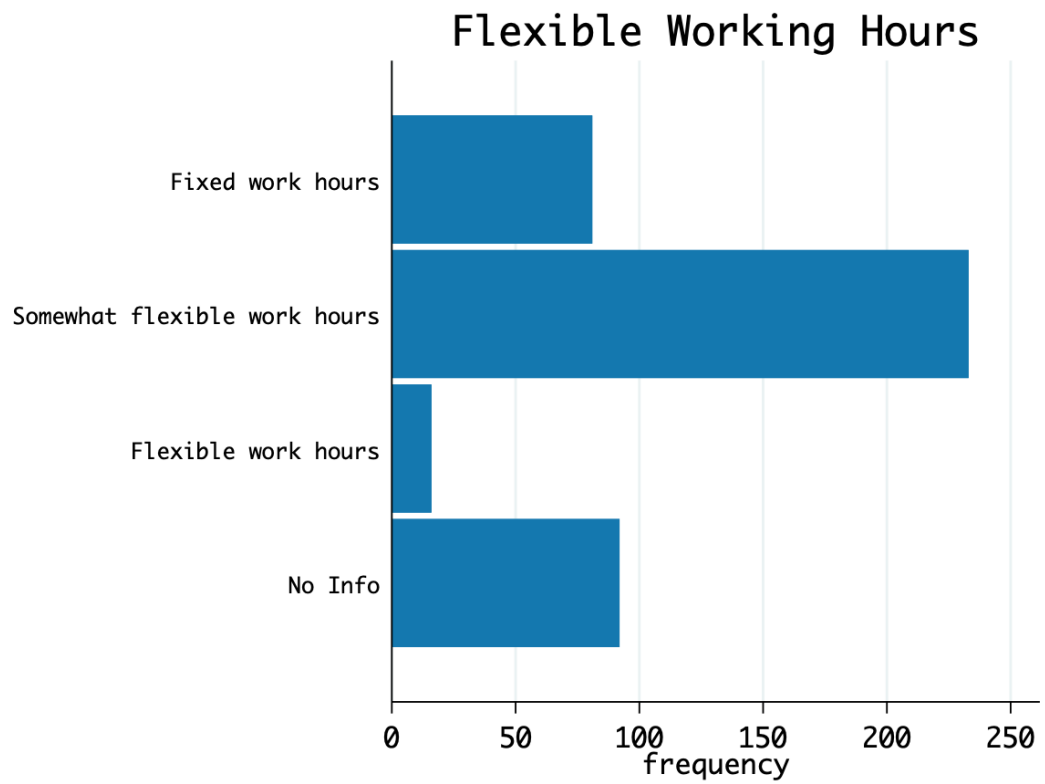
**Figure 4.2:** Percentage of Jobs Applied to, by Occupation



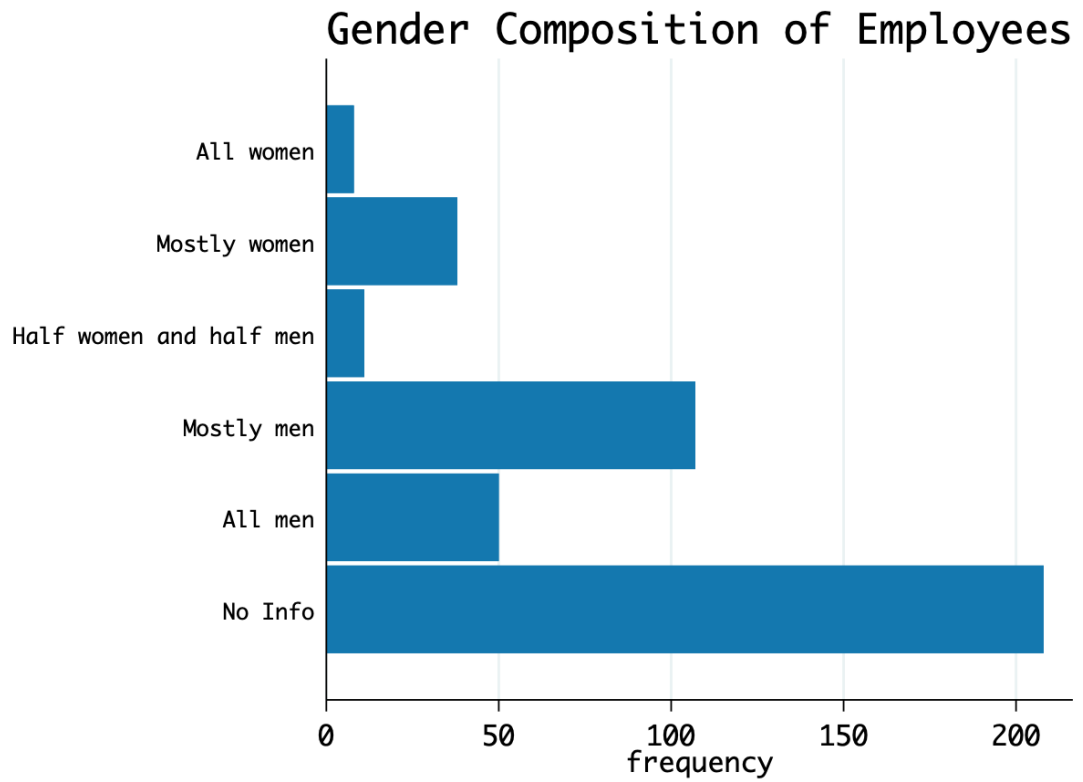
**Figure 4.3:** Occupations - Job Postings Requiring High School Diploma or Higher



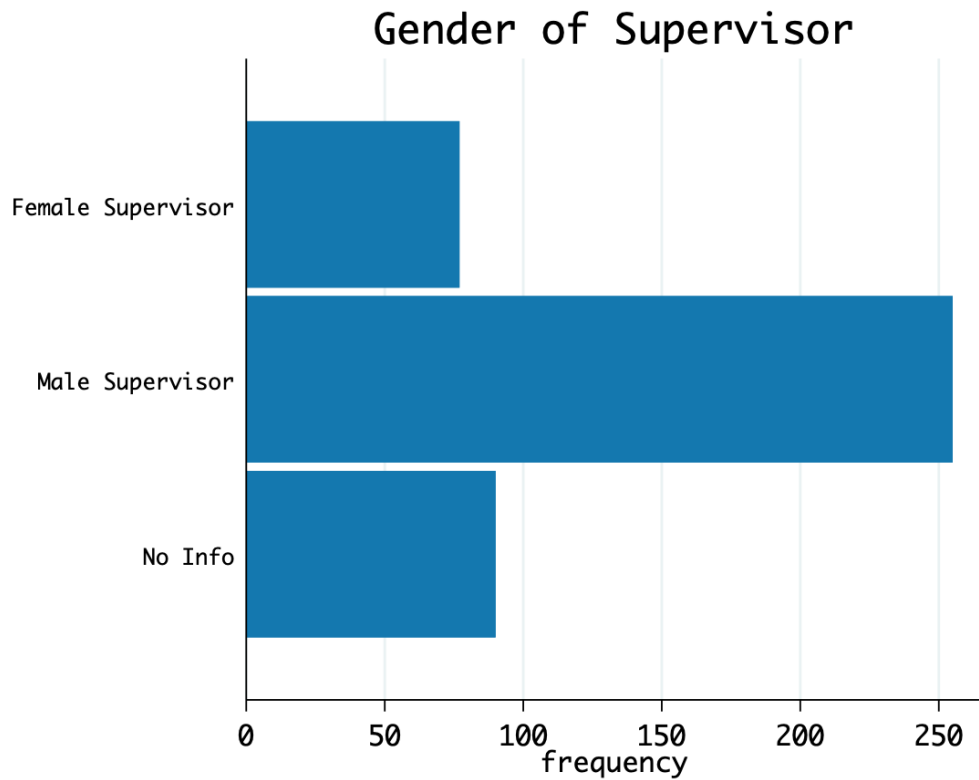
**Figure 4.4:** Salary- Job Postings Requiring High School Diploma or Higher



**Figure 4.5:** Work Hours - Job Postings Requiring High School Diploma or Higher



**Figure 4.6:** Gender Composition - Job Postings Requiring High School Diploma or Higher



**Figure 4.7:** Gender of Supervisor - Job Postings Requiring High School Diploma or Higher

This table provides results of compensating differentials analysis of the minimum salary for open job postings as a function of observable job characteristics of those job postings.

**Table 4.6: Compensating Differentials: Job Postings**

VARIABLES	(1) Minimum salary for the position	(2) Minimum salary for the position	(3) Minimum salary for the position	(4) Minimum salary for the position
All female employees	-3,358 (2,301)	-1,698 (2,365)	-3,439* (1,904)	2,318 (9,063)
Mostly female employees	-3,539 (3,044)	399.5 (3,969)	-2,047 (3,447)	1,907 (11,279)
Half female, half male employees	5,519 (3,631)	3,334 (2,793)	1,969 (6,031)	2,940 (10,030)
Mostly male employees	6,156 (4,931)	5,456 (4,593)	9,033 (6,042)	8,553 (12,318)
All male employees	-4,092** (1,440)	-3,226* (1,557)	-111.9 (3,068)	1,623 (12,078)
Male supervisor	-1,994 (4,159)	-5,272 (4,702)	-21,357*** (5,537)	-24,306** (10,305)
Female supervisor	-9,725 (5,818)	-10,545 (6,689)	-23,396*** (6,307)	-26,329*** (4,939)
Partially flexible working hours	2,021 (2,257)	3,837 (2,628)	1,836 (5,860)	2,433 (6,491)
Willing to accept applications from women	3,435** (1,638)	4,930*** (1,608)		
Sales/Marketing Officer		6,122*** (1,883)		-1,945 (12,909)
Manager/Assistant Manager		20,962*** (2,491)		13,138 (12,914)
Customer Service/Enumerator		10,580*** (3,095)		127.1 (14,821)
Telemarketing/Call Center Agent		1,373 (2,779)		-2,885 (17,832)
Data Entry Operator		-3,343 (2,557)		-1,50e-10 (3.73e-10)
Teacher		-282.2 (2,831)		-3,600 (12,400)
Research and Writing Jobs		1,750 (2,867)		3,988 (7,880)
Accountant/Cashier		3,753 (2,326)		-2,248 (8,093)
Administration/Operations		2,702 (2,229)		-2,684 (11,844)
Computer Operator		-1,610 (1,940)		
Receptionist		-2,587 (2,232)		-6,350 (7,903)
Supervisor/Controller		8,210*** (1,371)		
Lab Assistant		-4,909** (2,052)		-11,553 (12,318)
Software Developer		16,356*** (2,566)		16,946* (8,092)
Doctors/Nurses		6,754** (2,865)		5,093 (11,279)
Designer		11,920*** (2,991)		13,447 (12,318)
Engineer		12,514*** (3,336)		8,447 (12,318)
Lawyer		6,106* (3,430)		2,093 (11,279)
Journalist/Media Officer		-4,331 (2,831)		
Constant	18,505*** (2,406)	12,000*** (7.13e-09)	40,000	39,873** (14,821)
Observations	377	377	53	53
R-squared	0.109	0.328	0.138	0.361

*Notes:* Columns (1) and (2) include all job postings with salary information. Columns (3) and (4) include job postings included in the experiment with salary information. Standard errors clustered on occupation. One job omitted because it was an outlier with much higher salary than all other job postings, with a salary of 200,000 PKR/month.

### 4.3 Additional Results

This first table presents results for a simple Intent to Treat for the information experiment. There isn't a significant impact of simply being randomized to receive treatment. This is because individuals in the treatment group are sorting away from jobs without information to jobs with information about the relevant margins, and thus observably similar to the control group in overall behavior.

**Table 4.7:** Information Experiment: Intent to Treat

Panel A: Information Experiment: Gender Composition		
VARIABLES	(1) Applied for job	(2) Applied for job
Treat Info Gender Comp	0.00179 (0.00322)	-0.00186 (0.00698)
Observations	20,650	8,110
Sample	All	Active
Panel B: Information Experiment: Gender of Supervisor		
VARIABLES	(1) Applied for job	(2) Applied for job
Treat Info Gender Sup	-0.00208 (0.00333)	-0.00380 (0.00726)
Observations	20,650	8,110
Sample	All	Active

*Notes:* Includes job covariates for natural log salary, flexible working hours, occupation fixed effects, and area fixed effects. Also includes covariates for the number of matches in that round of matching, indicator for receiving calls from Job Asaan to apply for jobs (i.e. complete CV), and strata FE. SE are clustered on individual, and reported in parentheses. Mean application rate in the pure control group is 0.051 for all jobseekers, and 0.067 for jobseekers active before the experiment. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

This table presents treatment effects on beliefs about the gender composition and supervisor gender by occupation at the end of completed calls. The sample size of

individuals who stayed on the call until this point is very low, and given that many respondents are receiving few matches on each call, this analysis does not pick up significant treatment effects.

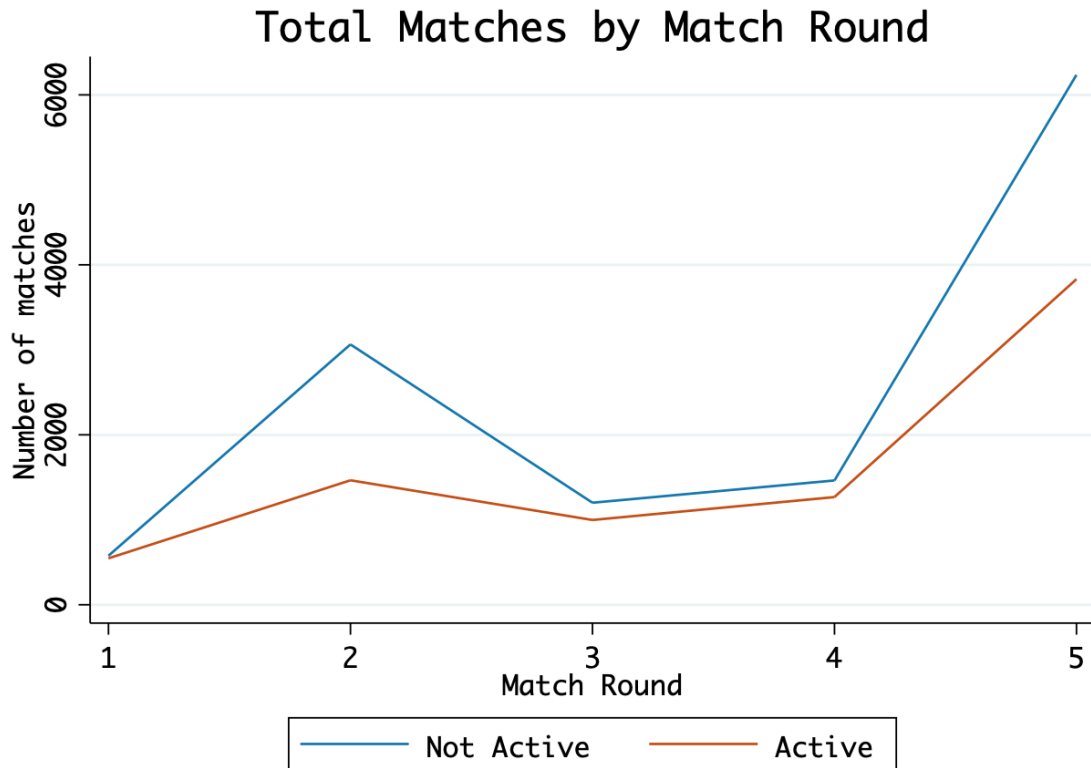
**Table 4.8: Information Updating**

Panel A: Belief about Percent of Employees that are Male, by Occupation				
VARIABLES	(1)	(2)	(3)	(4)
	gc	gc	gc	gc
Treatment: Information about Gender of Supervisor	0.230 (1.466)			
Treatment: Information about Gender Composition		-0.869 (1.603)		
Treatment: Either Information Treatment			-1.150 (1.672)	
Treatment: Prime				-1.397 (1.574)
Observations	728	728	728	693
R-squared	0.235	0.236	0.236	0.260
Panel B: Belief about Probability of having a Male Supervisor, by Occupation				
VARIABLES	(1)	(2)	(3)	(4)
	gs	gs	gs	gs
Treatment: Information about Gender of Supervisor	1.772 (1.502)			
Treatment: Information about Gender Composition		-0.560 (1.472)		
Treatment: Either Information Treatment			0.533 (1.535)	
Treatment: Prime				-0.423 (1.456)
Observations	1,164	1,164	1,164	1,127
R-squared	0.130	0.128	0.128	0.132

*Notes:* Regresses belief on treatment indicator; includes occupation fixed effects. Standard errors clustered on individual. This question was asked at the end of the call for every occupation that the individual matched to. Was only asked on completed calls. Panel A conducted on match rounds 1-3. Panel B conducted on match rounds 4-5. Standard errors clustered on individual.

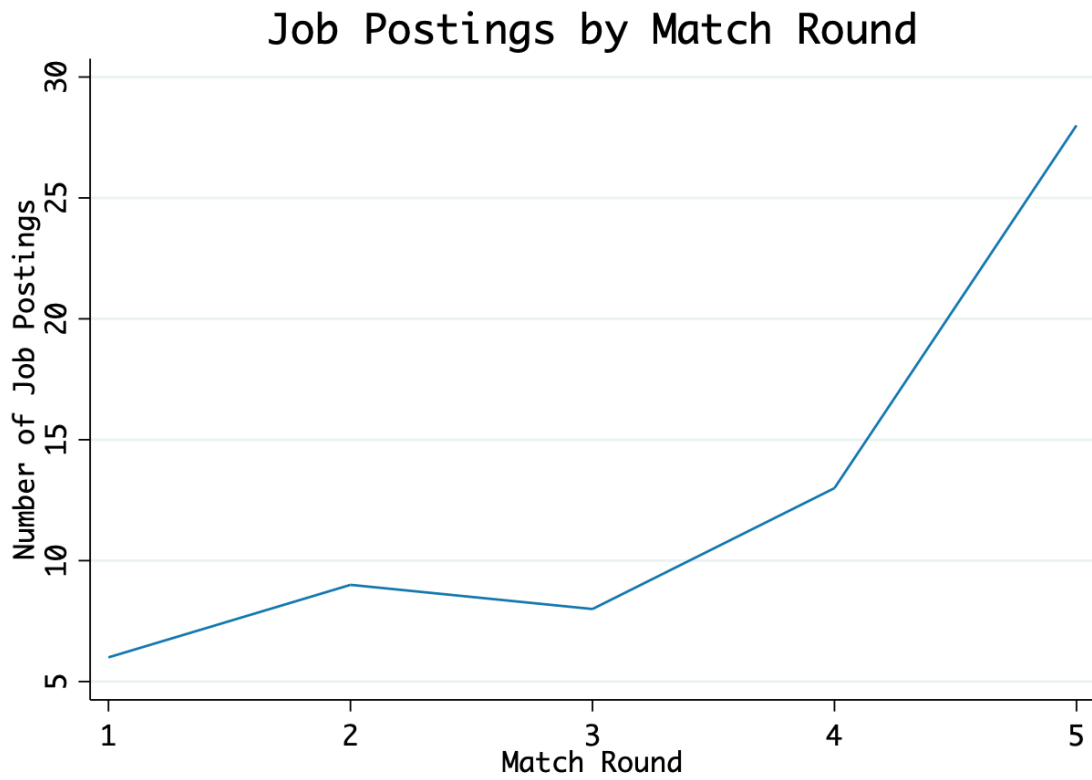
## 4.4 Matches and Application Behavior

Commensurate with the distribution of job postings over the match rounds, the total number of matches is also highest in round 5, as seen in Figure 4.8.

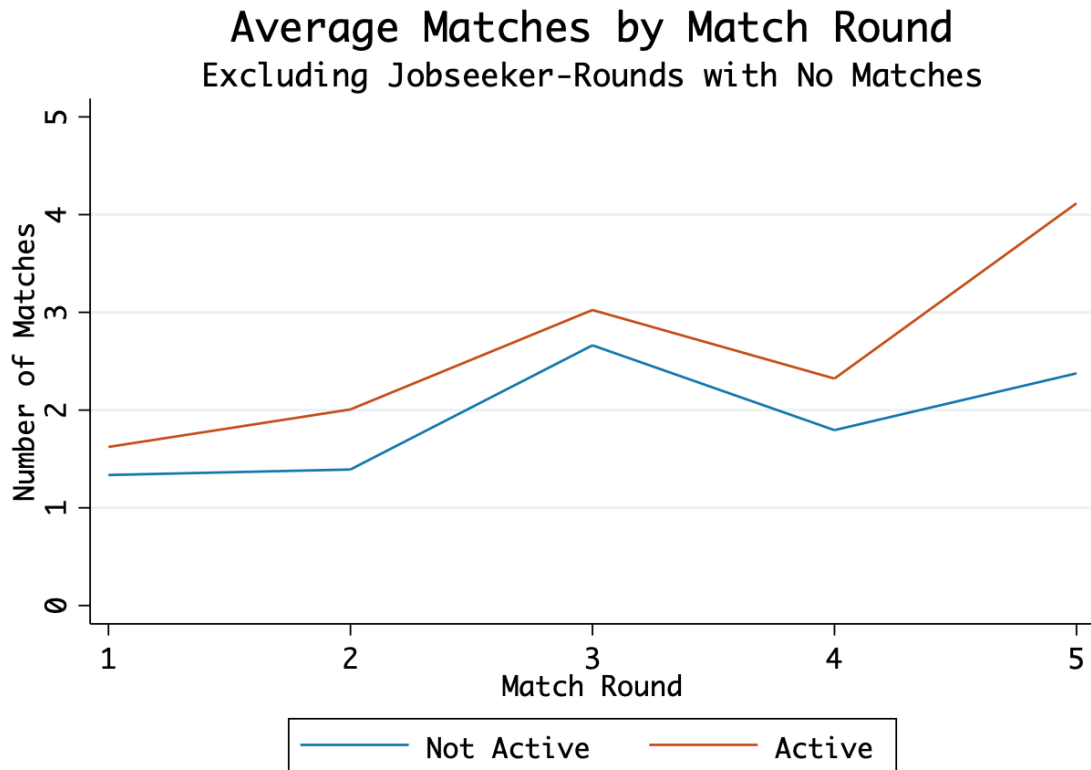


**Figure 4.8:** Total Number of Matches by Match Round

Round 2 exhibits a large number of job matches as well, consistent with the fact that there were many job postings for teachers in that round, an occupation in which about half of Job Asaan jobseekers are interested.



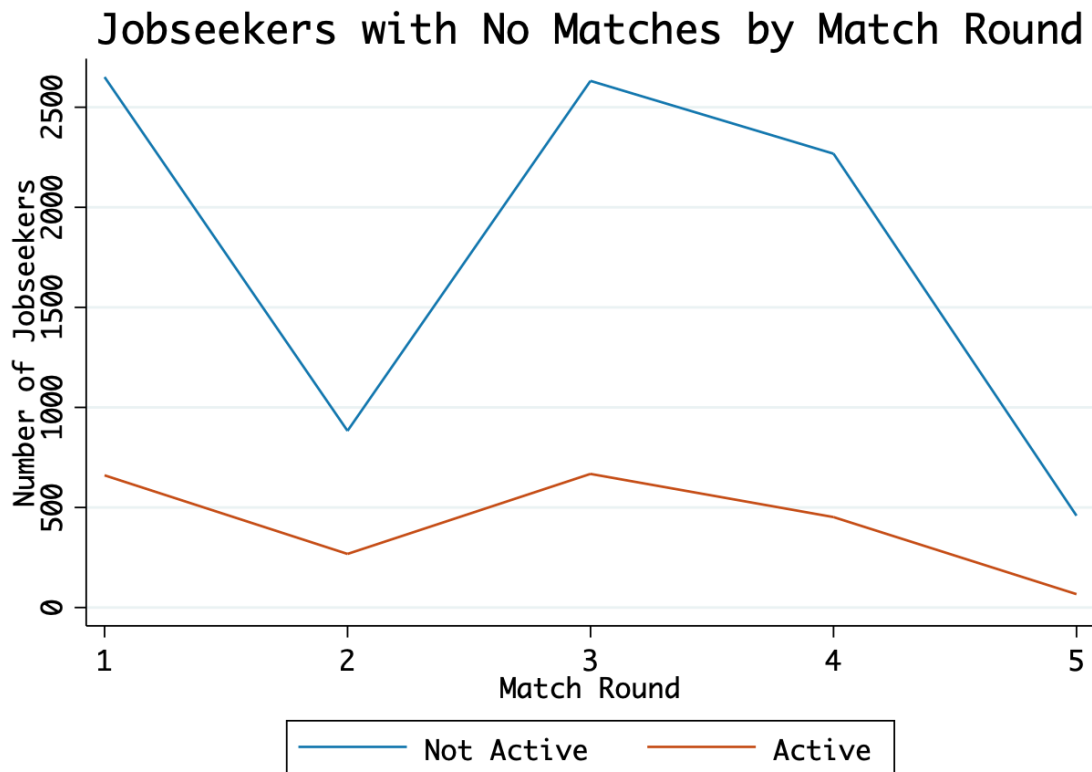
**Figure 4.9:** Number of Job Postings by Match Round



**Figure 4.10:** Average Number of Matches by Match Round

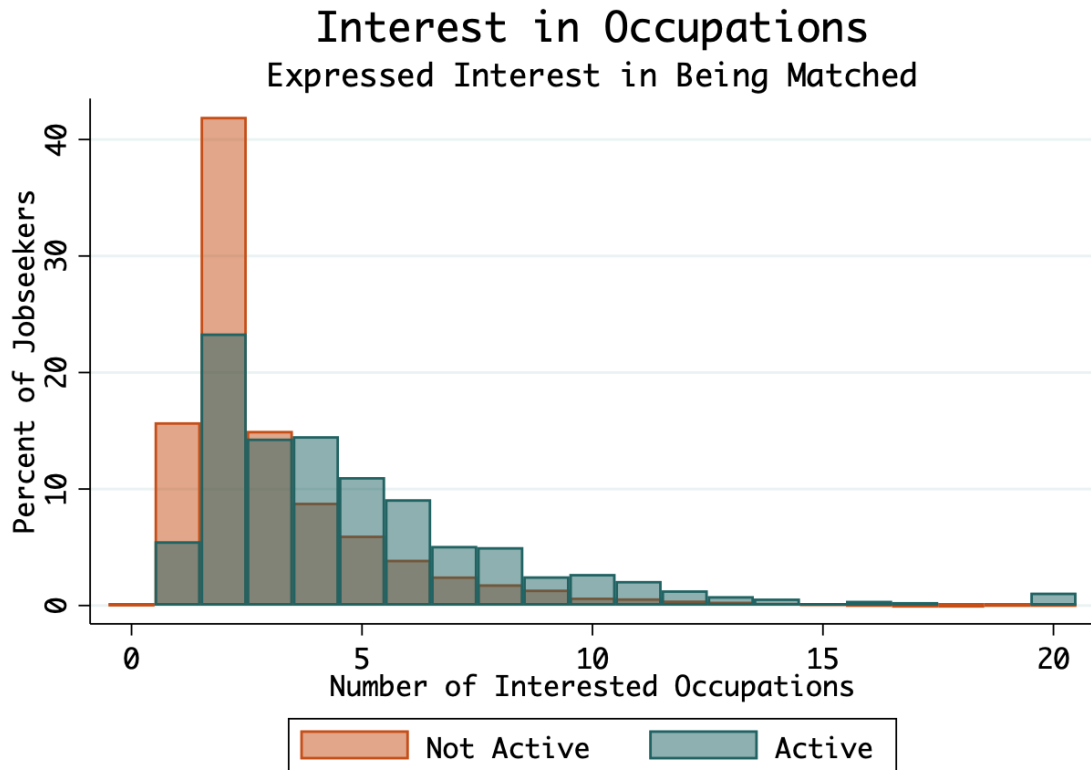
*Notes:* Excludes jobseekers with no matches in that round.

Figure 4.10 shows that the distribution of number of matches is also similar for jobseekers who were inactive or active prior to the experiment. Dropping jobseekers who have no matches in a given round, jobseekers receive on average 1-3 matches in a round, except in match round 5, where this increases to 4 matches on average, for active jobseekers. Inactive jobseekers are more likely to have received no matches in a given round, than active jobseekers, as seen in Figure 4.11.



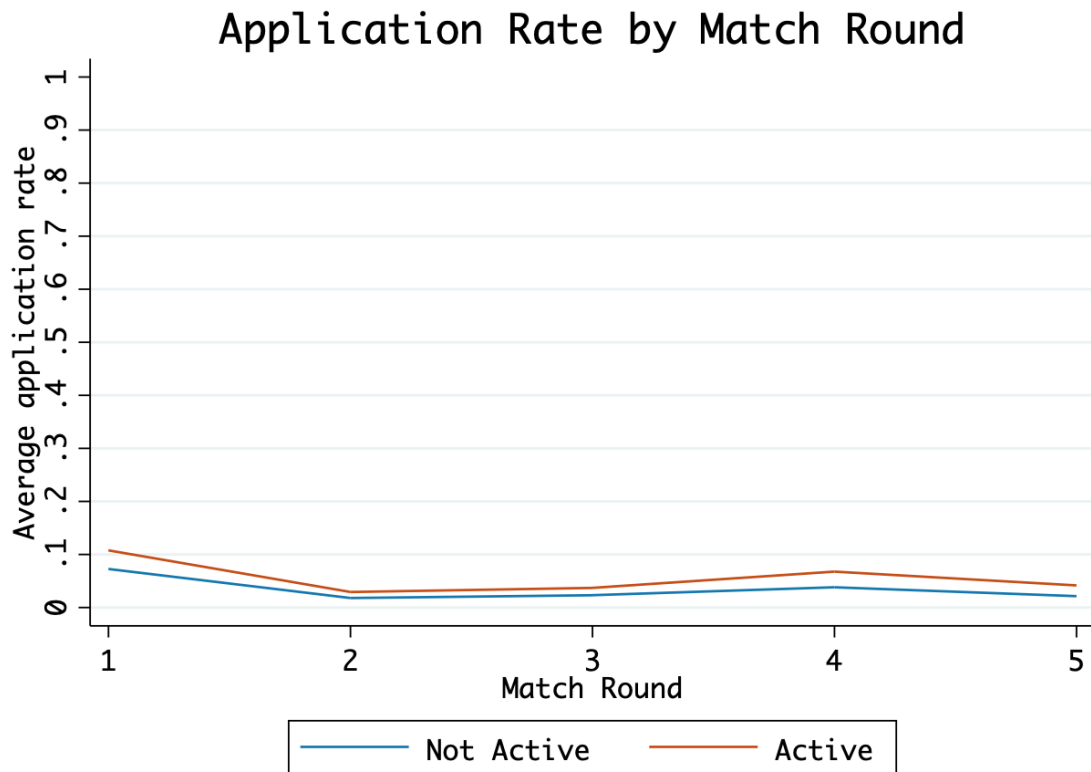
**Figure 4.11:** Number of Jobseekers with Zero Matches by Match Round

This is due in part to the fact that active jobseekers expressed interest in being matched to twice as many occupations on average as inactive jobseekers at baseline, as seen in Figure 4.12.



**Figure 4.12:** Number of Occupations in which Jobseeker Expressed Interest

Furthermore, 50% of inactive jobseekers did not express interest in being matched with any of the twenty broad occupations. Thus mechanically, they would not have matched to any jobs, as we explicitly stated to them at sign up that we would not contact them about job matches other than in occupations in which they expressed interest in matching.



**Figure 4.13:** Application Rate by Round

Regardless, the trends in application rate are similar across inactive and active jobseekers, conditional on being matched as seen in Figure 4.13. However, for every match round, the application rate during the experiment among jobseekers active before the experiment began, is higher than for jobseekers inactive before the experiment began. The highest application rate is in the first round of matching, when jobseekers also received only one to two matches in the round, on average. The application rate decreases for subsequent rounds when the number of matches is higher. This is consistent with multiple job matches either signaling a booming labor market, and thus returns to waiting and seeing the next round of matches before applying, or simply that a larger batch of matches is harder for the jobseeker to parse through.

To address whether jobseekers are behaving in a way that suggests that jobseekers are interpreting the number of matches as a signal of labor market opportunities, I regress the decision to apply to a match on the number of matches that the respondent received in that round, and an increasing set of lags for up to five rounds prior (using the number of matches in the match round previous to the experiment as the final lag). The results are reported in Table 4.9. Here, across all specifications, there is a negative association between the number of matches that the jobseeker received in the given round, and the decision to apply. However, the lagged number of matches have an insignificant statistical relationship with the decision to apply. The one exception is the second column, where fourth and fifth round application decisions are also significantly associated with lagged number of matches, though the signs vary, and the coefficients are less significant than for the number of matches in the given round. Thus, in empirical analysis of application behavior, I condition only on the number of matches in the given match round. This is consistent with the idea that a larger number of matches is harder for the jobseeker to process.

**Table 4.9: Application Rate by Number of Matches**

VARIABLES	(1) Applied for job	(2) Applied for job	(3) Applied for job	(4) Applied for job	(5) Applied for job	(6) Applied for job
Number of Matches in Current Round	-0.00376 (0.00260)	-0.00585*** (0.00158)	-0.00355*** (0.00116)	-0.00245*** (0.000915)	-0.00321*** (0.000869)	-0.00304*** (0.000630)
Number of Matches in Lag 1 Round	0.00419 (0.00411)	0.00113 (0.00334)	-0.00210 (0.00218)	-0.000665 (0.00192)	0.000452 (0.00159)	
Number of Matches in Lag 2 Round	-0.00441 (0.00921)	-0.00516 (0.00406)	-0.000306 (0.00297)	0.00103 (0.00226)		
Number of Matches in Lag 3 Round	0.00554 (0.00703)	0.00806** (0.00349)	0.00482* (0.00291)			
Number of Matches in Lag 4 Round	0.00238 (0.00673)	0.00637 (0.00502)				
Number of Matches in Lag 5 Round	-0.00377 (0.00868)					
Constant	0.0563*** (0.00825)	0.0689*** (0.00719)	0.0646*** (0.00679)	0.0565*** (0.00575)	0.0636*** (0.00587)	0.0639*** (0.00597)
Observations	3,832	5,100	6,098	7,563	8,110	8,110
R-squared	0.005	0.008	0.005	0.003	0.004	0.004

*Notes:* SE are clustered on the individual, and reported in parentheses. Sample is all matches for all active jobseekers (defined before randomization) during the five rounds of the experiment. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

## 4.5 Priors and Rankings

The rankings and priors questions were structured in the same way at baseline and endline. First, the jobseeker was asked to which occupations she was interested in being matched. She could select as many positions as she wanted, and could specify 'other' if she wanted to pursue an occupation not available on the list<sup>1</sup>. The full list of occupations is as follows:

1. Sales/Marketing Officer
  2. Manager/Assistant Manager
  3. Customer Service Officer/Enumerator
  4. Telemarketing Officer/Call Center Agent
  5. Data Entry Operator
  6. Teacher
  7. Research and Writing Jobs: Content Writer/Research Assistant/Analyst
  8. Accountant/Cashier
  9. Administration/Operations Officer/Clerk
  10. Computer Operator
  11. Receptionist/Front desk officer/Telephone Operator
  12. Supervisor/Controller<sup>2</sup>
  13. Lab Assistant
  14. Software Developer/Graphic Designer/IT Specialist
  15. Doctors/Nurses<sup>3</sup>
  16. Designer
  17. Engineer
- 

<sup>1</sup>In practice, the responses in the 'other' category fit into the preexisting categories, but were used by the jobseeker to emphasize which occupation she was most interested in.

<sup>2</sup>This type of position would oversee more blue-collar work than a Manager/Assistant Manager.

<sup>3</sup>This category is a catch-all for the medical field.

18. Lawyer
19. Journalist/Media Officer
20. Armed Forces - Police, Army, Firemen, Security Guard, etc

At baseline, the ranking questions were phrased as follows: “Which are your top 3 most preferred job titles? Please rank the following job titles.”. They were then asked for their “Most preferred (Rank 1)”, “Second most preferred (Rank 2)”, and “Third most preferred (Rank 3)” occupations. If the jobseeker had selected three or more occupations with which to be matched, she was only shown those occupations to rank. If she selected fewer than three occupations, she was shown the full list to rank.

At endline, the ranking question was reworded slightly to function better over the phone. The rankings questions were phrased as follows: “In the following list, which types of job are you most interested in?”. They were then asked “Which type of job would you be most interested in joining, from this list? (Rank 1)”, “Of the remaining jobs in the list, which would you be most interested in joining? (Rank 2)”, and “Of the remaining jobs in the list, which would you be most interested in joining? (Rank 3)”. The same filtering of occupations was applied, with the exception that if they selected only one or two occupations at the beginning of the form, they are reminded of those occupations when ranking. Finally, the order that the occupations are presented in, is randomized at endline.

For the early version of the signup form, rankings were not asked, but rather, priors were asked for six specific occupations reflecting the most common occupations that jobseekers wanted to be matched to, and the most common occupations that sought to hire women with a high school diploma or higher: Sales/Marketing Officer, Manager/Assistant Manager, Telemarketing Officer/Call center agent, Teacher, Computer Operator, and Receptionist/Front desk officer/Telephone Operator. For the small number of jobseekers who filled out this version of the signup form, the endline survey asks

them to rank these occupations, and provide their beliefs on these occupations.

In each case when beliefs are asked, the questions are structured in the following way:

1. What salary would you expect to receive each month for a job with job title XX?

Suppose that an average firm in Lahore with an opening for XX has 100 employees across all positions.

2. How many of these 100 employees would you expect to be male?
3. What is the smallest number of male employees you would expect at the firm?
4. What is the largest number of male employees you would expect at the firm?  
Across different firms, suppose there are 100 open positions for a XX in Lahore, which are all currently hiring.
5. Of these 100 open positions, how many do you think would hire a woman?
6. How many of these 100 positions do you believe will have a male supervisor?
7. What is the smallest number of these 100 positions that you believe would have a male supervisor?
8. What is the largest number of these 100 positions that you believe would have a male supervisor?

## 4.6 Control Function Estimation of Occupational Choice

This estimation requires a total of four instruments, to instrument for the four endogenous belief measures. As described in Section 1.5, the matches within occupation are exogenous to the jobseeker's behavior and choices, conditional on experience, educa-

tion, and the fact that the jobseeker expressed interest in that occupation. Thus, the number of matches by occupation is the first instrument. Next, the percent of jobs in the occupation to which the jobseeker matched with mostly or all female employees, interacted with the treatment indicator for being randomly selected to receive information about gender composition is the second instrument. The percent of jobs in the occupation to which the jobseeker matched with a female supervisor, interacted with the treatment indicator for being randomly selected to receive information about gender of the supervisor is the third instrument. Finally, the total salary across all matches in that occupation that the jobseeker received is the fourth instrument. This is taken as exogenous since the matches by occupation is exogenous to the jobseeker's decisions, conditional on her initial experience, education, and that she expressed interest in being matched to jobs in that occupation.

In the first stage, each of the four endline beliefs are regressed on the four instruments, a vector  $X_i$  which includes covariates on education and work experience (which were used to match jobseekers to job postings). Standard errors are clustered on the individual. The residuals from these four equations (one for each endogenous belief) are included as covariates in the estimation of Specification 1.12 as a second stage to implement the control function estimator. Standard errors in this second stage are also clustered on individual, and are bootstrapped as a single process across both stages. The sample for this analysis is all responses to the endline survey where the respondent provided rankings over most preferred occupations and beliefs data (described previously).

**Table 4.10: Occupational Choice: First Stages**

VARIABLES	(1) Endline Belief: Mean Salary	(2) Endline Belief: Mean Percent Female	(3) Endline Belief: Mean Prob Female Supervisor	(4) Endline Belief: Mean Prob Hire Woman
Mean Prob Mostly/all Female Employees in Matches X Treat Info Gender Comp	-5.585*** (0.959)	8.874*** (1.644)	6.111*** (1.787)	7.145*** (1.407)
Total Salary Across all Matches (1000 PKR)	0.0692*** (0.0222)	-0.0978*** (0.0362)	-0.125*** (0.0454)	-0.0763** (0.0300)
Total Number of Matches	-0.637** (0.247)	0.400 (0.360)	0.503 (0.381)	0.611* (0.331)
Mean Prob Female Supervisor in Matches X Treat Info Gender Sup	-0.884 (1.017)	3.758** (1.475)	0.231 (1.674)	0.113 (1.283)
Total Number of Matches w Any Flex Hours	-1.309*** (0.315)	2.117*** (0.571)	1.797*** (0.660)	1.512*** (0.533)
Observations	2,421	2,421	2,421	2,421
R-squared	0.061	0.059	0.028	0.039
F	25.57	18.80	7.456	11.33

Notes: Standard errors clustered on individual. Standard errors reported in parentheses.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 4.11: Occupational Choice**

VARIABLES	(1) RO Logit	(2) RO Logit	(3) RO Logit - w Control Function
Endline Belief: Mean Salary	-0.0263*** (0.00611)	-0.0288*** (0.00581)	-0.0164 (1.283)
Endline Belief: Mean Percent Female	0.0105*** (0.00294)	0.00918*** (0.00241)	0.233 (0.742)
Endline Belief: SD Percent Female	0.0151 (0.0133)		
Endline Belief: Mean Prob Female Supervisor	0.00858*** (0.00309)	0.00357 (0.00249)	-0.250 (1.107)
Endline Belief: SD Prob Female Supervisor	0.0393*** (0.0151)		
Endline Belief: Mean Prob Hire Woman	-0.0132*** (0.00287)	-0.0131*** (0.00261)	0.0101 (1.414)
Total Number of Matches w Any Flex Hours	0.112*** (0.0329)	0.108*** (0.0307)	-0.0761 (0.876)
Observations	2,267	2,421	2,421

*Notes:* Standard errors clustered on individual. First stages for control function estimates in Column (3) are reported in Appendix Table 4.10. For Mean Salary: F-stat is 25.57. For Mean Percent Female: F-stat is 18.80. For Mean Prob Female Supervisor: F-stat is 7.456. For Mean Prob Hire Woman: F-stat is 11.33. Column (3) includes bootstrapped standard errors, clustered on individual. All estimates are rank-ordered logit. Outcome variable is ranking of top three most preferred occupations. Standard errors reported in parentheses.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The results from the control function estimator are included in Table 4.11 in the Appendix. The first two columns are identical to what is presented in the main text, without controlling for endogeneity. The third column includes the analysis with the control function estimator. Table 4.10 reports the first stage estimates. Owing to the low sample size due to low response on the endline survey, the first stages are relatively underpowered. This is reflected in the second stage estimates (column 3) which have high standard errors. Overall, with the endogeneity of beliefs addressed in this specification, believing that the occupation is likely to have more women in the workplace or has a higher expected probability of hiring a woman is associated with a higher rank of the occupation. However, a higher expected salary, higher expected probability of

having a female supervisor, and greater number of matches with flexible working hours are all associated with a lower rank. These results should be interpreted with caution since the first stage is underpowered.

# Chapter 5

## Appendix to Chapter 2

### 5.1 Summary Statistics

**Table 5.1:** Summary Statistics: Women (Individual)

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>	<b>N</b>
Ever married	0.939	0.239	0	1	280024
Separated or Divorced	0.012	0.111	0	1	280024
Secondary Educ or Higher	0.587	0.492	0	1	280024
Weight in KG	51.497	10.835	15	172	261772
Height in CM	152.092	6.162	80	210.2	261701
Smoker	0.002	0.04	0	1	265435
BMI	22.214	4.263	12.02	59.95	261417
Anemic	0.525	0.499	0	1	260600

**Table 5.2:** Summary Statistics: Men (Individual)

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>	<b>N</b>
Ever married	0.759	0.428	0	1	271508
Separated or Divorced	0.009	0.092	0	1	271508
Secondary Educ or Higher	0.75	0.433	0	1	271508
Weight in KG	60.343	11.378	15.6	175	38171
Height in CM	164.068	7.257	80	229.9	38156
Smoker	0.145	0.352	0	1	39172
BMI	22.373	3.774	12.19	59.8	38132
Anemic	0.093	0.29	0	1	38018

**Table 5.3:** Summary Statistics: Wives (Couple)

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>	<b>N</b>
Ever had abortion	0.172	0.377	0	1	30858
Does not use contraception	0.406	0.491	0	1	30858
Own health care	0.742	0.438	0	1	30858
Large household purchases	0.731	0.443	0	1	30858
Decides visits to relatives	0.743	0.437	0	1	30858
Spend money husband earns	0.692	0.462	0	1	30858
Goes out without telling husband	0.269	0.444	0	1	30712
Neglects the children	0.333	0.471	0	1	30711
Argues with husband	0.298	0.457	0	1	30669
Refuses sex	0.14	0.347	0	1	30609
Doesn't cook properly	0.194	0.395	0	1	30729
Secondary Educ or Higher	0.207	0.405	0	1	30858
Literate	0.635	0.482	0	1	30858
Worked in last 12 months	0.315	0.464	0	1	30858
Weight in KG	51.8	11.057	15.8	159.5	30548
Height in CM	152.137	6.018	101.1	208.9	30547
BMI	22.323	4.331	12.21	59.45	30522
Smoker	0.001	0.03	0	1	30858
Anemic	0.532	0.499	0	1	30389
Man-Woman Age Diff	5.102	3.718	-13	29	30858
Man-Woman Height Diff	11.672	8.095	-75.900	67.8	30046
Man-Woman Years Educ Diff	1.183	4.211	-20	18	30858
Man-Woman Weight Diff	9.390	12.798	-100.6	123.5	30061
Woman earns more than Man	0.05	0.218	0	1	30858

**Table 5.4:** Summary Statistics: Husbands (Couple)

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>	<b>N</b>
Secondary Educ or Higher	0.257	0.437	0	1	30858
Literate	0.75	0.433	0	1	30858
Worked in last 12 months	0.983	0.128	0	1	30857
Goes out without telling husband	0.153	0.36	0	1	30715
Neglects the children	0.2	0.4	0	1	30715
Argues with husband	0.199	0.399	0	1	30661
Refuses sex	0.082	0.275	0	1	30661
Doesn't cook properly	0.099	0.298	0	1	30744
Weight in KG	61.247	11.79	15	175	30179
Height in CM	163.812	7.064	80	198.5	30167
BMI	22.775	3.915	12.19	59.8	30149
Smoker	0.14	0.347	0	1	30858
Anemic	0.102	0.303	0	1	30067

**Table 5.5:** Summary Statistics: Sibling Composition

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>
Youngest	0.215	0.411	0	1
Oldest	0.282	0.45	0	1
Num Siblings	3.708	2.136	0	17
Num Younger Siblings	1.895	1.661	0	15
Num Younger Sisters	0.866	1.054	0	9
Num Younger Brothers	0.929	1.004	0	11
Num Older Siblings	1.813	1.814	0	15
Num Older Sisters	0.847	1.103	0	11
Num Older Brothers	0.799	1.037	0	10
Youngest of gender	0.447	0.497	0	1
Oldest of gender	0.222	0.416	0	1
N		305142		

## 5.2 Further Mechanisms

**Table 5.6:** Male to Female Sex Ratio

VARIABLES	(1) Individual: Women	(2) Individual: Men	(3) Couple: Women	(4) Couple: Men
Mean gold price	0.531*** (0.00212)	0.517*** (0.00218)	0.528*** (0.00567)	0.528*** (0.00576)
Observations	280,024	271,508	30,858	30,858
R-squared	0.535	0.533	0.520	0.520
F	6257	5191	608	587

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Note:* Controls for mean oil price in year of birth. Controls for GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5.7: Sibling Composition**

Panel A: Girls						
VARIABLES	(1) Num Siblings	(2) Num Older Siblings	(3) Num Younger Siblings	(4) Num Younger Brothers	(5) Num Younger Sisters	(6) Youngest Sister
Mean gold price	0.000464* (0.000276) [0.088]	-0.00159*** (0.000251) [0.000]	0.00205*** (0.000236) [0.000]	0.000971*** (0.000140) [0.000]	0.00103*** (0.000158) [0.000]	-0.000228*** (7.32e-05) [0.003]
Observations	147,579	147,579	147,579	147,579	147,579	147,579
Mean	3.861	1.808	2.053	1.012	0.933	0.445

Panel B: Boys						
VARIABLES	(1) Num Siblings	(2) Num Older Siblings	(3) Num Younger Siblings	(4) Num Younger Brothers	(5) Num Younger Sisters	(6) Youngest Brother
Mean gold price	0.000604** (0.000267) [0.025]	-0.00164*** (0.000243) [0.000]	0.00224*** (0.000230) [0.000]	0.000968*** (0.000141) [0.000]	0.00109*** (0.000146) [0.000]	-0.000331*** (6.95e-05) [0.000]
Observations	157,563	157,563	157,563	157,563	157,563	157,563
Mean	3.564	1.817	1.747	0.851	0.803	0.448

*Note:* Controls for mean oil price in year of birth. Controls for GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. Westfall-Young multiple inference adjusted p-values (2000 iterations) in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5.8: Sibling Composition for Boys**

VARIABLES	(1) Youngest	(2) Youngest Sister	(3) Youngest	(4) Youngest Sister	(5) Youngest	(6) Youngest Sister	(7) Oldest Sister
Mean gold price	0.000894*** (6.71e-05)	0.000502*** (7.50e-05)	0.000951*** (6.49e-05)	0.000611*** (7.43e-05)	0.00113*** (6.51e-05)	0.000810*** (7.81e-05)	0.000293*** (6.28e-05)
Has only older sisters	-0.150** (0.0185)	-0.132*** (0.0260)					
Mean gold price X Has only older sisters	0.000349*** (9.93e-05)	0.000428*** (0.000136)					
Has only older brothers			0.0821*** (0.0221)	0.0990*** (0.0265)			0.636*** (0.0136)
Mean gold price X Has only older brothers			0.000159 (0.000117)	-5.43e-05 (0.000138)			-0.000133* (7.15e-05)
Have both older sister and brother					0.158*** (0.0207)	0.184*** (0.0229)	
Mean gold price X Have both older sister and brother					-0.000508*** (0.000109)	-0.000720*** (0.000120)	
Observations	169,994	169,994	169,994	169,994	169,994	169,994	169,994
Mean	0.248	0.497	0.248	0.497	0.248	0.497	0.505

*Note:* Controls for mean oil price in year of birth. Controls for GDP per capita at the year of birth level, linear time trend, average rainfall at the state and year of birth level, and state fixed effects. SE clustered on PSU and PSU-year group. All prices and monetary amounts are in USD, deflated to 2015 levels. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

# Chapter 6

## Appendix to Chapter 3

### 6.1 Summary Statistics

The table below provides summary statistics for coefficients and explanatory variables in the main analysis.

**Table 6.1:** Summary Statistics - Coefficients & Explanatory Variables

	Standardized Patient Sample					
	N	mean	sd	min	p50	ma
Age	318	43.176	10.473	22	42	73
Years of experience	318	17.557	9.924	0	16	44
MBBS (%)	318	.031	.175	0	0	1
BAMS (%)	318	.119	.325	0	0	1
Has other degree (%)	318	.088	.284	0	0	1
Practices allopathic medicine	318	.943	.231	0	1	1
Practices ayurveda, homeopathy, or unani (AYU)	318	.261	.44	0	0	1
Work hours	318	62.107	18.771	12	70	98
Number of patients	318	14.997	10.151	2.333	12.333	63.3
Works in a gov facility	318	.006	.079	0	0	1
Sells medicine	318	.66	.474	0	1	1
Infrastructure Index	318	-.152	.874	-1.246	-.38	6.1
Price	318	63.61	43.489	10	50	25
Donation to Smile Train	318	106.726	90.623	0	100	60
Donation over 100 INR	318	.258	.438	0	0	1

Notes: All rows provide summary statistics for the providers and their facility which we observe in this study as part of the standardized patient study. In order, the rows are age, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, an infrastructure index, the amount of donation to Smile Train in the experimental game, and whether that donation was above 100 INR. The infrastructure index is predicted from a principal components analysis of the following facility features: whether or not the facility has electricity, whether the facility has a power backup, the number of consulting rooms, the number of beds for day observation, whether the facility has a laboratory to provide tests, whether the facility can conduct X-rays, and whether the facility has a computer system. Barring the variables on donation to Smile Train, all variables were measured between July and September of 2014. The variables on donation to Smile Train were measured in June 2015.

## 6.2 Vignettes

Enumerators also conducted vignettes with healthcare providers - the enumerator described a child presenting symptoms of pneumonia and diarrhea (as separate cases), and asked the healthcare provider how they would diagnose and treat such a patient. This measures what healthcare providers know about correct diagnosis and treatment

procedures for two common conditions in the area.

**Table 6.2: Vignette Regressions - Diarrhea**

Panel A: Diagnosis						
VARIABLES	(1) Any diag	(2) Correct diag	(3) Num history Qs	(4) Num essential Qs	(5) Num cause Qs	(6) Num severity Qs
Donation over 100 INR	-0.00254 (0.0117)	0.0244 (0.0386)	0.0585 (0.277)	0.0596 (0.227)	0.0819 (0.192)	-0.0223 (0.125)
Observations	377	377	377	375	375	375
R <sup>2</sup>	0.046	0.108	0.136	0.093	0.107	0.067
mean	0.987	0.873	5.114	4.133	2.421	1.712
Panel B: Treatment						
VARIABLES	(1) Any treat	(2) Correct treat	(3) ORS	(4) Prescribed antibiotics (didn't know)	(5) Num antibiotics	(6) Treat poor patient same
Donation over 100 INR	0.00544 (0.00556)	-0.00546 (0.0209)	0.0444 (0.0345)	-0.0256 (0.0389)	0.0360 (0.0937)	-0.0155 (0.0502)
Observations	377	377	377	335	176	373
R <sup>2</sup>	0.267	0.139	0.288	0.078	0.310	0.113
Mean	0.992	0.0400	0.883	0.0990	0.955	0.794

Bootstrapped standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Covariates suppressed in table

Notes: Estimates obtained through OLS. Robust standard errors, clustered at the provider level, are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, and the following covariates: age, age squared, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, and an infrastructure index.

**Table 6.3: Vignette Regressions - Pneumonia**

Panel A: Diagnosis						
VARIABLES	(1) Any diag	(2) Correct diag	(3) Num history Qs	(4) Num essential Qs	(5) Num cause Qs	(6) Num severity Qs
Donation over 100 INR	-0.0270 (0.0263)	-0.0750* (0.0418)	-0.476 (0.341)	-0.157 (0.170)	-0.0462 (0.165)	-0.111** (0.0535)
Observations	377	377	377	376	376	375
R <sup>2</sup>	0.085	0.077	0.175	0.113	0.092	0.098
mean	0.963	0.844	4.385	1.785	1.577	0.208
Panel B: Treatment						
VARIABLES	(1) Any treat	(2) Correct treat	(3) Prescribed antibiotics (didn't know)	(4) Num antibiotics	(5) Treat poor patient same	
Donation over 100 INR	-0.00903 (0.0126)	-0.0874*** (0.0277)	0.00292 (0.0170)	0.00366 (0.103)	-0.0283 (0.0605)	
Observations	377	377	332	377	295	
R <sup>2</sup>	0.082	0.090	0.282	0.189	0.131	
mean	0.992	0.0900	0.0240	1.191	0.786	

Bootstrapped standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Covariates suppressed in table

Notes: Estimates obtained through OLS. Robust standard errors, clustered at the provider level, are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance based on p-values less than 0.1, 0.05, and 0.01. Each specification includes district fixed effects, and the following covariates: age, age squared, years of experience, whether the provider has an MBBS, whether the provider has a BAMS, whether the provider has other educational qualifications, whether the provider practices allopathy (standard Western medicine), whether the provider practices Ayurveda or other natural/non-medical treatments, the caseload on an average day (across seasons), whether the provider is a public provider, whether the provider sells medicines, an average fee for the visit, and an infrastructure index.

## Conclusion

The three chapters of this dissertation explore the role of culture and reputation in economic decisions made by individuals, households, and healthcare providers in developing country settings. The results highlight that adhering to cultural norms and maintaining community reputation can explain actions such as the types of jobs that women choose to apply to, fertility behavior and long-run household decision-making, and the effort that healthcare providers exert with patients.

In urban Pakistan, I find that cultural norms about women and men being separate influence women's job search. Educated women are more likely to apply to jobs when they have information about the gender of the supervisor, and particularly when they learn that a job has a female rather than male supervisor. However, when reminded about family job search advice, which makes cultural norms about gender roles more salient, women are more likely to apply to a job if they have information about gender of coworkers. This pattern suggests that there is a discrepancy between what women want for themselves in their jobs, and what they believe is socially desirable within their family, which impacts their job search. Job search is a first step to employment, and this result highlights that cultural norms can partially explain low rates of female employment and labor force participation in settings like Pakistan.

Gold has cultural and economic significance across India. In particular, families plan for their daughter's wedding expenses from the time of her birth, and gold is an important element of these wedding expenses. Consistent with this important role that gold plays culturally, I find a significant relationship between global gold prices in the year of birth and children's sibling composition overall, which differs by gender. Furthermore, I find that gold price in the year of birth has a negative relationship with the likelihood of being married at adulthood, and a negative relationship with health outcomes and use of contraception among married couples. This result highlights that

the cultural importance of gold could have long-run impacts on household decision-making and well-being.

Finally, in the coauthored third chapter, I find evidence in rural India that health-care providers exert effort with patients in a way which is consistent with reputation being a significant motivator for their behavior. Providers who exhibit noticeably strong publicly observable signals of generosity also exert more effort with patients when they know that they are being observed, but do not provide observably different clinical care than their counterparts when they do not know that they are being observed. This result suggests that at least a portion of healthcare providers in rural India are motivated by the idea of having a strong reputation of being generous in their community, which translates to their approach to patient care.

These three essays are set in developing countries, but the broader theme that social norms and reputation can play an important role in economic decisions is relevant across settings. The results highlight that individuals' preference to adhere to context-specific social norms should be accounted for in designing policy incentives.

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# Biography

Nivedhitha Subramanian matriculated at Duke in 2015 to begin a Ph.D. in Public Policy (Economics Concentration). Her research has been supported at Duke by the Duke University Center for International and Global Studies (2018-2020), the Brown-Nagin Graduate Fellowship (2018-2019), the Sanford School of Public Policy PhD Small Grant Award (2016-2020), and Summer Research Fellowships from the Graduate School (2018, 2019). Her dissertation research has been supported by a National Science Foundation Doctoral Dissertation Research Improvement Grant and her dissertation writing has been supported by an American Association of University Women American Fellowship. Nivedhitha's PhD was conferred in May 2020.

Prior to joining Duke, Nivedhitha earned a MA in Economics in 2013 at Northwestern University and a SB in Economics in 2010 from the Massachusetts Institute of Technology (MIT), with a minor in Applied International Studies. She previously worked as a Research Assistant on the Oregon Health Study and other projects studying health insurance markets in the United States, for Professor Amy Finkelstein at MIT/National Bureau of Economic Research. She also previously worked at the World Bank as a Research Assistant for Dr. Jishnu Das, on projects studying education markets in rural Punjab, Pakistan. Through these projects, she became interested in gender and development.